

CONCURRENTLY PART-MACHINE GROUPS FORMATION WITH IMPORTANT PRODUCTION DATA

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Abstract

This work presents an algorithm for design of cellular manufacturing system. It considers sequence of operation for every component as ordinal level data. The ratio level data includes operation time per unit, production volume and machine capacity. A matrix model is developed to incorporate ordinal level data and ratio level data. Model is then standardized. From this, Part – Part correlation model is formed. This is undergone through principle component analysis. Now, Feature-Vector and New Standardized Sequence Part Load matrices are formed. These are used for grouping purpose. Part-machine orthographic view is used for concurrent part-machine family formation. Performance of algorithm is comparable and of good quality with existing methods in its class. To facilitate industrial application, it can be implemented by using free software, Scilab and/or commercial softwares.

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Key Words: Cellular Manufacturing, Part-Machine Families, Algorithm

1. INTRODUCTION

Cellular manufacturing (CM) is an applied concept of group technology and Just-in-time. It changes the conventional practice of manufacturing from functional production into small to medium-sized batch oriented production. The reported advantages of CM are such as better management of labour, tooling and production time, reduction of space, work in process inventory as well as paper work etc.

The basic problem in the design of cellular manufacturing system lies in the identification and grouping of parts that share similar process into families and their associate machines into cells, the ideal CM solution is to ensure all parts in a family fully processed within a cell. Parts that are manufactured by more then one cell are known as exceptional parts. There should be a minimum number of parts requiring intercell travel.

2. LITERATURE REVIEW

Techniques to develop possible solution are plentiful in the literature. These techniques can be classified into machine-part grouping approaches, the machine grouping approaches and the part grouping approaches. The machine-part grouping approach consists of the simultaneous identification of machine cells and part families, the part grouping approach attempts the initial formation of part families and followed by assignment of machines to those families. The machine grouping approaches are based on first identification of machine cells and then assign parts to those machines.

The main theme throughout the most research papers is clustering the unit valued (i.e. binary 0 or 1) entries of part-machine incidence matrix alone [1-11]. Many researchers considered similarities coefficients based approaches to solve cell formation (CF) problem.

Similarity coefficients methods are found more flexible than other CF approaches [12]. An approach, average voids value (AVV) is proposed which indicates the average number of newly produced voids, when a pair of machine groups is combined [13].

Some parts can not be processed in a cell. These parts need intercell travel for further operations. Different order sequence of machine may result in different total intercellular movement distance unit. When production volume is large, total number of intercell movements will be further large. Part-machine grouping without considering operation sequences also tends to distort the real extent of material handling efforts within and outside the cells [6, 14-17]. Nair and Narendran proposed CASE (1998) – SCM based model [15] using sequence data only and Accord (1999) – SCM based model [16] using ordinal and ratio level data. They emphasized use of operation sequence, operation time, production volume and machine capacity for grouping. George et al. [14] proposed an interactive cluster approach, a SCM based model considering ordinal and ratio level data. However, they [14, 16] considered unity production volume in their models. In the design of cellular manufacturing systems, many production factors should be involved when the cells are created, e.g. operation sequences, part production volume and machine capacity [18].

Despite a large number of papers on cell formation being published, only a handful incorporate operation sequence in intercell movement calculations and consider production volume [19]. Many studies only considered limited information, ignoring other important factors, such as operation sequence, machine capacity, and part demand, need to be incorporated to obtain more realistic results [20, 21]. Genetic algorithm approach is used by researchers [19, 20]. Fuzzy ART neural network algorithm is also used [17, 21]. Among many methods utilized in machine cells formation, the similarity coefficient method is most widely used. Production sequence and product volumes, if incorporated properly in determining the machine cells, can enhance the quality of solutions and reduce the number of intercellular movements [22]. Alhourani and Seifoddini [22] have considered ordinal level data that is machine sequence and ratio level data as production volume in their SCM model. However, they did not consider other important shop floor realities that are operation time and machine capacity in the SCM model.

Another practical problem faced by the methods developed so far is the fact that most of them have been demonstrated for relatively small data sets. Miltenburg and Montazemi [23] described computational problems encountered with traditional algorithms in an industrial context involving 5498 part types. To cluster data sets of such sizes, a smaller part population had to be selected intuitively, and portions of the problem had to be 'swapped' into memory as they were needed for the computations. There are about 3000 parts processed at Harnischfeger Plant in Oak Creek, Wisconsin [24]. Similar reservations about the limited applicability of traditional procedures for industry-size data sets have been voiced by others [6]. This is serious limitation for difficult and complex techniques such as neural network, simulated annealing, genetic algorithms and tabu search, etc.

