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Dynamic Modeling of Manufacturing Capability for Robotic Disassembly in Remanufacturing

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Abstract

Product disassembly plays an important role in the sustainable manufacturing, and it is usually the first step in remanufacturing process, which determines the efficiency and capability of remanufacturing. Industrial robot (IR) as an intelligent manufacturing equipment to increase the productivity and reduce energy consumption (EC), has been applied to semi-automated product disassembly, and the thing that matters is studying and modeling of manufacturing capability for robotic disassembly in remanufacturing. In this paper, the IR disassembly capability is modeled dynamically using OWL, based on the mapping relation which associating the disassembly capability attributes and the real-time data. Furthermore, a method of association rules mining (ARM) based on bees algorithm (BA) is proposed to mine the association relationships from the data of disassembly processes. The effectiveness of the proposed modeling method is validated by a case study, and the results show that the dynamic modeling method could efficiently reflect the current state and dynamic capability of IRs during product disassembly process in remanufacturing.

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Keywords: Industrial Robot; Disassembly Capability; Meta-data Model; Association Rules Mining; Ontology

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1. Introduction

In order to deal with the challenge of resource shortage and environmental pollution, the concept of sustainable manufacturing and remanufacturing is put forward in the academic and industrial circles. Product disassembly is not only an essential part of sustainable manufacturing, but usually the first step in the remanufacturing process, and it will affect the various aspects of remanufacturing in [1,2]. Product disassembly is needed not only for end-of-life purposes, but also for product service and maintenance during product useful life in [1]. With emergence of the concept of man-machine cooperation, human-robot disassembly has become the focus of attention. However, there are lots of challenges on the human-robot disassembly currently and manual disassembly is limited. At present, industrial robots can be used in product disassembly to achieve semi-automated intelligent production, thereby enhancing the efficiency of disassembly, reducing operation cost, decreasing the energy consumption, optimizing the cycle time, increasing the flexibility, etc.

In the IR disassembly process, on one hand, the running state of IR should be monitored, and on the other hand, the on-demand task sequence should be planned. Therefore, it is necessary to analyze and research the disassembly capability of the industrial robot and to develop the digital model of manufacturing capability for robotic disassembly in remanufacturing.

This paper is organized as follows. Section 2 gives the relevant research on industrial robot and disassembly. Section 3 presents an ontology model of industrial robot disassembly capability.In this part, it is divided into three steps. Firstly, the multidimensional data model of IR in disassembly process is proposed. In the next step, a method of ARM based on bees algorithm is presented. Finally, there is an ontology model of IR disassembly capability based on the association rules. In section 4, combining with a case study, the developed method is verified and analyzed by a prototype system. Finally, a conclusion and outlook to further work will be given.

2. Related work

The manufacturing capability of industrial robots is realized through actuators, sensors, computers and other auxiliary facilities, which is able to complete welding, spraying, disassembly and other tasks coordinately and efficiently in [3]. The factors that affect the manufacturing capability of the robot in different processing tasks are different, for example, payload plays a crucial role in the process of mixing, cutting and assembly in [4]. The core ontology in the field of industrial robot is proposed by literature in [5], which can describe and share the knowledge of the robot. An ontology model of multi-robot system is presented by using the ontology technology, to describe the manufacturing capability of IR and the tasks that are executed in [6].

At present, the academic circles begin to pay attention to the sustainable manufacturing capability of industrial robots, so that the research on the dynamics and kinematics of the energy consumption of robotic system has become a hot spot. In [7], it designs a comprehensive experimental, using periodic excitation signal, to predict each join torque of IR and realizes the dynamic model identification. In [8], it proposes a general hybrid model of energy consumption, which analyzes the relationship between operation state and energy consumption. It analyzes the influence factors of the energy consumption of IR through the research on the speed, acceleration, load, brake control and trajectory of the robot body, and the corresponding optimization measures are given in [9,10,11]. Paryanto et al. study energy consumption and dynamic behavior of six axis IR in assembly system and analyze the electrical parameters and dynamic response of each axis by using the method of combining the simulation and experiment in [12].

