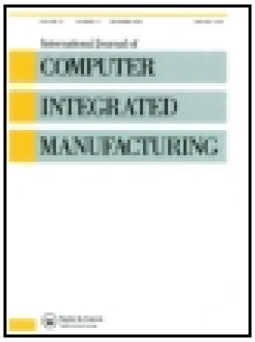

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ARTICLE

A decision-making methodology for the cloud-based recycling service of smart products: a robot vacuum cleaner case study

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ABSTRACT
The smart product represents a new type of products, which contains software and hardware components. Many obsolete smart products are required to be recycled each year. In the developing countries, the inappropriate treatment of obsolete smart products contaminates the natural environment. This study aims to coordinate the abilities of social recycling organisations and improve the recovery rate of waste smart products. A framework of the recycling service for smart products is proposed based on the concept of cloud manufacturing. In the framework, a smart product ontology is designed to integrate the lifecycle data generated by the smart product. To decide the recycling choice of the components of smart products with the lifecycle data, a fuzzy-rule-based decision method is proposed. In cloud-based recycling service, the abilities of different recycling factories are virtualised as a pool of recycling resources. The virtualisation is achieved by the recycling resource ontology. In order to select optimal recycling resources and encapsulate the recycling service, a grey-relational-analysis-based method is proposed. A robot vacuum cleaner, which is a smart product, is adopted to demonstrate the proposed decision methods. The results show that the methods are effective for deciding the cloud-based recycling service for smart products.

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Recycling service; decision method; smart product; cloud manufacturing

1. Introduction

In recent years, the electronic technology has changed the way to design and use products. The new type of products is called the smart product which contains software and hardware components such as microchips and sensors (Rijsdijk and Hultink 2009; Abramovici, Göbel, and Dang 2016). Smart products are able to collect, process and produce data in the middle of life (MOL). Some examples of the smart product are the robot vacuum cleaner (RVC), the air cleaner, the unmanned aerial vehicle, etc. Their extraordinary characteristics include personalisation, situatedness, adaptiveness, network capability and proactivity (Ahram, Karwowski, and Amaba 2011). For example, an RVC can be set to different working modes according to the user requirement. It is able to explore the house and plan the working route. Furthermore, the RVC can be controlled by apps remotely with the network capability and the apps are also capable of collecting parameters and condition.

A smart product contains components made of materials such as metal, plastic, ceramic, rubber, etc. Meanwhile, printed circuit board (PCB) is the core component of smart products. The PCB contains copper, gold, silver and other precious metals. Plastics such as ABS, PVC, PP and POM are also widely used (Bobba, Ardente, and Mathieux 2016). Smart products should be recycled properly at the end of life (EOL), otherwise, the waste materials may contaminate the environment and harm the public health. In the current recycling process, the obsolete products are presorted and dismantled manually. The selected components, which have hazardous substances or valuable materials, are disassembled (Pintzos et al. 2016). The remaining components are carried to the shredder, and they are shredded to fractions. The fractions contain plastics, metal, rubber, etc., which are further processed by the magnetic separator (Parajuly et al. 2016).

If an RVC is recycled by the shred-and-separate approach, the recovery rate of metals should reach 92% and the recycling rate of plastics may about 45% (Parajuly et al. 2016). Parajuly et al. (2016) highlighted that the recycling rate will be higher if more components are disassembled. Disassembly is a labour-intensive operation and the labour cost of disassembly is high in developed countries. The robot disassembly technique may reduce such cost (Vongbunyong, Pagnucco, and Kara 2016). However, the factories equipped with robots may not have the ability to recover metals and recycle plastics. On the other hand, the labour cost is pretty low in developing countries, but most developing countries do not have techniques to handle obsolete smart products properly. So, a better system for recycling waste products can be built if factories with different abilities work collaboratively.

This paper takes the concept of cloud manufacturing (CMfg) to support the collaboration, sharing and management of the abilities of different recycling factories. In recent years, CMfg has become a hotspot in the manufacturing industry and it is regarded as a service model for intelligent and collaborative manufacturing (He and Xu 2015). Internet of things, cloud computing, big data analytics and cyber-physical systems are the key techniques of CMfg (Mourtzis and Vlachou

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2016; Mourtzis, Vlachou, and Zogopoulos 2017). Distributed manufacturing abilities (e.g. machine tools, software, robots, etc.) are virtualised as manufacturing resources (Ren et al. 2015). In the CMfg platform, the manufacturing resources are combined to executable manufacturing services according to the customer requirement.

The decision methods for cloud-based recycling of smart products are proposed in this research. A smart product ontology (SPO) is designed to integrate the begin of life (BOL) and MOL data of smart products. With the conceptualisation provided by the SPO, the real object of a smart product in the physical world can be formally represented as a virtual object in the conceptual world (Abramovici, Göbel, and Dang 2016). A fuzzy-rule-based decision method for the recycling choice of waste components is proposed by analysing the BOL and MOL data of smart products. The recycling choice includes reuse, remanufacturing, material recovery, incineration, landfill and special handling. On the other hand, the abilities of different recycling factories are virtualised by the recycling resource ontology (RRO), which forms a pool of recycling resources. The recycling resource is matched by keywords and numerical parameters. The matching result is a set of recycling resources. To select recycling resources and encapsulate them into the recycling service, a grey-relational-analysis-based method is proposed.

The rest of this paper has five sections. Section 2 reviews the decision methods of recycling and cloud manufacturing. Section 3 introduces the framework of the cloud-based recycling service for smart products. Section 4 proposed the decision methods of the cloud-based recycling service. Section 5 demonstrates the proposed methods with an RVC. The last section, section 6, concludes the paper and highlights future works.

2. Literature review

The decision methods for waste products have been widely studied. Previous studies contribute basic theories to this research. Meanwhile, the sensor-embedded product, which is a kind of smart products and able to collect the lifecycle data, inspires the proposed novel ideas. So, the decision methods for sensor-embedded products are reviewed. This section also summarises the virtualisation and encapsulation methods presented in studies of CMfg.

2.1. The decision methods for waste products

The decision methods for waste products usually take into account criteria such as environmental, social, economic, etc. Bufardi et al. (2003) compared scenarios with respect to conflicting criteria, a multiple criteria decision aid (MCDA) method was developed for supporting users in the selection of the best scenario for recycling waste products. Jiang, Zhang, and Sutherland (2011) developed a multi-criteria decision-making (MCDM) model for selecting the remanufacturing technology. The pair-wise comparison approach of analytic hierarchy process (AHP) is employed to select the portfolio of the remanufacturing technology. Jun et al. (2012) studied the selection of the best recovery options of components for minimising the total recovery cost of waste products. The problem is formulated with a mixed integer nonlinear programming model and a heuristic algorithm is proposed to resolve it. The information of waste products may be incomplete. To address the problem, Chan (2008) presented an alternative decision-making process to generate an optimal solution from a list of recycling options under the uncertain condition. The process uses grey relational analysis (GRA), and the multi-criteria weighted average is proposed to rank the product recycling options with respect to several criteria at the material level.

The preference of stakeholders is also important in the decision methods. Ziout, Azab, and Atwan (2014) proposed a method that guides the process of decision-making on the recovery option of waste products. The method considers all stakeholders related to the recycling process, which offers decision-maker flexibility to accommodate for different cases. Bufardi et al. (2004) proposed an MCDA approach to aid the decision-maker in selecting the best-compromised alternative on the basis of his/her preferences. The approach takes into account the performances of alternatives with respect to the relevant criteria including environmental, social and economic. Ma and Kremer (2015) incorporated the designer's perception of sustainability dimensions including economic, environmental and social impact into the determination of the recycling strategy. The approach transfers the design preferences into sustainability analysis through fuzzy-logic-based transformation equations.

2.2. The decision methods for sensor-embedded products

The lifecycle information of waste products is usually incomplete. To collect the lifecycle data and improve the decision methods, the sensor-embedded product was studied. Radio-frequency identification (RFID) is used as the sensor to gather the information of products. Parlikad and McFarlane (2007) showed that the availability of product information has a positive impact on deciding the product recovery strategy, and discussed how RFID-based product identification can be employed to provide the necessary information. Stankovski et al. (2009) presented a new way for the identification of products/components and their tracking during the whole lifecycle, from the manufacture and assembly phase to the disassembly phase. The information about the products/components can be accessed and analysed during the lifecycle. Ilgin and Gupta (2011) evaluated the impact of sensor-embedded products on the various performance measures of an air conditioner disassembly line. The results show that the collected information improves revenue and profit. The cost of backorder, disassembly, disposal, holding, testing and transportation has been significantly reduced. Chen et al. (2017) proposed an integrated method for electromechanical products disassembly decision-making based on the lifecycle data recorded by the RFID.