Principal component analysis is employed for evaluating the feasibility of CM without initial part matrix clustering [3]. Albadawi et al. [2] proposed factor analysis based clustering approach. Matrix based multivariate analysis model [8] is used to find eigenvalues and eigenvector for grouping. However, all these [2, 3, 8] do not consider sequence, operation time, production volume and machine capacity. Lokesh Kumar [25] proposed an algorithm with operation sequence, operation time and production volume using principal components analysis. However, he did not consider machine capacity.

Further, most of existing methods require a prior specification of the upper limit on number of machine within a cell and or the number of cells. This contradicts the fundamental philosophy of GT that groups exist naturally and the task of analysis is to identify them if they exist [9, 26]. Moreover, there is a limited industrial application due to unavailability of

software programme supporting solution approaches of CF problem or the software is expensive [27].

Now, one can conclude that a few of existing approaches are designed to accommodate realistic shop conditions such as operation sequence, operation time, production volume and machine capacity all together in a simple user friendly model and to be able to form part families and machine groups simultaneously. This paper presents an algorithm APMOSTVC. APMOSTVC stands for an Algorithm for Concurrent Part families and Machine groups formation with Operation Sequence, operation Time, production Volume and machine Capacity.

3. APMOSTVC- METHODOLOGY OF PART-MACHINE GROUP FORMATION

In this section, we describe methodology of algorithm APMOSTVC for formation of part families and machine groups. It is as follows:

3.1 Mathematical representation of machine – part

Here, parts are treated as objects and machines as attributes of that part. The requirement of part is represented in the form of object-attribute (i.e. part-machine) matrix.

Columns and rows of matrix represent part and machine, respectively. This matrix is named as Machine Sequence Part Matrix, *MSPM*. Representations of various matrices are as follows:

- Machine Sequence part Matrix (*MSPM*) representation:
 $MSPM(I, J)$ element value is I , if part J visit first in sequence to machine I , this value is 2, if part J visit second in sequence to machine I . This value is 3, if part J visit third in sequence to machine I . And so on.
- Machine Part Operation time Matrix (*MPOTM*) representation:
 In *MSPM* matrix replace sequence number with processing time of part-machine combination i.e. $MPOTM(I, J)$ represent processing time of part I on machine J .
- Production Volume Matrix (*PV*) representation:
 Now, represent production volume of part as matrix *PV*. $PV(I, J)$ represents production volume of J^{th} part.
- Machine Capacity (*MC*) representation:
 $MC(I, I)$ element represent machine capacity of I^{th} machine.
- Set-up time (*Setime*) matrix representation:
 Here, we represent set-up time. $Setime(I, J)$ represents set-up time of part J on machine I . In the same manner other idle time can be taken.

3.2 Part load matrix representation

Now, ratio level data (i.e. operation time, production volume and machine capacity) is represented as part load matrix (*PLM*) as follows:

(1) If operation time is available only. $PLM(I, J) = MPOTM(I, J)$

(2) If operation time and production volume is available only.

$$PLM(I, J) = MPOTM(I, J) \times PV(1, J)$$

(3) If operation time, production volume and machine capacity is available,

$$PLM(I, J) = MPOTM(I, J) \times PV(1, J) / MC(I, 1)$$

3.3 Integration of ordinal level (i.e. sequence) and ratio level data

Further, ordinal level and ratio level data has to be integrated. Physical significance of operation can be visualized as flow of material or parts. Operation sequence has an impact on flow of material handling. Material handling is aimed to be smooth and minimum. Ratio level data influences within-cell-load variation. Within-cell-load variation is desirable to be minimum. Inter-cell travel is zero, if all parts and machines are in one cell, but the within-cell- load variation is maximum. In contrast, when one cell has one machine type, the within-in-cell load variation is zero, but intercell travel is maximum. These are contradictory factors. One has to take trade off. Therefore, Nash [28] principal of bargain should be used. This approach is used by Nair and Narendran [16] and George et al. [14]. From this discussion, we conclude the integration of ordinal level data and ratio level data by a matrix, Sequence Part Load Matrix, $SPLM$. Element $SPLM(I, J)$ is given as:

$$SPLM(I, J) = MSPM(I, J) \times PLM(I, J) \quad (1)$$

3.4 Machine – part analysis and grouping approach

In part-machine grouping, a large number of variable (i.e. parts and machines are to be reduced into small number of part families and machine groups. In other words, this problem need dimension reduction on the basis of some similarity measures or coefficients. This is achieved as follows:

I. Standardized Sequence Part load Matrix ($SSPLM$) creation:

Sequence Part Load Matrix, ($SPLM$) is to be standardized to form standardized sequence part load matrix ($SSPLM$) by using relation [29, 30]:

$$SSPLM(I, J) = \frac{SPLM(I, J) - SPLM(J)}{SD(J)} \quad (2)$$

Where, $SPLM(J)$ is the mean of elements of J^{th} column of matrix $SPLM(I, J)$,
 $SD(J)$ is standard deviation of elements of J^{th} column of matrix $SPLM(I, J)$.