Disassembly process has two main issues. First, is to determine to which level disassembly should be done; second is determining the optimal sequence of disassembly processes in [13]. In [14], a typical stochastic model of disassembly time analysis based on the established random disassembly network diagram is proposed, as well as the different disassembly decision criteria. An efficient and machine readable dynamic disassembly information model is presented in [15]. The basic method of intelligent disassembly planning is reviewed in [16]. Feng et al. describe a disassembly process information model that contains four key components in [17]. In [18], it presents a reverse assembly strategy for disassembly by using a manual and semi-automated method. An ergonomic work system has been designed for human-robot cooperation in future production systems in [19]. In [20], it states that the energy efficient robot configurations leads to reduce overall energy consumption for assembly.

The most previous researches are focused on disassembly sequence optimization and manufacturing capability of the robotic system. However, there is few research pays attention to the manufacturing capability for robotic disassembly. In this paper, a model of IR disassembly capability is established using OWL, which can reflect current state and dynamic capability.

3. Dynamic modeling of manufacturing capability for robotic disassembly

The disassembly process of industrial robots involves the fusion of the multi-source data, which can be used to acquire and mine knowledge. The ARM based on bees algorithm is proposed from the multi-source data of robotic disassembly, so as to facilitate extracting the concepts and attributes of robotic disassembly capability. In order to solve the above problems, a multidimensional data model of IR in disassembly process is presented firstly.

3.1. Meta-data model of manufacturing capability for robotic disassembly

The data sources of the disassembly process of IR include end-of-life product, disassembly equipment, disassembly task, disassembly process, sensor data and so on. Division of data structure, including structured data, such as the operation parameters of IR stored in the relational database; semi-structured data, such as the production log data and technical specifications; and unstructured data, such as communication XML and 3D modeling data. From the data type, it can be divided into discrete data and stream data. In addition, it can be described from four dimensions: technique, environment, time and equipment.

