OPTIMAL DESIGN OF MANUFACTURING CELLS CONSIDERING MACHINE USAGE PERCENTAGE

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This paper demonstrates an exclusive design methodology in Cellular Manufacturing (CM) considering machine usage percentage as ratio data. This research correctly emphasized the fundamental of ratio data and proposed a novel and precise mathematical formulation of the design problem. This multi-objective model carefully optimizes the total exceptional utilization (TEU), number of voids and total cell utilization (TCU). Due to the novelty in the model, a new data generation technique is proposed. The test datasets are obtained and tested using IBM CPLEX tool successfully. The contribution of this research is twofold. First; the ratio data concept is correctly emphasized and a precise mathematical model is developed. Second, since the model is new and datasets are not readily available, therefore a dedicated data generation model is proposed.

Keywords: Machine Utilization Percentage; Ratio Data; Cellular Manufacturing; Optimization.

1. Introduction

In the last few decades manufacturing firms are enhanced enough in terms of productivity, flexibility and quality of production. In fact manufacturing systems have encountered key challenges due to the evolution in manufacturing methodologies and policies. [3,37] In this regard newer manufacturing philosophies such as Group Technology (GT) and its application, CM is playing a vital role. [1,34] Strategically GT forms part families based on similarities (attributes or processing requirements) and assigns them to the appropriate machine cells to exploit the benefits of mass production such as reduction in throughput times, reduction in work in process, reduction in tool requirements, improvement in product quality and improvement in overall control of operations. As an application of GT, CM provides a mixed setup of jobshop (variety) and flowshop (higher production) and demonstrates an alternative form of manufacturing system. [2] The major objective of CM is to dismantle the production system into several tiny systems that practically utilize the processing similarities of parts and machines. [35,36] The method of assigning part families to the machine cells, is described as the cell formation problem (CFP). It is also termed as machine-part grouping problem (MPGP) which deals with machine-part incidence matrix (MPIM) and attains block diagonal cellular structure to form cells. An MPIM is packed with zeroes and non-zeroes depending upon the machining requirement of parts. It is termed as 'ratio data'. [3] Binary (0-1) CFPs are mostly explored in the past few decades,

[4,5,6,7,8,9,10,] however binary (0-1) data ignores important production factors such as processing time, production volumes, machine hours etc. [12] Therefore ratio data is proposed in most logical way. Many researchers have used ratio data in their research. [3,13,14] In the course of the research, the workload data and ratio data are assumed synonymous and from this a transformed incidence matrix could be obtained which is known as processing time matrix. [13] The total processing time on a machine for any part is the product of its production quantity and its unit processing time. All the non-zeros in the incidence matrix are switched to ratio values. The subsequent workload values would take any value in the ratio scale (0-1). However, none of the past articles shows the right way to obtain the workload ratio (fractional figure) from total processing time. Thus, the available workload datasets are not prominent and consistent. This discussion is further extended in section #2.
To solve any type of CFPs a large number of solution methodologies are available in literature of CM since early 80s. These are exact methods, graph theoretic approaches, mathematical programming, similarity coefficient based techniques, clustering algorithms, soft-computing techniques such as neural network, meta-heuristics and fuzzy methods etc. [15] However the direction of the research indicates towards soft-computing techniques due to its robust convergence properties and difficulties in obtaining global optimal solution. [16] Therefore, many meta-heuristic based techniques are being applied to CFPs for better solutions during past two decades. [17] These are genetic algorithms (GA), [18,19,20] tabu search, [21,22] simulated annealing, [8,23] ant colony optimization (ACO) [24,25] particle swarm optimization (PSO), [9,26,27] bee's algorithm, [28] water flow-like algorithm, [29] firefly-inspired algorithm, [10] bacteria foraging algorithms [30] etc. All of these previous research works are pointing out towards the need of some reliable mathematical model that can be optimized with ease. [38]
In this work, an attempt is made to develop the cells considering ratio data based on machine utilization, a real-time production factor. To solve this problem, machine utilization based real-valued data matrix is considered. A novel mathematical formulation is also proposed. The said model has been tested using various test problems generated using universal data generation algorithm proposed here and compared to the solutions obtained using branch and bound (B&B) algorithm of IBM CPLEX tool successfully.
Next sections demonstrate this research work completely. Problem definition and the mathematical formulation are provided in section #2. Performance metric is portrayed in section #3. Section #4 exhibits the results and analysis followed by the conclusions in section #5.

