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A FRAMEWORK FOR SIMULTANEOUS RECOGNITION OF PART FAMILIES AND OPERATION GROUPS FOR DRIVING A RECONFIGURABLE MANUFACTURING SYSTEM

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Abstract:
With markets becoming increasingly competitive and customers demanding new product types/styles with ever-shortening life cycles, the conventional manufacturing systems have been rendered unfit in fulfilling the new manufacturing objectives of flexibility and responsiveness. Reconfigurable Manufacturing Systems (RMS) has been envisaged to have the capability to face these challenges by providing the exact functionality and capacity that is needed, exactly when it is needed. In RMS, products/parts are grouped into families, each of which requires a particular manufacturing system configuration in terms of the Reconfigurable Machine Tools (RMTs), their layouts etc. The system is reconfigured to produce the next family, once the production of the current family is finished, and so forth. The foundation for the success of an RMS, therefore, lies in the issue of 'recognition of appropriate sets of part families'. In the present work, a methodology based on adaptation of hierarchical clustering procedure is proposed so as to simultaneously yield sets of part families at different similarity levels and the corresponding operation groups.

Key Words: Reconfigurable Manufacturing System, Part Family Recognition, Hierarchical Clustering

1. INTRODUCTION

Reconfigurable manufacturing systems have been identified as manufacturing systems which provide the exact functionality and capacity that is needed, exactly when it is needed by rapidly rearranging or changing their constituent components [1, 2, 3, 4]. In RMS, each part may require a particular system configuration depending on the operations required for its manufacturing. However, RMS is made economically more attractive by recognizing part families having similar operations so that the whole family requires a single system configuration to manufacture all its member parts [5]. One part family is manufactured at a time by a system configuration having suitably configured RMTs catering to its operational requirements. The production of next family starts only when the system is reconfigured as per the operations required for the next family [5]. Therefore, the issue of finding appropriate part families and corresponding operation groups is central to the problem of designing a reconfigurable manufacturing system. These tasks are accomplished by applying the philosophy of group technology (GT) that takes advantage of the similarities between design characteristics and/or manufacturing attributes and/or functions of the given set of parts to group together similar parts for a common purpose.

The objective of this work is to propose a systematic procedure for simultaneous recognition of part families and corresponding operation groups for an effective and economic working of an RMS. The proposed procedure is an adaptation of agglomerative hierarchical clustering algorithm founded on two postulations. First, each part is manufactured using alternative operation sequences, all equally weighted. Second, a higher value of similarity measure implies a higher commonality of operations leading to less machine idleness. Therefore, an operation sequence that associates with a part family at the highest value of the similarity measure will be selected and the remaining will be discarded.

The paper has been structured as follows. Section 2, casts a glance on application of GT in the design of manufacturing systems, comparing RMS with cellular manufacturing systems (CMS). Section 3 presents the details of RMS model considered in this study. There is a whole gamut of literature available on methods for obtaining families of parts and groups of machines, especially in the context of CMS. As reconfigurable manufacturing paradigm has its own distinct characteristics, these methods cannot be directly adopted. In section 4, methodologies of cell formation in CMS are reviewed with the objective of identifying one that can be conveniently modified and adapted for the RMS model considered in this study. A discussion is presented on the attributes to be considered for formation of RMS part families, similarity coefficient and alternative operation sequences with reference to the considered RMS model. Building upon this foundation, a procedure for simultaneous recognition of parts families and the formation of corresponding operation groups has been proposed in section 5 and a numerical demonstration of the same has been presented in section 6. Finally, section 7 gives the conclusions and indicates the scope for future work.

2. GT APPLICATION IN DESIGN OF MANUFACTURING SYSTEMS: A GLANCE

Between the extremes of few part types produced in high volumes on dedicated manufacturing systems and a large variety of parts produced in few numbers in a job shop, there is an important category of batch manufacturing, which constitutes approximately 75% of total discrete part manufacturing activities [6]. The traditional process layouts have high material handling and tooling costs, complex scheduling and loading, lengthy setup times and high quality control costs associated to them, which significantly affect manufacturing cost, quality and delivery lead times. However, to compete in the increasingly challenging global environment characterised by demand for high flexibility and responsiveness, it is essential to improve productivity in manufacturing to increase market share and profitability. Application of GT in the design of manufacturing systems is an approach directed at these objectives. GT adoption in batch manufacturing allows the manufacturing system to gain economic advantages similar to those of dedicated manufacturing systems and at the same time helps in gaining the flexibility of job shops. Design of manufacturing systems such as flexible manufacturing systems (FMS), CMS etc. has been founded on the concepts of GT.