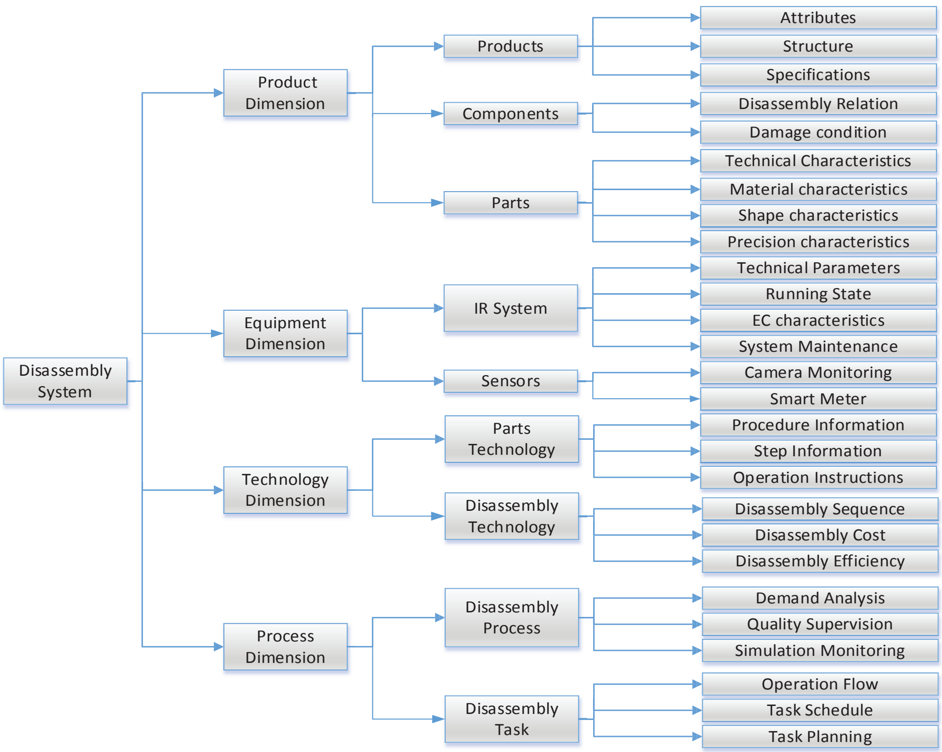


Fig. 1. Multi-dimensional data for disassembly process

Fig. 1 presents a four dimensional data model of IR disassembly process, which is classified and summarized from product dimension, equipment dimension, technology dimension and process dimension. Product dimension is divided into products, components and parts. Equipment data is mainly divided into the IR system data and sensor data. Technology dimension is composed of parts technology and disassembly technology. Process dimension is a description of the record and task for the disassembly process. In the disassembly process, the ubiquitous problems are caused by big data combined with the number, type, speed and accuracy. To describe accurately and share the data globally is the key for better use of disassembly multi-source data.

Meta-data is used to describe the data or documents of data structure in application, namely, the data about data, and is the kernel of data ETL. In Fig. 2, a disassembly meta-data model for IR is given, which is divided into four layers: meta-meta model, meta model, analysis model and instance. At the bottom of the model is IR disassembly system, including all the basic information and data sources. The upper layer is the analysis model layer, which is the data model layer used to describe the data and documentations related to the process of disassembly. The meta-data layer contains meta-data of data, meta-data of process and meta-data of task. There is a data model that contains the geometric data of the product, the parameters of the IR, the disassembly task, robotic running state and sensor's detection on the left. Process meta-data is the perception, recording and monitoring of the disassembly process, such as Mean Time Between Failures(MTBF). Meta-data model of task is a data model abstraction of disassembly sequence, product data model and disassembly planning.

Meta-data model of IR disassembly provides a good organization, description and management of data, giving a unified data model for data mining as well.

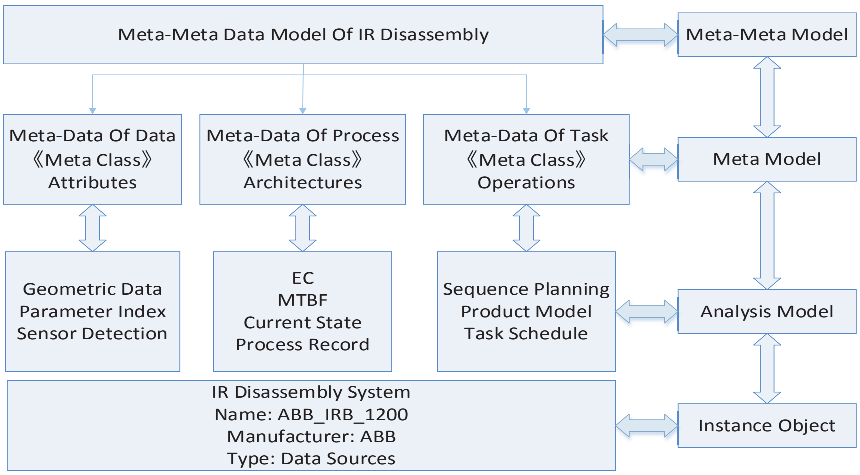


Fig. 2. Meta-data model of IR disassembly

3.2. Association rules mining in meta-data model for manufacturing capability

For the high-dimension, dynamic, massive and heterogeneous data sources of IR disassembly, data fusion is processed by using the meta-data model so as to facilitate the mining of concepts and attributes. Because of the high-dimension and multi-source data characteristics of IR disassembly, traditional association rules mining will make the number of the candidate set increase suddenly and result in a significant decrease in the efficiency of Apriori algorithm. Association rules mining is concerned with finding frequent item-sets, which is a process of global search and requires a global optimization algorithm to achieve the global optimal solution quickly. Next, the association rules mining steps based on the bees algorithm (ARM-BA) is given.

