Difficulty and Complexity Definitions for Assembly Task Allocation and Assignment in Human–Robot Collaborations: A Review

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Abstract

This paper presents a literature review on the different aspects of task allocation and assignment problems in human–robot collaboration (HRC) tasks in industrial assembly environments. In future advanced industrial environments, robots and humans are expected to share the same workspace and collaborate to efficiently achieve shared goals. Difficulty- and complexity-aware HRC assembly is necessary for human-centric manufacturing, which is a goal of Industry 5.0. Therefore, the objective of this study is to clarify the definitions of difficulty and complexity used to encourage effective collaboration between humans and robots to leverage the adaptability of humans and the autonomy of robots. To achieve this goal, a systematic review of the following relevant databases for computer science was performed: IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, and ASME Digital Collection. The results extracted from 74 peer-reviewed research articles published until July 2022 were summarized and categorized into four taxonomies for 145 difficulty and complexity definitions from the perspectives of 1) definition-use objectives, 2) evaluation objectives, 3) evaluation factors, and 4) evaluation variables. Next, existing definitions were primarily classified according to the following two criteria to identify potential future studies on the formulation of new definitions for human-centric manufacturing: 1) agent specificity and 2) common aspects in manual and robotic assemblies.

Keywords: Difficulty, Complexity, Assembly, Task allocation, Task assignment, Human–robot collaboration

1. Introduction

Several developed countries have proposed concepts and implemented initiatives to develop innovative manufacturing processes, as represented by *Industry 4.0* [1] in 2011, *Industrial Internet Consortium* [2] in 2014, *Made-in-China 2025* [3] in 2015, and *Industry 5.0* [4] in 2021. In the context of related international efforts, developing human–robot collaboration (HRC) systems in industrial environments is a promising initiative in the context of international efforts [5, 6].

Recent developments under Industry 5.0 have prompted transformations from traditional system-centric manufacturing, which was driven by efficiency, quality improvements, and cost reductions, to human-centric manufacturing, placing the well-being of industry workers at the center of manufacturing processes [7].

However, approaches for creating synergies between robots and humans to improve the effectiveness and efficiency of collaborative tasks remain to be identified. To execute collaborative tasks, they must be allocated depending on the estimated feasibility of distributing resources or duties based on their difficulty and complexity. Simultaneously, the allocated tasks should be appropriately assigned to the corresponding agents; i.e., humans or robots should be appointed for a specific job, task, or responsibility. As surveyed in [8], numerous approaches have been formulated to create HRC assembly systems. Here, sequential tasks are performed continuously in the assembly line of the manufacturing process, and task assignment through smooth interaction with mutual understanding of the difficulty and complexity of individual agents is essential. We believe that the following two points are important for human-centric HRC.

1. Human workers are aware that robots can identify and perform tasks that are difficult and complex for human workers.
2. Human workers are aware that robots can appropriately entrust humans with tasks that are difficult for them to the human side.

Satisfying these conditions requires aiming for the concept shown in Fig. 1. A considerable number of definitions have been proposed, but they are not organized or categorized well to facilitate user navigation. Therefore, the motivation of this

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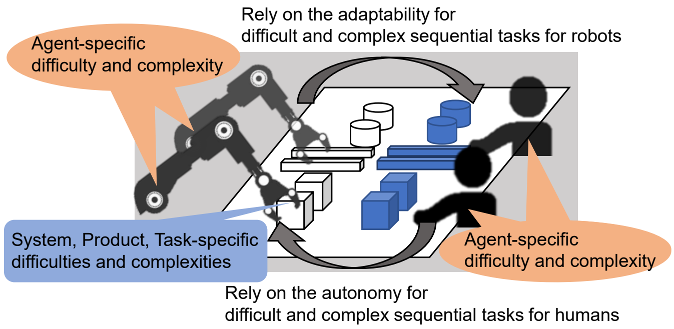


Figure 1: Difficulty and complexity-aware HRC assembly

review is to investigate these definitions, classify and organize them into taxonomies, and discuss remaining problems on difficulty- and complexity-based task allocation and assignment problems in HRC for assembly operations.

To achieve human-centric manufacturing, we not only need to investigate human-specific definitions, but we also need to clearly organize them in a manner that distinguishes them from other definitions. Therefore, the goals of this study are as follows: 1) to systematically identify relevant definitions, measures, and evaluation aspects; 2) to propose a taxonomy considering common, human-centered, and robot-specific factors; and 3) to identify emergent approaches, open issues, and challenges, in the context of HRC assembly. This study makes two contributions, as will be described in Sections 1.1 and 1.2.

1.1. Agent Specific Definitions

The first contribution is the identification of not only the common definitions of difficulty and complexity, which focus on the system, product, and task, but also agent-specific definitions for manual and robotic operations. We created a user guide by categorizing definitions into four levels: definition-use-objective, evaluation-objective, evaluation-factor, and evaluation-variable definitions. Thus, researchers investigating evaluation methods of difficulty and complexity for task allocations and assignments required in HRC assembly systems can easily access categorized definitions with reference links.

1.1.1. Comparison with Other Surveys and Reviews

This review classifies definitions in terms of research-specific objectives and calculation variables to clarify the relationships between various previous use cases. In terms of classification, this study presents the following three main differences and innovations compared to similar previous studies:

- Campbel *et al.* [9] proposed a typology and classification approach for several types of task complexities in terms of psychological experience, task–person interaction, and objective characteristics. They only focused on organizing task complexities, but unlike our organization, their organization did not include other common factors (systems and products).
- Badrous *et al.* [10] proposed a method for determining the relationships between products and assembly system complexities based on the various complexities encountered in manufacturing processes. Unlike the complexities specific to manufacturing systems and target products, this review considers not only tasks, products, and systems but also *agents* to identify the differences and similarities among a wider range of definitions.
- In 1996, Goldwasser *et al.* [11] analyzed various complexity measures, focusing on two-handed assembly sequences. Unlike the previous studies, the scope of this review was extended to include various scenarios associated with HRC assembly systems and not just two-handed assembly systems.

1.1.2. Scope of Investigations

Conventional methods address task allocation and assignment using various approaches for different objectives: transparent role allocation based on shared mental models of a human and robot [12], agent capability [13, 14, 15] or agent skill-based task allocation and scheduling [16], complexity-based task allocation [17, 18], task allocation utilizing a decision-support system [19], and task allocation based on human–robot trust model [20]. Modern approaches to task allocation and assignment have been developed based on independent hypotheses according to the application requirements. Other studies examined task allocation and assignment methods for multi-robot systems [21, 22, 23, 24]; however, multi-robot systems differ significantly from HRI and HRC systems. This study aims to analyze the prevalent approaches with a focus on understanding the current situation of difficulty and complexity definitions and outstanding HRC assembly system issues.

Difficulty and complexity have a broader range of meanings in HRC-based task allocation and assignment, because these attributes are typically derived from multiple factors. Through investigations following the procedure described in the following section, the approaches can be categorized primarily based on common, human-centered, and robot-specific factors by focusing more on the agent. To the best of our knowledge, no survey or review paper on this topic has been published.

1.2. Insights on Future HRC Research

The second contribution is a thorough discussion of emerging approaches and potential research directions for future HRC assembly systems by analyzing the results of the systematic search and differentiating common and agent-specific factors, identifying relationships between difficulty and complexity, and illustrating the co-occurrences of categorization pairs considered in previous studies.

The main focus of this review is to identify the current limitations and future prospects of agent-specific definitions rather than definitions that regularly evaluate the common task, product, and system aspects. Common definitions have been thoroughly investigated under the conventional vision frequently observed in previous paradigms, where the primary motivation is to achieve efficient mass production. In this review, we examined the relationship between relevant common, human-centered, and robot-specific definitions from different vantage points. Based on an analysis of the investigation results, the remaining emergent issues and potential research directions for future practical applications are discussed.

The remainder of this paper is organized as follows. Section 2 describes the methodology used to systematically search for relevant research articles on HRC assembly applications. Section 3 details the findings of this study and provides taxonomies of definitions for measuring or determining the different aspects of difficulty and complexity of various assembly systems. Section 4 discusses the relationships among the different taxonomies and between difficulty and complexity. Section 5 presents the emerging approaches, challenges, and research gaps. Finally, conclusions are summarized.

2. Review Protocol

This review follows the systematic review conducted by Coronado *et al.* [25]. The main steps for conducting the systematic review are as follows: 1) identification of needs for the review; 2) definition of research questions; 3) definitions of the search strategy; 4) study selection of criteria and procedures; 5) study quality assessment; 6) data extraction and synthesis; and 7) report of results. The needs identification in step 1 was performed as described in Section 1. Sections 2.1–2.3, and Section 3 describe the work conducted for steps 2–6, and step 7, respectively.

2.1. Research Questions

The research questions (RQs) guiding this study are as follows:

1. **RQ1:** *What aspects of HRC assembly systems have been developed with existing definitions, and to what extent?*
2. **RQ2:** *Which definitions have been used to evaluate the agent-specific difficulty and complexity?*
3. **RQ3:** *What are the emerging approaches and potential research directions for future HRC assembly systems?*

The results of this systematic search are incorporated into the taxonomies, diagrams, and tables presented in Section 3. RQ1 aims to identify the relevant and well-defined measures and metrics for difficulty and complexity used for task allocation and assignment in HRC assembly systems. Consequently, taxonomies are proposed to classify and understand their applications. RQ2 aims to identify frequently discussed definitions for evaluating agent-specific difficulty and complexity. The number of articles that evaluate each identified factor is registered to answer this question. Finally, RQ3 aims to determine the emerging aspects or methods of HRC. These challenges are presented from the perspective of the effective HRC principles.

2.2. Search Strategy

Similar to [25], the search string is defined as *(Difficulty OR Complexity) AND (Assembly) AND (Human OR Robot)*. This string is utilized to search for research articles in computer science-related databases, including IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, and ASME Digital Collection. For this search, only articles published until July 2022 are considered and sorted by relevance. Table 1 presents the advanced setting configurations used for each database, which is optimized to eliminate irrelevant articles for the search results as much as possible.

Table 2 lists the results obtained from each database. After applying the following search criteria, 74 articles are obtained that are investigated in this review. The breakdown based on publication type is 35, 37, and 2 for journal papers, conference papers, and books, respectively. Moreover, the breakdown based on article types is two for review, survey, or systematic study, and 72 for regular papers.

2.3. Study Selection, Quality Assessment, and Data Extraction

The article selection process involves selecting and applying the inclusion and exclusion criteria [98]. The selection of articles for review comprises of two steps. In step 1, articles are excluded based on their abstracts and titles. In case of uncertainty, the entire articles are read. In this step, the following *inclusion criteria* are applied.

1. An article focuses on presenting an HRC framework or system for assembly tasks (*e.g.*, machine components and items of furniture).
2. An article gathers, presents, or evaluates definitions of difficulty and complexity that can be applied in collaborative assembly environments.
3. An article collects, presents, or evaluates definitions of the difficulty and complexity of assembly tasks performed by humans or robots alone.

For each database, the search process concludes if no article meets any inclusion criteria after 50 consecutive articles. The first exclusion rule reduced the number of initial target articles from 958 to 171. The articles are thoroughly read in a step-by-step manner. In step 2, the results from step 1 are used to apply the following *exclusion criteria*:

1. An article does not define difficulty and complexity, does not explain definitions clearly, or only evaluates the technological suitability of a specific hardware (*e.g.* sensors and actuators) or algorithm (*e.g.* perception, decision-making, and control).
2. An article is inaccessible in full-text, has less than two pages, is not peer-reviewed, is not written in English, or is a duplicate of other studies by the same authors (*i.e.* presenting either the same or similar frameworks or results in different publication types).

After applying the exclusion criteria, a total of 67 articles were obtained. In step 3, seven articles are added, which propose the original definitions cited in the obtained articles. Finally, 74 articles were compiled and 145 definitions with some overlap were extracted. Note that the search and data extraction processes in this study were performed by Authors 1–3. All authors reviewed the results. Moreover, articles with differences in understanding were discussed to reach consensus among the authors of this paper.

Table 1: Advanced setting used for searching related articles in each database

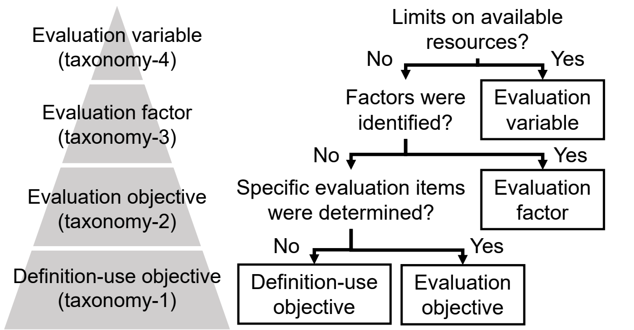
Database	Year range	Subject areas	Content type	Other setting
IEEE Xplore	1981-2022		Conferences, Journals, Magazines, and Standards	
ScienceDirect	1996-2022	Engineering, Computer Science, Decision Science, and Neuroscience	Review and Research articles	Searched with "title, abstract, or author-specified keywords"
SpringerLink	1983-2022		*1 Article *2 Conference paper *3 Article *4 Conference paper	*3 Discipline was set as Engineering *4 Discipline was set as Engineering
ACM Digital Library	1951-2022			*5 Searched with "title, abstract, author keyword"
ASME Digital Collection	1944-2022			*6 Searched with "abstract"

*1~4 For each of the four conditions, the first 50 articles were extracted.
*5,6 In addition to articles found by common search conditions, articles found by searching after adding this search condition were included.

Table 2: The number of articles found in each database and results after applying inclusion (step 1), exclusion (step 2) criteria, and adding related original articles (step 3)

Database	Search	Target	Step 1	Step 2	Step 3
IEEE Xplore	583	230	49	38	39*1
ScienceDirect	184	184	28	10	12*2
SpringerLink	70,579	200	44	9	11*3
ACM Digital Library	11,203	150	25	6	6*4
ASME Digital Collection	13,879	194	25	4	6*5
Total	96,428	958	171	67	74

*1 [26, 27, 28, 29, 30, 31, 32, 33, 11, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 15, 61, 62]
*2 [63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74]
*3 [75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85]
*4 [86, 87, 88, 89, 90, 91]
*5 [92, 93, 94, 95, 96, 97]



(a) Hierarchy (b) User guide

Figure 2: Relationships between taxonomies with different levels of abstraction

3. Difficulty and Complexity Definitions

First, we provide an overview of the search and categorization results in Section 3.1, followed by an explanation of the definitions classified by agent, system, product, and task in Sections 3.2–3.5, respectively.

3.1. Overview of Search and Categorization Results

To clarify and organize conventional methods, this section elaborates on the prevailing definitions and proposes four different taxonomies: definition-use objective (taxonomy-1), evaluation objective (taxonomy-2), evaluation factor (taxonomy-3), and evaluation variable (taxonomy-4), categorizing them to make a large number of definitions easier to comprehend. Taxonomies were generated from the investigation results of reviewed studies within the scope of this paper.

To summarize the taxonomies generated based on different aspects, this section discusses the relationships among them. Fig. 2 (a) presents the hierarchical structure of the abstraction level pyramid, which includes four different aspects of the investigated definitions. The four aspects include *definition-use objective* (taxonomy-1), *evaluation objective* (taxonomy-2), *evaluation factor* (taxonomy-3), and *evaluation variable* (taxonomy-4). Note that the definition-use objective and evaluation variable taxonomies are objectively examined based on the facts stated in the articles under investigation. However, because the evaluation objective and evaluation factor are subjectively examined based on the contents of the articles and intuitions of the authors, the taxonomy may be counterintuitive for readers. Fig. 2 (b) directs the readers to look for specific definitions of the relevant taxonomy.

In this paper, we organize definitions from four perspectives considering various backgrounds and situations so that several readers (engineers, researchers, etc.) can easily locate the desired definition. First, note that when constructing an HRC assembly system, certain cases have restricted input resources for the assumed system. For instance, at times, 3D models of assembled parts cannot be used, and only black-and-white sketches can be employed. In such situations, it is not possible to select a definition from among those available, and examining the inputs required to compute each definition is necessary. Therefore, if the answer to the question "Limits on available resources?" is "Yes," it may be efficient to search from the classification tree using the *evaluation variable* (taxonomy-4), which represents the input variable used to calculate the complexity or difficulty.

By contrast, if the input resource is not restricted, the search can be modified according to three different situations. If the answer to the question "Evaluation factors were identified?" is "Yes," the desired definition can be identified by checking taxonomy-3, which describes the relevant evaluation factors. Furthermore, if the answer to "Specific evaluation items were determined?" is "Yes," then taxonomy-2, which is classified according to the evaluation objective, can be used to identify appropriate definitions. Conversely, if the answer is "No," the desired definition can be obtained by searching the taxonomies presented in taxonomy-1, which is classified according to the definition-use objective.

The primary purpose of this study is to identify common and unique factors among robots and humans. However, identify-

Table 3: Two-type classifications for the 74 articles

Item	Class	Count
Citation	Highly cited (≥ 50)	16*1
	Not highly cited (< 50)	58*2
Article type	Review / Survey	2*3
	Regular	72*4
Publication type	Journal / Book	37*5
	Proceedings	37*6

*1 [26, 27, 28, 64, 11, 76, 36, 86, 67, 77, 68, 95, 46, 69, 88, 50]
*2 [75, 63, 29, 30, 31, 32, 33, 34, 65, 35, 66, 37, 38, 92, 93, 39, 40, 94, 41, 42, 43, 44, 87, 45, 47, 48, 78, 49, 96, 79, 89, 80, 70, 71, 90, 51, 52, 81, 97, 72, 53, 91, 54, 55, 56, 73, 57, 82, 58, 59, 60, 15, 61, 62, 83, 85, 74, 84]
*3 [69, 85]
*4 [63, 65, 60, 59, 47, 15, 58, 33, 57, 52, 53, 61, 55, 49, 39, 45, 43, 48, 31, 56, 54, 44, 42, 35, 32, 62, 30, 37, 41, 40, 38, 34, 29, 51, 73, 70, 71, 74, 72, 78, 83, 81, 82, 75, 79, 80, 84, 89, 91, 90, 96, 97, 92, 11, 50, 28, 26, 68, 36, 46, 64, 88, 86, 87, 95, 27, 67, 94, 77, 76, 66, 93]
*5 [46, 57, 52, 61, 55, 39, 56, 36, 40, 29, 73, 70, 71, 74, 68, 63, 65, 69, 72, 64, 78, 83, 85, 81, 82, 75, 79, 80, 84, 86, 95, 96, 97, 67, 77, 76, 66]
*6 [87, 60, 59, 47, 15, 58, 33, 53, 49, 45, 43, 48, 31, 54, 44, 42, 35, 32, 62, 30, 37, 41, 38, 34, 51, 89, 91, 90, 92, 11, 50, 28, 26, 88, 27, 94, 93]

Table 4: Two-type classifications for the 145 definitions

Item	Class	Count
Definition type	Complexity	114
	Difficulty	31
Study type	Application	54
	Proposal	91
Perspective type	Subjective	16
	Objective	129
Quantification type	Continuous	129
	Discrete	16

ing factors that are under evaluation using only the definition names and examples of usages in previous articles is complicated; therefore, readers should also pay attention to these factors and the variables used to determine them while looking for definitions. Readers need to be aware that the classifications based on definition-use objectives and evaluation objectives are made only for definitions with precedents, whereas evaluation factors for definitions are investigated from the viewpoint of general applicability by considering a wider range of applications rather than the specific purposes of previous studies.