In CMS productivity is improved by exploiting similarities in manufacturing requirements such as machining operations, tooling, setups, material handling etc. Parts having similar manufacturing requirements are grouped into part families and processed together by dedicated machine cells. Therefore, GT implementation decomposes a large manufacturing system into smaller subsystems (cells), each specialized in the production of a part family. But, the highly unpredictable market environment and ever-shortening product life cycles have rendered these permanent cells inefficient [4]. Fortunately, the growing research and development in modular machines, RMTs and other supporting technologies has paved the way for the new manufacturing paradigm of RMS that promises customised flexibility with high responsiveness [1, 2, 4, 7]. In RMS, each part requires a specific system configuration. System can be reconfigured every time a new/next part order is to be executed. However, each reconfiguration incurs cost in rearranging the resources. Application of GT in RMS design can help in reducing the number of such reconfigurations required by dividing the large number of part types into a smaller number of families having similar manufacturing requirements. Therefore, GT application in RMS may enable it to execute a large part mix in fewer reconfigurations of the system.

3. THE PROPOSED RMS MODEL

The RMS model considered for study is assumed to be exposed to a complex environment, characterized by fierce competition, highly variable demand, compulsion to adopt new processes, frequent changes of the product mix and frequent introduction of new products. It possesses the features described below.

1. Manufacturer receives orders for Q different part types for manufacturing in the next reconfiguration cycle. The order receipt is closed at a certain pre-defined time limit before the completion of running reconfiguration cycle to provide sufficient time for the reconfiguration exercise. Out of the Q part types, only those P (≤Q) part types are accepted which satisfy two conditions as per company policy: (i) the total order di of all the customers for a particular part type pi must exceed a pre-decided minimum quantity, $D_{min(i)}$ (i.e. $di \geq D_{min(i)}$) and (ii) the anticipated execution time of all the orders must not exceed a predefined maximum allowable reconfiguration cycle span.

2. Each part, p_i is manufactured in ordered quantity, d_i using various machining operations by one of the various alternative operation sequences.

3. These part types are divided into F part families so that $1 \leq F \leq P$. Therefore, in extreme cases, either all the part types will fall in the same family or each family will be consisting of only one part type. The key attribute of a part family is that all the part types within a family require same operations and hence same production resources.

4. At any time the cell is constituted of suitably configured RMTs to cater to operational requirements of one part family only. The production of next family starts only when the cell is reconfigured as per the operations of this new family after the completion of the present family. Reconfiguration of the cell is achieved by relocation and reconfiguration of RMTs to enable them to perform operations required for the new family. RMTs are reconfigured using various combinations of basic modules (BMs) and auxiliary modules (AMs) [1-7]. The reconfiguration of the system that enables it to cater to a new family is defined as Primary Reconfiguration (PR). The sequence, in which the various part families are considered for production is termed as Primary Reconfiguration Sequence (PRS).

5. All the parts belonging to a family require common RMTs but they may have different routes through these RMTs. Therefore while switching over the production from one part to another within a family; the relocation of RMTs may be required. The reconfiguration of the cell that enables it to cater to next part within the same family is defined as Secondary Reconfiguration (SR). The sequence, in which the parts belonging to a family are considered for production is termed as Secondary Reconfiguration Sequence (SRS).

6. A Reconfiguration Cycle (RC) is completed when all the parts are manufactured as per the planned PRS and SRSs. Reconfiguration Cycle Span or simply the Cycle Span (CS) of an RMS is the time taken to execute the whole RC.

4. LITERATURE REVIEW, DISCUSSION AND APPOSITE DEDUCTIONS

4.1 Attributes

The operations dictate the type of machine tools needed and the sequence of operations impacts the flow of the material. Therefore, the operations and their sequences are among the most relevant attributes for the design of a CMS, where the aim is to configure permanent cells [6]. In the proposed RMS model, it has been assumed that all the parts belonging to a family are manufactured on a system configuration that provides all the resources required for their manufacturing. If the parts of a family follow different routes, the cell may undergo secondary reconfigurations to accommodate it. It implies that for a part to be a member of a family, commonality of operations is a sufficient condition and therefore the exact route need not be considered. Further, in CMS demand data has a direct influence on cell formation. For evenly distributing the work load amongst the cells, it is necessary either to include the part type(s) with heavy demand in smaller families or provide duplicate copies of machines. In the proposed RMS all the parts are manufactured sequentially (one after the other) on the same system and orders are accepted as per a predefined policy which ensures that the manufacturing time of all the parts does not exceed the cycle span of the cell. Therefore, demand data will also not influence the decision of part family formation. Thus, the operations required to manufacture a part are the most relevant attributes for the considered RMS model, consistent with the objective of minimising the number and hence,

cost of reconfigurations. Therefore, binary part-operation incidence matrix (POIM) that ignores the information on exact routes is sufficient input for this problem.

4.2 GT Methods

GT application in CMS cell formation (CF) problem incorporates two sub-problems: the identification of 'part families' and formation of 'machine groups'. In a RMS design problem also 'Part Family' recognition and 'Operation Groups' formation are preliminary requirements. A broad literature review of cell formation techniques in CMS was conducted to identify a suitable technique to fulfil the requirements of RMS model in hand.

