Adaptive Clustering Algorithm for Recycling Cell Formation : An Application of Fuzzy ART Neural Networks

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The recycling cell formation problem means that disposal products are classified into recycling part families using group technology in their end-of-life phase. Disposal products have the uncertainties of product status by usage influences during product use phase, and recycling cells are formed design, process and usage attributes. In order to deal with the uncertainties, fuzzy set theory and fuzzy logic-based neural network model are applied to recycling cell formation problem for disposal products. Fuzzy C-mean algorithm and a heuristic approach based on fuzzy ART neural network is suggested. Especially, the modified Fuzzy ART neural network is shown that it has a good clustering results and gives an extension for systematically generating alternative solutions in the recycling cell formation problem. Disposal refrigerators are shown as examples.

Key Words : Fuzzy Theory, Fuzzy C-Mean Algorithm, Fuzzy ART neural network, Recycling Cell Formation

1. Introduction

As the environmental regulations concerning the disposal of discard products are rapidly increasing to protect the natural environment, the planning of the end-of-life phase of products is becoming more important for manufacturers (Park and Seo, 2003). The term recycling means reuse, further use or reutilization, of products or parts in life cycle. Within recycling, it can be distinguished between treatment and recycling process. The process of treatment includes refurbishing of subassemblies and components as well as reprocessing of materials. The recycling process involves shredding or disassembly of the product. Disassembly leads not only to the recovery of pure material fractions, but also to the isolation of hazardous substances and the separation of reusable components and subassemblies (Alting, 1995 ; Park et al., 1999).

A number of efforts aimed at disposing products that are easy to gain economic and environmental benign are currently in progress. To avoid costly product retirement, designers must identify ideal end-of-life strategies before specifying the structural attributes of the product (Rose et al., 2000). Post life extension strategies include policies to reuse, remanufacture, recycle and recover the product at the end of its life (Roche et al., 2001). There is a commonality between the desirable characteristics product specifications that enhance each of the end-of-life strategies. Most of the current methodologies have been developed independently of each other,

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e.g. design for disassembly and material compatibility (Roche et al., 2001). Knight and Sodhi (2000) present an analysis procedure that can be used to support evaluation of product design for efficient bulk recycling and the combination of disassembly and bulk recycling. Ha et al. (2003) investigated the waste plastic separation method from mixed plastics for or waste plastic recycling in the separation system. Remanufacturing can be an economically and environmentally superior end-of-life alternative to material recycling (Williams and Shu 2001). They presented the results of electronics and electromechanical products' waste-stream analyses, including the identification of discard reasons and associated root causes.

A disassembly-oriented recycling system is to collect material, labor, capital and knowledge needed for the disassembly of a product and for preparing the later treatment of its fraction (Zusman, 1994). Recycling should deal with products usually not designed for recycling, and in general it can neither restricted itself to a special type, nor can it add much to the obsolete product value (Simon, 1991 ; 1992). To cope with these challenges, recycling system requires more efficiency and flexibility. Considering an adequate type of a system, cellular recycling system is favorable. Cellular recycling system could reduce recycling costs and increase productivity and flexibility by the classification of disposal products.

The recycling cell formation problem means that disposal products are classified into recycling part families using group technology in their end of life phase. Disposal products have the uncertainties of product status by usage influences. The existing clustering approaches to group technology problem can be classified as matrix based methods, mathematical programming algorithms, and graph theory based methods. In addition, the heuristic approches such as pattern recognition techniques, fuzzy logic approaches, expert system based methods, neural network, and genetic algorithm are applied (Chu, and Hayya, 1991 ; Kusiak, 1985 ; Xu, 1989).

The recycling would justify uncertain product with the process characteristic by usage influence, as well as incomplete or erroneous information about various products. Thus recycling cells are formed considering the notion of design, process and usage attributes.

In this paper, a new approach to the design of cellular recycling system is proposed, which can deal with the recycling cell formation and assignment of identical products concurrently. Fuzzy clustering algorithm and fuzzy-ART neural network are applied to describe the states of disposal product with the membership functions and to make recycling cell formation. The modified fuzzy ART neural network is suggested and applied to form the recycling cell.

This paper is organized as follows. The next section describes the characteristics of the recycling process. In Section 3, the group approach with grouping attributes is presented. In order to form recycling cells, fuzzy C-mean and fuzzy-ART algorithms are proposed. Section 4 presents the solution procedures using disposal refrigerators. Two evaluation methods for recycling cells are suggested in section 5. Finally, section 6 concludes the paper with a summary.