The following four sections will help readers understand the basic information of the collected definitions, the method to map the definitions to relevance factors (taxonomy-3), two research-objective-based taxonomies (taxonomies-1 and -2), and evaluation variables to calculate factors (taxonomy-4). To explain this, we first identify different factors of difficulty or complexity in the definitions related to each category (agent, system, product, and task), following which we organize different definitions of these factors in terms of evaluation and intended use. Finally, we present a categorization of the definitions based on various objectives, focusing on the specific variables to be computed.

3.1.1. *Types of Collected Articles and Extracted Definitions*

To briefly understand the search results, the extracted 145 definitions found in 74 articles were classified in terms of definition (difficulty or complexity), study (application or proposal), perspective (subjective or objective), and quantification (continuous or discrete) types. Tables 3 and 4 summarize the results of the two-type classification for the 74 articles and extracted 145 definitions, respectively.

As listed in Table 3, the article collection results appear unbiased, primarily in terms of the number of citations and types of publications. Sections 3.2–3.5 detail the 16 articles with more than 49 citations. The number of articles published in journals or books and the number of articles published in conference proceedings are the same.

In addition, only two review papers [69, 85] with different review objectives compared to this review were obtained. Unlike our review, Hu *et al.* [69] first reviewed state-of-the-art research in the areas of assembly system design, planning, and operations with a variety of products. In a review conducted by Chutima *et al.* [85], unlike ours, they first classified the robotic assembly line balancing problem based on the types of layouts, following which the clusters were further subdivided according to the concepts of man (worker), machine (robot), material (part/task) and method (problem/decision).

As listed in Table 4, the definitions of complexity are more than three times those of the difficulty. Section 4.2 discusses a factor that accounts for this difference in numbers. The most cited paper that proposes the definition of complexity is the aforementioned review paper authored by Hu *et al.* [69]. The authors proposed five complexity definitions for different targets: *product assembly complexity*, *operator choice complexity for activity*, *the total complexity of one assembly station*, *assembly machines complexity*, and *total assembly system complexity*. However, with regard to the definition of difficulty, the paper authored by Wolter *et al.* [27] is the most cited paper. Their study proposed the concept of *manipulability criterion*. The manipulability criterion favors the execution of difficult operations using parts that are easy to handle. These two most-cited papers do not focus on agent specificity.

The study type distinguishes the extracted definitions into two groups: one group consists of articles that simply use the definitions proposed by other articles (referred to as application), and the other group consists of articles that propose new definitions (referred to as proposal). If the calculation formula or meaning of a definition is modified slightly from its original definition, or if the definition is used for a slightly different purpose, the definition is included in the proposal class. Consequently, more articles corresponding to the proposal class were obtained than those corresponding to the application class.

The perspective type indicates whether the difficulty or complexity measurement or estimation method is subjective or objective. Because the subjective perception of difficulty and complexity is difficult, it is natural for objective definitions to be a large number. For instance, Ye *et al.* [36] proposed metrics including *rating for assembly understanding (RU)*, *rating for meeting the feasibility criterion (RF)*, and *rating for meeting the goodness criteria (RG)*. Rating methods were used to assess the understanding and difficulty of assembly operations in virtual environments. This method is typically used to evaluate human subjectivity using questionnaires.

The quantification type distinguishes between continuous and discrete expressions based on their degree of difficulty and complexity. Qualitative metrics are categorized as discrete metrics. Numerous definitions that can be calculated as continuous quantities have been proposed; if they can be used appropri-

Table 5: Results of free-format classifications for *difficulty* definitions

Item	Examples
Target system	Automobile mixed-model assembly line [68], Human worker [86], Human worker on assembly line [90], HRI system [79], Hybrid assembly line [59], Manipulator with motion capture system [51], Manual assembly [75], Manufacturing system [27], Multiple off-the-shelf (OTS) sensor-based system [62], Robotized assembly system [53], VR system [36]
Target product / object	Air-cylinder [36], Automobile [68], Carburetor [33], Chair [51], Electrical product [59], Electronics new product [72], Facility which has low accessibility such as tank vent pipe [86], Flashlight [28], Lego-car [60], Object in contact [34], Piston [75], Rigid, polyhedron, and static objects [30], Task board [62]
Target task	Arithmetic tasks [79], Assembly [27, 28, 33, 34, 62], Assembly planning with VR [36], Bimanual pin insertion [51], Disassembly [86], HRC assembly [59], Inspection [60], Manual handling [75], Manual insertion [75], Manufacturing [81], Robotized assembly [53]

Table 6: Results of free-format classifications for *complexity* definitions

Item	Examples
Target system	Assembly line [46], Assembly system [78], Automobile mixed-model assembly line [68], Collaborative system [55], Flexible assembly system (Robot, parts feeders and assembly station) [80], Foot pedal based interface [44], Forging system [66], HRC system [54, 83], HRI system [79], Mechanical devices and/or sensory devices [26], Human-multi-robot collaboration system [15], Human worker [86], Hybrid cyber-physical assembly system [70], Joint assembly manufacturing systems and advanced driver assistance systems [73], Machine assembly line [29], Manufacturing system [27, 76, 67, 94, 77], Mixed-model assembly line [43, 95], Mixed-model assembly systems [69], Mobile robot [42], Mobile robot with sensors [41], Multiple mobile arms [50], Multirobot and multicontact system [40], Reconfigurable production system [84], Robotic work cell [88], Robot system [61], Single armed robot [91], Single arm with force estimator [57], 6 DoF haptic interface [49], Team of homogeneous robots [87], Two-armed robotic system [56], Two-robot assembly work cell [65], Two video camera [45], Virtual assembly system [39], Virtual manipulation system [64]
Target product / object	Aluminum profiles [56], Automobile car body [47], Automotive body [88], Automotive electrical connectors [71], Box or L/S-objects [49], Cantilever and annular [57], Chair [50], Complex structures with applications in intelligent construction and manufacturing [87], CPU fans and books [61], Cubes with bolts [45], Die-set [39], Electric bell [64], Electronic components [26], Exact functional replicas [42], Flashlight [28], Friction-testing machine [64], Forging part [66], Furniture [54], Laptop computer [69], LEGO bricks [37, 44, 58], Metallic structure [55], Model-aircraft engine [64], Multifunctional copier [46], Pendulum and box tower [48], Printed circuit board [65], Printing machine [76], Program [89], Screw [52], Toy plane made of plastic parts [91], Two objects in contact [38], Wheel support [35]
Target task	Arithmetic tasks [79], Assembly [63, 27, 28, 31, 92, 96, 97, 91, 38, 46, 78, 56], Complex contact manipulation tasks [49], Cyber-physical assembly [70], Desktop assembly and book shelving [61], Distributed assembly [87], Electronic assembly [26], Forging [66], HMI-based assembly [44], HRC assembly [48, 54, 55, 83, 85], HRC in manufacturing [88], Human-multi-robot assembly [15], Joint assembly and driver assistance [73], Machine assembly [29], Manufacturing [76, 67, 94, 77], Mechanical assembly [64, 32], Maintenance [86], Manual assembly [45, 71, 74], Mechanical disassembly [64], Mixed-model assembly [95, 69], Multirobot manipulation tasks [40], Multi-robot assembly [50, 58], Multi-robot parallel assembly [47], Multi-stage mixed-model assembly [68], Product and program development [89], Reconfigurable production [84], Robotic navigation [41], Selective disassembly [37], Self-replication [42], Single station automated manufacturing system [80], Snap-fit assembly [57], Two-handed assembly [11], Two-robot assembly [65], Virtual assembly [39]

ately, the corresponding degree can be evaluated from various perspectives. Discrete expressions are subdivided into yes/no questions or indicators expressed in several classes. For instance, Wilson *et al*. [64] considered *prismatic product*, *linearizable product*, and *stack product*. These represent yes–no questions that investigate product features related to complexity. The aforementioned rating metrics proposed by [36] are defined as rating scales with seven levels, which can be used to make human ratings of complexity feasible.

Furthermore, research articles that introduce definitions are evaluated based on target systems (dual-arm, single-arm, mobile robot, etc.), target products or objects (metal product, furniture, etc.), and target tasks (HRC assembly, robotic assembly, human assembly, etc.). Tables 5 and 6 summarize the target system, target product or object, and target task employed in previous studies as free-format classifications for definitions of difficulty and complexity, respectively. Papers proposing related definitions have been listed in the tables. For difficulty, 11, 13, and 11 different types of systems, products or objects, and tasks were obtained, respectively. For complexity, 35, 33, and 35 of those were obtained. From these tables, researchers can refer to the actual examples used in previous studies and design the experimental setups.

3.1.2. Mapping to Key Aspects

To maximize human adaptability and robot autonomy, task allocation and assignment should consider difficulty and complexity in terms of an agent's physical constraints, physiology, and performance factors. Therefore, we developed graphs that categorized definitions in more detailed classes in terms of human-centered and robot-specific factors to clarify the relationships among the extracted definitions for both difficulty and complexity. The tables in Figures 3 and 4 list the categorized *difficulty* and *complexity* definitions, respectively. This shows a taxonomy (taxonomy-3) that assigns evaluation factors. Both tables show four different bars representing common factors, human-centered factors, robot-specific factors, and team composition levels (a concept to represent a human–robot team type proposed in [99]). The categories named common, human-centered, and robot-specific are marked as applicable based on the definitions described in the corresponding articles. Evaluation objectives are considered to determine whether each category is applicable to the definition. The team composition level is marked based on the authors' decisions, considering the applicability of definitions for three different composition levels: the systems consisting of 1) only n humans, 2) only m robots, and 3) n humans and m robots.

The details of the important definitions (cited from 50 or more articles) are explained in Sections 3.2–3.5, and are introduced chronologically in each section. Section 3.2 explains agent-specific definitions, which are specific to common interaction factors and humans and robots, as depicted in Figures 3 and 4. The definitions of common factors other than the interaction factors displayed in Figures 3 and 4 are further subdivided into *system*, *product*, and *task*, as explained in Sections 3.3–3.5.

3.1.3. Looking at Relations among Definitions from Objectives

One objective of this review is to provide readers with access to definitions that can measure difficulty and complexity.

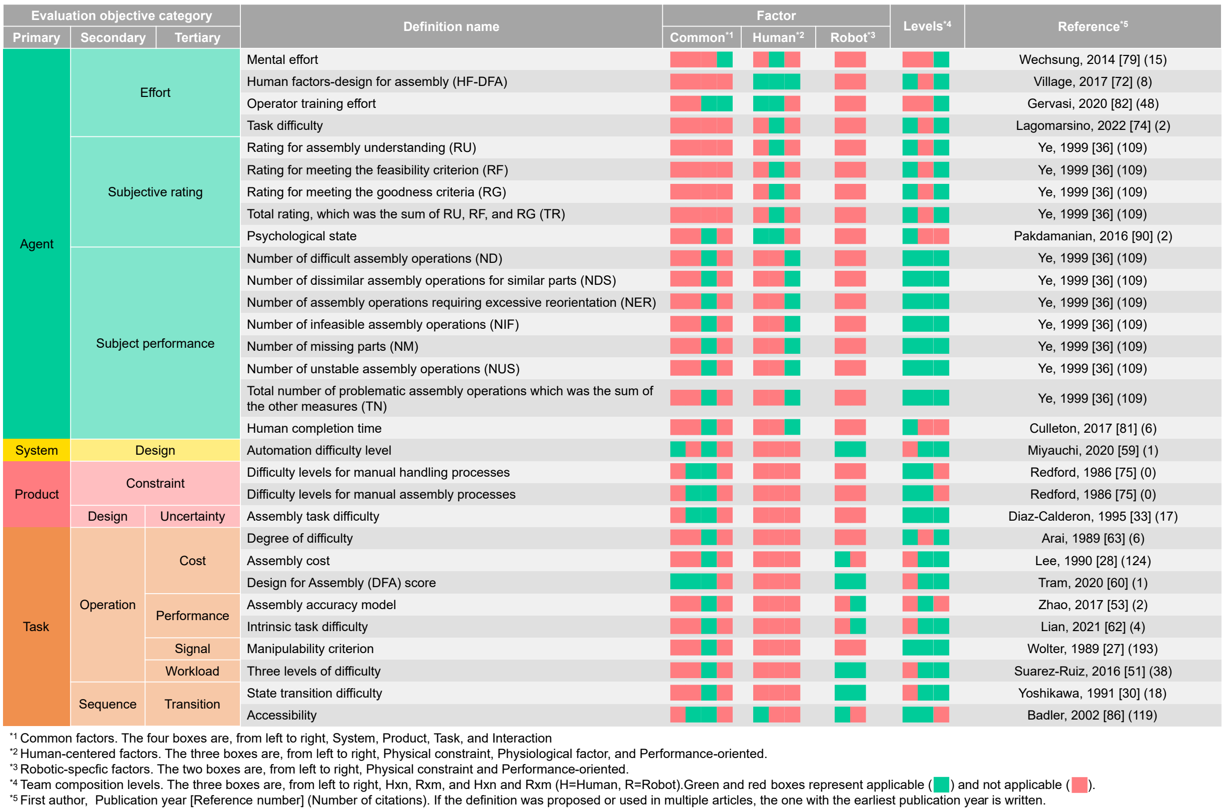


Figure 3: Factor-aware categorization for *difficulty* definitions (taxonomy-3)

To consider various backgrounds and situations, we organized the definitions from two aspects other than the evaluation factor. For this purpose, tree-structure taxonomies are developed, classifying the 145 extracted (difficulty and complexity) definitions into categories, so as to overlook the definitions with different evaluation and definition-use objectives. This abstracted objective-based classification enables readers to find definitions that have precedents in the past, even if they are unable to identify the factors to be evaluated but only have objectives.

Fig. 5 shows the common tree root connected to four primary categories: agent, system, task, and product. The primary category grows from this root, followed by secondary and tertiary categories. The leaf nodes indicate the corresponding definition information. The categories described in each intermediate node correspond to those shown in Figures 3 and 4. They are arranged alphabetically from top to bottom in the figures. The definitions of leaf nodes are sorted from top to bottom according to the year of publication of the corresponding article.

Figures 6–9 show the four trees based on the evaluation objectives of the definitions and represent components for the evaluation-objective taxonomy (taxonomy-2). Fig. 5 shows the five labels assigned to each definition to add information. The five labels are the Reference number, First author, Publication year, Number of citations, and Definition type (difficulty or complexity). Labels are drawn under each box, showing one definition. Fig. 10 presents the number of evaluation-objective-oriented definitions.