(1) Encoding

The integer encoding is used to represent the solutions. Each rule is considered as one solution in the search space, each one is represented by a vector **S** of *N* bits and their positions are defined as follows:

1) S[i] = 0 if the item i is not in the solution **S**.
2) S[i] = 1 if the item i belongs to the antecedent part of the solution **S**.
3) S[i] = 2 if the item i belongs to the consequent part of the solution **S**.

Example 1: Let $T = \{t_1, t_2, ..., t_6\}$ be a set of items. **S1**={1,0,2,0,1,2} represents the rule *R1*: $t_1, t_5 \Rightarrow t_3, t_6$.

(2) Initialization

The size of the group *N*, iterative algebra *T*, the empirical parameters α, β, *R*, neighborhood search radius *ngh*, support threshold *minSupp* and confidence threshold *minConf* are given by user.

(3) Fitness Evaluation

$$fitness(s) = \alpha \times conf(s) + \beta \times supp(s) \tag{1}$$

For each invalid solution **S** where *conf(s)* > *minConf* and *supp(s)* > *minSupp*, fitness(S)= -1 otherwise.Here, *conf(s)* means the confidence of solution **S** and *supp(s)* means the support of solution **S**.

(4) Neighborhood Search

$$f = s \pm r \times ngh \tag{2}$$

Where *f* means the number of foraging bee, *s* means the number of scouter bee, *r* is a random number obeying the uniform distribution from 0 to 1. The neighborhood search is obtained by changing from a given solution **S** one bit in a random way.

Example 2: Change the second bit in **S1**:**S2**={1,1,2,0,1,2}.

(5) Global Search

Redistribute the non optimal rules randomly in the solution space. Evaluating the fitness of all the bees in each **S** and sort it from high to low so as to select best one as the next scout bee.

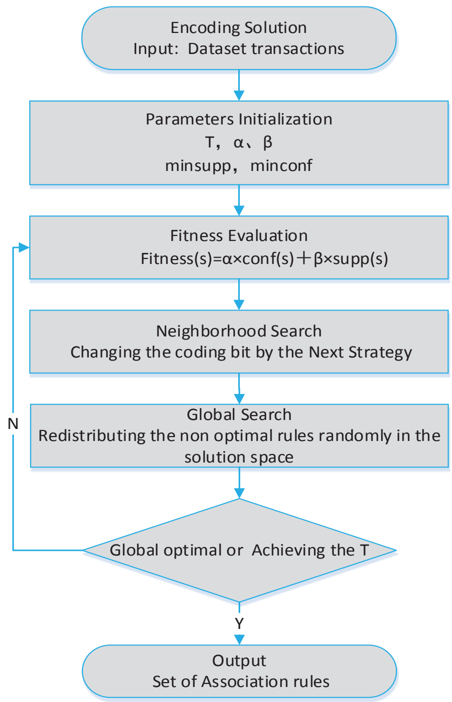


Fig. 3. ARM based on BA

Fig. 3 shows the flow chart of ARM based on BA. For instance, the relationship between energy consumption, speed, load and trajectory can be extracted from these association rules based on interest-model. The disassembly capability model for representing IR will be proposed using OWL after defining the existence and type of semantic relations between concepts.

3.3. Dynamic modeling of manufacturing capability

In the process of IR disassembly, the factors that affect the disassembly capability are the technical parameters of IR themselves, the robotic running state index and the disassembly task index. Among them, the parameters of the robotic system are static data, which are the fixed technical indexes of the robotic disassembly. Running state data of IR is the real-time data of the robotic kinematics, which is the dynamic matching index of the energy consumption and efficiency. Disassembly task data is an effective way to record the time, cost and efficiency of disassembly process, which will be used to assess and evaluate the quality and efficiency of disassembly. As shown in Fig. 4, an important technical index and the basic structure of IR disassembly capability are given. In order to describe the disassembly capability of industrial robots, some definitions are given according to the relationship between the concepts of the former mining.