2. Characteristics of the Recycling Process

Recycling deals with a huge variety of products from various producers and production years, as it usually cannot restrict itself to a spectrum of products from only one manufacturer. Uncertainty is caused by the varying product's life expectancies and generates a temporal dispersion of product abandonment. Arrival levels of each type of product and the product mix show non-deterministic properties. Product deterioration degrees are usually different because they are distributed in many different places. Product attributes are not always affected by usage function. Two other factors, time and media, can serve as examples of influences that cause deterioration from the original condition of the product. While deterioration like wear and material fatigue can be predicted, the abuse of the product, i.e., using a product for the purpose other than the original one, generates deterioration that cannot be foreseen. This makes an additional level of uncertainty in recycling, which is unknown in planning manufacturing systems.

Alternate recycling plans for a product can be predicted by the original product design and the analysis of AND/OR graph. The plans mean all the enumeration of the disassembly options of a product. Assuming that the design attributes are known, and that information is complete, a preliminary plan can be done at the phase-out stage according to the product/subassemblies and parts condition. The grouping of products by preliminary data becomes an ineffective task. Considering all these aspects, recycling cells are formed.

3. The Grouping Approach

In this section the aims are to present the grouping approaches for given disposal products. Considering design, process and usage attributes, recycling cells are formed by using fuzzy C-means and fuzzy-ART algorithms which deal with the uncertainties by usage influences.

3.1 Grouping attributes

At first, grouping is done by the nominal attributes of products, i.e., its design attributes. The design attributes, which are important for the recycling process include :

- country of origin (material parameters)
- year of production,
- size and weight,
- product type,
- material composition, parts,
- subassemblies,
- joining techniques,
- hazardous potential, and so on.

A grouping based solely on the design attributes would be insufficient for the representation of the wide range of variant caused by usage influences. Furthermore, if we take into account the optional process attributes, it will lead to high computational complexity. Thus design, process and usage attributes are considered as recycling grouping attributes. Process and usage attributes reflect the following producer's phase-out conditions :

- Non-loosenable joint due to corrosion,
- missing/additional parts,
- deformation,
- breakage of parts, etc.

3.2 Fuzzy clustering approach

One common weakness with many conventional analytical method of cell formation is that they implicitly assume that the part families are mutually and collectively exclusive. In reality, it is clear that some products definitely belong to certain part families, but there exist parts whose lineages are much less evident. Thus the fuzzy cluster approach offers a special advantage over conventional clustering. It does not only reveals the specific family to that a product belongs to, but also provides the degree or grade of each product family.

Assume that there are n products and p machines to group into c products families and corresponding recycling cells. Conventional clustering methods implicitly assume that disjoint part families exist in the data set ; a part can only belong to one part family. The classification results can be expressed as a binary matrix. In many cases, part families are not completely disjoint ; the separation of part families is fuzzy. Consequently, the concept of fuzzy subsets could offer an advantage over conventional clustering and could allow a representation of the degree or grade of membership of a part associated with each part family. In fuzzy clustering, the classification results can expressed as a matrix :

$$U=\begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ u_{n1} & u_{n2} & \cdots & u_{nn} \end{bmatrix} \tag{1}$$

such that

$$0 \leq u_{ik} \leq 1,\ i=1,\ 2,\ \cdots,\ c\ ;\ k=1,\ 2,\ \cdots,\ n \tag{2}$$

$$\sum_{i=1}^{c} u_{ik}=1,\ k=1,\ 2,\ \cdots,\ n \tag{3}$$

$$0 \leq \sum_{i=1}^{c} u_{ik} \leq n,\ i=1,\ 2,\ \cdots,\ c \tag{4}$$

Constraint (2) ensures that u_{ik} value can be fractional between 0 and 1, then k-th part does not belong to i-th part family. Therefore, a part could belong to several part families with different degree of membership. Constraint (3) ensures that each part will belong to one part family only. Constraint (4) ensures that each part family will consist of at least one part. Therefore, a part could belong to several part families with different degrees of membership.