The classification of the *agent*, aspect shown in Fig. 6, can be grouped into four secondary categories: capability, effort, subjective rating, and subject performance. These categories are related to human worker capability, agent effort in operations, subjective assessment in agent operations, and objective performance evaluation of agent operations. In the classification of the *system* aspect shown in Fig. 7, note that they can be grouped into four secondary categories: configuration, design, kinematics, and state, which are related to the placement of equipment, design of each component, function of each component, and state of the system that changes during operations, respectively. In the classification of the *product* aspect shown in Fig. 8, they are grouped into three secondary categories: constraint, design, and sequence. Furthermore, the design category can be distinguished by its shape, structure, time, and uncertainty. The secondary categories (constraint, design, and sequence) are related to the constraints required for each product (especially, the constraints required during assembly), product design, and assembly order according to the product, respectively. Tertiary categories are divided according to each characteristic derived from product design. In the *Task* aspect shown in Fig. 9, the definitions are divided into two groups: *operation*, which is related to the task difficulty and complexity derived from the behavior of the agent and system, and *sequence*, which is related to the task difficulty and complexity derived from the order of the multiple connected tasks. Furthermore, operations can be distinguished by their cost, environment, performance, signal, time, and workload. Similarly, sequences can be distinguished based on their quantities and transitions. In addition, the work-

Evaluation objective category			Definition name	Factor			Levels[*4]	Reference[*5]
Primary	Secondary	Tertiary		Common[*1]	Human[*2]	Robot[*3]		
Agent	Capability		Human capability					Zhang, 2020 [15] (8)
	Effort		Operator choice complexity (OCC)					Zhu, 2008 [95] (212)
			OCC in station level					Zhu, 2008 [95] (212)
			OCC in system level					Zhu, 2008 [95] (212)
			Choice complexity					Busogi, 2017 [52] (8)
			Agent effort					Lamon, 2019 [55] (23)
System	Configuration		Material handling systems complexity					Kuzgunkaya [77] (117)
			System complexity					Kuzgunkaya [77] (117)
			Supply chain complexity					Hu, 2008 [68] (437)
			Levels of complexity					Shi, 2012 [88] (84)
			Complexity levels of assembly process					Rodriguez, 2019 [56] (33)
			Reconfiguration complexity					Beauville, 2022 [84] (0)
			Assembly complexity information entropy					Yan, 2011 [47] (3)
	Design		Assembly machines complexity					Hu, 2011 [69] (582)
			Degrees of complexity					Deaton, 2015 [89] (4)
			Number of iterations					Deaton, 2015 [89] (4)
			Robotic assembly system flexibility					Chutima, 2022 [85] (13)
			Types of robots					Chutima, 2022 [85] (13)
	Kinematics		Number of fingers					Wilson, 1994 [64] (383)
			Number of hands and monotonicity					Wilson, 1994 [64] (383)
			Agent dexterity					Lamon, 2019 [55] (23)
	State		Buffer type complexity					Kuzgunkaya, 2006 [77] (117)
			Machine complexity					Kuzgunkaya, 2006 [77] (117)
			Active elements					Liu, 2007 [42] (8)
Product	Constraint		C-constraints					Park, 1993 [31] (7)
			Prismatic product					Wilson, 1994 [64] (383)
			Stack product					Wilson, 1994 [64] (383)
	Design	Shape	G-constraints					Park, 1993 [31] (7)
			Shape complexity factor					Tomov, 1999 [66] (16)
		Structure	Assembly complexity					Rodriguez-Toro, 2002 [92] (22)
			Component complexity					Rodriguez-Toro, 2002 [92] (22)
			Task complexity of one step					Stork, 2008 [44] (11)
			Complexity of distributed assembly task					Hsieh, 2010 [87] (4)
			Complexity of model					Rosati, 2015 [80] (16)
			Run time performance					Bessler, 2018 [91] (15)
		Time	Time-dependent complexity					Suh, 1999 [76] (298)
			Time-independent complexity					Suh, 1999 [76] (298)
		Uncertainty	Assembly complexity with parts entropy					Sanderson, 1984 [26] (101)
			Process assembly complexity					Elmaraghy, 2003 [67] (189)
			Product assembly complexity					Elmaraghy, 2003 [67] (189)
	Sequence		Directionality criterion					Wolter, 1989 [27] (193)
			Number of directions					Goldwasser, 1996 [11] (120)
			Number of re-orientations					Goldwasser, 1996 [11] (120)
			Length of assembly algorithm (sequence)					Wilson, 1994 [64] (383)
			Depth of an assembly sequence					Goldwasser, 1996 [11] (120)
			Linearizable product					Wilson, 1994 [64] (383)
Task	Operation	Cost	Task complexity					Lamon, 2019 [55] (23)
		Environment	Fixture complexity criterion					Wolter, 1989 [27] (193)
			Environmental complexity					Anderson, 2007 [41] (18)
		Performance	Error rate					Wechsung, 2014 [79] (15)
		Signal	Hjorth complexity					Doltsinis, 2020 [57] (16)
		Time	Time complexity (computational complexity)					Shin, 1990 [29] (32)
			Asymptonic time complexity					Hirukawa, 1994 [32] (46)
			Relative complexity					Chutima, 2022 [85] (13)
			Task complexity (time)					Badler, 2002 [86] (119)
			Cycle time					Chutima, 2022 [85] (13)
		Workload	Complexity of each working step					Huber, 2010 [45] (24)
			Assembly complexity					Zeylikman, 2018 [54] (11)
			Assembly complexity factor (Hinckley)					Su, 2010 [46] (62)
			Design-based complexity (Shibata)					Shibata, 2003 [93] (21)
			Design-based complexity (Su)					Su, 2010 [46] (62)
			Process-based complexity (Shibata)					Shibata, 2003 [93] (21)
			Process-based complexity (Su)					Su, 2010 [46] (62)
			Number of tasks					Chutima, 2022 [85] (13)
			WEST ratio					Chutima, 2022 [85] (13)
	Sequence	Quantity	System complexity					Zhu, 2007 [43] (28)
			Number of possible collaborative assembly sequences					Gualtieri, 2021 [83] (13)
			Order strength					Chutima, 2022 [85] (13)
		Transition	Structural preference index					Lee, 1990 [28] (124)
			Inter-cluster structural complexity					Lee, 1990 [28] (124)
			Intra-cluster structural complexity					Lee, 1990 [28] (124)
			Parameterized complexity					Yuan, 2011 [48] (3)
			Contact states and graph complexity					Klingbeil, 2014 [49] (6)
			Structural complexity					Owensby, 2014 [96] (43)
			Assembly flexibility					Chutima, 2022 [85] (13)
			Precedence graph structures (PGS)					Chutima, 2022 [85] (13)

[*1] Common factors. The four boxes are, from left to right, System, Product, Task, and Interaction.
[*2] Human-centered factors. The three boxes are, from left to right, Physical constraint, Physiological factor, and Performance-oriented.
[*3] Robotic-specfic factors. The two boxes are, from left to right, Physical constraint and Performance-oriented.
[*4] Team composition levels. The three boxes are, from left to right, Hxn, Rxm, and Hxn and Rxm (H=Human, R=Robot). Green and red boxes represent applicable ( ) and not applicable ( ).
[*5] First author, Publication year [Reference number] (Number of citations). If the definition was proposed or used in multiple articles, the one with the earliest publication year is written.

Figure 4: Factor-aware categorization for *complexity* definitions (taxonomy-3)

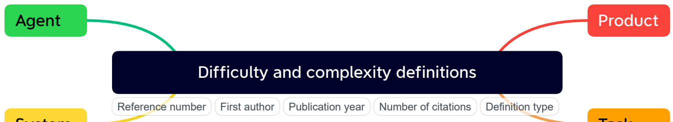


Figure 5: Common root of trees to provide taxonomies for definitions. Each leaf node shows the definition name with five labels attached: 1) Reference number, 2) First author, 3) Publication year, 4) Number of citations, and 5) Definition type (Difficulty or Complexity).

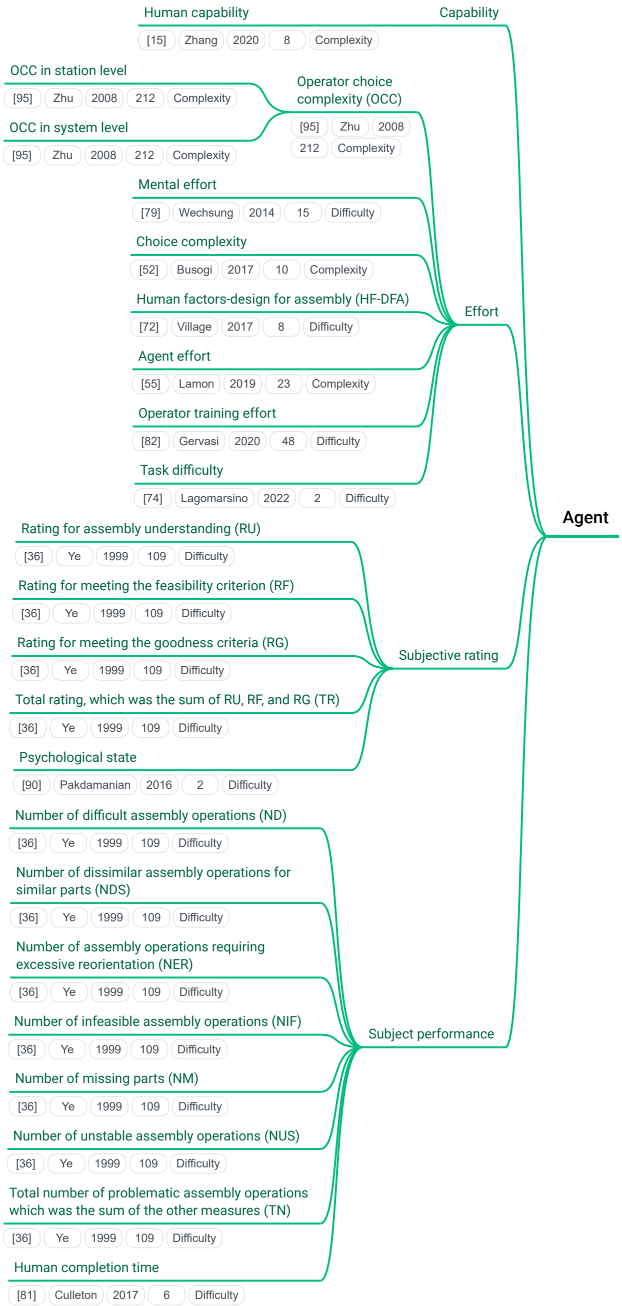


Figure 6: *Evaluation-objective*-oriented tree (taxonomy-2) of the definitions that evaluate *Agent* aspects

load is subdivided as shown in Fig. 9.

Considering the definitions obtained from a different perspective, Figures 11–14 display the genealogies created based on the definition-use objectives of the corresponding studies. As before, they are also assigned to the categories of agent, system, task, and product, and the primary text label grows from the root, as shown in Fig. 5, followed by the secondary and tertiary text labels. Finally, leaf nodes indicate corresponding definition information. Fig. 15 shows the number of definition-use-objective-oriented definitions.

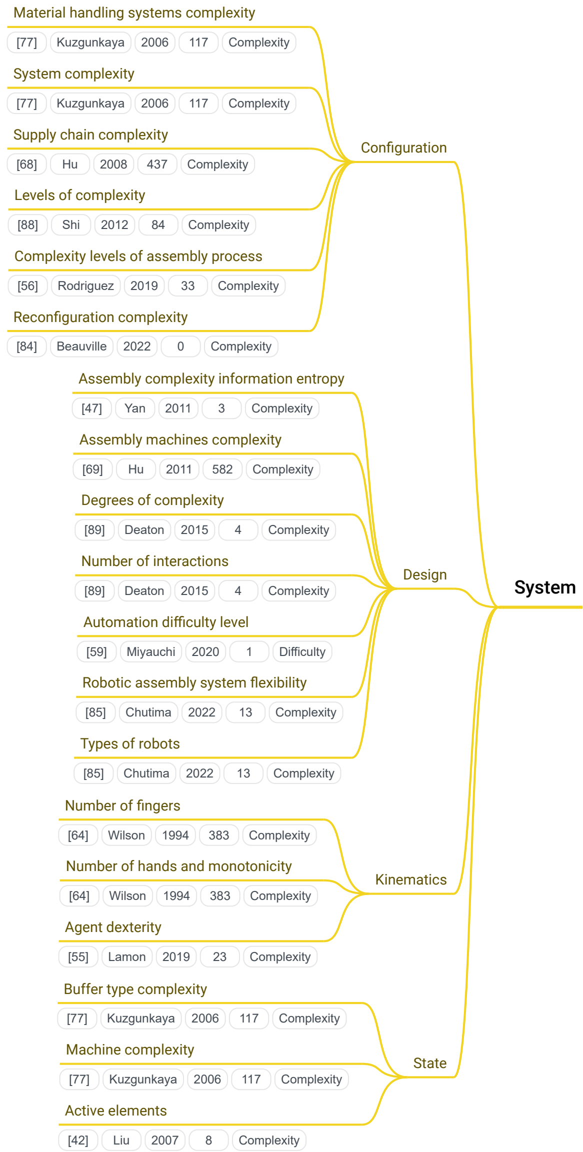


Figure 7: *Evaluation-objective*-oriented tree (taxonomy-2) of the definitions that evaluate *System* aspects

Definitions were classified in terms of the definition-use objectives of the corresponding studies. In each graph, the definitions are structured to represent parent-child relationships among definitions, and the related definitions are grouped together. Researchers can use these figures as references to address difficulties for various purposes. Specifically, a user can discover a preceding definition from the root node by following the text label corresponding to their purpose.

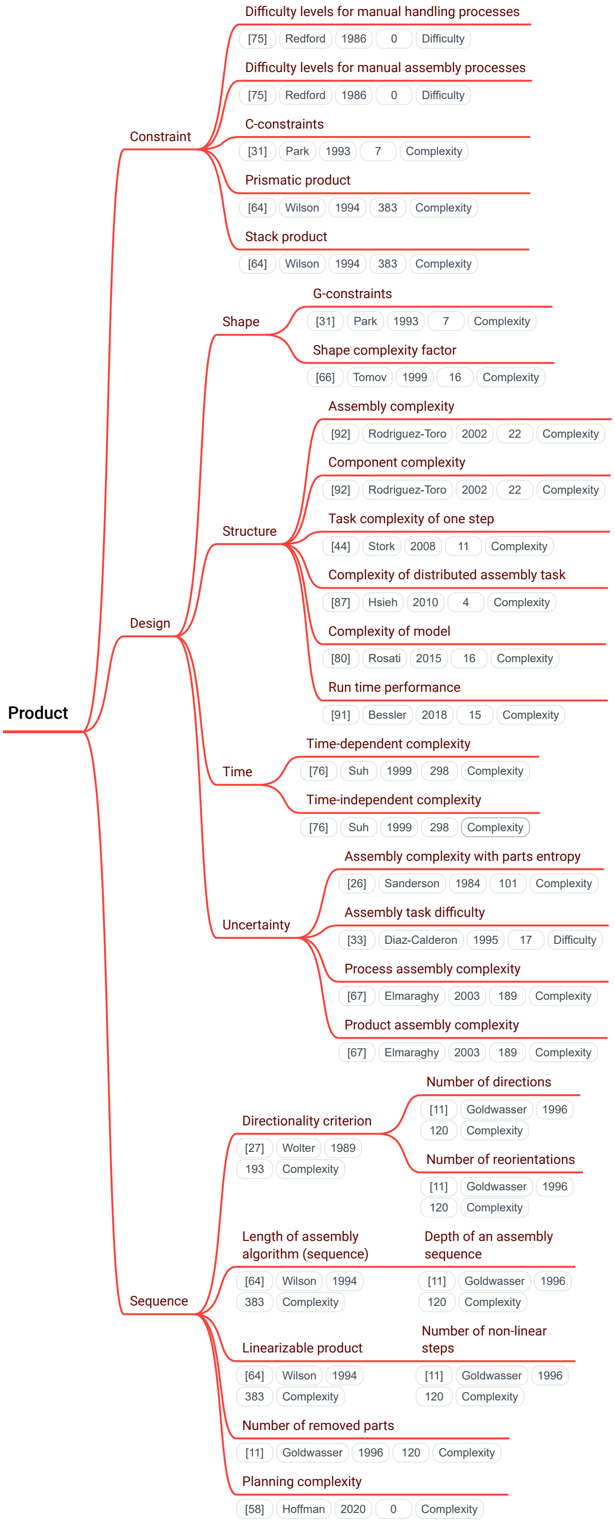


Figure 8: *Evaluation-objective*-oriented tree (taxonomy-2) of the definitions that evaluate *Product* aspects

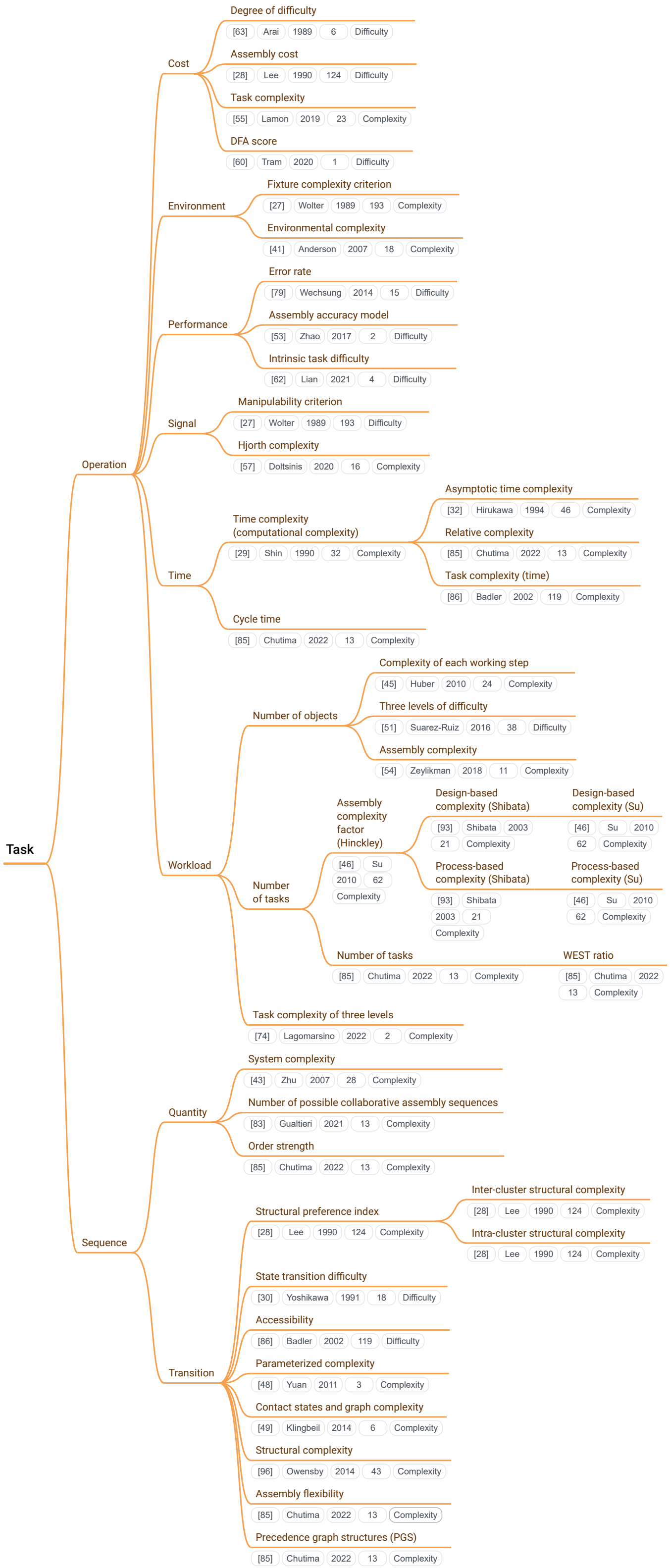


Figure 9: *Evaluation-objective*-oriented tree (taxonomy-2) of the definitions that evaluate *Task* aspects

3.1.4. Identifying Variables to Calculate Factors

Figures 16–19 show the trees representing another taxonomy (taxonomy-4) based on the evaluation variables used to calculate the definitions. By examining the differences in the input variables for the calculation, it is possible to determine whether the definitions are available for the user's initial objectives. The primary category developed from the root illustrated in Fig. 5, followed by the secondary tertiary and more specific

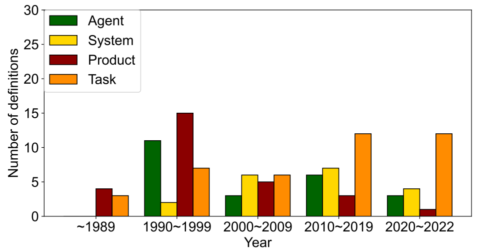


Figure 10: Number of *evaluation-objective*-oriented definitions

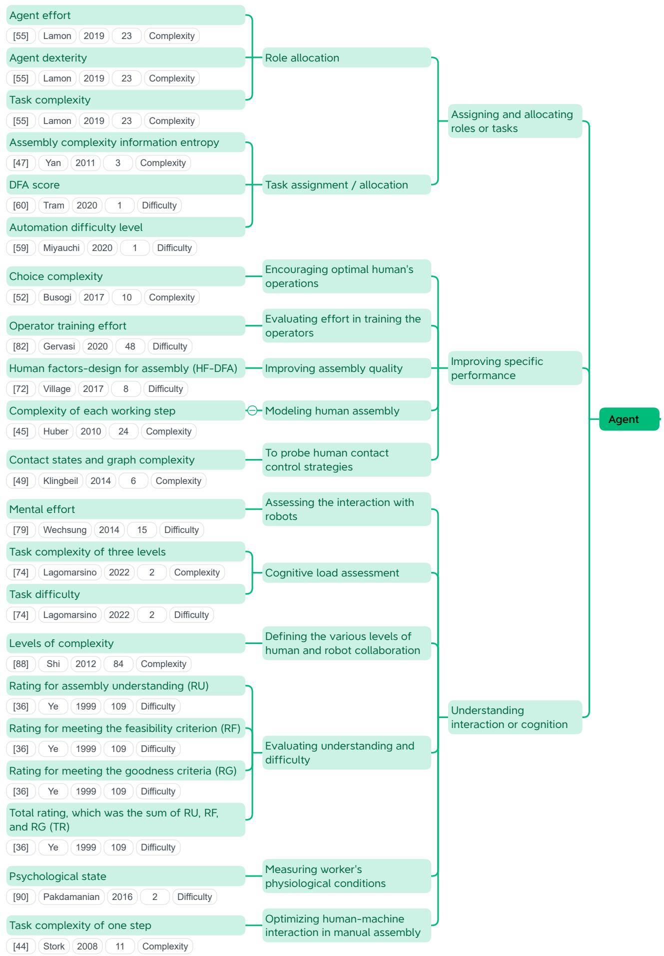


Figure 11: *Definition-use-objective*-oriented tree (taxonomy-1) of the definitions that evaluate *Agent* aspects

categories. Lastly, leaf nodes indicate corresponding definition information. The intermediate nodes that show category names are alphabetically arranged from top to bottom in the figures. The definitions of leaf nodes were sorted from top to bottom according to the year of publication of the corresponding article. Fig. 20 presents the number of evaluation-variable-oriented definitions.