II. Part-Part Correlation Matrix ($PPCM$) Creation:

Now Part-Part Correlation matrix, $PPCM$ is formed from matrix $SSPLM$ by using similarity coefficient [31]. It is given as:

Element $PPCM(I, J) = 1$, if $I = J$,

$$\text{Otherwise, } PPCM(I, J) = \frac{1}{m} \sum_{k=1}^m [SSPLM(K, I) \times SSPLM(K, J)] \quad (3)$$

Where: m = number of machines. This matrix indicates similarity between parts.

III. Machine-part dimension reduction:

Now, next logical step is to reduce large number of variables (machine parts) into small set of factors. Principle component analysis transforms a given set of interrelated variables into a new set of variables (i.e. principle components). The principle components are in correlated linear combinations of original variables and account for total variance of original data. The principle component is the best summary of linear relationship among existing original data. The second component is second best and so on. This property enables to separate data into district clusters when projected into a space by first few principle components. This approach can be studied by literature [29, 30, 32, 33]. Now, we consider parts as original set of variables and correlation matrix, $PPCM$ showing the correlation between each pair of parts. In PCA method, principle components are extracted by finding eigen vectors and eigen values for equation: $det(PPCM - \lambda(J) \cdot I_m) = 0$; $J \in (1, p)$ where I_m is identity matrix.

$\lambda(J) \in (\lambda_1 \geq \lambda_2, \dots \lambda_p)$ are eigen values (real and non-negative).

$\{F_1, F_2, \dots F_p\}$ are corresponding eigen vectors of matrix *PPCM*. Eigen vector and eigen values are determined by standard method of matrix algebra. The eigen vector with highest eigen value is the first principle component, second principle component for second highest eigen value and so on.

Each rows of *PCA* matrix, represent a point in multidimensional space (no. of axis/ dimensions equal to no. of principle components). The line joining this point and origin of coordinate system is a vector (also that part). Orthographic projection of this vector in space on a plane of projection made of first and second principle components represents that part. This projected view is used for grouping purpose. Readers are advised to refer paper [25] for detailed description.

IV. Feature Vector Creation:

To be precise, if you originally have a p dimensional data, you got eigen vectors and eigen values, choose only first p_s eigen vectors, then final data set has only p_s dimensions. The next step is to form a feature vector. This is formed by taking few or all eigen vectors in descending order of eigen values [34, 35].

$$\text{Feature-Vector} = (F_1, F_2) \quad (4)$$

F_1 and F_2 are first and second principle components of a part, respectively.

V. New standardized sequence Part Load Matrix (*NSSPLM*) Creation:

Now, new standardized sequence Part Load Matrix (*NSSPLM*) is created. It is given by relation [34, 35]:

$$\text{NSSPLM} = \text{Feature-Vector}^T \times \text{SSPLM}^T \quad (5)$$

SSPLM^T and Feature-Vector^T are Transpose of matrix *SSPLM* and Feature-Vector respectively. Elements of *NSSPLM* represent original data (*SSPLM*) solely in terms of chosen eigen vectors (i.e. principle components or feature vector). Basically, we have transformed our data so that it is expressed in terms of the patterns between them. Each rows of *NSSPLM* matrix, represent a point in multidimensional space (no. of axis/ dimension equal to no. of principle components). The line joining this point and origin of coordinate system is a vector (also a machine). Orthographic projection of this vector in space on a plane of projection made of first and second principle components represents that machine. This projected view is used for grouping purpose. Readers are advised to refer paper [25] for detailed description.

VI. Machine-Part Orthographic View grouping:

Next step is to group machine and parts. It is done by machine-part orthographic view grouping analysis. The main objective of a PCA is to reduce the dimensionality of a set of data. This is particularly advantageous if a set of data with many variables lies, in reality, close to a two-dimensional subspace (plane). In this case the data can be plotted with respect to these two dimensions, thus giving a straightforward visual representation of what the data look like, instead of appearing as a large mass of numbers to be digested. Biplots similarly provide plots of the m observations, but simultaneously they give plots of the relative positions of the p variables in two dimensions. Furthermore, superimposing the two types of plots provides additional information about relationships between variables and observations that is not available in either individual plot [33].