It has been observed that the descriptive procedures available in the literature are not highly sophisticated or accurate, whereas, mathematical programming approaches are incompletely formulated and computationally complex [8]. Random search algorithms such as simulated annealing, genetic algorithms and neural networks provide solutions, which do not depend on the initial solution and have an objective value closer to the global optimal. However, the gain in applying these general algorithms may be undone by the computational effort, since these procedures are slower than other procedures [9]. Non-hierarchical clustering methods such as ISNC [10], ZODIAC [11] and GRAFICS [12], require the information on the number of groups to be formed in advance. But this is undesirable in RMSs. In addition, the arbitrariness of the initial partition of the data set could lead to unsatisfactory results.

For the RMS model under consideration in which only binary POIM is required as initial input, the use of either array based clustering methods or the hierarchical clustering methods seem to be justifiable. Array based clustering methods also called matrix manipulation methods attempt simultaneous grouping of parts and machines through block diagonalisation by reordering rows and columns of the binary incidence matrix. Some of the main matrix manipulation methods are Bond Energy Algorithm [13, 14], Rank Order Clustering [15, 16], Modified Rank Order Clustering [17], Direct Clustering Analysis [18] and Cluster Identification Algorithm [19]. Though these methods achieve acceptable results with low computational cost, they have the disadvantage that results obtained have a dependency on the configuration of initial incidence matrix [15, 17, 19]. Also, it has been observed that in many cases disjoint part families are not identified even with a well structured matrix [9].

The hierarchical clustering procedure groups together similar objects on the basis of the similarities in their attributes. Hierarchical algorithms, which can be agglomerative ('bottom-up') or divisive ('top-down'), find successive clusters using previously established clusters. Agglomerative algorithms begin with each object as a separate cluster and merge them into successively larger clusters based on commonality in attributes measured by a similarity coefficient. On the other hand divisive algorithms begin with the whole set as one cluster and proceed to divide it into successively smaller clusters. It has been observed that in the context of part family formation or machine group recognition, only agglomerative procedure has been used [20].

The traditional representation of this hierarchy is a tree called a dendogram, with individual elements at the top end and a single cluster containing every element at the bottom. Agglomerative algorithms begin at the top of the tree, whereas divisive algorithms begin at the bottom. Cutting the dendogram at a given precision level (similarity level expressed in %) gives a set of families at selected precision. As the precision decreases, a coarser clustering occurs that is distinguished by a smaller number of large size clusters.

In addition to the fact that hierarchical clustering is a well-proven and most broadly implemented method in almost all the fields of Engineering and Science, following are other relevant reasons to adopt this method for part family formation in the present problem:

- it can be easily adapted as per the specific requirements of different problems by suitably defining logically and/or probabilistically justifiable similarity coefficients,

- in CMS cell formation problems, the selection of a set of families are generally made from the dendogram by restricting either precision level or the number of groups. In the presented RMS model it has been proposed that families corresponding to that level of the dendogram have to be selected which minimises the sum of primary reconfiguration costs, secondary reconfiguration costs, material handling costs, machine idle costs etc.

In the light of these facts, agglomerative hierarchical clustering has been selected to use in the present study with appropriate modifications and adaptations for simultaneous formation of part families at various precision levels and operation groups.

The three most widely used hierarchical clustering methods are single linkage clustering (SLC) [21], average linkage clustering (ALC) [22] and complete linkage clustering (CLC) [23, 24]. In SLC, two groups are merged together merely because two parts, one from each group have high similarity to each other. If this process continues, it results into a string effect known as chaining. Since CLC is the antithesis of SLC, it is least likely to cause chaining. ALC produces reasonable results between these two extremes [9] and therefore it is considered as most appropriate for this study.

4.3 Similarity Coefficient

The coefficient that measures the similarity between two objects (parts in our case) on the basis of commonalities between attributes (operations in our case) is called a similarity co-efficient. Selection of an appropriate similarity coefficient is most important for the success of any clustering method. This will influence the shape of the clusters, as some objects (parts) may be close to one another according to one similarity coefficient and further away according to another. Therefore, while choosing a similarity coefficient for a clustering problem, all its specific characteristics, requirements and objectives must be taken into consideration. The similarity coefficient chosen must have a logical and/or probabilistic justification.

The most common similarity coefficient used in GT applications using 'binary object attribute incidence matrix' (POIM in our case) is Jaccard similarity coefficient. The Jaccard coefficient is defined as the size of the intersection divided by the size of the union of the attribute (operation) sets of the corresponding objects (parts). The Jaccard similarity coefficient (S_{mn}) between a pair of objects (m, n) is calculated by equation (1).

$$S_{mn} = \frac{a}{a+b+c}, 0 \le S_{mn} \le 1 \tag{1}$$

where, a number of common operations between two parts,
b number of operations that are required only for part m and
c number of operations that are required only for part n.

In the present study also, the Jaccard similarity coefficient has been used.