The classifications of *agent*, *system*, *product*, and *task* aspects shown in Figures 16–19 can be grouped into secondary categories. The secondary categories are ergonomics, number of choice, performance, reachability map, and subjective rating. Tertiary and specific categories follow similar definitions.

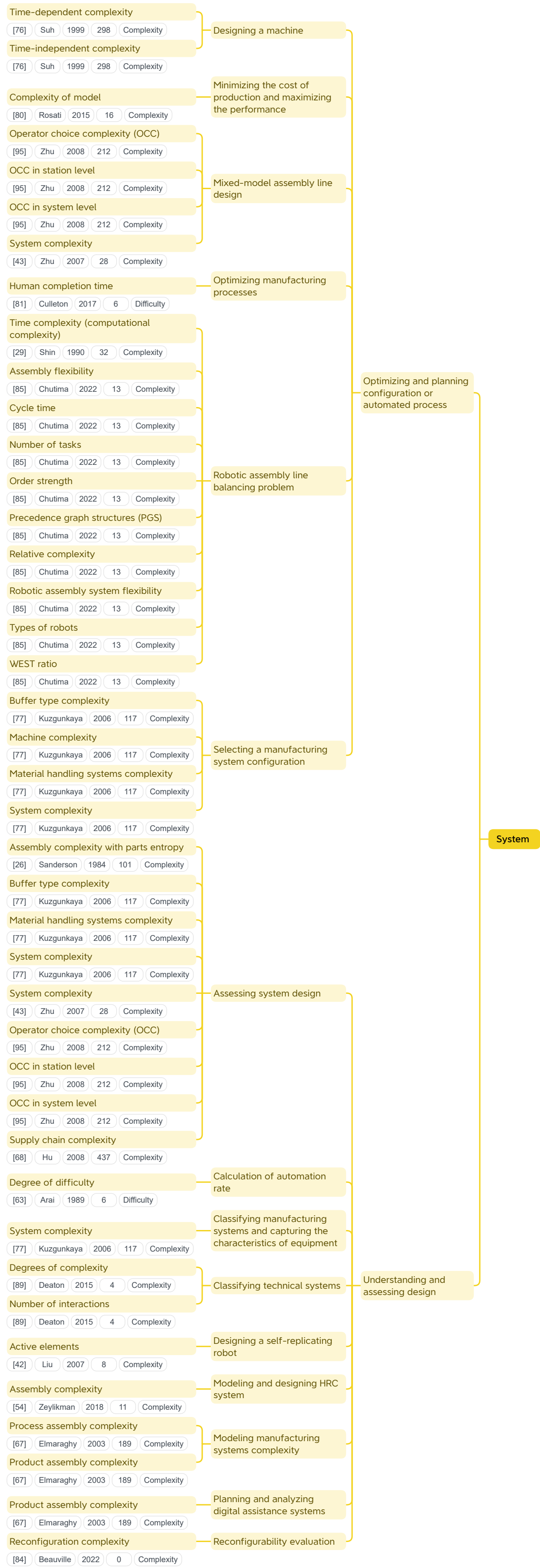


Figure 12: *Definition-use-objective*-oriented tree (taxonomy-1) of the definitions that evaluate *System* aspects

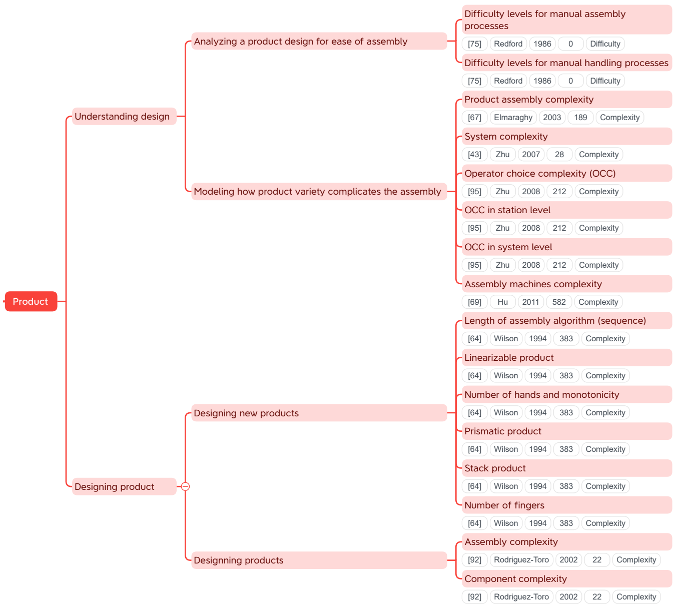


Figure 13: *Definition-use-objective*-oriented tree (taxonomy-1) of the definitions that evaluate *Product* aspects

In many instances, there are multiple input variables in the definition calculation, and when this is the case, the definition may span multiple categories. The same definition can be located in other trees using the number following the asterisk mark $*$ at the end of the displayed definition name.

In this study, the articles cited from at least 50 articles are described in the following sections: agent, system, product, and task. In the subsequent sections, we describe representative definitions, and Section 4 discusses the relationship between the four taxonomies.

3.2. Agent

In the case of complexity of agent, to characterize the operator performance in making choices, Zhu *et al.* [95] considered that the operator must choose the correct part from all possible variants according to the customers' order at each assembly station and defined the term *operator choice complexity (OCC)* (or choice complexity). OCC represents a kind of complexity in a part choice process, which can be described as:

$$H(X) = H(p_1, p_2, ..., p_M) = -C \sum_{m=1}^{M} p_m \log p_m, \qquad (1)$$

where C is a constant depending on the base of the logarithm function chosen and the probability of a choice taking the mth outcome is defined as p_m, for $m = 1, 2, ..., M$.

On a station, in addition to the part choice, the operator perform sequential assembly tasks. For instance, all fixture, tool, and procedure choices contribute to the operator choice complexity. Zhu *et al.* number the sequential assembly task from 1 to K and denote C_j as the total complexity of station j, which is a weighted sum of the various types of choice complexity at

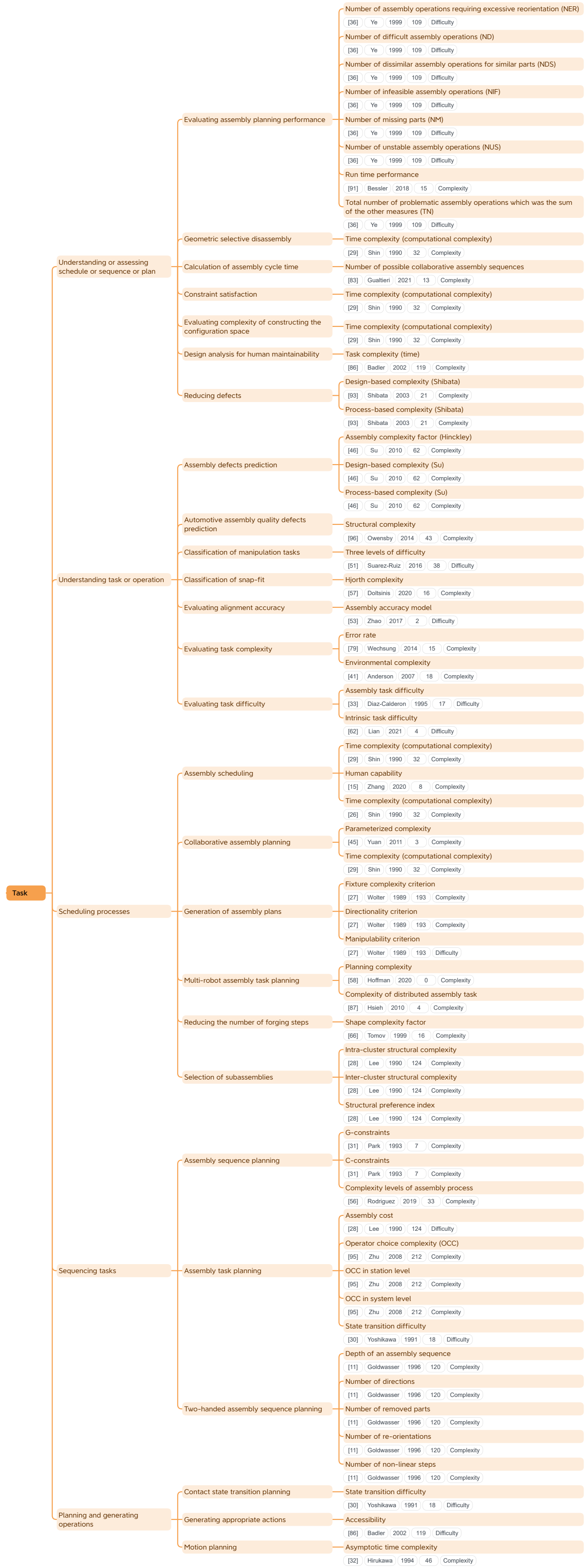


Figure 14: *Definition-use-objective*-oriented tree (taxonomy-1) of the definitions that evaluate *Task* aspects

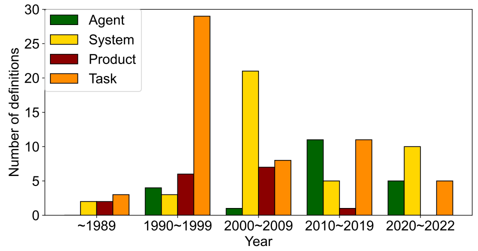


Figure 15: Number of *definition-use-objective*-oriented definitions

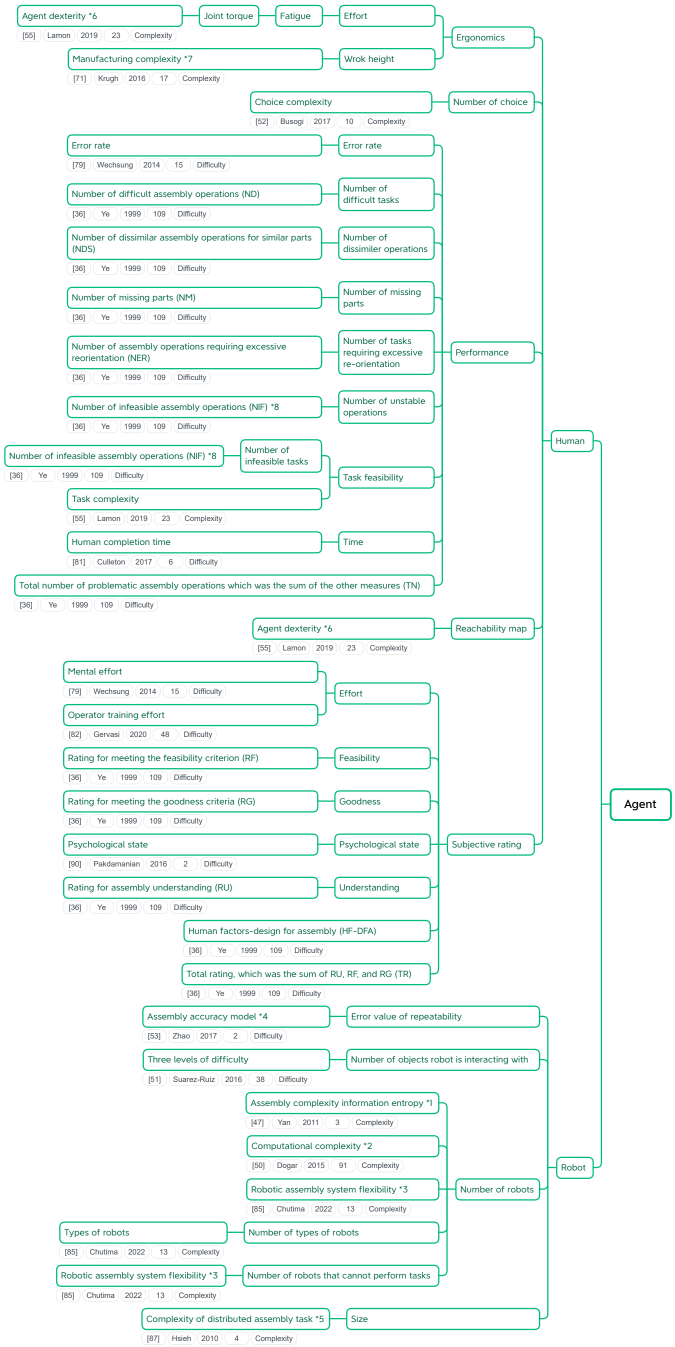


Figure 16: *Evaluation-variable*-oriented tree (taxonomy-4) of the definitions that evaluate *Agent* aspects

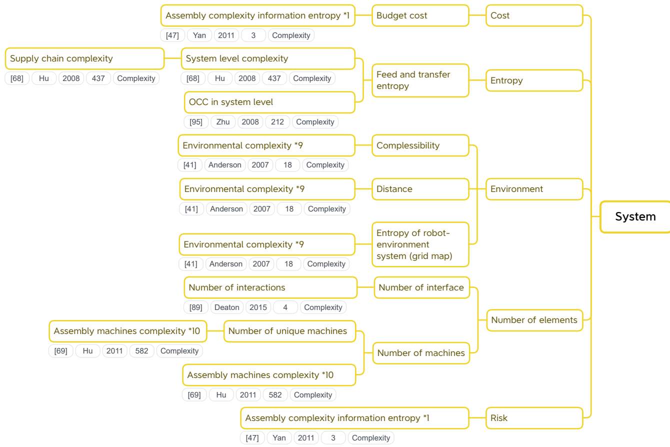


Figure 17: *Evaluation-variable*-oriented tree (taxonomy-4) of the definitions that evaluate *System* aspects

the station,

$$C_j = \sum_{k=1}^{K} \alpha_j^k (a_j^k + b_j^k H_j^k), \quad \alpha_j^k > 0, \quad k = 1, 2, ..., K, \tag{2}$$

where α_j^k represent task difficulty weights of the kth assembly task at station j, a_j^k's and b_j^k's are empirical constants related to the nominal human performance, and H_j^k is the entropy calculated based on the variant mix ratio relevant to the kth task at station j. For simplicity, they assume that $a_j^k = 0$ and $b_j^k = 1$, $\forall j, k$. Then Equation (2) reduces to

$$C_j = \sum_{k=1}^{K} \alpha_j^k H_j^k, \quad \alpha_j^k > 0, \quad k = 1, 2, ..., K. \tag{3}$$

This is called as *OCC in station level*.

Based on the OCC, they also defined *OCC in system level*. For an assembly line with n workstations, numbered 1–n sequentially, based on Equation (1), we can calculate the entropy H for the variants at each station. The propagation of complexity in a multi-stage system can be estimated based on choice complexity during sequential assembly tasks at a station is affected by the variety added at its upstream stations (*incoming complexity*), and how variants added at the station influence its downstream stations (*outgoing complexity*). The incoming complexity at station j, C_j^{in}, represents the complexity at the station from its upstream stations. The incoming complexity at stations j and n can be calculated as follows:

$$\begin{aligned} C_j^{\text{in}} &= C_{0,j} + C_{1,j} + \cdots + C_{j-1,j} \\ &= a_{0,j}H_0 + a_{1,j}H_1 + \cdots + a_{j-1,j}H_{j-1}, \end{aligned} \tag{4}$$

$$\begin{aligned} C_n^{\text{in}} &= C_{0,n} + C_{1,n} + \cdots + C_{n-1,n} \\ &= a_{0,n}H_0 + a_{1,n}H_1 + \cdots + a_{n-1,n}H_{n-1}, \end{aligned} \tag{5}$$

where C_j^{in} represents the incoming complexity at stations j, and $j = 1$–n, H_j represents the entropy of variants added at station j; H_0 is the entropy of variants due to the base part; a_{ij} is the coefficient that represents complexity impact on station j due to variety added at station i.