2. Problem Formulation

Venugopal and Narendran [12] were first to describe ratio data scientifically. It is re-defined here as,

t_{ij} = unit processing time (hour/unit) of part j on machine i; $1 \leq i \leq q$ and $1 \leq j \leq p$
n_j = production volume of part j
MH_i = available machine hours of machine i

U = [u_{ij}] is an ($p \times q$)-machine-component incidence matrix where
u_{ij} = Percentage utilization of machine i induced by part j

$$u_{ij} = \frac{(t_{ij} \times n_j)}{MH_i} \quad (1)$$

where,

$$u_{ij} = \begin{cases} zero, & if\ part\ j\ is\ not\ being\ processed\ by\ machine\ i \\ non\ zero, & if\ part\ j\ is\ being\ processed\ by\ machine\ i \end{cases} \quad (2)$$

Eq. (1) produces an MPIM *U*, which is generally acknowledged as *operational time*. Ideally, the elements (u_{ij}) of *U* do not actually point to any absolute values. These elements are spotted as some ratio/fractional values (Hours ÷ Hours). Hence, these are unit-less by character. Hence these elements are not 'operational time' definitely. Wu [31] has termed this as 'capacity percentage', which is also imprecise as the 'capacity' of a machine is identified as 'available machining hours' however 'capacity percentage' is an ambiguous idiom. According to the production engineering personnel, this is termed as 'utilization' of the machine expressed in 'percentage value'. Moreover, Wu's work is more focused on the existence of identical machines in the system whereas in ratio data based CFP; all the machines are separately considered as standalone items.

u_{ij} states a fractional value of machining hours of i^{th} machine to process the total volume of j^{th} part. This indicates "percentage utilization of machine", which is more reasonable and appropriate terminology than the "operational time".

Mahapatra and Pandian [14] (p. 637) stated *'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 in the incidence matrix and zeros to remain in its same positions.'*, which generates random ratio valued matrix without any restriction. However, this procedure is ambiguous and unscientific, which do not realistically impose the practical assumptions and limitations.

To correctly present this phenomenon a constraint (Eq. 3) is recommended with Eq. (1).

Constraint:
Eq. (3) depicts that the sum of percentage utilization of all the parts over i^{th} machine is required to be less than or equal to 1. This is because; the total utilization of i^{th} machine would never exceed 100% in reality.

$$\sum_{j=1}^{p} u_{ij} \leq 1 \quad (3)$$

In spite of this fact, a particular machine rarely runs all the time in a particular work shift (8 hours). [32] Thus the total machine utilization for a particular machine practically never reaches 100% and generally remains in the range of 0.1 to 0.9 (10%-90%).

In experience closely all the previous articles based on ratio data, ignored the above indicated constraint (Eq. 3) which is a critical issue while generating the test datasets. Even the pioneer research by Venugopal and Narendran [12] did not particularly consider this phenomenon. Therefore picking up the published test problems from the past literature would be an incorrect step for this research. To rectify this issue, a novel 'real valued data generation algorithm' is proposed in this article. The algorithm is,

Input:

A. Option 1 will generate the number of machines (*q*) and number of parts (*p*) randomly
B. Option 2 would ask users to specify the number of Machines and Parts (*q, p*)

Output:

$q \times p$ real valued incidence matrix

Steps:

Generate random ratio matrix of size (q×p),
if ($0 < q \leq 10$)
Restrict density of zeroes in the range of 40-50% in generated matrix
else if ($10 < q \leq 20$)
Restrict density of zeroes in the range of 60-70% in generated matrix
else
Restrict density of zeroes in the range of 80-90% in generated matrix
end

end
end
Restrict each row sum ≤ 1

This above stated algorithm not only includes Eq. (3) in data generation method but also controls the number of zeroes in the matrix. Percentage of zeroes must remain in the range of 40-50% in small size datasets ($q < 10$), 60-70% in medium size datasets ($10 \leq q < 20$) and 80-90% in large datasets ($q \geq 20$), which is also included in the algorithm to attain more realistic test problems.

This technique would definitely eliminate the difficulty of unavailability of the test data henceforth. Any researcher/student can generate datasets of any size based on their choice for research or study purpose.

2.1. *Mathematical Model*

Designing manufacturing cells is generally a multi-objective problem. Researchers while designing a mathematical formula of the said problem, consider various objectives.

Objectives such as intra-cell and inter-cell material handling costs, cell load variations, grouping efficiencies, exceptional elements (bottleneck machines) etc. are usually considered in the mathematical models of real valued CFPs. However machine utilization has never been practiced as ratio data for CFPs in past. Therefore, a new mathematical formulation is required for the problem considered in this paper. For that matter a novel mathematical formulation, which is multi-objective minimization type, is proposed in Eq. (10). This problem minimizes total utilization of exceptional elements (TEU), maximizes total in-cell utilization (TCU) and minimizes total number of voids.