2.3. Cloud manufacturing and cloud remanufacturing

For the past few years, some enterprise CMfg service frameworks and platforms have been implemented. The techniques and approaches have been proposed to encapsulate various virtualised manufacturing resources and capabilities as cloud-based services (He and Xu 2015). Liu, Li, and Wang (2015) presented a new CMfg architecture in which machining services are encapsulated within each service provider with standardised machining task description strategies. Qiu, He, and Ji (2016) proposed a specific CMfg mode of polymer material industry. The optimal selection algorithm of the service composition for flexible polymer manufacturing system was studied. Similarly, Mai et al. (2016) proposed a framework for a 3D printing service platform for CMfg.

To select the service of the CMfg, some criteria have been proposed. Cao et al. (2016) established a service selection and scheduling model with criteria time, quality, cost and service (TQCS). A fuzzy decision-making theory is used to transform TQCS values into relative superiority degrees. Sheng et al. (2016) established an intelligent searching engine of CMfg service in small- and medium-sized enterprises. The searching engine is based on the ontology language for service, it analyses the matching degree of ontology concepts and constraints. Zheng, Feng, and Tan (2016) proposed an approach for selecting manufacturing resource to assist the requester to obtain optimal manufacturing services. A design-preference-based quality of service (QoS) description model of CMfg was designed and a QoS computation model based on fuzzy theory was presented for measuring QoS.

At the EOL phase of the product lifecycle, the interrupted information exchange is the main hindrance to developing an integrated and collaborative remanufacturing environment (Wang et al. 2014). To overcome the bottleneck, Wang and Wang (2014) introduced a novel service-oriented remanufacturing platform based on the CMfg concept. Systematic design and information management mechanism were developed to streamline the processes throughout the lifecycle of products. The study proposes that semantic web service and standards can be adapted to further support the cloud remanufacturing services. Meanwhile, it is necessary to establish a standardised description methodology to profile the service data.

2.4. *Summary of the literature review*

To summarise the studies mentioned above, the decision methods, such as AHP, for waste products have been studied widely. As the input of the decision methods, the lifecycle data of products are proved useful in deciding the recycling choice of waste products. On the other hand, some studies propose service selection methods and service description models of CMfg. The concept of a service-oriented remanufacturing platform based on the CMfg was proposed.

However, the cloud-based recycling service for smart products requires further research. First of all, the criteria such as environmental, social and economic have been taken into account in processing waste products. Nevertheless, the lifecycle data collected by the smart product have not been adequately used to decide the recycling choice. Second, the description model of cloud-based recycling service has not been presented although Wang and Wang (2014) introduced the concept of cloud remanufacturing. At last, the method for selecting recycling resources and encapsulating them into the recycling service has not been presented.

3. The description of the cloud-based recycling service for smart products

A typical recycling network of waste products is shown in Figure 1. The recycling network involves collection and pre-sorting points, disassembly factory and recycling factory (Shih 2001). The recycler collects waste products from sources such as cities, schools, office buildings and manufacturers. Then, the waste products are classified according to type, size and

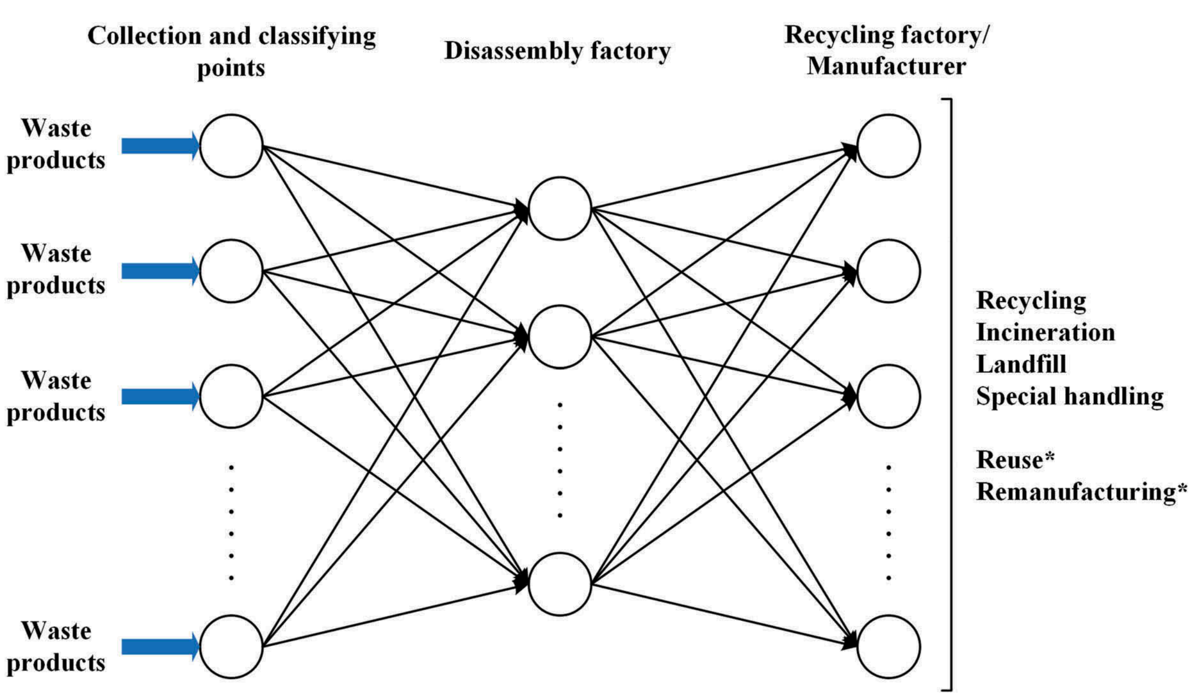

Figure 1. The recycling network of waste products.

weight. After the classification, the waste products are sent to disassembly factories, valuable components and components with hazardous materials are disassembled. The components are further classified according to function, material, size and weight. If the components can be reused or remanufactured, they will be carried to manufacturers. In this case, there is no requirement for incineration or landfill. Incineration and landfill are not environmental-friendly choices. Other components are forwarded to recycling factories, which will be further processed into the pure metal stream or for plastic recovery. The remaining part that cannot be recycled is delivered to incineration or landfill (Sodhi and Reimer 2001).

The framework of the cloud-based recycling service for smart products is shown in Figure 2. It is designed on the basis of the recycling network of waste products. According to the framework, there are four characters related to the recycling service. The characters are the designer of smart products, the user of the recycling service, the recycling expert and the provider of recycling resources. The lifecycle information of traditional products is missing or incomplete. It is hard for the recycler to estimate whether the component is reusable or not for lacking of expert knowledge. The smart product, which is defined as a new type of products, is able to collect MOL data. On the basis of the characteristic of smart products, this paper takes the lifecycle data of smart products to decide the optimal recycling service.

The framework shown in Figure 2 depicts a platform for managing recycling resources, collecting the MOL data of smart products and deciding the recycling service. The designer submits the BOL data of smart products to the platform. The BOL data includes the bill of material (BOM), blueprint, CAD model, etc. Smart product instances are the virtual objects of smart product entities, which organise the lifecycle data of the products with SPO. Based on the instances and the pool, a decision engine is designed to make the recycling choice with the expert knowledge. On the other hand, the recycling abilities are virtualised to recycling resources that form a pool. A set of feasible recycling resources are matched as the candidate resource for executing recycling tasks. In order to select optimal recycling resources, a decision engine is proposed. The recycling resources are then encapsulated to the recycling service.