3.2.1 Fuzzy C-mean algorithm

The problem of fuzzy clustering has received much attention, and several algorithms for solving it have been proposed (Chu and Hayya, 1991). In this paper, the generalized fuzzy C-mean (FCM) algorithm is applied to recycling cell formation. Since the number of possible U matrices that satisfy constraints (2) to (4) is infinite, an objective criterion to optimize the solution is required. The sum of square error function in any inner product form:

$$J_m(U, v)=\sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^m(d_{ik})^2 \quad (5)$$

In equation (5),

$$(d_{ik})^2=|x_k-v_i|=\sqrt{\sum_{j=1}^{p}(x_{kj}-v_{ij})^2}$$

is the desired membership function ;

$$x_k \in X, \text{ where } X=\{x_1, x_2, \cdots, x_n\}$$

is a data set of n parts ;

$$v=\{v_1, v_2, \cdots, v_c\}$$

is the center of cluster u, i.e., the mean vector of the parts in the ith part family ;

$$U=[u_{ik}]$$

is a matrix of fuzzy c-partition of X ;

$$\{u_{ik}\}^m=\{u_{ik}(x_k)\}^m$$

The solution procedure consists of eight steps :

(1) Choose the desired number of part family c, $1<c<n$.

(2) Choose a value m, $m>1$, for the degree of fuzziness.

(3) Choose a membership function, $|\cdot|$.

(4) Choose a value ξ for the stopping criterion.

(5) Choose an initial classification matrix, $U^{(0)}$.

(6) For iteration $l=0, 1, 2, \cdots$, calculate the mean vector $V_i^{(l)}$ for the fuzzy cluster center

$$u_{ik}^{(l)}=\frac{\sum_{k=1}^{n}(u_{ik})^m x_k}{\sum_{k=1}^{n}(u_{ik})^m}, \quad 1\leq i\leq c \quad (6)$$

(7) Update $U^{(1)}$ using $V_i^{(l)}$ and :

$$u_{ik}^{(l)}=\frac{1}{\sum_{j=1}^{c}\left\{\frac{d_{ik}}{d_{jk}}^{\frac{2}{(m-1)}}\right\}}, \quad 1\leq k\leq n \quad (7)$$

(8) Compare $U^{(1)}$ to $U^{(l+1)}$. If $|u_{ik}^{(l+1)}-u_{ik}^{(l)}|\leq m$, stop ; otherwise, go back to step (6).

3.3 Fuzzy ART algorithm

Fuzzy ART is an unsupervised category learning and pattern recognition network (Huang, 1995). It incorporates computations from fuzzy set theory into the Adaptive Resonance Theory (ART) based neural network (Carpenter, 1991). Fuzzy ART is capable of rapid, stable clustering of analog or binary input patterns. This network consists of two layers, the input (F1) and the output (F2) layers. The number of possible categories can be chosen arbitrarily large. At first step each category is said to be uncommitted. A category becomes committed after being selected to code an input pattern. Each input I is presented by an M-dimensional vector $I=(I_1, I_2, \cdots, I_M)$, where each component I_i are in the interval $[0, 1]$. One set of weight vectors $W_j=(W_{j1}, W_{j2}, \cdots, W_{jM})$ are used to represent output category j. Initially $W_{j1}=W_{j2}=\cdots=W_{jM}=1$, for all j.

To categorize input patterns, the output nodes receive net input in the form of a choice function, T_j. The following choice function is used

$$T_j(I)=\frac{|I\wedge v_j|}{a+|v_j|} \quad (8)$$

where a is the choice parameter ;

$\wedge$ is the fuzzy AND operator, defined as $(X\wedge Y)_i=\min(x_j, y_j)$;

and the definition of the norm of a vector X is

$$|X|=\sum_{i=1}^{M}|x_i|$$

The fuzzy AND operator reduces to the Boolean AND operator in the case of binary vectors. The category of output node with the highest value of T_j becomes nominated to claim the incoming pattern where

$$T_j(I)=\max\{T_j : j=1, 2, \cdots, N\} \quad (9)$$

To accept the nomination of the category the match function should exceed the vigilance parameter (ρ); i.e.,

$$\frac{|I\wedge v_j|}{|I|}\geq\rho \quad (10)$$

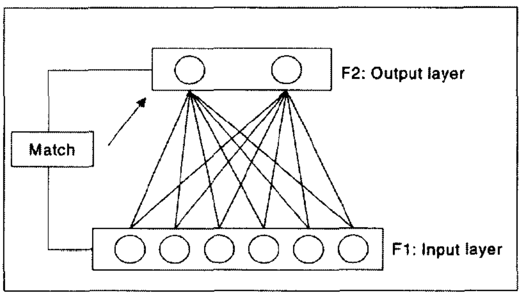

Fig. 1 Simplified representation of fuzzy ART

If the first nominated category does not pass the similarity test, an uncommitted node should be committed to the input pattern in the fast learning mode.