4.4 Alternative Operation Sequences

The operations required to manufacture a part and their sequences are stated on a process plan. Process planning is not only a science; it is an art too, involving creativity, innovation, independent thinking, personal preferences and experience. Therefore, a process plan for manufacturing of a part cannot be unique. Further, the fact that each part can have more than one process plan provides more added flexibility in the design of a manufacturing system. Therefore, in the proposed RMS, it has been postulated that a part can have more than one alternative operation sequences. In their CMS models, authors of references [25] and [26] proposed the distribution of the demand of a part among all alternative process plans in the proportion of their usage factors, which indicate the preference given to a process plan. However, reference [26] pointed it out that it would not be preferable to execute all process plans due to enhanced complexity of production planning and associated

additional costs. Therefore, it was proposed to assign equal priority to all process plans and then the best among all alternative plans were selected based on least intercellular movement [26]. The plan so selected would be used for the manufacturing of full demand volume of the concerned part type.

In the proposed RMS model also, it has been proposed to give equal priority to all alternative operation sequences and to select only one operation sequence from the set of alternatives for the manufacturing of full demand volume of the concerned part. If a part is manufactured with more operation sequences in any proportions, it results into more reconfigurations and obviously more associated costs.

A part is associated to a family based on the number of common operations that it shares with other members of the family. An RMT has to remain idle when a member of the family does not require an operation. A higher value of similarity coefficient implies a higher number of operations are common and therefore less machine idleness. Therefore, it is proposed to choose best among all alternative operation sequences based on the highest similarity coefficient. It implies that all the operation sequences will be used in the clustering procedure and an operation sequence that associates itself with a part family at the highest similarity level will be selected and rest will be discarded straightaway.

5. MODIFIED HIERARCHICAL CLUSTERING PROCEDURE FOR RMS

In Figure 1, the basic steps of hierarchical clustering algorithm have been described. Even though, the basic steps are common, researchers have evolved and used a wide spectrum of similarity coefficient definitions and applied a wide choice of adaptations of this basic clustering procedure [9] conforming to the distinct features of the specific problems. The modified agglomerative average linkage hierarchical clustering algorithm proposed in this work uses a special naming scheme as given below.

(a) A part type pi and its jth operation sequence are represented by an object named as a decimal numeral ‘i.j’. The integer part (i) and fractional part (j) respectively represent the part type number and the operation sequences considered. For example, if a part type p2 has three alternative operation sequences, objects named as 2.1, 2.2 and 2.3 will represent three combinations.

(b) If the part type p_i has only one operation sequence, then its representation will be object i.0. The objects so named (as in a & b) are called single part objects as each represents a part family consisting of only one part type (as on the top of the dendogram). Therefore, if as_i is the number of operation sequences for a part type p_i, the total number of objects, M in POIM will be: $\sum_{i=1}^{P} as_i$.

(c) A new family formed by grouping together two existing families is represented by an object named as k.0, where k=h+1. h is the highest integer used to represent an object among all existing objects. The object so created is called a multipart object as it represents a cluster of more than one parts grouped as a family.

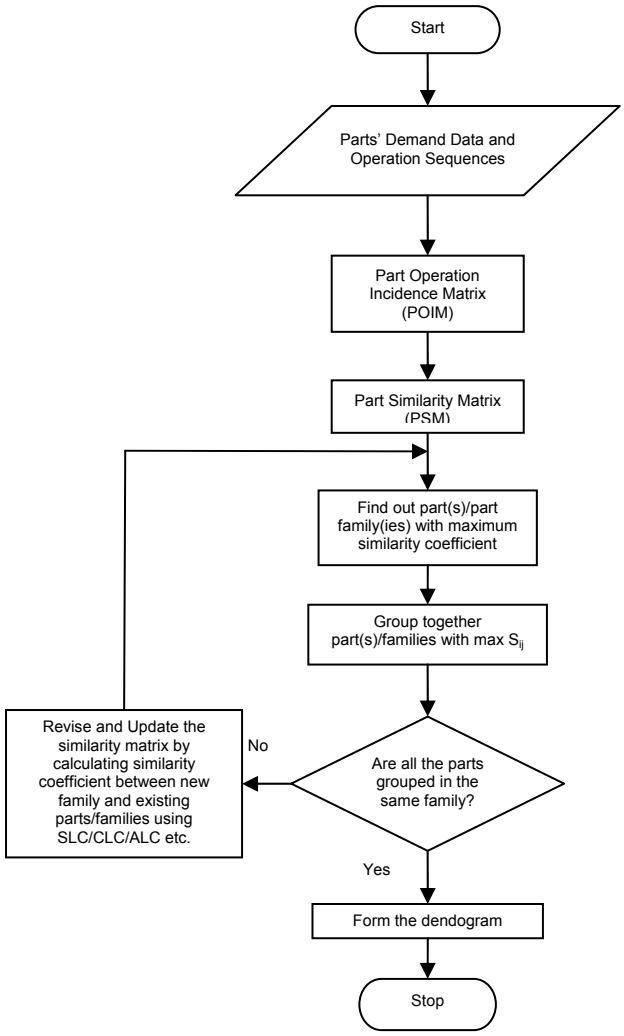

Figure 1: Hierarchical clustering algorithm.

The proposed procedure is as given below.

Step 1: Obtain the information of total demand orders (d_i) of all the Q part types for next reconfiguration cycle and all their alternative operation sequences (Table I). Accept a part type pi for manufacturing as per company's policy.