Represent X-axis, Y-axis as first principle components (i.e. first eigen vector) and second principle components (i.e. second eigen vector), respectively. Plot each variable (i.e. parts) with coordinates as (principle component₁, principle component₂). Join this point with zero of coordinates system with a line. This line represents that part. Plot also each attribute (i.e. machine) with coordinates (*NSSPLM* column 1, *NSSPLM* column 2). Joint this point with zero of coordinate system with a dotted line. This dotted line represents that machine. Thus, all parts and machines are represented by firms/dotted lines, respectively. This plot is named as

Machine-Part Orthographic View. Parts with almost similar angular distance from first principle component axis are grouped together. Similarly, machines with almost similar angular distance are grouped together. Readers are advised to refer paper [25] for detailed description.

3.5 Performance measurement

Group efficiency (GE) does not represent true grouping performance for ordinal and ratio level data, since it treats all operation equally. Harhalakis et al. [6] proposed group technology efficiency (*GTE*), considering ordinal level data (i.e. sequence of operation). Grouping technology efficiency is given by Eq. (6):

$$GTE = \{ (I_p - I_r) / I_p \} \quad (6)$$

and the number of intercell travels actually required by system:

$$I_r = \sum_{J=1}^p \sum_{W(J)=1}^{(n(J)-1)} t_{n(J)W(J)} \quad (7)$$

where: p = total number of parts in system (i.e. CF problem),

$J = J^{\text{th}}$ part in system (i.e. CF problem),

$n(Z)$ = maximum number of operation required for J^{th} part,

$t_{n(j)w(j)} = 0$, if operation $W(J)$ and $W(J+1)$ are performed in same cell,
 $= 1$, otherwise.

Maximum numbers of intercell travel possible in system:

$$I_p = \sum_{k=1}^{nopf} \sum_{J=1}^{noprk(k)} [n(J, K) - 1] \quad (8)$$

where: $nopf$ = total number of part families or cells,

$noprk(k)$ = total number of parts in K^{th} cell,

J = part number in a cell,

$N(J, K)$ = maximum number of operations required by J^{th} part in K^{th} cell.

GTE does not involve ratio level data. Lokesh Kumar [25] proposed Ratio grouping efficiency (*RGE*). It is given as ratio of Machine utilization net gain (*MUNG*) to sum of Machine utilization opportunity gain (*MUOG*), Intercell travel loss (*ICTL*) (i.e. value of exceptional elements) and void value (i.e. value of voids, *VV*).

Ratio grouping efficiency,

$$RGE = \{ (MUNG) / (MUOG + ICTL + VV) \} \quad (9)$$

$$MUNG = MUOG - ICTL \quad (10)$$

$$MUOG = \sum_{k=1}^{nopf} \sum_{I=1}^{nomck(k)} \sum_{J=1}^{nprfk(k)} [N_v(I, J, K) \cdot PLM(I, J, K) \cdot PV(1, J, K)] \quad (11)$$

$$VV = \sum_{k=1}^{nopf} \sum_{I=1}^{nomck(k)} \sum_{J=1}^{nprfk(k)} [N_v(I, J, K) \cdot PLM(I, J, K) \cdot PV(1, J, K) / W_pfk(k)] \quad (12)$$

where: $nomck(k)$ = number of machines in K^{th} cell,

$N_v(I, J, K) = 0$, if I^{th} machine, J^{th} part in cell K has occupied elements,

$= 1$, if I^{th} machine, J^{th} part in cell K is a vacant element,

$PLM(I, J, K)$ = operation time of I^{th} machine for J^{th} part in K^{th} cell,

$PV(I, J, K)$ = production volume of I^{th} part in K^{th} cell,

$$ICTL = \sum_{I_1=1}^{n_e} [t_h(I_1, J_e) \cdot PV(1, J_e) + t_{cc}(J_e)] \quad (13)$$

where: n_e = number of exceptional elements,

$PV(1, J)$ = Part Production volume of J_e^{th} exceptional part,

$t_h(I_1, J)$ = Handling time for J_e^{th} exceptional part,

$t_{cc}(J_e)$ = Transportation time for J_e^{th} exceptional part,

$Setuptime(I, J, K)$ = setup time for I^{th} machine, J^{th} part in K^{th} cell

(one can also take load/unload and other idle times in account) [25].