The weight vector of winner category is updated as follow :

$$v_j^{(new)}=\beta(I\wedge v_i^{(old)})+(1-\beta)(I\wedge v_j^{(old)}) \quad (11)$$

Three parameters determine the dynamics of a Fuzzy ART network, 1) the choice parameter $\alpha>0$, which is suggested to be close to zero, affects the search procedures. The choice parameter controls the choice of a category whose weight vector W_j is the largest coded subset of input vector I (if such category exists) ; 2) the learning rate parameter, $\beta\in[0, 1]$, which defines the degree to which the weight vector W_j is updated (recoded) with respect to an input vector claimed by node J ; and 3) the vigilance parameter, $\rho\in[0, 1]$, which defines the required level of similarity of patterns within clusters.

3.3.1 The modified fuzzy ART neural network

The modified method uses fuzzy ART to generate a hierarchy of alternative clustering. Inputs

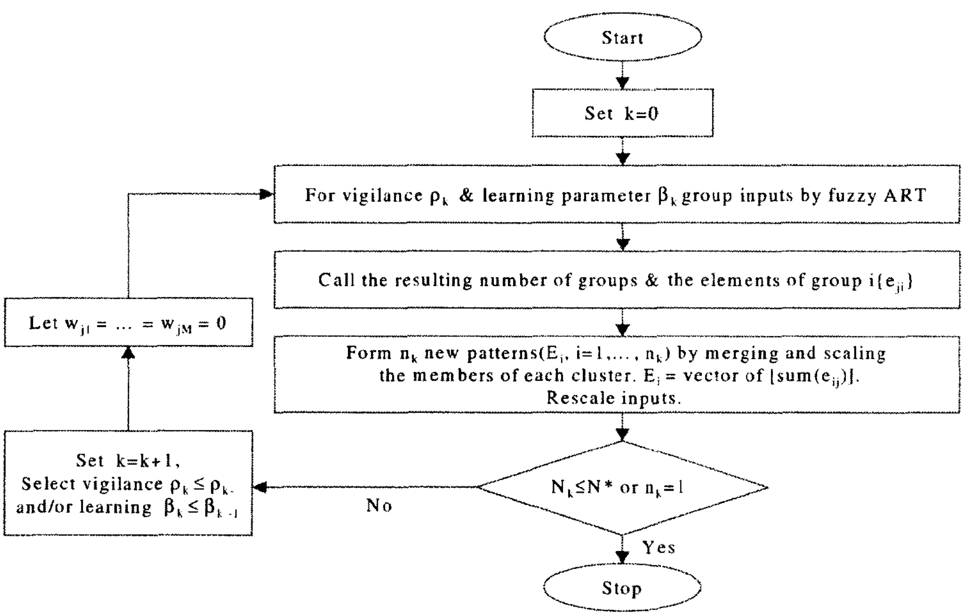

Fig. 2 Flow chart of modified fuzzy ART neural network

are progressively merged until the fewest number of cells is formed or the desired number of cells is reached. The algorithm is as follows (see Fig. 3):

Step 1 : Set $k=0$.

Step 2 : Group inputs by fuzzy ART for vigilance ρ_k and learning β_k.

And call the resulting number of groups and the elements of group $i \cdot \{e_{ji}\}$.

Step 3 : Each cluster obtained in step 2 may have more than one member.

And form n_k new patterns $(E_I, I=1, 2, \cdots, n_k)$ by merging scaling the numbers of each cluster $(E=\text{vector}[\text{sum}(e_{ij})])$.

Finally, rescale inputs.

Step 4 : If either $n_k \leq N^*$ or $n_k=1$, then stop. Otherwise, set $k=k+1$ and select vigilance $\rho_k \leq \rho_{k-1}$ and then go to step 2. (Notice that if we go back to step 2, we use a new fuzzy ART network in which $W_{j1}(0)=W_{j2}.=\cdots W_{jM}(0)=1$)

M^*=the desired number of clusters

In fuzzy ART, the number of clusters is determined by the values that the user chooses for parameter α and β, and the input matrix. This method uses fuzzy ART iteration.