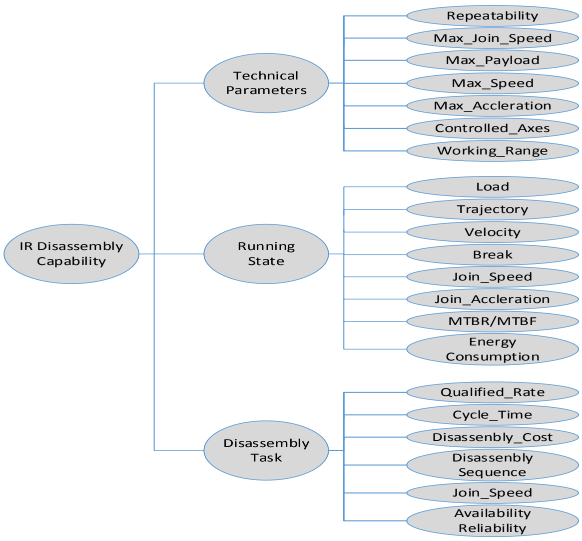


Fig. 4. Basic structure of IR disassembly capability

Definition 1: Ontology of Technical Parameters

Tech_Param=(IR_Weight,Max_Payload,Max_Speed,Max_Join_Speed,Max_Acceleration,Controlled_Axes,Working_Range,Repeatability,...) (3)

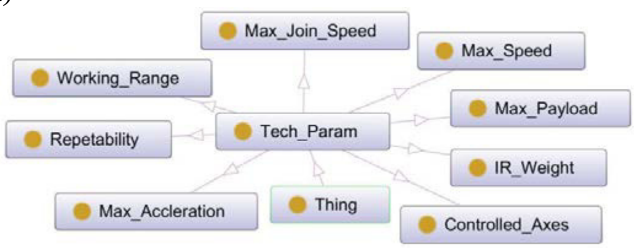


Fig. 5. Ontology of technical parameters

Fig. 5 gives an ontology of technical parameters, which describes static parameters of IR.

Definition 2: Ontology of Disassembly_Process

Disassembly_Process=(Trajectory,Break,Payload,Velocity,Join_Speed,Join_Accleration,Current_State_IR,Energy_Consumption,...) (4)

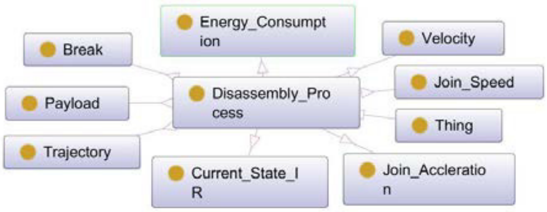


Fig. 6. Ontology of technical parameters

Fig. 6 shows an ontology model of disassembly process, which represents the dynamic parameters characteristics about running state and EC in the disassembly process of IR.

Definition 3: Ontology of Disassembly_task

Disassenbly_Task=(Qualified_Rate,Cycle_Time,Disassenbly_Cost,Disassenbly_Sequence,Current_State_Task,Availability ,Reliability,...) (5)

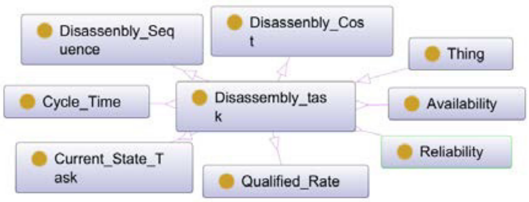


Fig. 7. Ontology of disassembly task

Fig. 7 gives an ontology model of disassembly task, which describes the relevant attributes and information of disassembly task.