Integrating ordinal level and ratio level data, a general model of performance measure is proposed: Weighted sequence ratio efficiency (*WSRE*). It is represented by Eq. (14):

$$WSRE = \alpha \cdot RGE + (1 - \alpha) \cdot GTE \quad (14)$$

where α is a constant ranging from zero to one [25]. Nair & Narendran and George et al. have taken objectives as minimum within-cell-load variation, minimum intercell travel volume and combined objective function of these two conflicting objectives, with ordinal level data and ratio level data. Readers are advised to refer papers [14, 15, 16] for detailed description. It is extremely difficult to provide detailed description here due to length of paper constraint.

4. APMOSTVC

An algorithm for Concurrent part families and machine groups formation (Step-by-step procedure):

Step 1 – Matrix representation of data for input:

- (a) Create Machine Sequence Part Matrix (*MSPM*) according to section 3.1 – I.
- (b) Create Machine Part Operation time Matrix (*MPOTM*) according to section 3.1 – II.
- (c) Create Production Volume Matrix, *PV*, Machine Capacity Matrix, *MC*, and set-up time Matrix, *Setime*, as described in section 3.1 – III, IV and V, respectively.

Step 2 – Create Part Load Matrix according to section 3.2 as:

- (a) If operation time is given only:
 $PLM(I, J) = MPOTM(I, J)$
- (b) If operation time and production volume is given:
 $PLM(I, J) = MPOTM(I, J) \times PV(1, J)$
- (c) If operation time, production volume and machine capacity is given:
 $PLM(I, J) = [MPOTM(I, J) \times PV(1, J) / MC(I, J)]$

Step 3 – Create Sequence Part Load Matrix, *SPLM* according to section 3.3 as:

$$SPLM(I, J) = MSPM(I, J) \times PLM(I, J)$$

Step 4 – Create standardized sequence Part Load Matrix *SSPLM*, as described in 3.4 – I.

Step 5 – From Part Part correlation Matrix, *PPCM* as described in section 3.4 – II.

Step 6 – Determine principle components (i.e. eigen vectors and eigen values) of *PPCM* matrix as described in section 3.4 – III.

Step 7 – Make feature vector i.e. take first two principle components (eigen vectors) and form a matrix with these eigen vectors in columns, described in section 3.4 – IV as follows:

$$Feature\ Vector = (F_1, F_2)$$

Step 8 – Determine New Standardized Sequence Part Load Matrix, *NSSPLM* as described in section 3.4 – V. *NSSPLM* is a vector product of transpose of *Feature Vector* and transpose of *SSPLM*.

Step 9 – Do Machine-part orthographic view cluster analysis as described in section 3.4 – VI.

Step 10 – Compute performance measures i.e. *GTE*, *RGE*, *WRSE* etc.

5. RESULT AND DISCUSSION

We consider a problem (A.I.C.A.) of size $12 \text{ parts} \times 10 \text{ machines}$. It is considered by George et al. [14]. We also consider 0.1 minutes for loading/unloading and transportation time for AGV's from one cell to another cell. Table I represent machine-part matrix. It represents ordinal level data (i.e. sequence) and ratio level data (i.e. ratio of product of operation time and production volume to machine capacity). From this, sequence part load matrix, *SPLM* by using Eq. (1) is formed. Now, Standardized Sequence Part load matrix, *SSPLM* by using Eq. (2) is formed from *SPLM*. Next, Part – Part correlation matrix, *PPCM* by using Eq. (3) is formed from matrix *SSPLM*. Now, *PPCM* matrix is undergone through principle components analysis as described in section 3.4 – III. Here, we got principle component (*PCA*) matrix. First two principle components i.e. first and second column of *PCA* matrix are used for grouping purpose. *Feature-Vector* i.e. Eq. (4) is created taking first two principle components i.e. first and second column of *PCA* matrix.

Now, new standardized sequence part load matrix, *NSSPLM* by using Eq. (5) is formed from *Feature-Vector*. Next, parts using *Feature-Vector* matrix and machines using *NSSPLM* matrix is drawn on Machine-Part Orthographic View as described in sections 3.4 – IV and 3.4 – VI, respectively. Finally, parts and machine represented on Machine-Part Orthographic View are shown in Fig. 1. Part families and machine groups are represented by Table I. Part family-1 has parts p1, p5, p9 and p10. It belongs to machine group-1 with m1, m3, m4, m6 and m8. Part family-2 has parts p2, p3, p7, p8 and p12. It belongs to machine group-2 with machines m2, m5 and m10. Part family-3 has parts p4, p6 and p11. It belongs to machine group-3 with machines m7 and m9. This solution is the same configuration as proposed by George et al. Results of this problem are shown in Table III. Exceptional elements are 5. Grouping Efficiency is 85.00. Group Technology Efficiency is 80. Ratio Grouping Efficiency is 81.16. Weighted Sequence Ratio Efficiency is 80.58. Combined objective function is 0.610.