The goal of the proposed method is to prevent a premature clustering of a pattern. This method improves the performance of Fuzzy ART neural network. In Fuzzy ART, the first member(input) of an output node is dominant and moves the weight vector of that node towards its position. Therefore, for a low vigilance value, several inputs which are not very similar to this first member are forced to be grouped with it. Bur with a high value of vigilance, only very similar inputs will be grouped in other output nodes. The grater the number of clusters, the less the nodes are biased to their first members. Reducing the value of the learning parameter affects the number of clusters in the same way that reduction of the vigilance parameter affects the number of clusters. But, changes in learning parameter do not change the number of clusters as much as changes of vigilance parameter would do. In addition, initial weight vector is adjusted by user according to the relative importance of node. Normally, the clustering of members is influenced by the value of heavy weight, the user can manipulate the neural network.

This iterative method allows the weights to decrease slowly and enable more similar patterns to be grouped together. If the first member of a cluster is missing a specific attributes, it reduced the related weight attributes to zero. If all the members of the cluster do not possess that specific attributes, then this cause no problem. But, if some of the members have that attributes, the

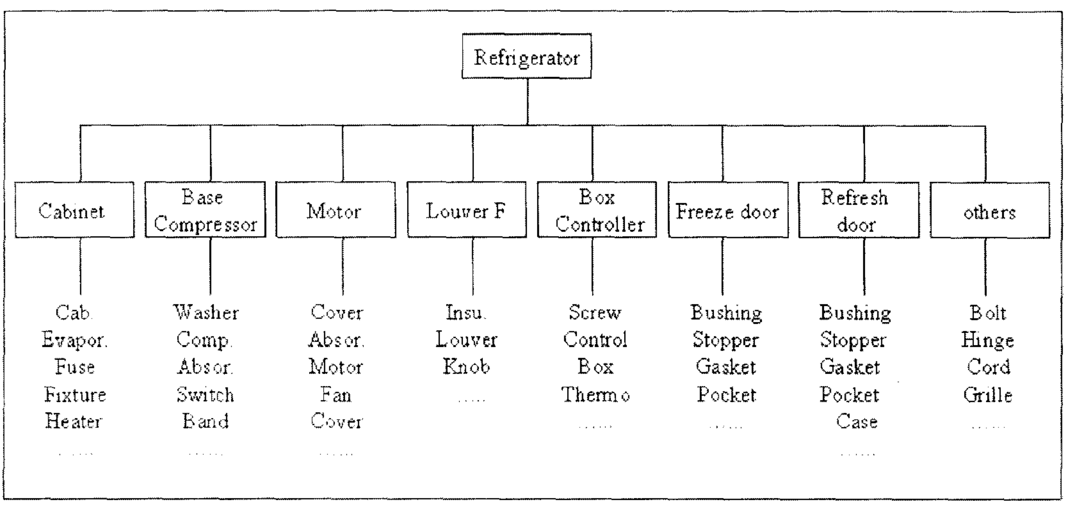

Fig. 3 Structure of a refrigerator

decreasing the value of weight attributes lead to poor cluster and a difficult-to-interpret weight vector. Knowing that the value of each attributes (in a weight vector) reflects the importance assigned to that attribute in the cluster. If an attribute is equal to zero, it means that the weight does not know anything about that attribute. So, by grouping only very similar patterns, the better clustering results are obtained by merging similar patterns and reentering them into the network again as new input.

4. A Case Study

Disposal refrigerators are shown as examples for recycling cell formation. A refrigerator consists of 8 modules as shown in Fig. 3 : Cabinet, Base compressor, Motor, Louver, Box controller, Freeze door, Refresh door, others, and the number of components are one hundred approximately.

For the purpose of protection against heat, CFC is injected to the refrigerator. Most countries regulate the CFC, because it destroys ozone layer. In addition, certain materials of composing refrigerators pollute the ground and ground water. Therefore hazardous materials are avoided. New regulations prohibit the disposal of electronic appliances in landfill and adapt the "Take-back" concept. If they are disposed, the high disposal fees are imposed or disposition is forbidden. Consequently, these regulations push companies to contribute themselves to new environmentally conscious design and recycling of refrigerator in order to minimize the environmental impact.

4.1 Recycling selections

Recycling target is not a complete disassembly, but rather to find an optimum ; level which clearly benefits the recycling efforts. Disposal of appliances will be reclaimed from the households by recycling center. The actual prehandling procedure basically consists of following stages.