4. The decision methods of the cloud-based recycling service for smart products

4.1. The design of SPO

The SPO is inspired by the idea of semantic data management (SDM) ontology. The SDM ontology proposed by Abramovici, Göbel, and Dang (2016) handles components information,

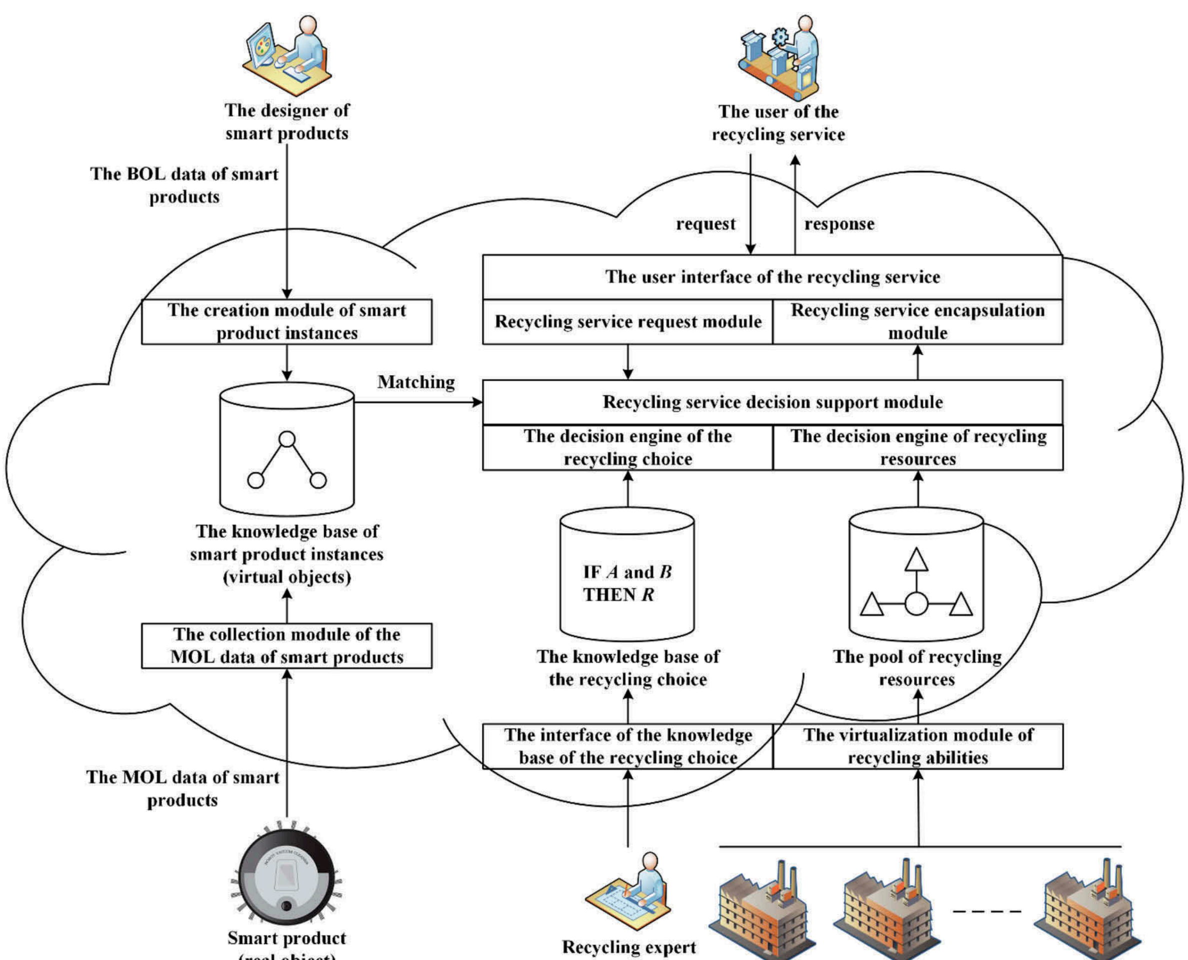

Figure 2. The framework of the cloud-based recycling service for smart products.

structure information and smart product usage information. Specifically, it semantically integrates virtual product models and the feedback data of the physical product. The SPO is the implementation of the SDM ontology. The instance of the SPO is a digital twin of the real smart product. The ontology of smart products is shown in Figure 3. It has seven classes including *Product, Smart_product, Robot_vaccum_cleaner, Module, Component, Material* and *Usage*.

Class *Product* describes the basic knowledge of the product. The value of attribute *body_size* is the maximum size in three dimensions. The value can be represented by a triple $(length, width, height)$. Attribute *weight* is the total weight of a product. Attribute *designer* and *manufacturer* express the designer and manufacturer of a product. The production date of a product is recorded by attribute *assembly_date*. Attribute *cad_file_url* links the design data of a product.

Class *Smart_product* is the subclass of class *Product*. The smart product is equipped with the network module, which has the ability to connect a network and exchange data. The value of attribute *mac_address* is the mac address of the network module. The value is a globally unique identifier. Attribute *communication_protocol* is a set of communication methods that the smart products can support. The methods are WiFi, Bluetooth, wired network and so on. Attribute *firmware_version* describes the version of the software of the smart product. Attribute *power* and *power_voltage* are power supply parameters. If the smart product can be controlled remotely, the attribute *remote_control* should be set to *true*. Otherwise, the value should be set to *false*.

Class *Module* describes the functional and non-functional module of products. In a product, the functional module is responsible for one or more specific tasks. The non-functional module, on the other hand, is the subassembly existing in the disassembly process. Functional modules are designed to perform specific tasks, and they are more likely to be reused. The value of attribute *working_cycles* indicates the number of cycles that a product has been reused. The non-functional module is not supposed to be reused, the attribute *working_cycles* of a non-functional module is set to *null*.

Class *Component* describes the knowledge of the component. The definitions of the attributes are similar to the attributes of class *Product* and class *Module*. Particularly, attribute *production_date* indicates the time that the component is made.

Class *Material* describes some characteristics of the material. A component is made up of one or multiple types of materials. In the real world, components made of different materials are recycled in different facilities. So, some subclasses of class *Material* should be designed to subdivide the concept material. For the purpose of illustration, class *Material* is inherited by class *Metal*, class *Polymer*, class *Composite* and class *Ceramic*.

Class *Usage* describes the MOL data of smart products. Attributes *start_time* and *operating_time* represent the usage time. Attribute *operating_parameter* is a data structure recording the operating information. Smart products are able to do self-inspection. The result of the self-inspection is saved in attribute *self_inspection*. Attribute *maintenance* is the maintenance log.

The SPO has four relations including *has_component, has_module, is_made_from* and *has_usage. has_component* is the relation of class *Product* and class *Component*. It is also the relation of class *Module* and class *Component. has_module* is the relation of class *Product* and class *Module*. A product has one or multiple components, and it has zero or

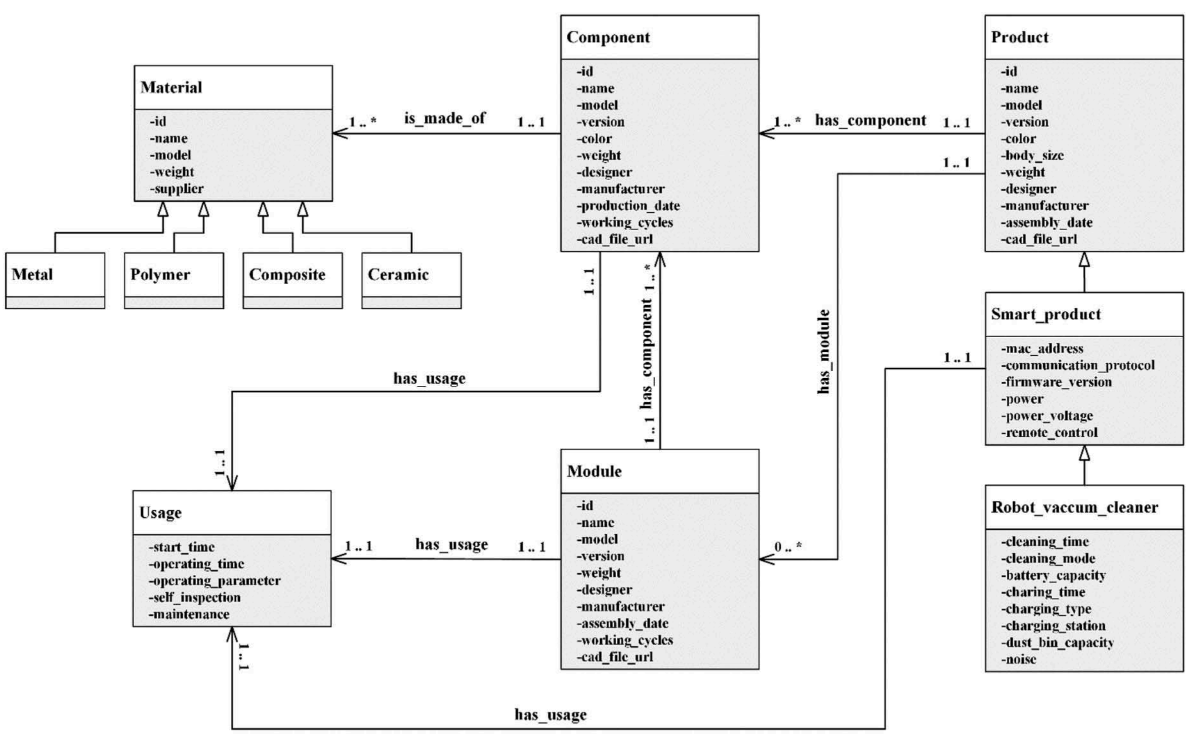

Figure 3. The ontology of smart products.

multiple modules. Meanwhile, a module has one or multiple components. The material of the instance of class *Component* is described by relation *is_made_of*. Relation *has_usage* expresses the MOL information of products, modules and components.