Next, a problem (ACCORD) [16] of size $10 \text{ parts} \times 8 \text{ machines}$ is considered. This problem is considered by Nair & Narendran. The Machine-Part Orthographic View is shown in Fig. 2. Part families and machine groups are represented by Table II. Part family-1 has parts p3, p8, p10. It belongs to machine group-1 with machines m1 and m8. Part family-2 has parts p2, p4 and p6. It belongs to machine group-2 with machines m4, m5 and m7. Part family-3 has parts p1, p5, p7 and p9. It belongs to machine group-3 with machines m2, m3 and m6. Part families and machine groups formed, here, are the same as given by Nair & Narendran. Number of intercell travels, combined objective function, *GTE* etc. are shown by Table III.

Further, the problems of other sizes from open literature [26, 37, 38, etc.] are also considered. The real valued matrix is produced by assigning random numbers in the range of 0.5 to 1 as uniformly distributed values by replacing the ones / zeros in the incidence matrix. Processing times, sequence number and unit demands were randomly generated. For each machine type required by each part, a sequence number was generated using a uniform distribution with parameters [1, 10] rounded to the nearest integer. For each machine type required by each part, a processing time was generated using a uniform distribution with parameters [1, 10] rounded to the nearest integer. The unit demand for each part was generated using a uniform distribution with parameters [10, 140] rounded to the nearest integer. Results on test data sets are shown by Table IV.

It is observed that the proposed algorithm APMOSTVC yields solution of good and comparable quality in its class [14, 16]. Research papers [15, 16] are important benchmark papers in area of CMS design. These are referred by many researchers. For instance, even Seifoddini has considered machine sequence and production volume only in 2007 [25]. Seifoddini [22, 24, 39] published several papers on CMS design as early as 1986 [39].

Table I: Output Machine Sequence Part Matrix (12×10), *MSPM*.

Parts →		p1	p5	p9	p10	p2	p3	p7	p8	p12	P4	p6	p11
Mc↓	OS/OT												
M1	OS	0	3	4	3	0	0	0	0	0	0	0	0
	OT	0	0.63	0.54	0.39	0	0	0	0	0	0	0	0
SPLMm3	OS	1	5	1	1	0	0	0	0	0	0	0	0
	OT	0.96	0.97	0.92	0.61	0	0	0	0	0	0	0	0
M4	OS	2	4	0	0	0	0	0	0	0	1	1	0
	OT	0.95	0.89	0	0	0	0	0	0	0	0.07	0.11	0
M6	OS	3	1	2	2	0	0	0	0	0	0	0	0
	OT	0.63	0.61	0.72	0.72	0	0	0	0	0	0	0	0
M8	OS	0	2	3	0	4	1	0	0	1	0	0	0
	OT	0	0.94	0.92	0	0.04	.08	0	0	0.02	0	0	0
M2	OS	0	0	0	0	1	2	1	1	3	0	0	0
	OT	0	0	0	0	0.86	0.88	1.2	1.0	0.7	0	0	0
M5	OS	0	0	0	0	3	4	3	0	2	0	0	0
	OT	0	0	0	0	0.54	0.49	0.81	0	0.72	0	0	0
M10	OS	0	0	0	0	2	3	2	2	0	0	0	0
	OT	0	0	0	0	0.67	0.73	0.83	0.62	0	0	0	0
M7	OS	0	0	0	0	0	0	0	0	0	3	3	1
	OT	0	0	0	0	0	0	0	0	0	0.83	0.99	0.77
M9	OS	0	0	0	0	0	0	0	0	0	2	2	0
	OT	0	0	0	0	0	0	0	0	0	0.72	0.76	0
<i>PV</i>		12	40	45	80	75	120	150	75	110	60	90	25
<i>Setime</i>		0.5	1.0	1.4	0.8	0.75	1.25	0.66	1.5	1.75	0.92	.33	0.6

Table II: Output Machine Sequence Part Matrix, *MSPM* (10×8).