- initial inspection, entry of item into the book keeping.
- separation, inspection, cleaning and repair of possibly reusable units and their redistribution through the recycling center etc.
- temporary storage and batching of appliances to be disassembled.
- drainage of CFC.
- disassembly of selected components to be reused as spare parts.
- disassembly and sorting of components made of materials which have a clearly defined individual recycling center.
- disassembly and sorting of potential hazardous elements and materials.
- crushing large steel, plastic structure
- storage and batching of appliances and disassembled fractions
- transportation to recycling companies, hazardous waste treatment plant, land fills, and so on.

There are five categories for recycling refrigerators as follows :

- reuse of parts.

Valuable parts such as compressor, controller are reusable as many as possible. In order to reuse the part, it is necessary to test reliability using statistics and queuing techniques.

- reprocessing of parts and materials.
- recycling of materials.
- collecting CFC at liquid state and reprocessing.
- waste treatment (landfill, incineration with special or regular).

4.2 Recycling attributes

Owing to usage influences, the condition of disposal refrigerators varies in many influences, many uncertainties exist. In this paper, various recycling attributes are considered. For example, it is important whether CFC drainage or not. By the existence of CFC, the membership function of fuzzy characteristics is determined to 0 or 1. The next recycling attributes is the condition of outer case which is made from steel. It is seamed by rubber in order to prevent moisture and air from infiltrating into the outer case and not to rust. The condition of seam between outer case parts (both upper and lower) is determined to the degree of rust or cleanness of membership function.

In addition to these recycling attributes, twelve other attributes are considered that they are described by [0, 1] states with fuzzy membership functions as follows: (1) the condition of motor (cover, tapping, screw), (2) the condition of compressor (cover, tapping), (3) the condition of box controller(the condition of seal, housing joining, rubber cap), (4) the condition of gasket and rubber (R, F), (5) the condition of thermostat, (6) the condition of screw tapping of each joining parts, (7) the condition of heater defrost, (8) the condition of evaporator, (9) the condition of seal of heater defrost part (glass tube and silicon rubber), (10) the condition of fixture fuse part (leak test), (11) the condition of cabinet (leakage of rubber silicon, catalyst, refrigerant, water), and (12) the condition of welding between parts.

4.3 Application examples

As an illustration for the fuzzy C-mean and fuzzy-ART grouping procedure, data were collected from both an experiment of disassembly disposal refrigerators and a recycling center. These data is obtained from twenty refrigerators from two companies. After carefully reviewing these data, and based on the experience of the expert, the twenty-one attributes were selected :

(1) length of life cycle (expected duration, year)
(2) take back (total cost and distance)
(3) type
(4) size (volume)
(5) total weight
(6) company
(7) the existence of CFC
(8) the degree of rust or cleanness of outer
(9) the condition of motor (cover, tapping, screw)
(10) the condition of compressor (cover, tapping)
(11) the condition of box controller (the condition of seal, housing joining, rubber cap)
(12) the condition of gasket and rubber of freezing door

Table 1 Data for the numerical example

Attributes / Products	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
1	0.6	0.5	1	0.3	0.4	1	1	0.2	0.8	0.7	0.5	1	1	0.8	0.7	1	0.7	1	1	0	0.8
2	0.7	0.8	0	0.2	0.3	0	1	0.5	0	0.5	0.7	1	1	0	0.6	1	0	1	1	1	0.6
3	0.5	0.6	1	0.6	0.7	0	0	0.3	0.8	0.7	0.6	0	1	0.8	0.5	0	0.8	0	0	0	0.2
4	0.8	0.4	0	0.5	0.6	1	1	0.5	0.8	0	0.3	1	0	0.7	0.6	0	0.7	0	1	1	0.9
5	0.7	0.5	1	0.4	0.5	0	1	0.2	0	0.7	0.5	0	0	0.8	0.7	1	0.8	1	0	1	0.8
6	1	0.3	0	0.5	0.6	1	1	0.5	0.8	0.8	0.2	1	1	0.6	0.5	1	0.6	0	1	1	0.7
7	0.9	0.7	1	0.5	0.6	1	0	0.4	0.7	0.6	0	1	1	0.7	0.3	1	0.7	1	1	1	0.9
8	0.6	0.5	1	0.6	0.7	1	1	0.1	0.8	0	0.5	0	0	0	0.2	0	0	0	0	0	0.3
9	0.7	0.6	0	0.3	0.4	1	1	0.2	0.7	0.7	0.3	1	0	0.7	0.3	1	0.7	1	1	1	1
10	0.8	0.5	1	0.5	0.6	0	0	0.2	0.8	0.8	0.3	1	1	0.8	0.8	1	0.8	1	1	0	0.8
11	0.7	0.7	0	0.4	0.5	1	0	0.4	0.9	0.7	0.5	0	0	0	0.2	0	0	1	1	1	1
12	0.9	0.4	1	0.6	0.7	1	1	0.5	0	0.5	0.5	1	1	0.8	0.7	1	0.8	0	0	0	0.2
13	0.9	0.4	0	0.4	0.5	1	0	0.2	0.8	0.9	0.4	0	0	0.5	0.1	0	0.5	0	1	1	0.8
14	0.7	0.5	0	0.5	0.6	1	1	0.3	0	0.7	0	1	0	0.6	0.5	1	0.6	1	1	0	0.9
15	0.8	0.6	1	0.4	0.5	0	1	0.2	0.7	0	0.5	1	1	0.8	0.7	1	0.7	1	0	1	0.6
16	0.7	0.7	1	0.5	0.4	0	1	0	0.8	0.6	0.3	0	0	0	0.3	0	0	0	0	0	0.1
17	0.8	0.6	0	0.3	0.4	1	1	0.1	0	0.6	0.5	0	1	0.5	0.4	1	0.7	1	1	1	1
18	0.7	0.5	1	0.2	0.3	1	0	0	0.6	0	0.5	1	1	0.8	0.8	1	0.8	1	1	1	0.9
19	0.6	0.6	0	0.3	0.4	0	0	0.2	0.5	0.9	0.4	0	0	0	0.1	0	0	0	0	0	0.2
20	1	0.5	0	0.4	0.5	1	1	0.1	0	0.7	0.5	1	1	0.9	0.8	1	0.7	1	1	1	1