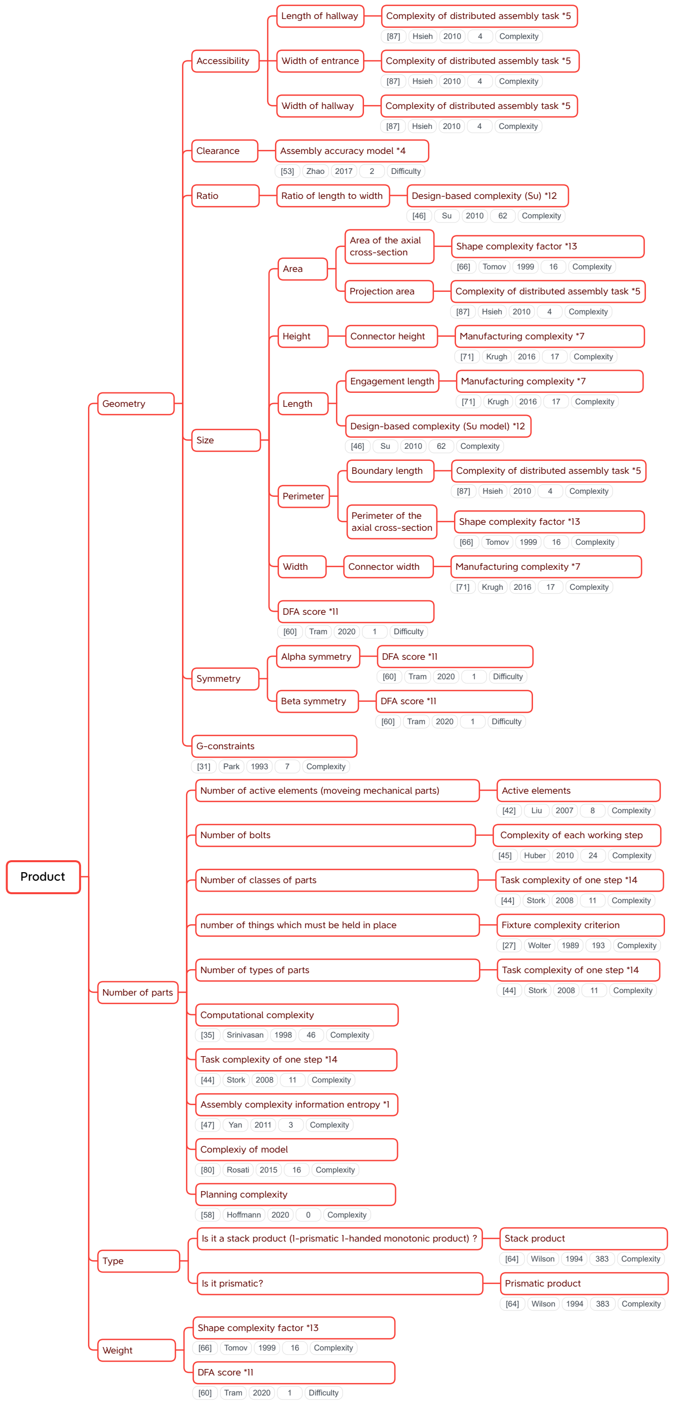


Figure 18: *Evaluation-variable*-oriented tree (taxonomy-4) of the definitions that evaluate *Product* aspects

The outgoing complexity at station j, C_j^{out}, represents the complexity flowing out of the station; that is, the amount of choice complexity caused by the addition of variants at the station, which impacts the operations of subsequent stations. Similarly, the equations for stations j and n are as follows:

$$\begin{aligned} C_j^{\text{out}} &= C_{j,j+1} + \cdots + C_{j,n} \\ &= (a_{j,j+1} + \cdots + a_{jn})H_j, \end{aligned} \tag{6}$$

$$C_{n-1}^{\text{out}} = C_{n-1,n} = a_{n-1,n}H_n, \tag{7}$$

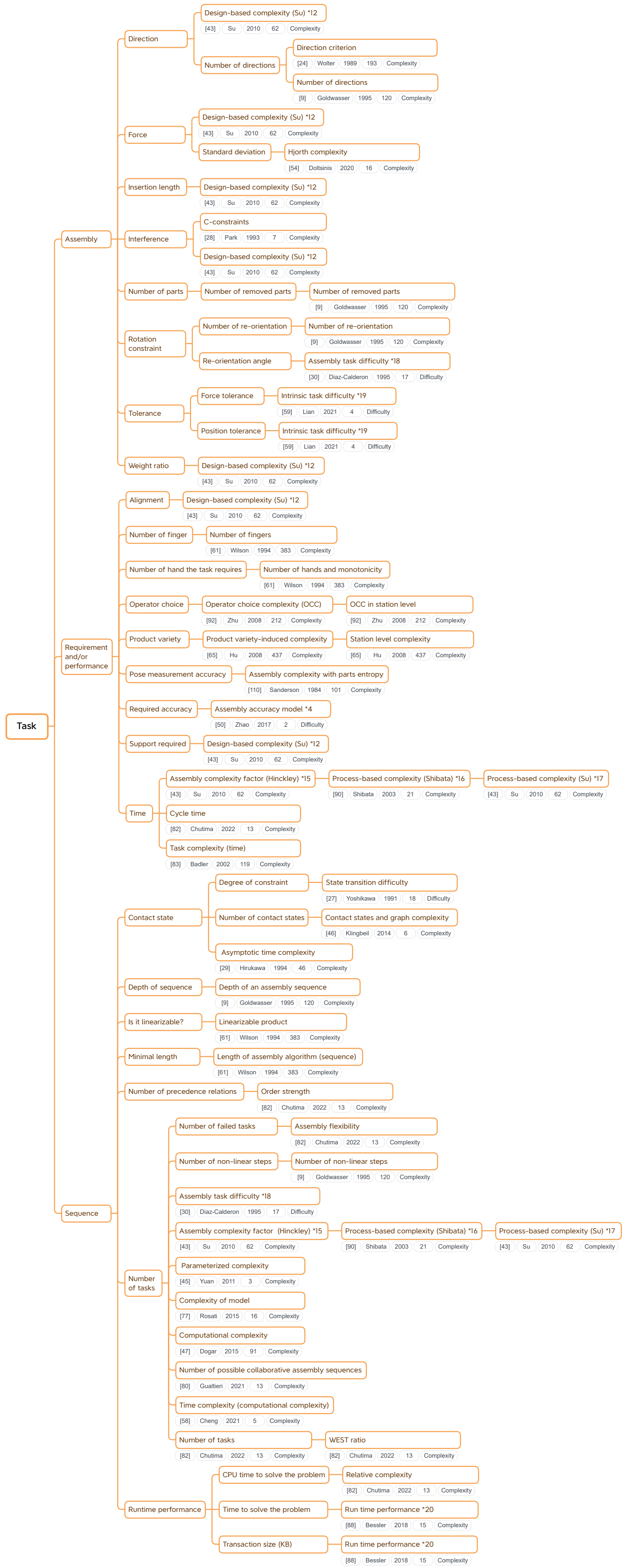


Figure 19: *Evaluation-variable*-oriented tree (taxonomy-4) of the definitions that evaluate *Task* aspects

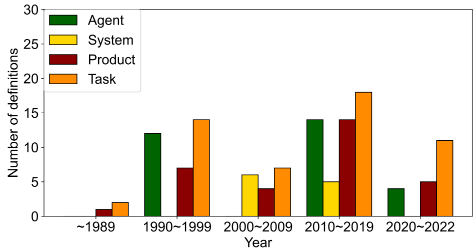


Figure 20: Number of *evaluation-variable*-oriented definitions

where C_j^{out} represents the outgoing complexity of station j, $j = 1$–n. In fact, by definition $C_n^{\text{out}} = 0$.

These OCCs (OCC in station and system levels) correspond to the physiological factor of human-centered factors and the effort category. Zhu *et al.* [95] used these definitions to model the manufacturing complexity in assembly lines. In a similar study, Busogi *et al.* [52] defined *choice complexity*, which refers to the difficulty operators face when selecting the appropriate component from a number of options available. Similarly, Zhu *et al.* [43] considered *feed complexity* and *transfer complexity* by assuming that the choice complexity is a result of the feature variants added at the current station. Hu *et al.* [68] consider *station level complexity* and *system level complexity* for multi-stage mixed-model assembly, which are similar to the OCC in station and system levels, to evaluate assembly system designs [68] and to model how product variety complicates the assembly [69].

Regarding the difficulty on the agent, Ye *et al.* [36] proposed metrics including the *rating for assembly understanding (RU)*, *rating for meeting the feasibility criterion (RF)*, *rating for meeting the goodness criteria (RG)*, and *total rating, which was the sum of RU, RF, and RG (TR)*. These rating methods were used to assess the understanding and difficulty of assembly operations in relation to human physiological factors.

Ye *et al.* [36] also proposed numerous types of definitions to evaluate subjective performance and rating. They define the *number of assembly operations requiring excessive reorientation (NER)*, *number of difficult assembly operations (ND)*, *number of dissimilar assembly operations for similar parts (NDS)*, *number of infeasible assembly operations (NIF)*, *number of missing parts (NM)*, *number of unstable assembly operations (NUS)*, and *total number of problematic assembly operations (TN)*, which is the sum of the other measures. All of these definitions are categorized as human performance-oriented factors because they are objective evaluations based on counts of specific assembly operations that directly relates to human work performance.

As depicted in Fig. 10, Fig. 15, and Fig. 20, with regard to definition-use-objective-oriented and evaluation-variable-oriented definitions, the number of agent-derived definitions has increased since 2011 when Industry 4.0 was advocated. The number of articles involving the definition or use of agent-related difficulty and complexity can be expected to increase over the years. As more attention is focused on the realization of collaborative robots, as advocated in Industry 5.0, the importance of agent-derived difficulty and complexity definitions should be reconsidered. In particular, defining agent-derived difficulty and complexity in human–robot interactions using human emotion sensing and online sensing technologies is important.

3.3. System

Measuring the difficulty and complexity derived from an assembly system can facilitate an agent's understanding of the expected performance and limitations of system aspects (*e.g.* the body structure and intelligence). Several formulations for the complexity of an assembly system have been proposed.

Similar to OCC, the complexity measure introduced by Kuzgunkaya *et al.* [77] is defined using an entropy-based index that refers to the reliability of each machine to describe its state in the manufacturing system, along with an equipment type index to take the effect of the various technologies employed into consideration. Especially, this complexity measure considers the complexity to be solved to achieve an adaptable manufacturing system to cope with the changing production environment, namely, reconfigurable manufacturing system (RMS). In addition to the reliability, transporters and buffers also introduce complexity because their usage needs should be managed to keep uninterrupted production. Because each resource in a manufacturing system is a potential source of uncertainty (*i.e.* complexity), the buffers, as well as the handling systems, should be taken into account. Based on these considerations, the total complexity of an RMS is a function of:

$$H_{\text{RMS}} = w_1 H_{\text{M}} + w_2 H_{\text{Buffer}} + w_3 H_{\text{MHS}}, \tag{8}$$

where H_{M}, H_{Buffer}, and H_{MHS} denote the complexity arising from the machines, the complexity of buffers, and the material handling system (MHS) complexity, respectively. The relative weights of the sub-complexities are represented by w_1, w_2, and w_3, respectively.

The following equation expresses the complexity due to the machines:

$$H_{\text{M}} = \sum_{i=1}^{M} \sum_{j=1}^{N} X_{ij} a_{ij} \sum_{k=1}^{2} p_{ijk} \log_2\left(\frac{1}{p_{ijk}}\right), \tag{9}$$

where p_{ijk} is the probability of a machine's state at stage i of machine configuration j, a_{ij} is the type index of machine X_{ij}, X_{ij} is the number of machines in stage i at machine configuration j, N is the maximum number of modules installed in a machine, and M is the number of stages in a system configuration.

The second component of a manufacturing system's complexity is related to the buffers. In a manufacturing system with M stages, there can be a maximum of $(M$–$1)$ locations for buffers. Let k be the number of product variants that can exist in the system. Then two aspects related to the state of the buffers are analyzed:

$$H_{\text{Buffer}} = H_{\text{Buffer\_State}} + H_{\text{Product\_Variant}}, \tag{10}$$

where $H_{\text{Buffer\_State}}$ is the state of the buffer (*i.e.* whether it is empty or not), and $H_{\text{Product\_Variant}}$ is the product variant in the system. The complexity caused by the empty/non-empty state in each location, $H_{\text{Buffer\_State}}$ is calculated as follows:

$$H_{\text{Buffer\_State}} = \sum_{i=1}^{M-1} b_i \Big(p_{i,\text{ne}} \log_2 \Big(\frac{1}{p_{i,\text{ne}}} + p_{i,\text{e}} \log_2 \Big(\frac{1}{p_{i,\text{e}}} \Big) \Big), \quad (11)$$

where $p_{i,\text{e}}$ is probability of the ith buffer being empty, $p_{i,\text{ne}}$ is the probability of the ith buffer being non-empty, and b_i is the buffer type index, M–1 is the number of buffers which is the same as the number of stages–1. In order to calculate $H_{\text{Product\_Variant}}$, the complexity caused by the assignment of the product variant in the system can be expressed as:

$$H_{\text{Product\_Variant}} = \sum_{i=1}^{M-1} \sum_{j=1}^{k} p_{ij} \log_2 \Big(\frac{1}{p_{ij}} \Big). \quad (12)$$

The MHSs provide flexibility depending on their features. A uni-directional conveyor can only provide one fixed direction whereas an automatic guided vehicle (AGV) can provide several options for alternate routes to accommodate machine failures. In order to differentiate these things, the complexity of various MHS technologies and types is represented similarly to the machine types. The complexity of MHSs is calculated as follows:

$$H_{\text{MHS}} = \sum_{t=1}^{T} m_t \sum_{k=1}^{2} p_{tk,\text{MHS}} \log_2 \Big(\frac{1}{p_{tk,\text{MHS}}} \Big), \quad (13)$$

where $p_{tk,\text{MHS}}$ is reliability of MHS, m_t is MHS type index, T is the number of transporters used in MHSs, and k is the state of transporter t.

These definitions, *system complexity*, *machine complexity*, *buffer type complexity*, and *material handling systems complexity* used in [77], are categorized as common factors related to system. Kuzgunkaya *et al*. used above definitions to evaluate systems and selected a manufacturing system configuration. Samy *et al*. [78] considered similar definitions *equipment complexity*, *material handling complexity*, *buffer equipment complexity*, and *assembly system complexity* to evaluate assembly system designs. Elmaraghy *et al*. [94] consider definitions named *equipment complexity code (ECC)* and *layout complexity code (LCC)* similar to the System complexity. The ECC consists of three fields for: 1) Machines, 2) Buffers, and 3) Transporters. The LCC consists of four fields, and classifies the manufacturing system layout attributes according to Type, Control, Programming, and Operation.

Hu *et al*. [68] emphasize that product variety-induced complexity exists at each and every element in the supply chain. Let n_i and n_j be the number supplier and assembler, $q_{uv}^{ij}(u = 1, 2, ..., n_i, v = 1, 2, ..., n_j)$ be the state probability that captures the variety in supplier i and assembler j and the mix ratio of element j. The complexity of any supply–assembly relationship is defined in the following form:

$$C_{ij} = -\sum_u \sum_v \tilde{q}_{uv}^{ij} \log_2 \tilde{q}_{uv}^{ij}, \quad (14)$$

where $\tilde{q}_{uv}^{ij}$ is the normalized q_{uv}^{ij}, that means $\tilde{q}_{uv}^{ij}$ can be calculated as:

$$\tilde{q}_{uv}^{ij} = \frac{q_{uv}^{ij}}{\Sigma_i \Sigma_j \Sigma_u \Sigma_v q_{uv}^{ij}}. \quad (15)$$

Then the complexity of an assembly supply chain can be calculated by summing the complexity values originating from all supply–assembly relationships.

$$C_{sc} = \sum_i \sum_j C_{ij}. \quad (16)$$

When only the feed complexity is considered, the supply chain complexity becomes an extension of the complexity of the system with the supply chain structure incorporated (*i.e.* C_{sc} can be calculated as the sum of the complexities originating from the assembly system and supply chain configuration).

A calculation example for the *supply chain complexity* is described in [68]. The definition-use objective of the study [68] was to design an assembly system and this metric corresponds to the physical constraint factor class of robot-specific factors.

Shi *et al*. [88] defined various levels of human and robot collaboration and addressed the levels of complexity that influence the probabilities of successful integration, referred to as *levels of complexity*. This definition is intended to provide consistent descriptions of the collaboration levels and to align them with the manufacturing processes. The development of these definitions was accomplished through interviews of several stakeholders, including robot manufacturers, system integrators, technology providers, safety professionals in occupational health and safety, manufacturing engineering, robotics technical specialists from automotive companies, and standards committee. The robotic systems are categorized as three levels: low, medium, and high according to the levels of human and robot collaboration. The probability of successful integration has been developed based on the specific characteristics of the following scenarios.

According to the study by Shi *et al*. [88], three characteristics of low-level human and robot collaboration are:

1. *The human does not interact directly with the robot or the robot end-of-arm-tooling (EOAT).*
2. *When loading parts, operators load to a fixture, rotary device, or other transfer devices.*
3. *Humans do not enter into the working range of the robot, of EOAT, or of parts being manipulated by the robot.*

One or multiple operators load directly to the robot EOAT with the following four characteristics:

1. *Robot is in automatic mode.*
2. *Robot servo drives are de-energized.*
3. *Robot is extended to full extension.*
4. *No robot motion or EOAT motion occurs until the human exits the robot working range AND initiates a secondary input.*

One or multiple operators and the robot perform simultaneous actions within the working range of the robot with the following four characteristics:

1. *Robot is in fully automatic mode.*
2. *Robot servo drives are energized.*
3. *Robot motions occur while a human is within any part of the robot's full working range.*
4. *Robot speeds and/or motions may be modified, by the robot controller, based upon sensor inputs or communication between the robot and the human.*

The levels of complexity correspond to both human-centered and robot-specific factors because the calculation factors are related to the physical constraints of both agents.

Hu *et al.* [69] explained *assembly machines complexity* that represents a system complexity related to robot-specific physical constraint as follows.

$$C_M = [\frac{n_M}{N_M} + \bar{I}_M][\log_2(N_M + 1)], \tag{17}$$

where C_M is the machine complexity, N_M is the total number of assembly machines, n_M is the number of unique assembly machines (an indicator of diversity), and $\bar{I}_M$ is the average complexity index of the N_M assembly machines.