Step 2: Construct POIM (Table II) progressively by adding the information corresponding to each operation sequence of each part type accepted for manufacturing. If O_p is the total number of operations, POIM is an M x O_p matrix. An entry of 1 in the matrix indicate that the part represented by object in the corresponding row require the operation in the corresponding column and vice versa for a 0 entry.

Step 3: Compute the value of similarity coefficient S_{mn} for each pair of objects (m,n) to form the part similarity matrix (PSM) (Table III). If the pair of objects under consideration represents the same part, S_{mn} is taken as zero. As it has been assumed that only one operation sequence is selected for manufacturing a part, these objects can not be paired. For all other pairs of objects, S_{mn} is calculated using a predefined relationship e.g. Jaccard coefficient. PSM so obtained is an M x M matrix. First three steps of the algorithm are depicted in a flow chart in Figure 2.

Step4: Find the pair(s) of objects having highest value in similarity matrix. If there is only one pair of such objects, go to step 7, otherwise go to the next step.

Step 5: Find out a pair for which both the objects are either of the following:

i. a multipart object i.e. a family formulated in a previous stage (i.e. k.0).
ii. an object representing a single part and its single operation sequence (i.e. i.0)

iii. an object representing a single part and one of its alternative operation sequences and fulfilling the condition that the objects representing rest of the alternative operation sequences for this part do not pair at this similarity level.

If no such pair exist, go to next the step otherwise skip it.

Step 6: Calculate maximum average linkage value for each pair in tie, with all other objects ignoring objects having the same parts as in objects in the pair considered. Find the pair that exhibits the highest maximum average linkage value.

Step 7: Check whether any object in the pair selected has only one part. If not, go to step 10.

Step 8: Check whether the part in each single part object have alternative operation sequences. If not, go to step 10.

Step 9: Update similarity matrix by deleting all rows and columns corresponding to objects representing alternative operation sequences.

Step 10: Join the two objects in the selected pair to form a new object (representing a part family) containing all the parts of two joining objects and name it as per the naming scheme described earlier.

Step 11: Go to step 13, if all the parts are grouped in one family.

Step 12: Go to step 4 after updating the similarity matrix by computing the similarity coefficient between the new object and older objects which were unaltered in the last step.

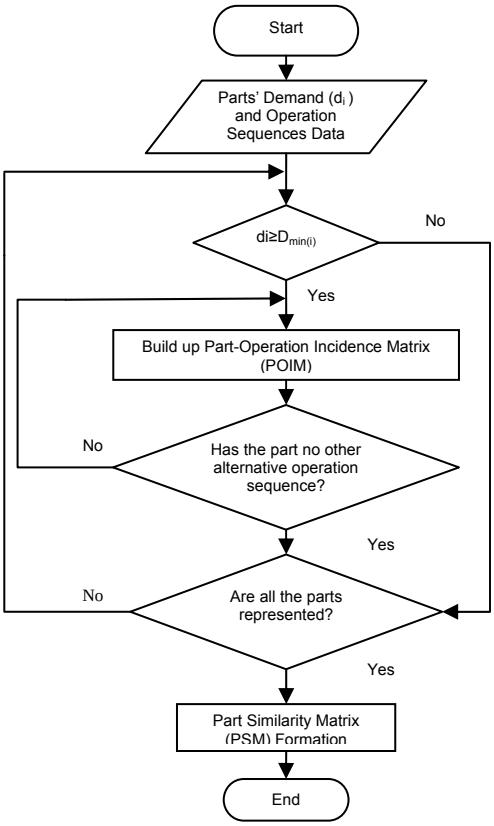

Figure 2: Procedure for POIM & PSM Formation (Steps 1 to 3).