Parts →		p1	p5	p7	p9	p2	P4	p6	p10	p3	p8
Mc↓	Sequence /ratio										
M2	Sequence	3	3	2	1	0	0	0	5	0	0
	Ratio	0.9	0.9	0.5	0.3	0	0	0	0.6	0	0
M3	Sequence	1	1	1	2	0	0	0	0	0	0
	Ratio	0.9	0.9	0.5	0.3	0	0	0	0	0	0
M7	Sequence	2	2	0	0	0	1	1	0	0	0
	Ratio	0.6	0.3	0	0	0	0.4	0.4	0	0	0
M4	Sequence	0	0	0	0	2	2	3	1	0	0
	Ratio	0	0	0	0	0.8	0.8	0.8	0.6	0	0
M5	Sequence	0	0	0	0	3	3	2	0	0	0
	Ratio	0	0	0	0	0.8	0.8	0.8	0	0	0
M6	Sequence	0	0	0	0	4	0	4	2	3	3
	Ratio	0	0	0	0	0.8	0	0.8	0.15	0.15	0.15
M1	Sequence	0	0	0	0	1	0	0	3	1	2
	Ratio	0	0	0	0	0.4	0	0	0.6	0.6	0.6
M8	Sequence	0	0	0	0	0	0	0	4	2	1
	Ratio	0	0	0	0	0	0	0	0.6	0.6	0.6
<i>PV</i>		12	40	75	45	75	60	90	80	120	110
<i>Setime</i>		0.5	1.0	1.5	1.4	0.75	0.92	0.33	0.8	1.25	1.75

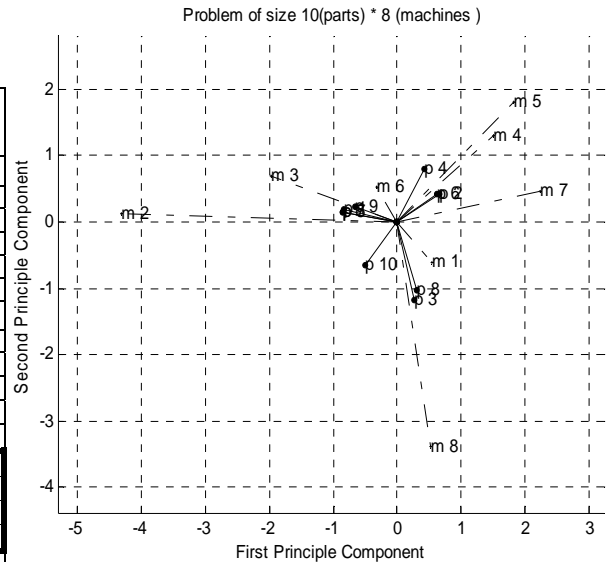


Figure 2: Orthographic View Part Grouping; problem 2: part machine ($p \times m$) size (10×8).

Table III: Comparison of the results of the proposed method over existing methods for the problem of size 12×10 (A.I.C.A.) and 10×8 (ACCORD).

	Factors considered	ACCORD	APMOSTVC	A.I.C.A.	APMOSTVC
1	Problem size ($m \times p$)	10×8	10×8	12×10	12×10
2	Exceptional elements	8	8	5	5
3	Grouping efficiency	0.897	0.897	0.85	0.85
4	Group technology efficiency (%)	68.20	68.20	80.00	80.00
5	Ratio grouping efficiency (%)	-	80.58	-	81.16
6	Weighted sequence Ratio efficiencies	-	72.24	-	80.58
7	Combined objective functions	0.517	0.517	0.610	0.610