4.2. The decision method for recycling choice

The smart product has the ability to collect usage information which is semantically organised by the SPO. A decision method based on fuzzy rules is proposed in this section to handle the MOL data and decide the recycling choice. The theory of fuzzy rules is derived from fuzzy set theory which was first proposed by Zadeh in 1965 (Zadeh 1965). Fuzzy set theory is primarily concerned with quantifying and reasoning using natural language in which the words have ambiguous meanings (Hong and Lee 1996). Let U be a universal set. A fuzzy set A in U is a membership function $\mu_A(x)$ where every element $x \in U$ associates a real number from the interval $[0, 1]$, and $\mu_A(x)$ is the grade of membership of x in A. Thus, the function maps elements of the universal set to the set containing 0 and 1, which can be denoted by expression (1).

$$\mu_A : U \to [0, 1] \tag{1}$$

In fuzzy-rule-based systems, knowledge is represented by IF-THEN rules. A fuzzy rule has two parts: an antecedent part stating conditions on the input variable(s); and a consequent part describing the corresponding values of the output variable(s) (Adriaenssens et al., 2004). The antecedent part of each fuzzy IF-THEN rule is specified by a combination of linguistic values. The input variable(s) and the linguistic values are mapped by membership functions. Fuzzy IF-THEN rules for a decision-making problem with n attributes can be expressed as expression (2) (Ishibuchi and Nakashima 2001).

$$\begin{aligned}&\text{Rule } R_j : \text{IF } x_1 \text{ is } A_{j1} \text{ and} \cdots \text{and } A_{ji} \text{ and} \cdots \text{ and } x_n \text{ is } A_{jn} \\ &\text{THEN } D_j, j = 1, 2, \cdots, N\end{aligned} \tag{2}$$

where $x = (x_1, \cdots, x_n)$ is an n-dimensional attribute vector. A_{ji} is the antecedent linguistic value such as short and long, where $i = 1, 2, \cdots, n$. D_j is consequent linguistic value. N is the number of fuzzy IF-THEN rules.

To decide the recycling choice of components and modules, five attributes are selected as the input variables of the fuzzy-rule-based system. The time range between the collection time and the start time of smart products is denoted by T_1. The operating time is denoted by T_2. The smart product is assumed to record the operating parameters that indicate the operating load. The operating load denoted by L has three levels including light, medium and heavy. To simplify the discussion, the load level is further assumed to be generated by the smart product automatically. The self-inspection result denoted by S is either pass or fail. The pass result implies the component or the module performs well. Otherwise, the component or the module is broken down. Regular maintenance is necessary for extending the lifetime of the smart product. The number of maintenance times divided by T_2 is maintenance frequency F.

Because the trapezoidal membership function is proved working well in the practice, this section adopted trapezoidal membership functions shown in Figure 4 to map numeric value to linguistic variables (Barua, Mudunuri, and Kosheleva 2014). Formulas (3)–(5) are the functions of linguistic value A_1, A_2 and A_3. According to the definition of attributes, the time range of T_1 and T_2 includes three levels short, medium and long. The frequency level of F includes low, medium and high. The consequents of IF-THEN rules for recycling choice are disassembly (only applicable for modules), recycling, incineration, landfill, special handling, reuse and remanufacturing. Components and modules vary in size, weight and material, so fuzzy rules are designed for a specified type of components or modules. Table 1 lists some fuzzy rules of the drive module of the RVC. Each component or module has 162 fuzzy rules.

$$\mu_{A_1}(x) = \begin{cases} 0, & x > b \\ \frac{b-x}{b-a}, & a \le x \le b \\ 1, & x < a \end{cases} \tag{3}$$

$$\mu_{A_2}(x) = \begin{cases} 0, & x < c \text{ or } x \ge f \\ \frac{x-c}{d-c}, & c \le x < d \\ 1, & d \le x < e \\ \frac{f-x}{f-e}, & e \le x < f \end{cases} \tag{4}$$

$$\mu_{A_3}(x) = \begin{cases} 0, & x < g \\ \frac{x-g}{h-g}, & g \le x \le h \\ 1, & x > h \end{cases} \tag{5}$$

4.3. The design of RRO

In the practice, different factories that are capable of recycling waste products usually have different types of facilities. The number of machines also varies from one factory to another.

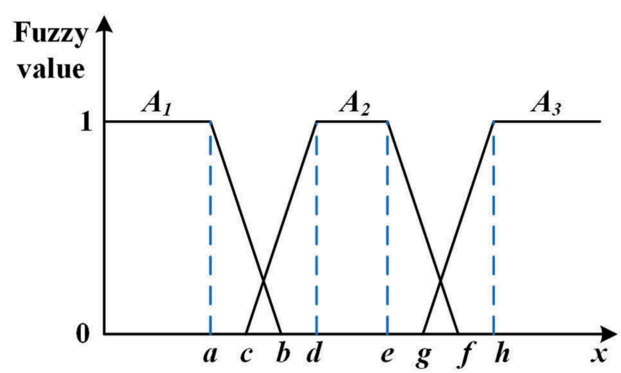

Figure 4. The membership function.

Table 1. A part of fuzzy rules of the drive module.

No	Fuzzy rule
1	IF T_1 is short and T_2 is short and L is light and S is pass and F is low THEN reuse
2	IF T_1 is medium and T_2 is short and L is light and S is pass and F is low, THEN reuse.
3	IF T_1 is high and T_2 is short and L is light and S is pass and F is low, THEN disassembly.
...	
162	IF T_1 is high and T_2 is high and L is heavy and S is fail and F is high, THEN disassembly.

Furthermore, a factory has its own custom, standard and workflow. There is no mechanism for factories to share their abilities for recycling waste products. In recent years, ontology has been widely applied in the virtualisation of resources. Li et al. (2013) studied the resource virtualisation and service encapsulation of a logistics centre, and ontology was used to express resources and encapsulate services. The virtualisation of manufacturing resources has been explored in the research of CMfg, researchers built ontologies for virtualising physical resources and encapsulating CMfg services (Luo et al. 2013; Zhang et al. 2015; Liu, Li, and Shen 2014). The ontology of recycling resources is shown in Figure 5. The RRO is designed to virtualise physical machines used for recycling waste products. The shared concepts of recycling resources are abstracted as four classes including *Resource, Capability, Status* and *Quality*. Each individual of class *Resource* is the specific resource that can be allocated to execute recycling tasks.

Class *Resource* describes the basic knowledge of resources. For each instance of class *Resource*, attribute *id* is the unique identification, and attribute *name* is the name of the resource. Attribute *provider* and *address* are the sources that the resource belongs to. Attribute *due_date* indicates the date that the resource will be unavailable.

Class *Capability* describes the ability of resources. Attribute *type* represents the category of the ability. The value of attribute *type* can be *disassembly, recycling, incineration, landfill, special handling, reuse* and *remanufacturing*. Attribute *component_category* is a set of component categories that the capability of the resource can process. Attribute *material* is a set of materials that the capability of the resource is able to process. Attributes *max_size, min_size, max_weight* and *min_weight* define the dimension and weight of waste products that can be processed by the capability of the resource. Attributes *time_per_unit, cost_per_unit* and *revenue_per_unit* declare the income and expense of the resource.

Class *Quality* describes the quality information of the capability of the resource. Attribute *service_time* is the number of times that the capability of the resource has served. If the value of attribute *service_time* is big, the resource tends to be more reliable. Similarly, if the value of attribute *on_time_delivery* is higher and the value of attribute *fault_rate* is lower, the resource should be better. Attributes *emission_per_unit* and *solid_waste_per_unit* show the environment feature.