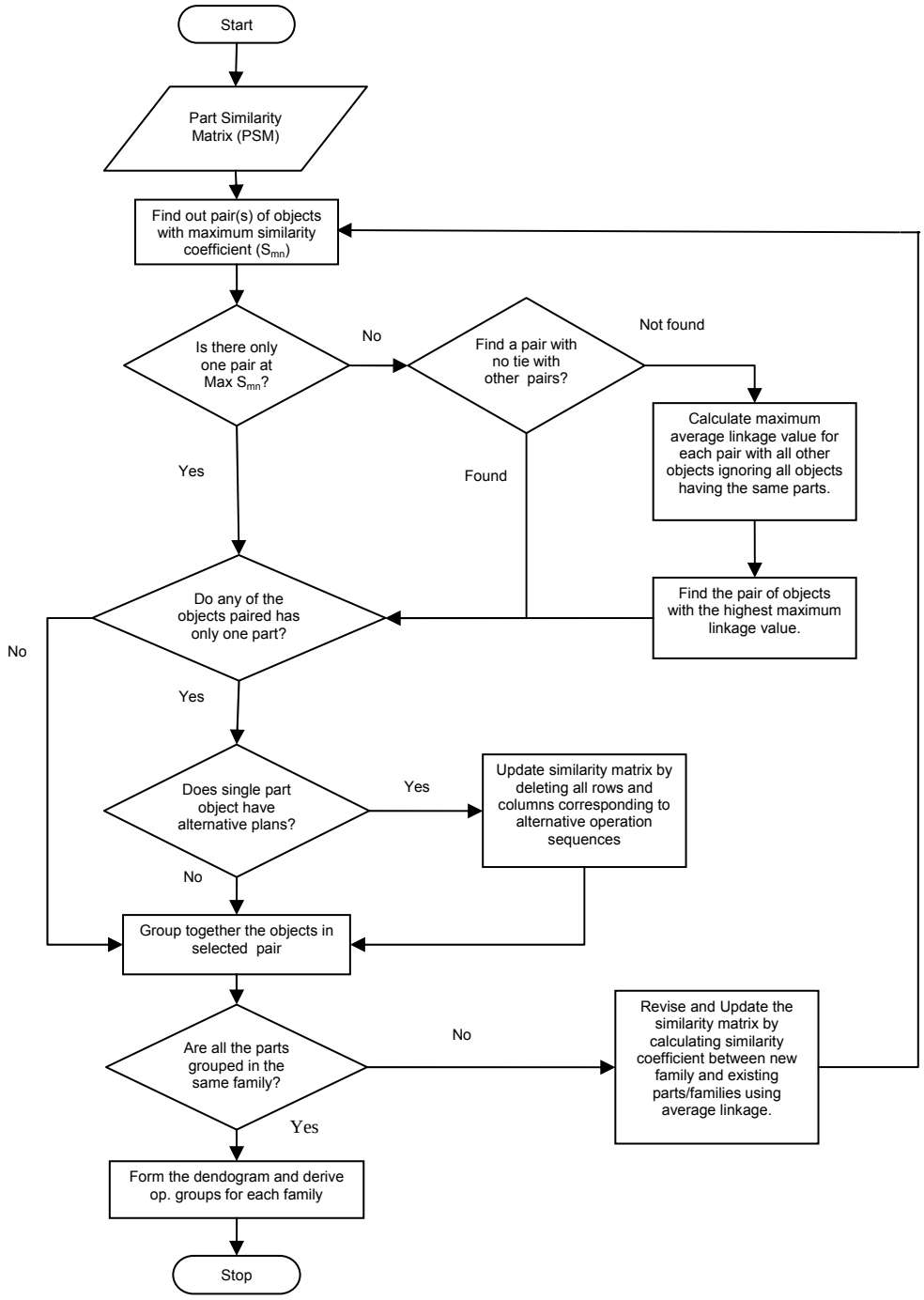

Figure 3: Adaptation of hierarchical clustering algorithm for RMS (Steps 4-14).

In the ALC method the similarity coefficient for a pair of objects is calculated as the average similarity between all the parts in them and is given by the formula

$$S_{uv} = \frac{\sum_{m \in u} \sum_{n \in v} S_{mn}}{p_u \, p_v} \qquad (2)$$

Where:

u,v Part families (objects)

m,n Parts belonging to family u and v respectively

p_u and p_v Number of parts in families u and v respectively.

Step13: Construct a dendogram (Figure 5) showing part families identified corresponding to different similarity levels and the selected operation sequences. Table IV depicts the information on the dendogram i.e. the part families and the operation sequence selected for each part. The information on Tables I and IV is translated into operation groups corresponding to each part family (Table V).

6. DEMONSTRATION THROUGH EXAMPLE

To demonstrate the use of the proposed procedure, consider a hypothetical situation where six operations are required for manufacturing of parts in next reconfiguration cycle. Table I shows the alternative operation sequences, the total demand, d_i and the minimum acceptable demand size $D_{min(i)}$ for each part type. POIM is constructed as shown in Table II. Any order $d_i<D_{min(i)}$ is not considered. The POIM (Table II) has total 13 objects and 6 operations.

Table I: Parts demand data and operations sequences.

Part No.	$D_{min(i)}$	Demand (d_i)	Operation Sequence(s)
1	40	60	1-3-6, 2-3-5
2	100	350	3-1-6
3	100	550	2-4-5, 1-3, 2-3-6
4	50	80	2-4, 1-2-3
5	50	100	1-2-4, 2-3-4, 5-4-3
6	100	150	1-6, 1-5
7	100	70	2-3-5, 2-3-6

Table II: Part operation incidence matrix (POIM).

Operation No.→ Object No.↓	1	2	3	4	5	6
1.1	1	0	1	0	0	1
1.2	0	1	1	0	1	0
2.0	1	0	1	0	0	1
3.1	0	1	0	1	1	0
3.2	1	0	1	0	0	0
3.3	0	1	1	0	0	1
4.1	0	1	0	1	0	0
4.2	1	1	1	0	0	0
5.1	1	1	0	1	0	0
5.2	0	1	1	1	0	0
5.3	0	0	1	1	1	0
6.1	1	0	0	0	0	1
6.2	1	0	0	0	1	0

PSM, as shown in Table III is formed by calculating the value of similarity coefficient S_{mn} for each pair of objects in POIM. $S_{mn} = 0$, if objects in a pair represent the same part (for example objects 3.1 and 3.2). Use Equation 1 for all other pairs. Referring to Table III, it is seen that there is only one pair of objects i.e. (1.1, 2.0) that corresponds to the highest similarity value of 1.