Wilson *et al.* [64] defined measures as *number of fingers*, and *number of hands and monotonicity* that represent the complexity of assembly system structure and they are common factors related to system and product.

According to Fig. 10, Fig. 15, and Fig. 20, several definitions have been proposed and used for evaluation objectives; however, only limited specific evaluation variables have been clearly defined. With increasing proposals for practical and flexible systems, progress toward the establishment of general indicators is likely.

3.4. Product

HRC systems enable the assembly of different products, including different parts (*e.g.* metal products [100] and furniture [101]). The constraint, design, and sequence for such assembly products affect the complexity of the products.

Wilson *et al.* [64] also defined measures as *length of assembly algorithm (sequence)*, *linearizable product*, *prismatic product*, and *stack product* that represent complexity of assembly products. A linear algorithm contains only linear instructions and is, therefore, a total ordering. A product that admits a linear algorithm is said to be *linearizable*. Many one-handed products are not linearizable and are, in general, less suitable for mass-production assembly lines. The nature and the number of degrees of freedom required to perform assembly motions described in instructions is another key measure of product complexity. Let the assembly instruction be *m-prismatic* if the set of motions is a sequence of at most m extended translations. Because single translations are much more cost-effective to execute than multiple translations, the class of products assembled by one-prismatic instructions is significant. One can further characterize the complexity of a product within this class by the minimal number of translation directions that are needed. A stack product is a one-prismatic one-handed monotonic product that admits an algorithm in which every instruction specifies translations in the same direction. For instance, large subassemblies of many small consumer electronic products are stack products. All definitions proposed by Wilson *et al.* relate to common factors regarding the product.

Suh *et al.* [76] explained *time-dependent complexity* and *time-independent complexity*. In the time-dependent complexity field, two different kinds of complexities are shown: combinatorial complexity and periodic complexity. In a system subject to combinatorial complexity, the uncertainty of the future outcome grows as a function of time; consequently, such a system cannot be stable and reliable over the long term. In systems with periodic complexity, the system is deterministic and capable of self-renewal over each period. In the time-independent situations, two kinds of complexities are shown: real complexity and imaginary complexity, which are orthogonal to each other. Absolute complexity is defined as a vector sum of the real and the imaginary complexities. These time-dependent and -independent definitions pertain to the class of common factor systems and products.

Sanderson *et al.* [26] formulated *assembly complexity with parts entropy* H_n as:

$$H_n = H_n(P_1, ..., P_n) = -\sum_{k=1}^{n} P_k \log_2 P_k, \tag{18}$$

where $P_1, ..., P_n$ are the probabilities of the parts positions. Obviously, above equation is deformed from Equation (1), it suggests that if $\log_2$ is selected, $C = 1$. More generally, we can consider the contributions to the entropy of part Q from position, H_Q^{p} and from orientation H_Q^{o}:

$$H_Q = H_Q^{\mathrm{p}} + H_Q^{\mathrm{o}}. \tag{19}$$

This metric corresponds to the common product factor class.

Elmaraghy *et al.* [67] defined *product assembly complexity* and *process assembly complexity*. The product complexity is represented by the product complexity index, CI_{product}, and is a function of the product information entropy H_{product}, the product diversity ratio $D_{R_{\mathrm{product}}}$, and the product relative complexity coefficient $c_{j,\mathrm{product}}$. The value of the relative product complexity coefficient is based on general manufacturing principles and is independent of the process type or the volume. The value increases according to the effort required to produce the final part. Using utility charts, the product complexity index CI_{product} was determined as a combination of the diversity ratio and the relative complexity and scaled by information entropy as:

$$\begin{aligned} CI_{\mathrm{product}} &= (D_{R_{\mathrm{product}}} + c_{j,\mathrm{product}}) \times H_{\mathrm{product}}, && (20) \\ &= \left(\frac{n}{N} + c_{j,\mathrm{product}}\right) \times \log_2(N+1). && (21) \end{aligned}$$

where H_{product} is the information entropy measure, N is the total quantity of information, n is the total quantity of unique information, and $D_{R_{\mathrm{product}}}$ is the measure of the uniqueness of the diversity ratio. The product manufacturing complexity coefficient $c_{j,\mathrm{product}}$ is defined as:

$$c_{j,\mathrm{product}} = \sum_{f=1}^{F} x_f \times c_{f,\mathrm{feature}}, \tag{22}$$

where c_f is the relative feature complexity coefficient and x_f is the percentage of the x^{th} dissimilar feature. Please refer to the paper [67] for the calculation of relative complexity coefficient $c_{f,\text{feature}}$ and more details.

In the machining environment, the process complexity constituents are as follows: in-process features and steps; types of tools, tool holders, and spindles; fixtures or set-ups; product orientations; type of machines; type of gauges to measure individual features and feature relationships; and material handling. The procedure to determine the relative complexity of the product is then employed to calculate the relative complexity of the x^{th} individual process constituent. The process complexity index is the sum of the individual constituent complexity values and product complexity, and is expressed as

$$PI_{\text{process}} = \sum pc_x + CI_{\text{product}}, \tag{23}$$

where the x^{th} individual process complexity index pc_x is:

$$pc_x = \left(D_{R_{\text{process},x}} + c_{\text{process},x}\right) \times H_{\text{process},x}. \tag{24}$$

Both of these two metrics used in [67] correspond to the common product factor class. Hold *et al.* [70] used this metric to plan and analyze digital assistance systems to achieve cyber-physical assembly.

Wolter *et al.* [27] associated directionality of assembly plans for products with the product complexity. Generally, we would prefer to insert all parts in a single direction, as much as possible. This simplifies the fixtures, requires a robot with less dexterity, and eliminates the need for additional operations to reorient the workpiece. The directionality criterion quantifies the number of distinct directions from which operations are performed. Plans that only require operations from a single direction are superior than those that require operations to be performed from all directions. They require a less dexterous robot, a simpler fixture, and fewer workpiece reorientations. This *directionality criterion* reflects the complexity in relation to the typical product and task factors.

Goldwasser *et al.* [11] examined *minimum depth of an assembly sequence (depth of an assembly sequence)*, *fewest number of directions (number of directions)*, and *fewest number of re-orientations (number of re-orientations)* to identify the sequence with the lowest complexity. The number of directions and number of re-orientations correspond to the product and task of common factors, respectively. The depth of an assembly sequence is related to the system of the common factor class. This fact suggests that they considered three different common factors to evaluate the product complexity.

The products subject to automatic or semi-automatic assembly are expected to largely differ from the current situation with the demands of society. Therefore, generalizing the difficulty and complexity of such products cultivated in the past is essential; this is to facilitate their applications to various products developed in the near future, rather than evaluating them based on product-specific factors.

3.5. Task

Different definitions of task difficulty and complexity are explored in terms of operation and sequence. Wolter *et al.* [27] regarded *fixture complexity* as a type of environmental task complexity consisting of common system and task factors. In most cases, partially built assemblies should keep holding themselves together as much as possible through a determined sequence. For example, when we place ten washers on a peg, it is better to place washers on the peg one by one than to hold the ten washers in place while inserting the peg. Fixture complexity measures the number of objects that must be held in place during assembly operations. Generally, insertion operations should be sequenced such that the assembly remains as stable as possible throughout all stages of the assembly process. Obviously, this is not the only factor that affects the prices of fixtures.

Badler *et al.* [86] conducted a design analysis for human maintainability and maintenance to reduce procedure costs by minimizing errors, task complexity (time), and instruction manual updates. This metric relates the product and task of common factors. Other studies often consider different units of time to define the complexity. There are *time complexity (computational complexity)* used in [29, 65, 35, 37, 38, 39, 40, 50, 73, 15, 61, 85], *asymptotic time complexity* [32], *relative complexity* [85], and *cycle time* [85].

Su *et al.* [46] used *design-based complexity factor* defined by Shibata [102] as follows:

$$Cf_{D_i} = \frac{K_D}{D_i}, \tag{25}$$

where K_D is an arbitrary coefficient for calibration with process-based complexity; D_i represents the ease of assembly (EOA) of workstation i, evaluated based on the method of design for assembly/disassembly cost-effectiveness (DAC) developed in Sony Corporation.

Based on collected defect data of semiconductor products, Hinckley found that the defect per unit (DPU) was positively correlated with total assembly time and negatively correlated with the number of assembly operations [103]:

$$Cf = \text{TAT} - t_0 \times \text{TOP}, \tag{26}$$

where TAT, TOP, and t_0 represent total assembly time for the entire product, total number of assembly operations, and threshold assembly time, respectively. Su *et al.* [46] used *process-based complexity* called the *Shibata model*. Shibata [102] remarked that the *assembly complexity factor (Hinckley)* [103] did not consider assembly design factors and could not evaluate the defect rate for a specific workstation.

Therefore, Shibata proposed the process-based complexity factor (Cf_{P_i}). In the Shibata model, the process-based complexity factor of workstation i is defined as follows:

$$Cf_{P_i} = \sum_{j=1}^{N_{ai}} \text{SST}_{ij} - t_0 \cdot N_{ai}, \tag{27}$$

where N_{ai} and SST_{ij} represent the number of job elements in workstation i and the time spent on job element j in workstation i, respectively.

Therefore, the Hinckley model takes only common task factors into account. Design-based complexity takes both the physical constraint and performance-oriented factors for robots and process-based complexity takes common system and task factors into account at the same time.

Krugh *et al.* [71] used the same Hinckley and Shibata models as well as the *Antani model* [104], which was built on the Hinckley, Shibata, and Su models by redefining the manufacturing complexity as a measure of the impact of design, process, and human factor variability on assembly. This is the first model that includes human factors with design and process variables as a comprehensive measure of manufacturing complexity.

Lee *et al.* [28] first defined two types of complexities: *inter-cluster structural complexity* and *intra-cluster structural complexity*. The intra-cluster structural complexity, $C_{\phi}(S)$, of a subassembly S is represented by a tuple $(\bar{d_w}, \eta_w)$. $\bar{d_w}$ is the average of the weighted degrees of individual nodes in the subassembly S. η_w is the weighted connectivity of S: $\bar{d_w} = \sum_{i=1}^{n} d_w(n_i)/n$ where $d_w(n_i)$ the weighted degree of a node n_i, is the sum of the weights of the edges incident upon n_i in the weighted ALG of S. Moreover, n is the total number of nodes in the weighted ALG of S. η_w is the sum of the weights of the edges belong to the minimal cut-set of the weighted ALG of S. The inter-cluster structural complexity, $C_{\pi}(S)$, of a subassembly S represents the complexity of the connection between S and the rest of the assembly. $C_{\pi}(S)$ is the sum of the weights of the edges connecting the subassembly with the rest of the assembly.

Based on the aforementioned two types, Lee *et al.* proposed the *structural preference index*, SPI(S). The SPI(S) of a subassembly S is measured by the two complexities: a higher SPI is assigned to a subassembly with a higher intra-cluster structural complexity and a lower inter-cluster structural complexity. SPI(S) is computed as follows:

$$\mathrm{SPI}(S) = \exp\{-[(1-\frac{\eta_w(S)}{n})+\gamma_1(1-\frac{\bar{d_w}(S)}{n})+\frac{\gamma_2 C_{\pi}(S)}{n}]\}, \quad (28)$$

where γ_1 and γ_2 are the assembly coefficients. All of the definitions by Lee *et al.* are included in the common product factor and robot-specific physical constraint factor classes.

Regarding the task difficulty, Lee *et al.* [28] proposed *assembly cost*. The cost of assembly of an edge depends on factors such as the difficulty of aligning and positioning parts, resistance during insertion, difficulty of part handling, and need to hold down a part after assembly. To be more specific, they consider that the cost of assembly of an edge is a function of the interconnection type of the edge, the relative stability of the edge after the interconnection is completed, the degrees of freedom of separation (DFS) of the two parts associated with the edge, the mating tolerance, the number of mating volumes involved in an edge, the number of connectors/retainers, and the weight of the mating part. The relative cost of assembly of an edge e_i, $C_r(e_i)$, $0 < C_r(e_i) \leq 1$, is then determined by:

$$C_r(e_i) = \sum_{i=1}^{5} \alpha_i X_i, \quad (29)$$

where X_1 is the relative cost as a function of interconnection type, X_2 is the relative stability associated with an interconnection type, X_3 is $1 - \mathrm{DFS}(e_i)/6$, X_4 is $1/[1 + \exp -(\text{\# of mating volumes} - 1)/\text{normalization factor}]$, and X_5 is $\min(1, 0.2 \times (\text{the number of connectors} - 1))$ α_i, $0 \leq \alpha_i \leq 1$, $i = 1, ..., 5$, are assembly coefficients, and $\sum \alpha_i \leq 1$. The values of α_i's and normalization factor are dependent upon the actual assembly environment, including whether it is manual assembly, robot assembly, or hard automation assembly. This metric corresponds to the common product factor and robot-specific physical constraint classes.

Wolter *et al.* [27] correlated manipulability of assembly plans with the task difficulty. Generally, we prefer to perform the more difficult operations with easier-to-handle components. For instance, when we attach a bolt to an engine block, we would prefer to fix the engine block while screwing in the bolt, rather than the other way around. The manipulability criterion favors performing difficult operations with parts that are easy to handle. For example, when attaching a spark plug to an automobile, it is the spark plug that should be rotated, and not the automobile. To estimate an overall manipulability rating for a plan, each part is given the manipulability rating, and each trajectory is given a difficulty rating. The product of these gives the rating for an operation. The manipulability of the plan is the sum of the ratings for all the operations. The *manipulability criterion* corresponds to the common product factor class.

Badler *et al.* [86] reported that *accessibility* must be considered when determining task difficulty. For example, disassembly sequences must consider human access. One of their case studies involved a fuel tank vent situated behind a small access panel inhibiting the direction of a human technician's approach and clearance. The allowable and necessary actions are limited to open elbow coupling, slide sleeve on elbow, rotate elbow, disconnect pressure sense tube, open pressurization tube coupling; slide sleeve on pressurization tube, and disconnect pressurization tube. This definition considers four factors: common product and task, human-centered physical constraint, and robot-specific physical constraint.

According to Figures 10, 15, and 20, the number of task-related definitions has increased over the years, particularly in evaluation-objective- and evaluation-variable-oriented definitions. Definitions of difficulty and complexity for collaborative tasks are expected, as advocated in Industry 5.0.

4. Discussions

4.1. Relationships between Difficulty and Complexity

As shown in the generated evaluation-factor-oriented taxonomy represented by Figures 3 and 4, relatively numerous difficulty definitions are obtained in the category named agent, and relatively numerous complexity definitions are obtained in the category named product and system. Moreover, both types of definitions (difficulty and complexity) were included in the category named task.

Based on this fact, the inclusion relationship between difficulty and complexity in terms of the four categories, namely,

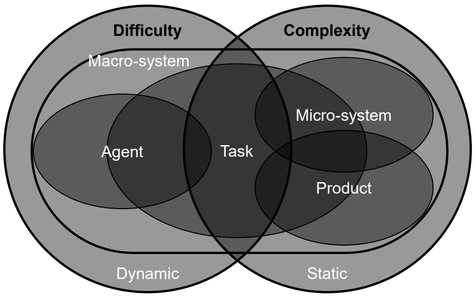


Figure 21: Inclusion relationship among common and agent-specific factors at the evaluation objective level

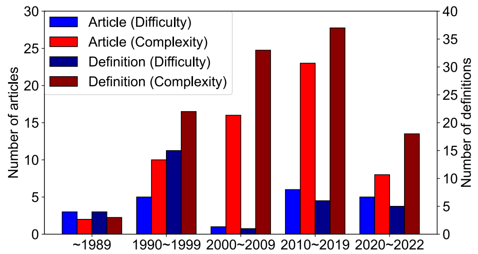


Figure 22: Number of articles proposing or using some definitions and number of definitions proposed or used in their articles

agent, system, product, and task, can be illustrated as shown in Fig. 21. Note that this does not show a rigorous inclusion relationship without excess or deficiency but merely expresses the existence of each category. The differences between complexity and difficulty were identified as *static* and *dynamic* concepts. *Complexity* is an inherent property of a system, product, or task. In addition, it is treated as a static property that does not involve an agent that uses it. In contrast, *difficulty* can be considered a dynamic property that results from someone feeling or understanding a static property. The *macro-system* in the figure indicates a system in a broad sense that includes agents (human and robot) and conditions (machine, product, task, and environment), whereas the *micro-system* indicates an independent system in a narrow sense that can be separated from the agent. Fig. 22 presents the trends followed by the number of articles and definitions since the 1980s. The articles included both types of articles that proposed or used one or more definitions. The greater number of articles and definitions of complexity than of difficulty, as shown in Table 4, can be explained by the fact that the definition of complexity, which indicates a static property, has been developed in the past, and difficulty, a dynamic property based on these static properties, has only been considered in recent years.

Fundamentally, the following expression may be a good way to describe this relationship. *Difficulties with agents in using objects with universal complexities*. The *objects* can be replaced with the system, product, and task. Regarding complexity, as represented by the *number of fingers*, *number of hands and monotonicity* [64] categorized as System, *complexity of model* [80], and *time-dependent and -independent complexities* [76] categorized as Product, there are composite definitions of complexity that consider both System and Product complexity factors. Similarly, the composite complexity between system-and-task and product-and-task has been considered in existing definitions (*reconfiguration complexity* [84], *c-constraints* [31], *run time performance* [91], *directionality criterion* [27], and *depth of an assembly sequence* [11]). Several definitions are categorized as Agent, and all definitions are related to the Task. *Human capability*, *choice complexity*, and *agent effort* are implicitly related to the Task because they represent the complexity originating from the capability of the number of tasks the human can handle, the complexity of the choice task, and the effort of agents on any task, respectively. For example, the *mental effort*, *HF-DFA*, *task difficulty*, and multiple subjective rating definitions proposed by Ye *et al.* [36] consider pure agent-specific difficulty.

To evaluate a target based on a proper understanding of the definitions, researchers and developers should be careful in understanding the relationship between the difficulty or complexity of HRC assembly systems with complex components.

4.2. Potential Implications and Applications of Taxonomies

To realize human-centric manufacturing, which is a goal of Industry 5.0, understanding situations perceived as difficult and complex by humans and robots is essential. For example, it may be possible to challenge human-centric manufacturing by incorporating more agent-specific elements into the framework used in previous studies [17, 18]. Malik *et al.* [17] developed a dynamic task allocation framework to realize a complexity-based HRC assembly by considering the complexity of parts, processes, and workspaces. To compute the complexity, they proposed a scoring method by defining more specific attributes for each of the three items.