Definition 4: Ontology of IR Disassembly

Disassenbly_IR=(Basic_Infomation,Tech_Param,Disassembly_Process,Disassenbly_Task) (6)

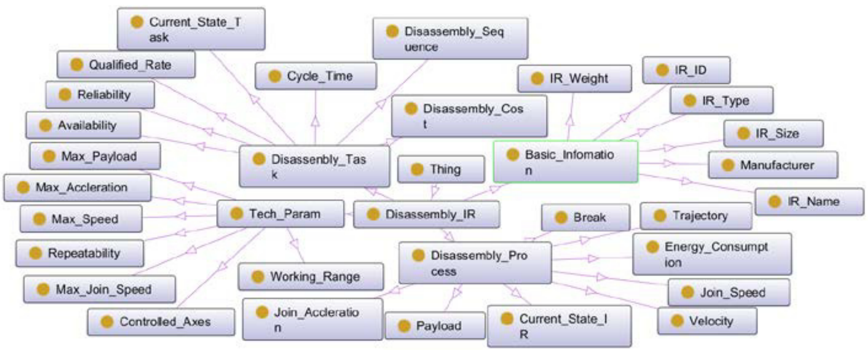


Fig. 8. Ontology of IR disassembly

In Fig. 8, there is an ontology of IR disassembly described by OWL using Protege, the concepts, attributes and relationships of IR disassembly process are mainly summarized.

In this paper, the dynamic mapping relationships between disassembly attributes and real-time data is established, as shown in Fig. 9. The dynamic mapping relationships divide into direction mapping, indirect mapping and inference. The value of the parameters such as speed can be added to the IR disassembly model directly. However, some data like energy consumption should be computed before added to the ontology model where the other parameters like capability index can only be obtained by reasoning.

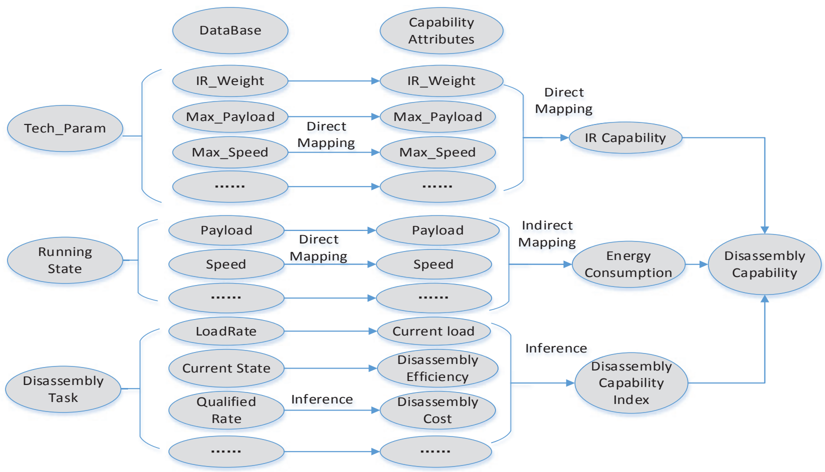


Fig. 9. Dynamic mapping relationship

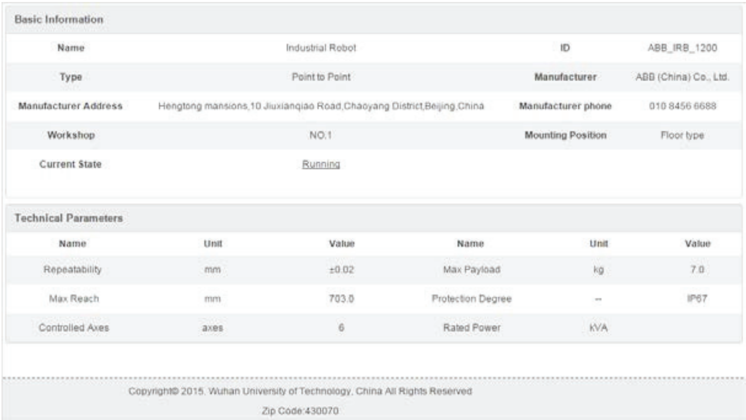
4. Case study and analysis

In order to verify the rationality and practicability of the method proposed in this paper, a set of experiments are investigated. In this section, an individual of IR: ABB_IRB_1200 is built, which is suitable for disassembly of end-of-life product. Besides, a prototype system is developed to monitor the running state data of ABB_IRB_1200 in the process of disassembly. Fig. 10 gives the basic information and technical parameters of IR in developed system . There are three steps:

(1) The data source is stored in the oracle database, and the meta-data model of disassembly process has been introduced in section 3. The ARM based on BA will be conducted after data set is given and an ontology model of IR disassembly is proposed like Fig. 8. We experiment BA-ARM on a common database about EC generated by robot studio. Here, changing the number of transaction by fixing the T to 200, *minsupp* to 0.2, *minconf* to 0.4 and α, β, r are all to 0.5. Fig. 11 shows that concerning the CPU time only, ARM-BA is better than Apriori and ARM on genetic algorithm (GA).

(2) The research object is the disassembly capability of IR in this paper, discussed mainly from energy consumption and efficiency of IR. The effects of break, speed, load and trajectory on EC of IR are monitoring in real time. Fig. 12 indicates that break influences the energy consumption, which means that affects the disassembly capability of IR. Fig. 13 describes the different payload in different running stage, and the EC is totally different. As shown in Fig. 14, the running speed is one significant factor determines the EC.

(3) Inference can be done based on the rules and real-time data. The current state of IR is given by Table 1. Some knowledge inference rules are proposed based on the ARM from the multidimensional data model for disassembly process.



Basic Information

Name	Industrial Robot	ID	ABB_IRB_1200
Type	Point to Point	Manufacturer	ABB (China) Co., Ltd.
Manufacturer Address	Hengtong mansions,10 Jiuxianqiao Road,Chaoyang District,Beijing,China	Manufacturer phone	010 8456 6688
Workshop	NO.1	Mounting Position	Floor type
Current State	Running		

Technical Parameters

Name	Unit	Value	Name	Unit	Value
Repeatability	mm	±0.02	Max Payload	kg	7.0
Max Reach	mm	703.0	Protection Degree	--	IP67
Controlled Axes	axes	6	Rated Power	kVA	

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Fig. 10. Basic information of IR in implementation system