Table III: Part Similarity matrix (PSM).

Objects	1.1	1.2	2.0	3.1	3.2	3.3	4.1	4.2	5.1	5.2	5.3	6.1	6.2
1.1	0.00	0.00	1.00	0.00	0.67	0.50	0.00	0.50	0.20	0.20	0.20	0.67	0.25
1.2		0.00	0.20	0.50	0.25	0.50	0.25	0.50	0.20	0.50	0.50	0.00	0.25
2.0			0.00	0.00	0.67	0.50	0.00	0.50	0.20	0.20	0.20	0.67	0.25
3.1				0.00	0.00	0.00	0.67	0.20	0.50	0.50	0.50	0.00	0.00
3.2					0.00	0.00	0.00	0.67	0.25	0.25	0.25	0.33	0.33
3.3						0.00	0.25	0.50	0.20	0.50	0.20	0.25	0.00
4.1							0.00	0.00	0.67	0.67	0.25	0.00	0.00
4.2								0.00	0.50	0.50	0.20	0.25	0.25
5.1									0.00	0.00	0.00	0.25	0.25
5.2										0.00	0.00	0.00	0.00
5.3											0.00	0.00	0.25
6.1												0.00	0.00
6.2													0.00

Objects	7.0 {1.1,2.0}	3.1	3.2	3.3	4.1	4.2	5.1	5.2	5.3	6.1	6.2
7.0 {1.1,2.0}	0.00	0.00	0.67	0.50	0.00	0.50	0.20	0.20	0.20	0.67	0.25
3.1		0.00	0.00	0.00	0.67	0.20	0.50	0.50	0.50	0.00	0.00
3.2			0.00	0.00	0.00	0.67	0.25	0.25	0.25	0.33	0.33
3.3				0.00	0.25	0.50	0.20	0.50	0.20	0.25	0.00
4.1					0.00	0.00	0.67	0.67	0.25	0.00	0.00
4.2						0.00	0.50	0.50	0.20	0.25	0.25
5.1							0.00	0.00	0.00	0.25	0.25
5.2								0.00	0.00	0.00	0.00
5.3									0.00	0.00	0.25
6.1										0.00	0.00
6.2											0.00

(a)

Objects	8.0 {7.0,6.1} i.e. {1.1,2.0,6.1}	3.1	3.2	3.3	4.1	4.2	5.1	5.2	5.3
8.0 {7.0,6.1}	0.00	0.00	0.56	0.42	0.00	0.42	0.22	0.13	0.13
3.1		0.00	0.00	0.00	0.67	0.20	0.50	0.50	0.50
3.2			0.00	0.00	0.00	0.67	0.25	0.25	0.25
3.3				0.00	0.25	0.50	0.20	0.50	0.20
4.1					0.00	0.00	0.67	0.67	0.25
4.2						0.00	0.50	0.50	0.20
5.1							0.00	0.00	0.00
5.2								0.00	0.00
5.3									0.00

(b)

Objects	8.0 {7.0,6.1} i.e. {1.1,2.0,6.1}	9.0 {3.1,4.1}	5.1	5.2	5.3
8.0 {7.0,6.1}	0.00	0.00	0.22	0.13	0.13
9.0 {3.1,4.1}		0.00	0.59	0.59	0.38
5.1			0.00	0.00	0.00
5.2				0.00	0.00
5.3					0.00

(c)

Objects	8.0{7.0,6.1} i.e. {1.1,2.0,6.1}	010.0 {9.0,5.1} i.e. {3.1,4.1,5.1}
8.0 {7.0,6.1}	0.00	**0.07**
10.0 {9.0,5.1}		**0.00**

(d)

Objects	11.0 {8.0,10.0} i.e. {1.1,2.0,3.1,4.1,5.1,6.1}
11.0 {8.0,10.0}	0.07

(e)

Figure 4: Tables (a-e) showing various stages of procedure for the demonstration problem.

Therefore, skip steps 5 and 6. Now, it is observed that both the objects have only one part each. The first object in the pair (i.e.1.1) has alternative operation sequence but the second object (i.e. 2.0) has no alternative operation sequence. Therefore, the similarity matrix in Table III is updated by deleting all rows and columns corresponding to object 1.2. The objects in the pair under consideration (i.e. 1.1 and 2.0) are joined to form a new family named as object 7.0. The new object is named 7.0, as the highest integer used to represent an object in previous stage of the procedure is 6 (objects 6.1 and 6.2).

Table IV: Part families identified at different precision levels.