By restructuring their framework to consider agent-specific factors in the complexity calculation, we could achieve a more human-centric HRC assembly. With objective functions designed for task allocation and assignment, we can set up a more practical problem for human-centric manufacturing. Notably, the hierarchical taxonomy defined in this paper may be useful in designing objective functions, as users can easily identify suitable definitions.

5. Challenges and Future Directions

This section discusses the challenges and future directions regarding task allocation and assignment in HRC assembly systems based on the investigation results, in terms of the evaluation factors shown in Figures 3 and 4. Figures 23 and 24 show the co-occurrence of all categorization pairs. As previously stated, task difficulty, system complexity, and product complexity have more definitions than others. This is an inevitable consequence of the relationship between the difficulty and complexity. In addition, many definitions consider both properties simultaneously for the system, product, and task as common factors; however, few consider the properties of interaction and agent-specificity with common factors simultaneously. Many parts are undefined, and a few mixed definitions simultaneously consider these multiple elements.

		Common				Human			Robot		Levels		
		System	Product	Task	Interaction	Physics	Physiology	Performance	Physics	Performance	Hxn	Rxm	Hxn & Rxm
Common	System		1	2	0	0	0	0	2	2	0	2	2
	Product			5	0	1	0	0	2	1	1	2	2
	Task				1	3	2	8	7	7	11	17	18
	Interaction					1	2	0	0	0	0	0	2
Human	Physics						3	1	1	0	1	0	2
	Physiology							1	0	0	6	0	8
	Performance								0	0	9	7	8
Robot	Physics									5	0	6	6
	Performance										0	7	6
Levels	Hxn											9	16
	Rxm												16
	Hxn & Rxm												

Figure 23: Co-occurrence of all category pairs applied for *difficulty* definitions. The larger the number, the darker is the red.

		Common				Human			Robot		Levels		
		System	Product	Task	Interaction	Physics	Physiology	Performance	Physics	Performance	Hxn	Rxm	Hxn & Rxm
Common	System		11	8	1	2	4	0	6	4	22	31	31
	Product			15	0	1	4	0	1	0	37	37	37
	Task				1	1	5	0	6	4	35	38	39
	Interaction					0	0	0	1	1	0	1	1
Human	Physics						2	0	1	0	3	2	3
	Physiology							0	1	2	10	4	8
	Performance								0	0	0	0	0
Robot	Physics									6	1	14	14
	Performance										3	21	21
Levels	Hxn											62	66
	Rxm												98
	Hxn & Rxm												

Figure 24: Co-occurrence of all category pairs applied for *complexity* definitions. The larger the number, the darker is the blue.

5.1. Agent-Centered Interactions

The least common category of definition is *interaction*, which is included in common factors. In addition, limited human-specific definitions have been acquired compared to other common and robot-specific factors, despite the fact that human-centric manufacturing is expected to be realized in Industry 5.0. The performance of manual operations that affects the difficulty and complexity of human operators differs according to each individual, compared with operations by robots. Therefore, both individuality and experience should be considered. Additionally, in future studies, ways to understand user-specific difficulties online through interactions should be explored.

The communication and physical interactions between human–robot, human–human, and robot–robot interactions may have been considered insufficiently. Tausch *et al.* [105] attempted to correlate studies from different fields such as psychological theory, HRI, and allocation optimization to create a new process model of ad hoc task allocation in human—robot interaction. Robot self-allocation in the absence of inputs can reduce the mental efforts of human workers and help balance the strain exerted on them. Tausch *et al.* highlighted the possibility that process control could influence the mental effort invested by a worker in an allocation decision. Frijns *et al.* [106] reviewed existing models of interpersonal communication and interaction that have been developed and applied in the context of HRI and social robotics. Previously, symmetric models in which human and robot agents are depicted to function in similar ways (similar capabilities, components, processes) have been proposed. Instead, Frijns *et al.* proposed an asymmetric interaction model referred to as an Asymmetric MODel of ALterity in Human–Robot Interaction (AMODAL-HRI).

As reviewed by Gomez [107], numerous safe collaborative human—robot systems have been proposed and applied in industrial environments. This review summarizes current regulations along with new concepts and discusses multidisciplinary approaches, such as techniques for the estimation and evaluation of injuries during human—robot collisions, mechanical and software devices designed to minimize the consequences of human—robot impacts, impact detection systems, and strategies to prevent collisions or minimize their consequences. Kumar *et al.* [108] listed previously proposed safe interaction and intuitive interface methods related to physical and cognitive interactions. Predicting the actions of humans to control robots safely and efficiently might be beneficial as, discussed in [109, 110]. In this context, the limited communication range among the agents [111] must also be considered. Wang *et al.* [112] and Sun *et al.* [113] developed teaching-learning-collaboration models for collaborative robots to learn from human demonstrations and assist their human partners in shared working situations. Digital-twin cyber-physical systems using humans and robots have been developed to facilitate learning and teaching processes [70, 114, 115].

In addition to offline frameworks, robust online allocations and assignments for human workers and robots based on environmental changes are required. Notably, the uncertainties associated with human workers challenge the task-planning and decision-making abilities of robots. When aiming at industrial tasks such as collaborative assemblies, dynamics in the temporal dimension and stochasticity in the order of procedures need to be further considered. Liu *et al.* [116] presented an interactive training framework using a deep reinforcement learning method. For human–robot collaborative assembly tasks in the case study, their method was demonstrated to be capable of driving a robot represented by one agent to collaborate with a human partner, even when the human performed randomly in task procedures. Other studies addressed dynamic scheduling [117], dynamic task allocation [118, 119], and dynamic task assignment [120]. The definition of difficulty and complexity in online dynamic interaction has not yet been examined, and we believe that studies using difficulty and complexity in this direction are promising.

5.2. System- or Environment-Centered Interactions

To the best of our knowledge, few definitions have been proposed regarding the difficulty and complexity of interactions between human workers, systems, and environments. To design a collaboration system based on a target product, the required assembly planning can be roughly divided into two phases: 1) long-horizontal planning, which designs systems and designs sequences [121, 122] and operations; and 2) short-horizontal planning, which generates tasks and motion skills that are feasible and efficient [123, 124]. Two different interactions must be considered for the two phases: the interaction between humans and robots within the system and the interaction between humans or robots and the environment. Each interaction is relevant to both phases. Definitions of the difficulty and complexity of such topics have not been proposed as common metrics, measures, or evaluation methods. Yan *et al.* [47] defined the minimal assembly complexity information entropy. Information entropy is a promising approach for evaluating complexity; however, there is room to discuss definitions of difficulty and complexity in multi-agent systems that consider agent-derived information entropy.

Villani *et al.* [125] summarized the relationships between safety, trust in automation, and productivity for consideration in HRC applications. Furthermore, Baltrusch *et al.* [126] examined the influence of HRC on job quality. Achieving practical applications without considering interactions between the required specifications is difficult. Moreover, these relationships significantly affect the difficulty and complexity. Johannsmeier *et al.* [13] proposed a framework for HRC that comprises three different architectural levels: team-level assembly task planner, agent-level skill planning, and execution level. Explicitly decomposed planning allows distinguishing between levels of difficulty and complexity, which can then be appropriately addressed; however, the difficulty and complexity of the combined planners in various environments has not been deeply considered in previous studies.

5.3. Benchmark

Several benchmarking protocols and performance metrics were presented by Wyk *et al.* [127] and Kimble *et al.* [128] to support the evaluation of robotic assembly and disassembly operations. They presented a set of performance metrics, test methods, and associated artifacts to aid in the development and deployment of robotic assembly systems. However, there have been no attempts to develop benchmarks to evaluate HRC assembly systems. Consequently, benchmarks are required to accelerate the development and research on practical HRC assembly systems.

First, because most previous studies considered the difficulty and complexity of assembly operations for static (not moving), rigid, and polyhedral objects, extending the limits of target objects, such as deformable objects and more complex shapes, is required. Once HRC research is driven by the establishment of commonly used benchmarks, discussions on the definitions of difficulty and complexity will naturally extend to more advanced scenarios. Second, for a new benchmark to act as a breakthrough for assembly systems concerning joint operations, the difficulty of a wider range of interaction tasks, such as handovers and collaborative heavy object manipulation [129], must be defined. Third, associating levels of difficulty and complexity with such interaction tasks based on existing definitions is also promising for defining the potential benchmark. For example, based on the complexity estimated by information entropy, it might be possible to design a benchmark with multiple levels according to the level of uncertainty for each of the four aspects: agent, product, system, and task. To explore more agent-specific definitions in the future, agent-specific uncertainties should be considered in benchmark design.

6. Conclusions

To move toward a more human-centered society and industry, HRI researchers need to broaden their focus from mere task fulfilment to more holistic perspectives enabling robots to collaborate with humans. Difficulty-and-complexity-aware HRC assembly is necessary for human-centric manufacturing, which is the goal of Industry 5.0. This study identifies measures and metrics that define the difficulty and complexity adopted or applied in the literature using a systematic approach, thereby answering RQ1. Taxonomies were proposed to classify common, human-centered, and robot-specific aspects. While these taxonomies are mainly constructed under the needs and concepts of HRC assembly for future human-centric manufacturing, they can also be applied to other robotic disciplines.

The taxonomies were presented in the agent aspect, which has received more attention in robotics literature, answering RQ2. Additionally, definitions are summarized from the four perspectives of the definition-use objective, evaluation objective, evaluation factor, and evaluation variable described in the literature to help researchers and practitioners easily reach an appropriate definition by differentiating between confusingly similar definitions. Finally, several emergent research areas are identified that can be relevant in the next few years, thereby answering RQ3.

This paper proposes holistic taxonomies of the definition of difficulty and complexity used for task allocation and assignment based on current trends in previous studies. Researchers and practitioners aiming to build HRC assembly applications will require the selection of suitable definitions to allocate jobs and effectively assign tasks to agents. The results summarized in the proposed taxonomies can be used as a reference by these researchers. However, more effort is needed to identify or propose measures and metrics for assessing human and robot interactions. Therefore, future studies should expand the proposed taxonomies in this direction.

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References

[1] H. Lasi, P. Fettke, H.-G. Kemper, T. Feld, M. Hoffmann, Industry 4.0, Bus. Inf. Syst. Eng., 6 (2014) 239–242.

[2] Smart factory applications in discrete manufacturing, White paper, Industrial Internet Consortium (IIC), (2017).

[3] L. Li, China's manufacturing locus in 2025: With a comparison of "Made-in-China 2025" and "Industry 4.0", Technol. Forecast. Soc. Change 135 (2018) 66–74.

[4] M. Breque, L. De Nul, A. Petridis, Industry 5.0 : towards a sustainable, human-centric and resilient European industry, Publications Office of the European Union, 2021.

[5] A. Hanna, K. Bengtsson, M. Dahl, E. Erős, P.-L. Götvall, M. Ekström, Industrial Challenges when Planning and Preparing Collaborative and Intelligent Automation Systems for Final Assembly Stations, in: Proc. IEEE Int. Conf. Emerg. Technol. Fact. Autom., 2019, 400–406.

[6] S. Hjorth, D. Chrysostomou, Human–robot collaboration in industrial environments: A literature review on non-destructive disassembly, Robot. Comput. Integr. Manuf. 73 (2022) 102208.

[7] Y. Lu, H. Zheng, S. Chand, W. Xia, Z. Liu, X. Xu, L. Wang, Z. Qin, J. Bao, Outlook on human-centric manufacturing towards Industry 5.0, J. Manuf. Syst. 62 (2022) 612-–627.

[8] A. Bauer, D. Wollherr, M. Buss, Human–robot collaboration: a survey, Int. J. Humanoid Robot. 5 (2008) 47—66.

[9] D. J. Campbell, Task complexity: A review and analysis, The Academy of Manag. Rev. 13 (1) (1988) 40—52.

[10] S. N. S. Badrous, Complexity of products and their assembly systems, Ph.D. thesis, Univ. of Windsor (2011).

[11] M. Goldwasser, J.-C. Latombe, R. Motwani, Complexity measures for assembly sequences, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), Vol. 2, 1996, pp. 1851—1857.

[12] A. Roncone, O. Mangin, B. Scassellati, Transparent role assignment and task allocation in human robot collaboration, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 2017, pp. 1014-–1021.

[13] L. Johannsmeier, S. Haddadin, A hierarchical human–robot interaction planning framework for task allocation in collaborative industrial assembly processes, IEEE Robot. Autom. Lett. (RA-L) 2 (1) (2017) 41—48.

[14] F. Ranz, V. Hummel, W. Sihn, Capability-based task allocation in human–robot collaboration, Procedia Manuf. 9 (2017) 182-–189.

[15] S. Zhang, Y. Chen, J. Zhang, Y. Jia, Real-time adaptive assembly scheduling in human-multi-robot collaboration according to human capability, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 2020, pp. 3860-–3866.

[16] R. M¨uller, M. Vette, O. Mailahn, Process-oriented task assignment for assembly processes with human–robot interaction, Procedia CIRP 44 (2016) 210-–215.

[17] A. A. Malik, A. Bilberg, Complexity-based task allocation in human–robot collaborative assembly, Ind. Robot 46 (2019) 471-–480.

[18] A. A. Malik, A. Brem, Digital twins for collaborative robots: A case study in human–robot interaction, Robot. Comput. Integr. Manuf. 68 (2020) 102092.

[19] N. Gjeldum, A. Aljinovic, M. C. Zizic, M. Mladineo, Collaborative robot task allocation on an assembly line using the decision support system, Int. J. Comput. Integr. Manuf. 35 (4-–5) (2022) 510-–526.

[20] H. Zheng, Z. Liao, Y. Wang, Human–robot trust integrated task allocation and symbolic motion planning for heterogeneous multi-robot systems, in: Proc. ASME Dynamic Syst. Control Conf., 2018.

[21] B. P. Gerkey, M. J. Matari´c, A formal analysis and taxonomy of task allocation in multi-robot systems, The Int. J. Robot. Res. (IJRR) 23 (9) (2004) 939—954.

[22] G. A. Korsah, A. Stentz, M. B. Dias, A comprehensive taxonomy for multi-robot task allocation, The Int. J. Robot. Res. (IJRR) 32 (12) (2013) 1495—1512.

[23] A. Khamis, A. Hussein, A. Elmogy, Multi-robot Task Allocation: A Review of the State-of-the-Art, Springer, 2015, pp. 31—51.

[24] N. Seenu, R. M. K. Chetty, M. M. Ramya, M. N. Janardhanan, Review on state-of-the-art dynamic task allocation strategies for multiple-robot systems, Ind. Robot 47 (6) (2020) 929—942.

[25] E. Coronado, T. Kiyokawa, G. A. G. Ricardez, I. G. Ramirez-Alpizar, G. Venture, N. Yamanobe, Evaluating quality in human–robot interaction: a systematic search and classification of performance and human–centered factors, measures and metrics towards an Industry 5.0, J. Manuf. Syst. 63 (2022) 392–410.

[26] A. Sanderson, Parts entropy methods for robotic assembly system design, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 1984, pp. 600–608.

[27] J.Wolter, On the automatic generation of assembly plans, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 1989, pp. 62—68.

[28] S. Lee, Y. Shin, Assembly planning based on subassembly extraction, in: Proc. IEEE Int. Conf. Robot. and Autom., 1990, pp. 1606—1611.

[29] K. Shin, Q. Zheng, Scheduling job operations in an automatic assembly line, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 1990, pp. 176—181.

[30] T. Yoshikawa, Y. Yokokohji, Y. Yu, Assembly planning operation strategies based on the degree of constraint, in: Proc. IEEE/RSJ Int.Workshop Intel. Robot. Syst., 1991, pp. 682—687.

[31] J. Park, M. Chung, K. Lim, Acquisition of assembly constraints without redundancies, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), Vol. 2, 1993, pp. 69—74.

[32] H. Hirukawa, Y. Papegay, T. Matsui, A motion planning algorithm for convex polyhedra in contact under translation and rotation, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 1994, pp. 3020-–3027.

[33] A. Diaz-Calderon, D. Navin-Chandra, P. Khosla, Measuring the difficulty of assembly tasks from tool access information, in: Proc. IEEE Int. Symp. Assem. Task Plann., 1995, pp. 87-–93.

[34] Y. Yu, Y. Yokokohji, T. Yoshikawa, Two kinds of degree of freedom in constraint state and their application to assembly planning, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), Vol. 3, 1996, pp. 1993—1999.

[35] H. Srinivasan, R. Gadh, Complexity reduction in geometric selective disassembly using the wave propagation abstraction, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), Vol. 2, 1998, pp. 1478—1483.

[36] N. Ye, P. Banerjee, A. Banerjee, F. Dech, A comparative study of assembly planning in traditional and virtual environments, IEEE Trans. Syst., Man, Cybern., Part C: App. Rev. 29 (4) (1999) 546-–555.

[37] M. Garcia, A. Larre, B. Lopez, A. Oller, Reducing the complexity of geometric selective disassembly, in: Proc. IEEE/RSJ Int. Conf. Intel. Robot. Syst. (IROS), 2000, pp. 1474—1479.

[38] D. Johnston, J. Xiao, Hierarchical analysis for determining disconnectedness in a contact formation, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 2002, pp. 3309-–3314.

[39] X. Yuan, S. Yang, Virtual assembly with biologically inspired intelligence, IEEE Trans. Syst., Man, Cybern., Part C: App. Rev. 33 (2) (2003) 159—167.