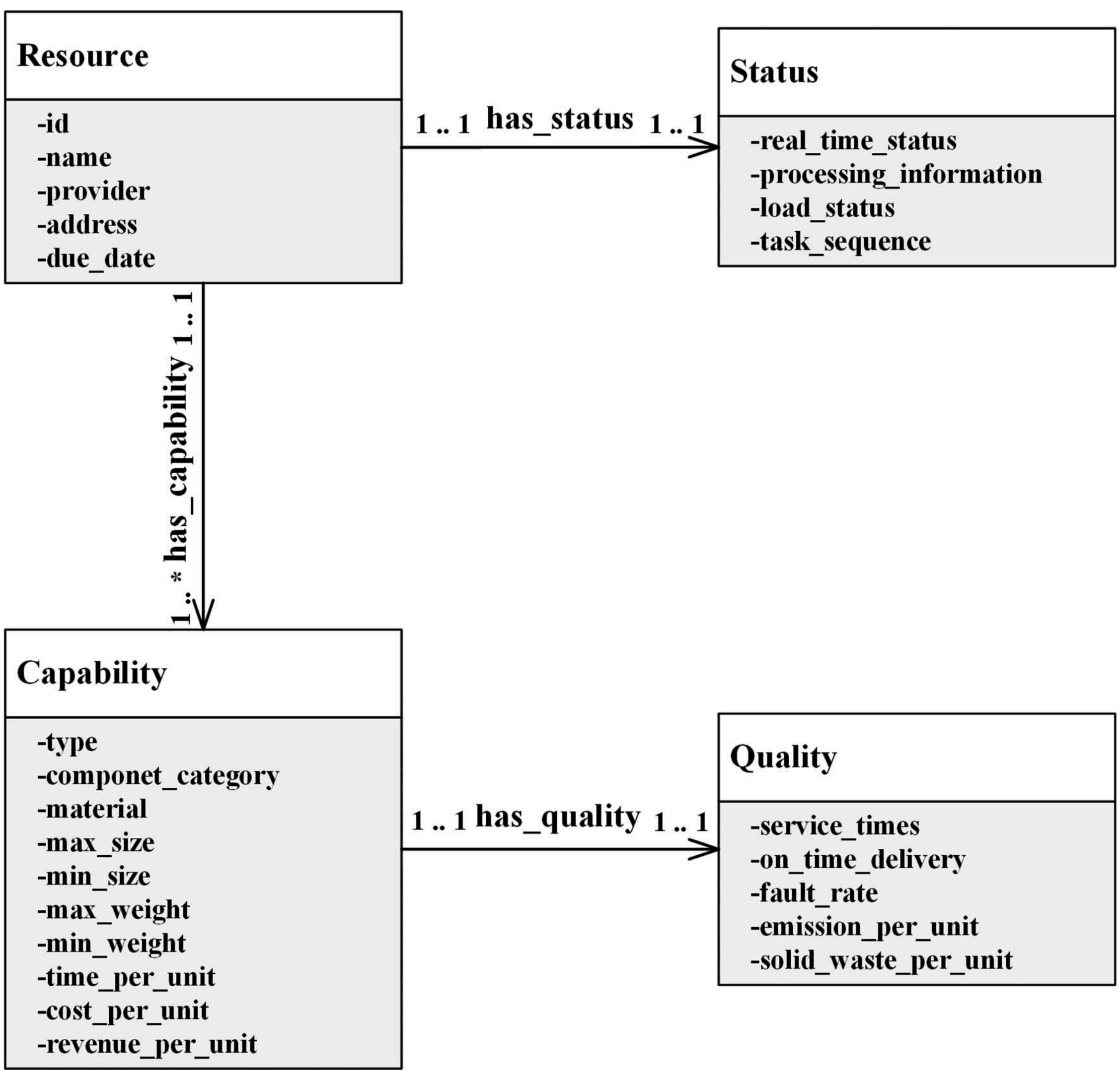

Figure 5. The ontology of recycling resources.

Class *Status* describes the condition of resources. The value of attribute *real_time_status* can be *running, maintaining, standby* and *shutdown*. Attribute *processing_information* shows the information of the task that the resource is executing. The value of attribute *load_status* can be *normal* and *overload*. Attribute *task_sequence* is a sequence of tasks that are waiting to be executed by the resource.

Relation *has_capability* is the relation of class *Resource* and class *Capability*, which means that the resource has capabilities and one resource has one or more capabilities. For example, a wrench can be used to disassemble bolts, and it also can be used to disassemble pins. Furthermore, relation *has_quality* is the relation of class *Capability* and class *Quality*. Relation *has_status* is the relation of class *Resource* and class *Status*. The instances of class *Resource* form a pool of resources that can be allocated to recycle waste products.

4.4. The method for selecting recycling resources

The recycling service platform has a pool of recycling resources. The recycling task includes disassembly, recycling, incineration, landfill, special handling, reuse and remanufacturing. Multiple recycling resources may be capable of executing one recycling task, but they have different cost, revenue, service quality and environment characteristics. The candidate resources are generally evaluated by these criteria. This kind of problem is defined as MCDM (Shyur and Shih 2006). Julong (1989) proposed the grey system theory which has been proven to be useful for dealing with poor, incomplete and uncertain information. GRA is a part of grey system theory. It is suitable for solving problems with complicated relationships between multiple variables (Morán et al. 2006). GRA combines the entire range of performance attribute values for every alternative into a single value. By applying GRA, MCDM problems can be easily solved by comparing alternatives with multiple attributes (Kuo, Yang, and Huang 2008).

GRA firstly translates the attributes of all alternatives into comparability sequences, and a reference sequence is defined according to these sequences. Then, the grey relational coefficient between all comparability sequences and the reference sequence is calculated. After that, the grey relational grade between all comparability sequences and the reference sequence is calculated. Finally, GRA ranks the grey relational grade, and the alternative that has the highest grade should be the best choice (Kuo, Yang, and Huang 2008). Table 2 lists eight attributes that are considered in this research to evaluate recycling resources. The proposed GRA procedure is presented in the following content.

Step 1 Calculating the normalised decision matrix and defining the reference sequence

The proposed MCDM problem is formulated by using a set of alternatives $(X_1, X_2, \cdots, X_m)$ and attributes $(k_1, k_2, \cdots, k_8)$. Then a decision matrix D is formulated as matrix (6).

$$D = \begin{bmatrix} X_1(k_1) & \cdots & X_i(k_1) & \cdots & X_m(k_1) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ X_1(k_j) & \cdots & X_i(k_j) & \cdots & X_m(k_j) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_1(k_8) & \cdots & X_i(k_8) & \cdots & X_m(k_8) \end{bmatrix} \tag{6}$$

Matrix D is normalised to matrix D' as matrix (7).

Table 2. The attributes that evaluate the recycling resource.

No	Attribute	Computation formula	Objective
1	Service time	*time_per_unit* × *weight* + *logistics_time*	↓
2	Service cost	*cost_per_unit* × *weight* + *logistics_cost*	↓
3	Recycling revenue	*revenue_per_unit* × *weight*	↑
4	Service times	*service_times*	↑
5	On time delivery	*on_time_delivery*	↑
6	Fault rate	*fault_rate*	↓
7	Service emission	*emission_per_unit* × *weight* + *logistics_emission*	↓
8	Service solid waste	*solid_waste_per_unit* × *weight*	↓

$$D' = \begin{bmatrix} X_1(k_1)' & \cdots & X_i(k_1)' & \cdots & X_m(k_1)' \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ X_1(k_j)' & \cdots & X_i(k_j)' & \cdots & X_m(k_j)' \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_1(k_8)' & \cdots & X_i(k_8)' & \cdots & X_m(k_8)' \end{bmatrix} \tag{7}$$

The attributes given by Table 2 have two categories that are the-larger-the-better attribute and the-smaller-the-better attribute. Equations (8) and (9) are used to normalise these two types of attributes, respectively.

$$X_i(k_j)' = \frac{X_i(k_j) - \min_i\{X_i(k_j)\}}{\max_i\{X_i(k_j)\} - \min_i\{X_i(k_j)\}} \tag{8}$$

$$X_i(k_j)' = \frac{\max_i\{X_i(k_j)\} - X_i(k_j)}{\max_i\{X_i(k_j)\} - \min_i\{X_i(k_j)\}} \tag{9}$$

where $i = 1, 2, \cdots m$ and $j = 1, 2, \cdots, 8$.