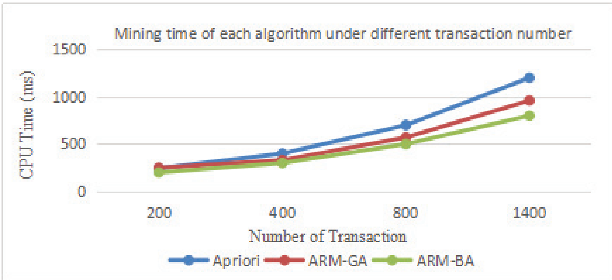

Fig. 11. Performance of ARM-BA

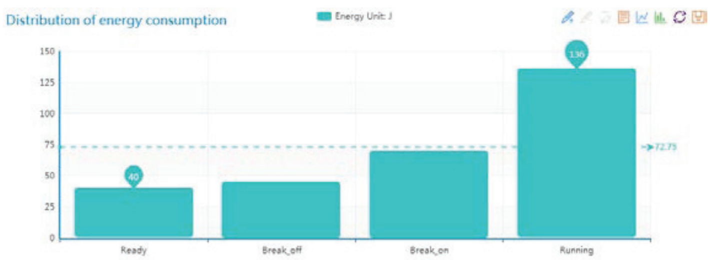

Fig. 12. Distribution of EC in different state

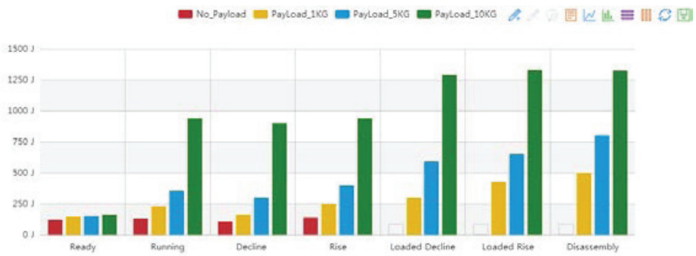

Fig. 13. Distribution of EC with different payload

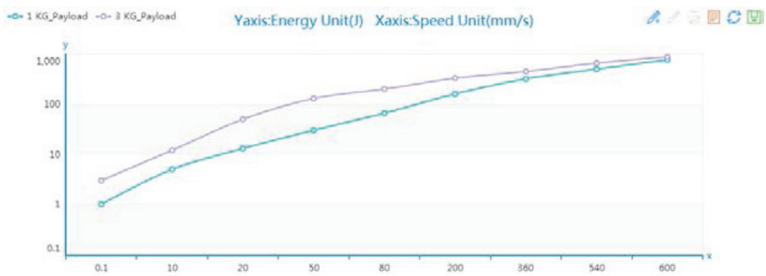

Fig. 14. Distribution of EC with different speed

[rule1:(?DP rdf:type fa:DisassemblyProcess), (?DP fa:hasEnergyConsumptionIndex ?ECI), lessThan(?ECI,1)-> (?DP fa:hasEnergyConsumption fa: Normal)].

[rule2:(?DP rdf:type fa:DisassemblyTask), (?DT fa:hasLoadRate ?LR),(?DT fa:hasCurrentState fa:Running),ge(?LR,1)->(?DT fa:hasCurrentLoad fa:OverLoad)].

[rule3:(?DP rdf:type fa:DisassemblyProcess), (?DP fa:hasDisassemblyAbilityIndex ?DAI), lessThan(?DAI,1)-> (?DP fa:hasDisassemblyAbility fa: Deficient)].

Rule 1: If the energy consumption index is less than 1, it indicates the energy consumption is normal in real time.

Rule 2: If the loading rate is greater than 1, the current disassembly task needs to be planned again.

Rule 3: If the disassembly capability index is less than 1, then the current disassembly capacity is insufficient.

Combined with the above rules and Table 1, we've got the idea that the energy consumption is abnormal (ECI=1.2>1), the current state (LR=1.1>1) is overload, and the disassembly capability is deficient.The results of the present study suggest that by using the ARM-BA algorithm and the proposed ontology model, the running state of IR can be monitored and the disassembly capacity will be predicted. Considering the effective of result obtained from the experiments, it’s possible to reduce energy consumption and plan disassembly sequence.

Table 1. Current State of ABB_IRB_1200

Property	Value
Task Name	Task 007
Current State	Disassembly
hasLoadRate	1.1
hasEnergyConsumptionIndex	1.2
hasDisassemblyAbilityIndex	0.9

5. Conclusions and future work

In this paper, the meta-data model of IR is given, the data source and classification of disassembly process are described. The running state data is mined and analyzed using ARM based on BA. Finally, a dynamic ontology model of IR disassembly capability is proposed, which can map relationships dynamically between disassembly attributes and real-time data. To illustrate the effectiveness and significance of the proposed framework, a demonstration case study on ABB_IRB_1200 is used. In addition, the ARM-BA is more efficient and easy to operate compared with traditional algorithms, such as ARM-GA. Last but not the least, the case study shows that the dynamic modeling method could efficiently reflect the current state and dynamic capability of IRs during product disassembly process in remanufacturing.

In the future, more association rules between the state attributes should be mined and analyzed. Further research should be conducted on enriching the knowledge base of IR disassembly capability ontology. Furthermore, it is necessary to perfect the meta-data model and improve the fitness function of the bees algorithm. Dynamic modeling method of manufacturing capability for human-robot disassembly in remanufacturing will be researched and proposed in the following study.

Acknowledgements

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