Precision (in %)	Part families & operation sequence for each part
7	{11.0} i.e {8.0,10.0} i.e. {1.1,2.0,3.1,4.1,5.1,6.1}
59	{8.0} i.e. {1.1,2.0,6.1}; {10.0} i.e. {9.0,5.1} i.e.{3.1,4.1,5.1}
67	{8.0} i.e. {7.0,6.1} i.e.{1.1,2.0,6.1} ; {9.0} i.e.{3.1,4.1}; {5.1}
100	{7.0} i.e. {1.1,2.0}; {3.1}; {4.1} ;{5.1} ;{6.1}

As all the parts are not grouped in one family yet, the similarity matrix is updated by computing the similarity coefficients between the new object (7.0) and the older objects using Equation 2. Table (a) in Figure 4 gives the updated similarity matrix. The procedure is repeated again beginning with step 4. Referring to table (a) in Figure 4, it is seen that there are six pairs of objects exhibiting the highest similarity value of 0.67. These are (7.0, 3.2), (7.0, 6.1), (3.1, 4.1), (3.2, 4.2), (4.1, 5.1) and (4.1, 5.2). Further, in the pair (7.0, 6.1), the first object 7.0 represents a family formulated in a previous stage and the second object 6.1 represents part 6 having an alternative operation sequence but the object representing that (6.2) do not pair at this similarity level. Therefore, the pair (7.0, 6.1) is selected at this stage. Skip step 6.

Now, It is observed that only object 6.1 has one part and it has an alternative operation sequence (i.e. 6.2).The similarity matrix in table (a) is updated to table (b) after deleting all the rows and columns corresponding to 6.2 and joining 7.0 and 6.1 to form a family namely 8.0.

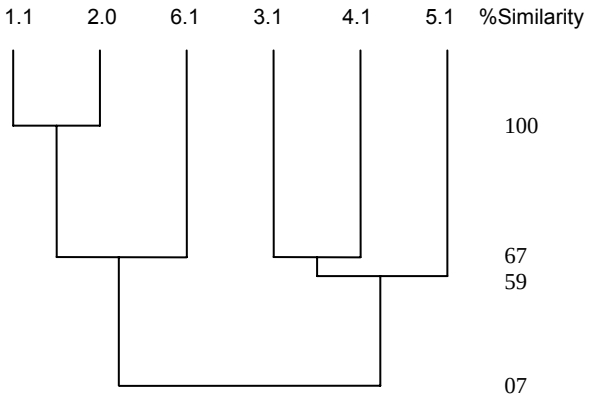

Figure 5: Dendogram.

Referring to table (b), it is seen that that there are four pairs of objects exhibiting the highest similarity value of 0.67. These are (3.1, 4.1), (3.2, 4.2), (4.1, 5.1) and (4.1, 5.2). None of the four pairs fulfil the desired requirement of step 6. Therefore as per step 6, the average linkage value for the first pair (3.1, 4.1) with all other objects in table (b) except 3.2 and 4.2 is determined. Therefore, using equation (2) we find the set of average linkage values for the pair (3.1,4.1) with 8.0, 5.1, 5.2, 5.3 respectively as (0.00 0.59 0.59 0.38). The maximum average linkage value for this pair is 0.59. Similarly, the values for the others pairs are calculated as 0.49, 0.59 and 0.59. As there is a tie on the highest maximum average linkage value, the first pair i.e. (3.1, 4.1) exhibiting this value is selected. It is observed that both the selected objects have one part each and both have an alternative operation sequence (i.e. 3.2 & 4.2 respectively).The similarity matrix in table (b) is updated to table (c) after deleting all the rows and columns corresponding to 3.2 and 4.2 and joining 3.1 and 4.1 to form a family namely 9.0.

Table V: Selected operation groups.

Part Family	Operation Group
{1.1,2.0}	1,3,6
{3.1,4.1}	2,4,5
{1.1,2.0,6.1}	1,3,6
{3.1,4.1,5.1}	1,2,4,5
{1.1,2.0,3.1,4.1,5.1,6.1}	1,2,3,4,5,6

The procedure is repeated until all the parts fall in one family. Tables (d) and (e) depict the subsequent steps for the demonstration problem. The part families identified and the selected operation sequences are compiled as shown in Table IV and depicted in Figure 5 in the form of a dendogram. Operation groups corresponding to each part family are formulated using the information in Tables 1 and 4 as shown in Table V.

7. CONCLUDING REMARKS

In the RMS model considered, the manufacturing system is configured to manufacture a particular family of parts and then reconfigured to manufacture the next one and so on. The significance of selecting an appropriate set of families lies in the fact that the costs incurred on system reconfigurations (both primary and secondary), material handling, machine idleness etc., depend on it. Consequently, the costs of the parts manufactured are directly related to the set of families selected. Therefore, recognition of part families is the foundation stone for the design of a reconfigurable manufacturing system. This research has presented a logical and systematic procedure to group the parts into families and simultaneously an operation sequence is selected from a set of operation sequences for each part. Therefore, an operation group corresponding to each part family is also recognized.

The outcome of the procedure is depicted on a dendogram showing different sets of part families at different similarity levels. The next most important step in RMS design is to choose one of these sets of families to meet the objectives of the company. Presently, the research on identification of parameters that impact the choice of a set of families from the dendogram, selection of RMTs for each operation group, generation of PRS and SRSs etc. is under progress.

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