The reference sequence is $X_0' = \left\{X_0(k_j)' | j = 1, 2, \cdots, 8\right\}$, where $X_0(k_j)'$ is defined by formula (10).

$$X_0(k_j)' = \max_i\left\{X_i(k_j)'\right\} \tag{10}$$

where $i = 1, 2, \cdots m$ and $j = 1, 2, \cdots, 8$.

Step 2 Calculating the grey relational coefficient

Based on the normalised decision matrix, the grey relational coefficients of the ith alternative and the reference sequence of the jth attribute is calculated as Equation (11).

$$\gamma_{i,k_j} = \frac{\Delta min + \rho \Delta max}{\Delta_i(k_j) + \rho \Delta max} \tag{11}$$

where $i = 1, 2, \cdots m$, $X_0(k_j)$ denotes the reference sequence and $X_i(k_j)$ denotes the comparative sequence. ρ is a distinguishing coefficient, $\rho \in [0, 1]$. It is used to expand or compress the range of the grey relational coefficient, and ρ takes 0.5 generally.

$$\Delta_i(k_j) = \left|X_0(k_j)' - X_i(k_j)'\right| \tag{12}$$

$$\Delta min = \min_i \min_j \Delta_i(k_j) \tag{13}$$

$$\Delta max = \max_i \max_j \Delta_i(k_j) \tag{14}$$

The grey relational coefficient matrix of the alternatives and the reference sequence is presented by matrix (15).

$$Y = \begin{bmatrix} y_{1,k_1} & \cdots & y_{2,k_1} & \cdots & y_{m,k_1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{1,k_j} & \cdots & y_{2,k_j} & \cdots & y_{m,k_j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y_{1,k_8} & \cdots & y_{2,k_8} & \cdots & y_{m,k_8} \end{bmatrix} \tag{15}$$

Step 3 Calculating the grey relational grade

The grey relational grade can be calculated using Equation (16).

$$g_i = \sum_{8}^{j=1} \omega_j y_{i,k_j} \tag{16}$$

where $i = 1, 2, \cdots m$.

In Equation (16), g_i is the grey relational grade of X_m and X_0. ω_j is the weight of attribute j and usually depends on the judgement of decision-makers. The sum $\sum_{j=1}^{8} \omega_j$ equals 1. The grey relational grade indicates the degree of similarity of the comparability sequence and the reference sequence. The reference sequence represents the best value of each attribute. Therefore, if a comparability sequence of an alternative has the highest grey relational grade, the alternative of that sequence will be selected as the best choice (Kuo, Yang, and Huang 2008).

5. Case study

5.1. The introduction of the RVC

An RVC, shown in Figure 6, is employed to demonstrate the proposed methods. In order to simplify the object, the components such as the electric wire and the plastic plug are omitted. Table 3 is the BOM of the RVC, which lists 30 components (modules). SA_1, SA_2 and SA_3 are three modules of the RVC. Module SA_1 is the module generated in the disassembly process. It does not have the specific function. Modules SA_2 and SA_3 are the drive module and the brush module, respectively. The drive module provides the driving force for the RVC, and the brush module cleans the floor. Module SA_1 contains vacuum cleaner module SA_4. The vacuum cleaner module is the functional module. Table 4 is the BOM of module SA_1, and Table 5 is the BOM of module SA_4.

Suppose a disassembly factory requests the decision service for recycling the RVC. A part of the ontology of the RVC is shown in Figure 7. The ontology collects the semantic information of the RVC to be recycled. Figure 7 demonstrates the semantic information of the anti-collision frame and the drive module. The semantic information of the RVC includes power voltage, power, weight, body size, noise, dustbin capacity, charging type, cleaning mode, etc. Figure 7 also gives the MOL information of the drive module, which records start time, operating time, operating parameter, self-inspection, maintenance, etc. The proposed fuzzy-rule-based decision method is adopted to decide the recycling choice of each component.

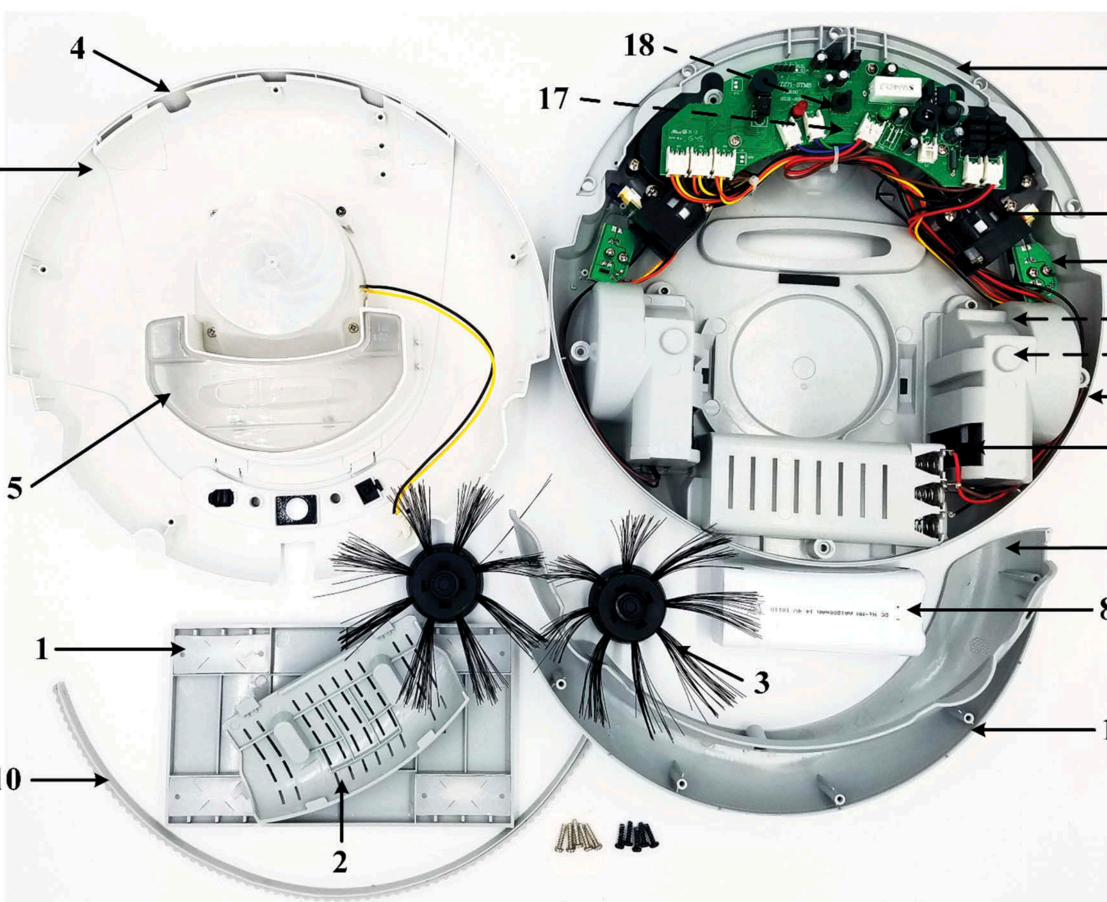

Figure 6. An RVC (only 20 primary components are annotated).

Table 3. The BOM of the RVC.

No	Component	Sub-assembly	Count	Total weight (g)	Material
$c_{0,1}$	Fixture for dust cleaning paper	–	1	50.1	ABS
$c_{0,2}$	Battery cover	–	1	19.3	ABS
$c_{0,3}$	Brush	–	2	15.9	ABS (PET)
$c_{0,4}$	Dust storage box cover	–	1	74.8	ABS
$c_{0,5}$	Dust storage box	–	1	43.1	PP
$c_{0,6}$	Subassembly of outer casing (upper) and vacuum cleaner module	SA_1	1	-	-
$c_{0,7}$	Anti-collision plate (lower)	–	1	35.2	ABS
$c_{0,8}$	Battery	–	1	282.8	Ni-Cr
$c_{0,9}$	Drive module cover	–	2	7.9	ABS
$c_{0,10}$	Buffer rubber	–	1	8.5	NBR
$c_{0,11}$	Anti-collision plate (upper)	–	1	42.7	ABS
$c_{0,12}$	Drive module	SA_2	2	-	-
$c_{0,13}$	Spring for the drive module	–	2	0.5	Steel
$c_{0,14}$	Control board	–	1	52.5	-
$c_{0,15}$	Brush module	SA_3	2	-	-
$c_{0,16}$	Anti-collision frame	–	1	24.3	ABS
$c_{0,17}$	Spring for anti-collision frame	–	1	0.5	Steel
$c_{0,18}$	Caster and frame	–	1	5.2	ABS
$c_{0,19}$	Sensor board	–	3	6.5	-
$c_{0,20}$	Outer casing (lower)	–	1	494.3	ABS
$c_{0,21}$	Screws for the main body	–	4	2.9	Steel
$c_{0,22}$	Screws for the anti-collision plate (lower)	–	3	2.0	Steel
$c_{0,23}$	Screws for the drive module cover	–	2	1.9	Steel
$c_{0,24}$	Screw inside the battery box	–	1	0.3	Steel
$c_{0,25}$	Screws for the anti-collision plate (upper)	–	2	1.3	Steel
$c_{0,26}$	Screws for the control board	–	3	2.0	Steel
$c_{0,27}$	Screws for the brush module	–	6	4.1	Steel
$c_{0,28}$	Screws and gaskets for anti-collision frame	–	2	2.2	Steel
$c_{0,29}$	Screw and gasket for the caster	–	1	1.1	Steel
$c_{0,30}$	Screws for the sensor board	–	6	1.9	Steel

Table 4. The BOM of module SA_1.