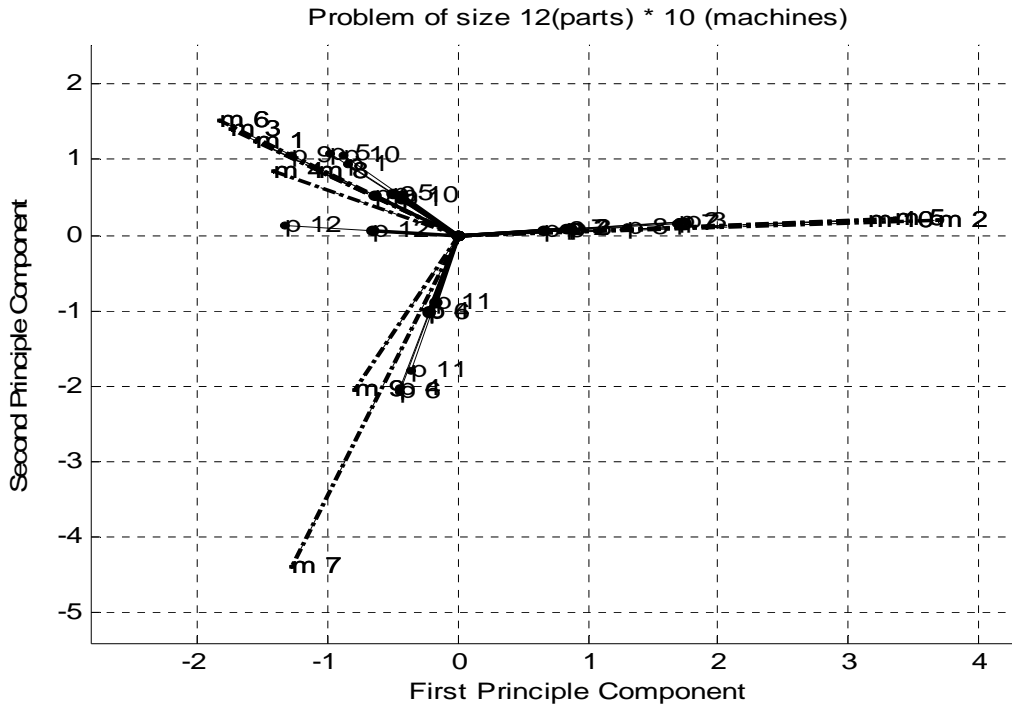


Figure 1: Orthographic View Part Grouping; problem 1: part machine ($p \times m$) size (10×12).

Table IV: Algorithm performance on test Data set.

Set No.	Problem Size		APOSTVUIT					APMOSTVC				
	No. of mc. m	No. of parts	Exceptional elements	Intercell moves	GTE	RGE	$WSCE$	Exceptional elements	Intercell moves	GTE	RGE	$WSCE$
1	4	5	0	0	100	85.48	92.74	0	0	100	85.48	92.74
2	5	7	1	1	85.81	82.25	84.03	1	1	85.81	82.25	84.03
3	5	8	6	5	64.30	80.17	72.24	6	5	64.30	80.17	72.24
4	6	19	2	2	85.61	74.75	80.18	2	2	85.61	74.75	80.18
5	12	20	8	8	83.93	73.29	78.61	8	8	83.93	73.29	78.61
6	12	20	11	9	79.00	72.56	75.78	11	9	79.00	72.56	75.78
7	20	20	3	3	94.5	87.86	91.18	3	3	94.5	87.86	91.18
8	15	30	20	16	77.81	70.63	74.22	20	16	77.81	70.63	74.22
9	20	37	24	24	72.50	70.10	71.30	24	24	72.50	70.10	71.30
10	25	50	48	45	70.15	66.1	68.13	48	45	70.15	66.1	68.13
11	20	55	14	18	82.30	73.90	78.10	14	18	82.30	73.90	78.10
12	28	60	38	37	71.60	64.30	67.95	38	37	71.60	64.30	67.95
13	30	65	57	50	77.88	68.48	73.18	57	50	77.88	68.48	73.18
14	32	80	52	58	75.67	72.83	74.25	52	58	75.67	72.83	74.25
15	35	90	53	55	78.89	71.43	75.16	53	55	78.89	71.43	75.16

6. CONCLUSION

In his work, an algorithm, APMOSTVC is developed and proposed for Concurrent formation of part families and machine groups. Most of the existing methods are solely based on binary (i.e. 0, 1) machine component incidence matrix only. But proposed algorithm is real-valued matrix based. A few researchers have employed either the operation sequence or a combination of processing time, total machine available time and volume of components, this paper considered all of these data concurrently. A matrix model is developed incorporating

important manufacturing shop floor realities machine sequence, operation time, production volume and machine capacity. The model is analyzed using principle component analysis. Among several techniques, a few researchers used principle component analysis technique. Machine-Part groups are formed by using graphical grouping techniques. Part families and machine groups are also formed concurrently.

The algorithm yields good and comparable solutions in its class [14, 16, 25] in negligible computational time. Even Seifoddini has referred papers [15, 16] in his paper [22] in 2007. He has considered ordinal level data that is machine sequence and ratio level data as production volume only in his SCM model. However, he did not consider other important shop floor realities that are operation time and machine capacity in his SCM model.

Part families and machine groups evolve naturally. Algorithm gives flexibility to designer by removing constraint on number of cells and/ on number of cell to be decided in advance. Moreover, algorithm has very good industrial application potential. It is simple easy to understand and implement. It does not require skills of complex optimization techniques and programming. Algorithm APMOSTVC can be implemented using free software, Scilab-platform [40]. It is matrix based free software. The programming in Scilab is easy and very user friendly. Further, there are much expensive commercial software (SPSS, SAS, STAD, XLSTATS etc.) that can be used with APMOSTVC.

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