(13) the condition of gasket and rubber of refreshing door

(14) the condition of thermostat

(15) the condition of screw tapping of each joining parts

(16) the condition of heater defrost

(17) the condition of evaporator

(18) the condition of seal of heater defrost part (glass tube and silicon rubber)

(19) the condition of fixture fuse part (leak test)

(20) the condition of cabinet (leakage of rubber silicon, catalyst, refrigerant)

(21) the condition of welding between parts.

4.4 Results of the application examples

4.4.1 Fuzzy C-mean algorithm

The fuzzy C-mean algorithm was applied to this data set $c=3$, $m=2$, $|\cdot|=$Euclidean distance, and $\xi=0.01$. The $U^{(0)}$ is obtained from the embodied heuristic. The final classification matrix is obtained by fourth iterations. Table 3 shows the clustered result.

Using final results, we can calculate the value of memberships for recycling cluster, and it means the degree of membership of each attributes associated with each part family.

Table 2 Clustered result of numerical example using FCM algorithm

Recycling Cells	Products
Recycling Cells #1	1, 4, 6, 7, 9, 12, 20
Recycling Cells #2	2, 5, 11, 14, 15, 17, 18
Recycling Cells #3	3, 8, 10, 13, 16, 19

Table 3 Members of recycling cell after first step

The First Step ($\rho=0.5$, $\beta=0.5$)	
Recycling Cells	Products
Recycling Cells #1	1, 4
Recycling Cells #2	14, 16, 19
Recycling Cells #3	3, 10
Recycling Cells #4	5, 9, 18
Recycling Cells #5	8, 15, 7
Recycling Cells #6	12, 13, 20
Recycling Cells #7	6, 7, 14
Recycling Cells #8	2, 11

This example illustrates how fuzzy c-mean clustering can help to design recycling cellular system. The final result must take into consideration the recycling workload balance, the material handling costs. Also, it is possible to evaluate the economic justification using the clustered result.

4.4.2 Fuzzy ART algorithm

The fuzzy ART algorithm was faced several shortcomings of the original algorithm. First, it can suffer from category proliferation. Second, practical cell formation problem dictates the need of more flexible, scaling issue. In order to overcome these difficulties, the Add method is used and choose the vigilance parameter (ρ) and learning parameter (β) properly.

Step 1 : Set $\rho=0.5$, $\beta=0.5$
Step 2 : Set $\rho=0.3$, $\beta=0.5$
Step 3 : Set $\rho=0.2$, $\beta=0.5$

In step 3, the number of recycling cell is reduced to 3 clusters. Here, the process is stopped since the goal value equals to the solution to the fuzzy C-Mean algorithm. Analyzing these results, it is an option that a user wants to definitely have $N*$ clusters. Otherwise, when the algorithm stop at step 3, the user can choose the best solution among all the generated clusters.