No.	Component	Sub-assembly	Count	Total weight (g)	Material
$c_{1,1}$	Outer casing (upper)	–	1	383.3	ABS
$c_{1,2}$	Vacuum cleaner module	SA_4	1	-	-
$c_{1,3}$	Screws for the vacuum cleaner module	–	4	2.9	Steel

Table 5. The BOM of module SA_4.

No.	Component	Sub-assembly	Count	Total weight (g)	Material
$c_{4,1}$	Fan	–	1	2.3	PC
$c_{4,2}$	Electric motor of the vacuum cleaner module	–	1	80.2	-
$c_{4,3}$	Frame of the vacuum cleaner module	–	1	3.4	PC
$c_{4,4}$	Screws for the electric motor of the vacuum cleaner module	–	4	2.9	Steel

5.2. The recycling choice of the components (modules) of the RVC

The drive module is used to illustrate the fuzzy-rule-based decision method. There are five linguistic variables including T_1, T_2, L, S and F. The parameters for the membership functions of linguistic variables T_1, T_2 and F are listed in Table 6. Suppose the collection date of the RVC is 17 March 2017, T_1 should be 45 d, T_2 should be 20 h and F should be 0 according to the MOL information of the ontology of the RVC. It can be calculated by the membership functions that T_1 is short, T_2 is short and F is low. It also can be concluded that the operating load L is light and the self-inspection result is the pass. According to the fuzzy rules listed in Table 1, the recycling choice of the drive module can be decided as *reuse*. The recycling choice of other components and modules can be decided similarly. Module SA_2 and module SA_3 can be reused. The decision result of component $c_{0,8}$ is *special handling*. Other components can be recycled.

5.3. Virtualised recycling resources

An example of virtualised recycling resources is shown in Figure 8, which is the disassembly resource. Figure 8 indicates that the status of the resource is the *standby*, and the resource is not executing task now. Other facilities related to recycling are all virtualised as recycling resources. The recycling resources form a pool in the cloud-based recycling service platform.

5.4. The evaluation of the recycling resources

The RVC has 1.153 kg components that are made of ABS. These components are used to demonstrate the grey-relational-analysis-based method for evaluation recycling resources. Suppose that there are five recycling resources that are capable of recycling ABS. The attributes of the recycling resources are listed in Table 7.

The attributes listed in Table 2 can be calculated with the value listed in Table 7. The calculation result is listed in Table 8. Then, the attributes are normalised by Equations (8) and (9). Table 9 is the result of normalisation. The logistics time per unit is assumed as 120 s/km, the logistics cost per unit is assumed as \$0.5/km, and the logistics emission per unit is assumed as 0.2 kgCO2/km. Suppose ρ equals 0.5, the grey relational coefficient can be calculated by Equation (11). Numbers 0.05, 0.2, 0.2, 0.1, 0.05, 0.05, 0.2 and 0.15 are assumed as the weight value of eight attributes. At last, the grey relational grade of each recycling resource is obtained by Equation (16). Table 10 lists the grey correlation coefficient and grey relational grade. Recycling resource 5 has the biggest grey relational grade, so it is selected as the resource to recycle the ABS of the RVC.

6. Conclusion

The new type of products, the smart product, contains materials such as metal, plastic, ceramic, rubber, etc. The waste materials will harm the public health if the smart product is not handled properly. Currently, the recovery rate of smart products is pretty low. In order to improve the recovery rate and coordinate the abilities of social recycling organisations, the concept of cloud manufacturing is taken in this study to support the collaboration, sharing and management of the

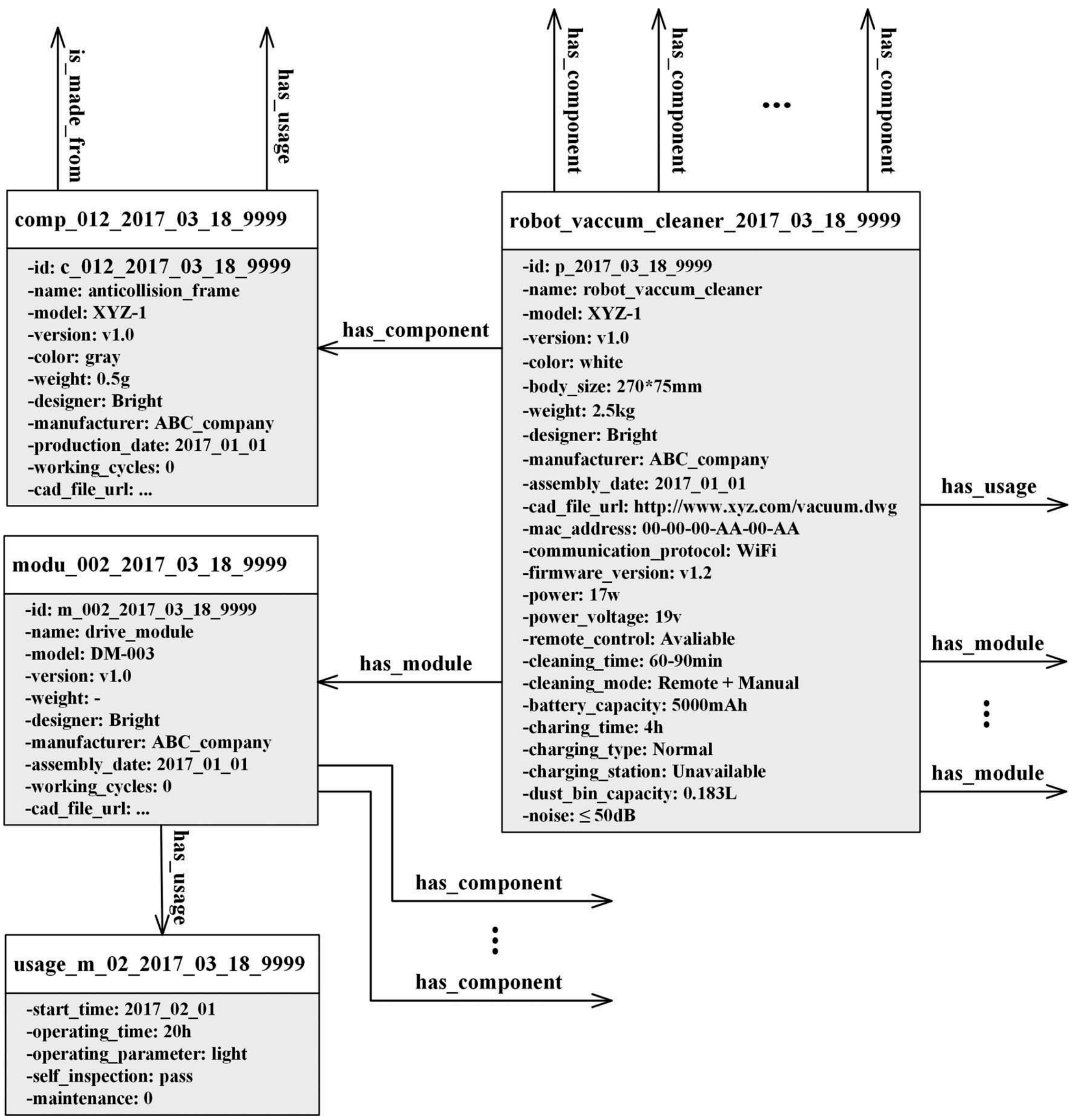

Figure 7. A part of the ontology of the RVC.