[40] C. Bonaventura, K. Jablokow, A modular approach to the dynamics of

complex multirobot systems, IEEE Trans. Robot. (T-RO) 21 (1) (2005) 26-–37.
[41] G. T. Anderson, G. Yang, A proposed measure of environmental complexity for robotic applications, in: Proc. IEEE Int. Conf. Syst., Man and Cybern. (SMC), 2007, pp. 2461-–2466.
[42] A. Liu, M. Sterling, D. Kim, A. Pierpont, A. Schlothauer, M. Moses, K. Lee, G. Chirikjian, A memoryless robot that assembles seven subsystems to copy itself, in: Proc. IEEE Int. Symp. Assem. Manuf., 2007, pp. 264-–269.
[43] X. Zhu, S. J. Hu, Y. Koren, S. P. Marin, N. Huang, Sequence planning to minimize complexity in mixed-model assembly lines, in: Proc. IEEE Int. Symp. Assem. Manuf., 2007, pp. 251—258.
[44] S. Stork, C. Stossel, A. Schubo, Optimizing human-machine interaction in manual assembly, in: Proc. IEEE Int. Symp. Robot and Human Interact. Commun., 2008, pp. 113-–118.
[45] M. Huber, A. Knoll, T. Brandt, S. Glasauer, When to assist? - modelling human behaviour for hybrid assembly systems, in: Proc. Int. Symp. Robot. German Conf. Robot., 2010, pp. 1-–6.
[46] Q. Su, L. Liu, D. E. Whitney, A systematic study of the prediction model for operator-induced assembly defects based on assembly complexity factors, IEEE Trans. Syst., Man, Cybern., Part A: Syst. Hum. 40 (1) (2010) 107-–120.
[47] P. Yan, M. Jiao, Research of multi-robot parallel assembly optimization base on pso-ss, in: Proc. Int. Conf. Robot, Vis. Signal Process., 2011, pp. 220—223.
[48] X. Yuan, Collaborative planning of assembly sequences with joint intelligence, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 2011, pp. 134—140.
[49] E. Klingbeil, S. Menon, K. Go, O. Khatib, Using haptics to probe human contact control strategies for six degree-of-freedom tasks, in: Proc. IEEE Haptics Symp., 2014, pp. 93—95.
[50] M. Dogar, A. Spielberg, S. Baker, D. Rus, Multi-robot grasp planning for sequential assembly operations, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 2015, pp. 193—200.
[51] F. Su´arez-Ruiz, Q.-C. Pham, A framework for fine robotic assembly, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 2016, pp. 421—426.
[52] M. Busogi, N. Kim, Analytical modeling of human choice complexity in a mixed model assembly line using machine learning-based human in the loop simulation, IEEE Access 5 (2017) 10434—10444.
[53] F. Zhao, H. Gu, C. Li, C. Chen, Accuracy analysis for robotized assembly system, in: Proc. IEEE Int. Conf. Robot. Biomim. (ROBIO), 2017, pp. 1850-–1855.
[54] S. Zeylikman, S. Widder, A. Roncone, O. Mangin, B. Scassellati, The HRC model set for human–robot collaboration research, in: Proc. IEEE/RSJ Int. Conf. Intel. Robot. Syst. (IROS), 2018, pp. 1845—1852.
[55] E. Lamon, A. De Franco, L. Peternel, A. Ajoudani, A capability-aware role allocation approach to industrial assembly tasks, IEEE Robot. Autom. Lett. (RA-L) 4 (4) (2019) 3378—3385.
[56] I. Rodrıguez, K. Nottensteiner, D. Leidner, M. Kaßecker, F. Stulp, A. Albu-Sch¨affer, Iteratively refined feasibility checks in robotic assembly sequence planning, IEEE Robot. Autom. Lett. (RA-L) 4 (2) (2019) 1416-–1423.
[57] S. Doltsinis, M. Krestenitis, Z. Doulgeri, A machine learning framework for real-time identification of successful snap-fit assemblies, IEEE Trans. Autom. Sci. Eng. (T-ASE) 17 (1) (2020) 513—523.
[58] A. Hoffmann, L. N¨aagele, W. Reif, How to find assembly plans (fast): Hierarchical state space partitioning for efficient multi-robot assembly, in: Proc. IEEE Int. Conf. Robot. Comput. (IRC), 2020, pp. 172-–177.
[59] T. Miyauchi, T. Yamada, Design problem of hybrid assembly line with humans and robots considering automation difficulty level, in: Proc. Int. Cong. Adv. Appl. Info., 2020, pp. 735—740.
[60] A. V. N. Tram, M. Raweewan, Optimal task allocation in human–robotic assembly processes, in: Proc. Int. Conf. Robot. Autom. Eng., 2020, pp. 158—162.
[61] Y. Cheng, L. Sun, M. Tomizuka, Human-aware robot task planning based on a hierarchical task model, IEEE Robot. Autom. Lett. (RA-L) 6 (2) (2021) 1136-–1143.
[62] W. Lian, T. Kelch, D. Holz, A. Norton, S. Schaal, Benchmarking off-the-shelf solutions to robotic assembly tasks, in: Proc. IEEE/RSJ Int. Conf. Intel. Robot. Syst. (IROS), 2021, pp. 1046—1053.
[63] T. Arai, Forecast of assembly automation in the automobile industry: Technological progress in robotics, Technol. Forecast. Soc. Change 35 (2) (1989) 133—148.
[64] R. H. Wilson, J.-C. Latombe, Geometric reasoning about mechanical assembly, Artif. Intell. 71 (2) (1994) 371-–396.
[65] K. Jiang, L. Seneviratne, S. Earles, Assembly scheduling for an integrated two-robot workcell, Robot. Comput. Integr. Manuf. 13 (2) (1997) 131-–143.
[66] B. Tomov, A new shape complexity factor, J. Materials Process. Technol. 92-–93 (1999) 439-–443.
[67] W. ElMaraghy, R. Urbanic, Modelling of manufacturing systems complexity, CIRP Ann. 52 (1) (2003) 363-–366.
[68] S. Hu, X. Zhu, H. Wang, Y. Koren, Product variety and manufacturing complexity in assembly systems and supply chains, CIRP Ann. 57 (1) (2008) 45—48.
[69] S. Hu, J. Ko, L. Weyand, H. ElMaraghy, T. Lien, Y. Koren, H. Bley, G. Chryssolouris, N. Nasr, M. Shpitalni, Assembly system design and operations for product variety, CIRP Ann. 60 (2) (2011) 715-–733.
[70] P. Hold, F. Ranz, W. Sihn, V. Hummel, Planning operator support in cyber-physical assembly systems, IFAC-PapersOnLine 49 (32) (2016) 60—65.
[71] M. Krugh, K. Antani, L. Mears, J. Schulte, Prediction of defect propensity for the manual assembly of automotive electrical connectors, Procedia Manuf. 5 (2016) 144—157.
[72] J. Village, F. Salustri,W. Neumann, Using action research to develop human factors approaches to improve assembly quality during early design and ramp-up of an assembly line, Int. J. Ind. Ergon. 61 (2017) 107-–119.
[73] X. Zhang, H. Lin, Performance guaranteed human–robot collaboration with POMDP supervisory control, Robot. Comput. Integr. Manuf. 57 (2019) 59-–72.
[74] M. Lagomarsino, M. Lorenzini, E. De Momi, A. Ajoudani, An online framework for cognitive load assessment in industrial tasks, Robot. Comput. Integr. Manuf. 78 (2022) 102380.
[75] A. H. Redford, Design for Assembly, Springer, 1986, pp. 33—63.
[76] N. P. Suh, A theory of complexity, periodicity and the design axioms, Res. Eng. Design 11 (1999) 116-–132.
[77] O. Kuzgunkaya, H. Elmaraghy, Assessing the structural complexity of manufacturing systems configurations, Int. J. Flexible Manuf. Syst. 18 (2006) 145—171.
[78] S. N. Samy, H. ElMaraghy, A model for measuring complexity of automated and hybrid assembly systems, The Int. J. Adv. Manuf. Technol. 62 (2012) 813—833.
[79] I. Wechsung, P. Ehrenbrink, R. Schleicher, S. M¨oller, Investigating the Social Facilitation Effect in Human–Robot Interaction, Springer, 2014, pp. 167—177.
[80] G. Rosati, M. Faccio, L. Barbazza, A. Rossi, Hybrid flexible assembly systems (H-FAS): bridging the gap between traditional and fully flexible assembly systems, The Int. J. Adv. Manuf. Technol. 81 (2015) 1289—1301.
[81] M. Culleton, C. Mcginn, K. Kelly, Framework for assessing robotic dexterity within flexible manufacturing, J. Intell., Robot. Sys, 87 (2017) 507-–529.
[82] R. Gervasi, L. Mastrogiacomo, F. Franceschini, A conceptual framework to evaluate human–robot collaboration, The Int. J. Adv. Manuf. Technol. 108 (2020) 841-–865.
[83] L. Gualtieri, E. Rauch, R. Vidoni, Methodology for the definition of the optimal assembly cycle and calculation of the optimized assembly cycle time in human–robot collaborative assembly, The Int. J. Adv. Manuf. Technol. 113 (2021) 2369-–2384.
[84] A. Beauville, N. Klement, R. Lionel, O. Gibaru, L. Durville, Framework for the design and evaluation of a reconfigurable production system based on movable robot integration, The Int. J. Adv. Manuf. Technol. 118 (2022) 2373-–2389.
[85] P. Chutima, A comprehensive review of robotic assembly line balancing problem, J. Intell. Manuf. 33 (1) (2022) 1-–34.
[86] N. I. Badler, C. A. Erignac, Y. Liu, Virtual humans for validating maintenance procedures, Commun. ACM 45 (7) (2002) 56-–63.
[87] M. A. Hsieh, J. Rogoff, Complexity measures for distributed assembly tasks, in: Perf. Metr. Intell. Syst. Workshop, 2010, pp. 97—100.
[88] J. Shi, G. Jimmerson, T. Pearson, R. Menassa, Levels of human and robot collaboration for automotive manufacturing, in: Perf. Metr. Intell. Syst. Workshop, 2012, pp. 95—100.

[89] J. Deaton, R. Allen, Development and application of system complexity measures for use in modeling and simulation, in: Proc. Conf. Summer Comp. Sim., 2015, pp. 1—6.
[90] E. Pakdamanian, N. Shiyamsunthar, D. Claudio, Simulating the effect of workers' mood on the productivity of assembly lines, in: Proc. Winter Sim. Conf., 2016, pp. 3440-–3451.
[91] D. Beßler, M. Pomarlan, M. Beetz, Owl-enabled assembly planning for robotic agents, in: Proc. Int. Conf. Auton. Agents and MultiAgent Syst., 2018, pp. 1684-–1692.
[92] C. Rodri´guez-Toro, S. Tate, G. Jared, K. Swift, Shaping the complexity of a design, in: Proc. ASME Int. Mech. Eng. Cong. Expo., 2002, pp. 641-–649.
[93] H. Shibata, B. Cheldelin, K. Ishii, Assembly quality methodology: A new method for evaluating assembly complexity in globally distributed manufacturing, in: Proc. ASME Int Mech. Eng. Cong. Exp., Vol. 1-–2, 2003, pp. 335-–344.
[94] H. A. ElMaraghy, A complexity code for manufacturing systems, in: Proc. Int. Manuf. Sci. Eng. Conf., Vol. Manufacturing Science and Engineering, Parts A and B, 2006, pp. 625—634.
[95] X. Zhu, S. J. Hu, Y. Koren, S. P. Marin, Modeling of manufacturing complexity in mixed-model assembly lines, J. Manuf. Sci. Eng. 130 (5) (2008).
[96] J. E. Owensby, J. D. Summers, Assembly time estimation: Assembly mate based structural complexity metric predictive modeling, J. Comput. Info. Sci. Eng. 14 (1) (2014).
[97] A. Patel, P. Andrews, J. D. Summers, E. Harrison, J. Schulte, M. Laine Mears, Evaluating the use of artificial neural networks and graph complexity to predict automotive assembly quality defects, J. Comput. Info. Sci. Eng. 17 (3) (2017).
[98] B. Kitchenham, Procedures for performing systematic reviews, Tech. rep., Keele Univ. (2004).
[99] A. A. Malik, A. Bilberg, Developing a reference model for human—robot interaction, Int. J. Interact. Design and Manuf. 13 (2019) 1541—1547.
[100] B. Sadrfaridpour, Y. Wang, Collaborative assembly in hybrid manufacturing cells: An integrated framework for human–robot interaction, IEEE Trans. Autom. Sci. Eng. (T-ASE) 15 (3) (2018) 1178-–1192.
[101] I. Sera, N. Yamanobe, I. G. Ramirez-Alpizar, Z. Wang, W. Wan, K. Harada, Assembly planning by recognizing a graphical instruction manual, in: Proc. IEEE/RSJ Int. Conf. Intel. Robot. Syst. (IROS), 2021, pp. 3115—3122.
[102] H. Shibata, Global assembly quality methodology: A new method for evaluating assembly complexities in globally distributed manufacturing, Ph.D. thesis, Stanford Univ. (2002).
[103] C. M. Hinckley, A global conformance quality model: A new strategic tool for minimizing defects caused by variation, error, and complexity, Ph.D. thesis, Stanford Univ. (1993).
[104] K. R. Antani, A study of the effects of manufacturing complexity on product quality in mixed-model automotive assembly, Ph.D. thesis, Clemson Univ. (2014).
[105] A. Tausch, A. Kluge, L. Adolph, Psychological effects of the allocation process in human–robot interaction – a model for research on ad hoc task allocation, Front. Psychol. 11 (2020).
[106] H. Frijns, S. Oliver, S. Koeszegi, Communication models in human–robot interaction: An asymmetric model of alterity in human—robot interaction (AMODAL-HRI), Int. J. Soc. Robot. 15 (2021) 473—500.
[107] S. Robla-G´omez, V. M. Becerra, J. R. Llata, E. Gonz´alez-Sarabia, C. Torre-Ferrero, J. P´erez-Oria, Working together: A review on safe human–robot collaboration in industrial environments, IEEE Access 5 (2017) 26754-–26773.
[108] S. Kumar, C. Savur, F. Sahin, Survey of human–robot collaboration in industrial settings: Awareness, intelligence, and compliance, IEEE Trans. Syst., Man, Cybern., Syst. 51 (1) (2021) 280—297.
[109] A. M. Zanchettin, A. Casalino, L. Piroddi, P. Rocco, Prediction of human activity patterns for human–robot collaborative assembly tasks, IEEE Trans. Ind. Info. 15 (7) (2019) 3934—3942.
[110] M.-L. Lee, W. Liu, S. Behdad, X. Liang, M. Zheng, Robot-assisted disassembly sequence planning with real-time human motion prediction, IEEE Trans. Syst., Man, Cybern., Syst. (2022) 1-–13.
[111] X. Bai,W. Yan, S. S. Ge, Distributed task assignment for multiple robots under limited communication range, IEEE Trans. Syst., Man, Cybern., Syst. 52 (7) (2022) 4259-–4271.
[112] W. Wang, R. Li, Y. Chen, Z. M. Diekel, Y. Jia, Facilitating human—robot collaborative tasks by teaching-learning-collaboration from human demonstrations, IEEE Trans. Autom. Sci. Eng. (T-ASE) 16 (2) (2019) 640-–653.
[113] Y. Sun, W. Wang, Y. Chen, Y. Jia, Learn how to assist humans through human teaching and robot learning in human robot collaborative assembly, IEEE Trans. Syst., Man, Cybern., Syst. 52 (2) (2022) 728-–738.
[114] X. V. Wang, Z. Kem´eny, J. V´ancza, L. Wang, Human-–robot collaborative assembly in cyber-physical production: Classification framework and implementation, CIRP Ann. 66 (1) (2017) 5—8.
[115] A. Bilberg, A. A. Malik, Digital twin driven human-–robot collaborative assembly, CIRP Ann. 68 (1) (2019) 499-–502.
[116] Z. Liu, Q. Liu, L.Wang,W. Xu, Z. Zhou, Task-level decision-making for dynamic and stochastic human–robot collaboration based on dual agents deep reinforcement learning, Int. J. Adv. Manuf. Technol 115 (2021).
[117] N. Nikolakis, N. Kousi, G. Michalos, S. Makris, Dynamic scheduling of shared human–robot manufacturing operations, Procedia CIRP 72 (2018) 9-–14.
[118] A. Tsalatsanis, A. Yalcin, K. P. Valavanis, Dynamic task allocation in cooperative robot teams, Int. J. Adv. Robot. Syst. 6 (4) (2009) 35.
[119] S. Choudhury, J. K. Gupta, M. J. Kochenderfer, D. Sadigh, J. Bohg, Dynamic multi-robot task allocation under uncertainty and temporal constraints, Auton. Robots 46 (1) (2022) 231—247.
[120] G. Bruno, D. Antonelli, Dynamic task classification and assignment for the management of human–robot collaborative teams in workcells, The Int. J. Adv. Manuf. Technol. 98 (2018) 2415—2427.
[121] K. Tariki, T. Kiyokawa, T. Nagatani, J. Takamatsu, Generating complex assembly sequences from 3D CAD models considering insertion relations, Adv. Robot. 35 (6) (2021) 337-–348.
[122] T. Kiyokawa, J. Takamatsu, T. Ogasawara, Assembly sequences based on multiple criteria against products with deformable parts, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 2021, pp. 975—981.
[123] K. Harada, T. Foissotte, T. Tsuji, K. Nagata, N. Yamanobe, A. Nakamura, Y. Kawai, Pick and place planning for dual-arm manipulators, in: Proc. IEEE Int. Conf. Robot. Autom. (ICRA), 2012, pp. 2281—2286.
[124] W. Wan, K. Harada, F. Kanehiro, Planning grasps with suction cups and parallel grippers using superimposed segmentation of object meshes, IEEE Trans. Robot. (T-RO) 37 (1) (2021) 166—184.
[125] V. Villani, F. Pini, F. Leali, C. Secchi, Survey on human–robot collaboration in industrial settings: Safety, intuitive interfaces and applications, Mechatronics 55 (2018) 248-–266.
[126] S. J. Baltrusch, F. Krause, A. W. de Vries, W. van Dijk, M. P. de Looze, What about the human in human robot collaboration?, Ergonomics 65 (5) (2022) 719-–740.
[127] K. Van Wyk, J. Falco, E. Messina, Robotic grasping and manipulation competition: Future tasks to support the development of assembly robotics, in: Proc. Robot. Grasping and Manip., 2018, pp. 190—200.
[128] K. Kimble, K. Van Wyk, J. Falco, E. Messina, Y. Sun, M. Shibata, W. Uemura, Y. Yokokohji, Benchmarking protocols for evaluating small parts robotic assembly systems, IEEE Robot. Autom. Lett. (RA-L) 5 (2) (2020) 883-–889.
[129] M. Raessa, J. C. Y. Chen, W. Wan, K. Harada, Human-in-the-loop robotic manipulation planning for collaborative assembly, IEEE Trans. Autom. Sci. Eng. (T-ASE) 17 (4) (2020) 1800—1813.