Table 4 Members of recycling cell after second step

The Second Step ($\rho=0.3$, $\beta=0.5$)	
Recycling Cells	Products
Recycling Cells #1	1, 4, 9, 12, 20
Recycling Cells #2	6, 7, 14, 18
Recycling Cells #3	2, 5, 15, 17
Recycling Cells #4	3, 19, 11, 13
Recycling Cells #5	8, 16, 19

Table 5 The final solution using Fuzzy-ART neural network

The Third (Final) Step ($\rho=0.2$, $\beta=0.5$)	
Recycling Cells	Products
Recycling Cells #1	1, 4, 6, 7, 9, 12, 20
Recycling Cells #2	2, 5, 11, 14, 15, 17, 18
Recycling Cells #3	3, 8, 10, 13, 16, 19

5. Evaluation and Discussion

As results of the experiments, three recycling cells are formulated so that they are helpful to evaluate the disposal products. The evaluation of worn-out products are able to maximize the recycling, economic profits, and minimize the environmental impacts. In order to pursue these objects, two evaluation methods for recycling cells are proposed.

The first method is ABC evaluation method similar to ABC inventory analysis. Disposal refrigerators are grouped three cells using FCM and Fuzzy ART algorithms. The results are applicable to ABC evaluation method. The focus of ABC evaluation method is on recycling cells (groups) in the ABC method in aspect of considering both manufacturing and recycling. Subassemblies are divided into subassemblies for reuse (category A, high manufacturing costs, long life time, long innovation cycles and high value components whose value volume accounts for 75% of the value of total production and recycling items), subassemblies for special reprocessing (category B, complex mixture, short lifetimes, short innovation cycles and high value components whose value volume accounts for 15% of the value of total production and recycling items) and subassemblies for recycling with existing technology (category C, low production costs, big volumes, high material costs and high value components whose value volume accounts for 5% of the value of total production and recycling items). The same degree of recycling is not justified for all items. But this method basically supports the choice of recycling strategy by simplifying product structure, and it has been tried out on an electric refrigerators case with a good result concerning assembly, disassembly, reuse, reprocessing and recycling in end of life phase.

The second method is the estimation system of disposal product based on database. The most frequent and time consuming activities in recycling operation involve the determination of recycling parameters of a part under particular part and process condition (i.e., fatigue, damages, and contamination) estimating the cost of reuse, and reproduce the part. It is a complex and time consuming task requires a great deal of knowledge and experience. Database has to be constructed to all information (i.e., materials, process constraints and parameters) about the objects. Each factor based on database must be estimated in the system. For example, the cleaning depends on factors such as the type, location of parts, the part configuration, and the type of loosing. Knowledge of the cleaning determination is incorporated into the rules of the system. Above all information are based on estimating recycling system. In addition, overhead factors are used in overhead cost calculation, and one based on the recycling rate and percentage profit, the other based on cost per hour are calculated. The total cost of recycling as determined by the system is listed along with recycling costs and displayed. This system supports the determination of the number of economic disassembly steps and the optimum recycling strategy. Using the Recycling information, the possible product structures are given as input along with information about the connections of components and components weights and material compositions.

Subsequently recycling groups are formed of parts which require the same recycling strategy. The tool operates with seven strategies : part reuse, part reprocessing, component recycling, material recycling, incineration and landfill of either hazardous components or not hazardous components with little value. Various product layouts are compared using an evaluation methodology focusing on ten key issues and allocating a score for each issue. The estimation process of recycling helps to assess environmental impacts. It also determine design alternatives based on the product cost allowing one to immediately make proper adjustment.

6. Conclusions

This paper introduced an approach to the planning of cellular recycling systems for disposal products. Naturally, worn-out products come in a wide range of various types. All of them show usage influence, namely alternations in their original condition, which, in turn, lead to varying life expectancies of each product. Therefore, forming the part families has to be accomplished under uncertainties of the product's condition.

The formation of the part families is based on usage attributes in addition to the design attributes. Grouping is done by fuzzy C-mean and fuzzy-ART algorithm, allowing to describe by membership functions to what degree a special group belongs to a certain family. As an example, the recycling system planning for used refrigerators is applied, demonstrating the grouping approach. Here design and usage attributes are utilized.

Those two evaluation methods for recycling cells are proposed. The first is ABC method similar to ABC inventory analysis, and the second is estimated in details.

The proposed grouping approach can help to solve the material flow, and the cell layout problems by integrating alternative recycling selections.

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