Table 6. The parameters of the membership functions of linguistic variables.

Linguistic variable	Parameter a	b	c	d	e	f	g	h
T_1	250	350	300	400	500	600	550	650
T_2	100	200	150	350	550	750	700	800
F	0.01	0.02	0.015	0.35	0.055	0.075	0.07	0.08

abilities of different recycling factories. This study proposes the decision methods of the cloud-based recycling service for smart products. The contributions are listed in the following content:

(1) Smart products have BOL information, and they are able to generate MOL data. The recycling process is usually decided by the BOL information and EOL status of products, the MOL data is not used to support the decision of the recycling service. An SPO is designed in this research to integrate the BOL and MOL information of the smart product. The SPO semantically organised the collected information which can be further applied to make the recycling decision.

(2) To decide the recycling choice of the components of smart products, a fuzzy-rule-based decision method is proposed. The method makes the decision with the lifecycle data of the smart product. The fuzzy rules formalise the recycling knowledge with linguistic values, and they reflect the experience of the real

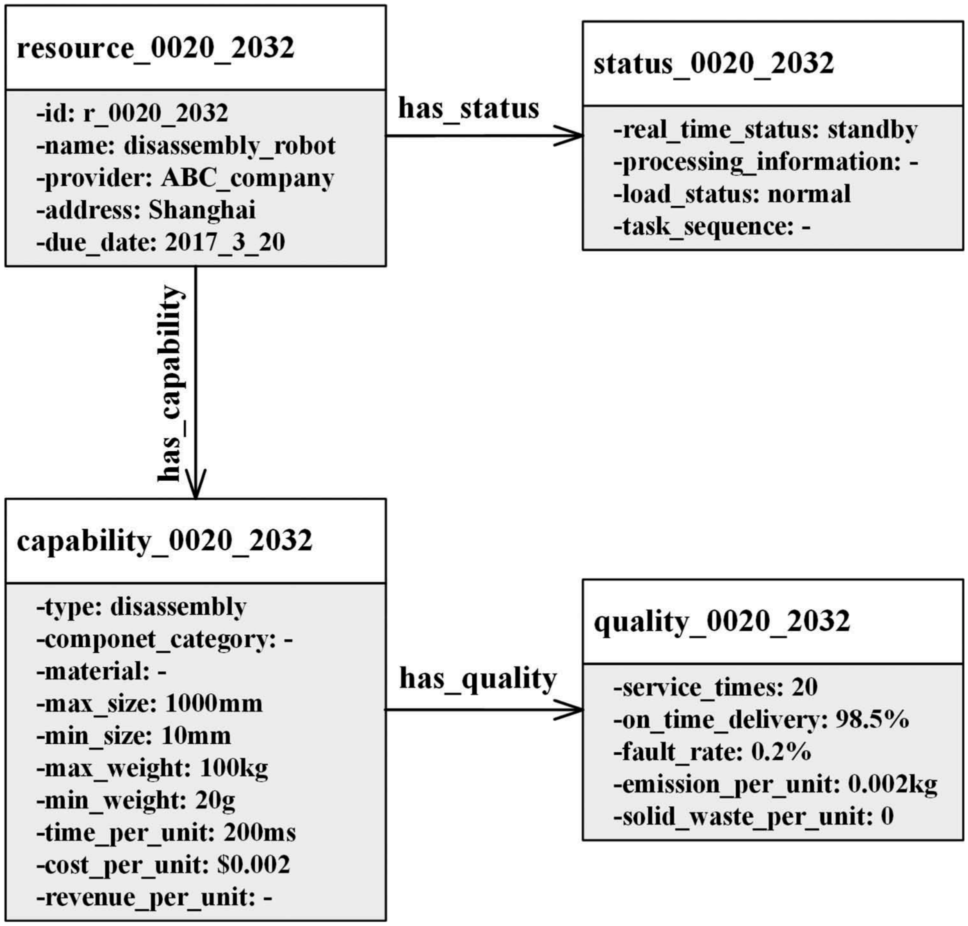

Figure 8. An example of virtualised recycling resources.

Table 7. The alternative resources for recycling ABS.

		Recycling resource				
	Attribute	1	2	3	4	5
1	*time_per_unit* (s)	0.022	0.034	0.036	0.043	0.056
2	*cost_per_unit* ($)	1.2	1.21	1.23	1.15	1.26
3	*revenue_per_unit* ($)	2.5	2.52	2.32	2.1	2.2
4	*service_times*	105	50	86	78	20
5	*on_time_delivery*	98.5%	99.0%	90.5%	95.5%	96.2%
6	*fault_rate*	0.02%	0.15%	0.16%	0.01%	0.12%
7	*emission_per_unit* (kg)	5.8	5.6	5.3	5.7	5.1
8	*solid_waste_per_unit* (kg)	0.2	0.22	0.16	0.23	0.18
9	*logistic_distance* (km)	20.5	23.5	25.6	15.2	10.8

Table 8. The calculation result.

		Recycling resource				
	Attribute	1	2	3	4	5
1	Service time	2460.0254	2820.0392	3072.0415	1824.0496	1296.0646
2	Service cost	11.6336	13.1451	14.2182	8.9260	6.8528
3	Recycling revenue	2.8825	2.9056	2.6750	2.4213	2.5366
4	Service times	105.0000	50.0000	86.0000	78.0000	20.0000
5	On time delivery	0.9850	0.9900	0.9050	0.9550	0.9620
6	Fault rate	0.0002	0.0015	0.0016	0.0001	0.0012
7	Service emission	10.7874	11.1568	11.2309	9.6121	8.0403
8	Service solid waste	0.2306	0.2537	0.1845	0.2652	0.2075

situation of recycling. By contrast, the numerical methods, such as AHP, are better in theoretical analysis and calculation.

(3) The abilities of different recycling factories are virtualised by the RRO. The recycling service platform builds a pool of recycling resources which can be matched, selected and encapsulated in a uniform way.
(4) There is a set of recycling resources of the pool that is capable of executing a single recycling task. A grey-relational-analysis-based method is proposed to select recycling resources. The selected resources are then encapsulated into the recycling service.

A smart product, RVC, is supposed to be recycled. In the case study, the SPO of the RVC is designed, and recycling resources are demonstrated. The fuzzy-rule-based decision method and the grey-relational-analysis-based method are proved to be effective for deciding the recycling service.

In the future, there are some topics that can be further developed. First of all, the sensors containing the technology of the internet of things can be studied along with the SPO. If there are more lifecycle data of smart products, the result of the recycling service decision will be more accurate. Second, there are eight attributes included in the grey-relational-analysis-based method. In order to make the MCDM powerful,

Table 9. The values after normalisation.

	Attribute	Recycling resource 1	2	3	4	5	
1	Service time	0.345	0.142	0.000	0.703	1.000	1.000
2	Service cost	0.351	0.146	0.000	0.719	1.000	1.000
3	Recycling revenue	0.952	1.000	0.524	0.000	0.238	1.000
4	Service times	1.000	0.353	0.776	0.682	0.000	1.000
5	On time delivery	0.941	1.000	0.000	0.588	0.671	1.000
6	Fault rate	0.933	0.067	0.000	1.000	0.267	1.000
7	Service emission	0.139	0.023	0.000	0.507	1.000	1.000
8	Service solid waste	0.429	0.143	1.000	0.000	0.714	1.000

Table 10. The grey correlation coefficient and grey relational grade.

	Attribute	Recycling resource 1	2	3	4	5
1	Service time	0.433	0.368	0.333	0.627	1.000
2	Service cost	0.435	0.369	0.333	0.640	1.000
3	Recycling revenue	0.913	1.000	0.512	0.333	0.396
4	Service times	1.000	0.436	0.691	0.612	0.333
5	On time delivery	0.895	1.000	0.333	0.548	0.603
6	Fault rate	0.882	0.349	0.333	1.000	0.405
7	Service emission	0.367	0.339	0.333	0.504	1.000
8	Service solid waste	0.467	0.368	1.000	0.333	0.636
	Grey relational grade	0.624	0.526	0.505	0.515	0.708

more attributes can be appended to the proposed method. Furthermore, the proposed decision methodology can be assessed in economic and ecological aspects. At last, a cloud service platform can be built on the basis of the theories proposed in this study. The platform will contribute to the global sustainable strategy.

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