Decision variables:
x_{ik} defines machine *i* in cell *k*, y_{jk} defines part *j* in cell *k*, a_{ij} defines mapping between machine *i* and part *j*

Total Utilization on Exceptional Elements (TEU) is expressed as,

$$minimize\ f1 = 0.5 \times \sum_{k=1}^{c}\sum_{j=1}^{p}\sum_{i=1}^{q}\left(x_{ik} - y_{jk}\right)^2 u_{ij} \tag{4}$$

Eq. (4) provides real value. In order to convert this into ratio value, it is divided with the total utilization of the plant. The new expression becomes,

$$minimize\ Z1 = 0.5 \times \frac{\sum_{k=1}^{c}\sum_{j=1}^{p}\sum_{i=1}^{q}\left(x_{ik} - y_{jk}\right)^2 u_{ij}}{\sum_{j=1}^{p}\sum_{i=1}^{q} u_{ij}} \tag{5}$$

Total Utilization of all Cells (TCU) is the sum of utilization of each cell. This is expressed as,

$$maximize\ f2 = \sum_{k=1}^{c}\sum_{j=1}^{p}\sum_{i=1}^{q} x_{ik} y_{jk} u_{ij} \tag{6}$$

Eq. (6) is also converted into ratio valued expression and provided in Eq. (7).

$$maximize\ Z2 = \frac{\sum_{k=1}^{c}\sum_{j=1}^{p}\sum_{i=1}^{q} x_{ik} y_{jk} u_{ij}}{\sum_{j=1}^{p}\sum_{i=1}^{q} u_{ij}} \tag{7}$$

Total No. of Voids are expressed using Eq. (8),

$$minimize\ f3 = \sum_{k=1}^{c}\sum_{j=1}^{p}\sum_{i=1}^{q}(1 - a_{ij})\, x_{ik}\, y_{jk} \tag{8}$$

Eq. (8) provides integer solutions. Thus, it is also converted into ratio-valued function of eq. (10).

$$minimize\ Z3 = \frac{\sum_{k=1}^{c}\sum_{j=1}^{p}\sum_{i=1}^{q}(1-a_{ij})\,x_{ik}\,y_{jk}}{\sum_{j=1}^{p}\sum_{i=1}^{q}a_{ij}} \quad (9)$$

Weighted Sum Objective Function of objectives *Z1, Z2, Z3*:

$Minimize\ F$

$$= w1 \times 0.5 \times \frac{\sum_{k=1}^{c}\sum_{j=1}^{p}\sum_{i=1}^{q}\left(x_{ik}-y_{jk}\right)^2 u_{ij}}{\sum_{j=1}^{p}\sum_{i=1}^{q}u_{ij}} - w2 \times \frac{\sum_{k=1}^{c}\sum_{j=1}^{p}\sum_{i=1}^{q}x_{ik}y_{jk}u_{ij}}{\sum_{j=1}^{p}\sum_{i=1}^{q}u_{ij}}$$

$$+ w3 \times \frac{\sum_{k=1}^{c}\sum_{j=1}^{p}\sum_{i=1}^{q}(1-a_{ij})\,x_{ik}\,y_{jk}}{\sum_{j=1}^{p}\sum_{i=1}^{q}a_{ij}} \quad (10)$$

w1, w2, w3 are the weight factors. The sum of weight factors,

$$w1 + w2 + w3 = 1 \quad (11)$$

$$u_{ij} = \begin{cases} non-zero, if\ part\ j\ is\ processed\ in\ machine\ i, \\ zero, if\ part\ j\ is\ not\ processed\ in\ machine\ i \end{cases} \quad non - zeros\ are\ machine\ utilizations \quad 1 \le i \le q; 1 \le j \le p \quad (12)$$

$$a_{ij} = \begin{cases} 1, if\ part\ j\ is\ processed\ in\ machine\ i, \\ 0, if\ part\ j\ is\ not\ processed\ in\ machine\ i \end{cases} \quad 1 \le i \le q; 1 \le j \le p \quad (13)$$

$$x_{ik} = 1\ if\ machine\ i\ is\ in\ cell\ k, else\ 0 \qquad \forall i,k \quad (14)$$

$$y_{jk} = 1\ if\ part\ j\ is\ in\ cell\ k, else\ 0 \qquad \forall j,k \quad (15)$$

$$\sum_{k=1}^{c} x_{ik} = 1 \qquad \forall i \quad (16)$$

$$\sum_{i=1}^{q} x_{ik} \ge 1 \qquad \forall k \quad (17)$$

$$\sum_{k=1}^{c} y_{jk} = 1 \qquad \forall j \quad (18)$$

$$\sum_{j=1}^{p} y_{jk} \geq 1 \qquad \forall k \tag{19}$$

Eq. (12)-(15) are the incidence matrices and decision variables and Eq. (16)-(19) are the assignment constraints, ensure that each machine/part is assigned to only one cell and each cell contains at least one machine/part. The value of the constants *w1, w2, w3* assign different load to the different objective. These are fixed in the range of $0 \leq w \leq 1$ and should satisfy eq. (11). In reality, the number of voids has lesser impact than TEU or TCU while attaining near-best solutions. However, in this study, same weights are assigned to all the objectives, TEU, TCU and total number of voids. These share the same importance and maintain simplicity in the model.

3. Performance Metric

A novel performance measure is recently proposed which is known as Utilization-based grouping efficiency (UGE). [33] This performance metric can competently deals with percentage utilization with all the facts ignored in all the previously published performance measures. This UGE is also a proven metric when compared with the previous metrics.

The new performance measure UGE is depicted in Eq. (20),

$$UGE = \frac{\left(\sum_{k=1}^{c}\left[U_{cell}^{k}\left(1-\frac{V_k}{E_k}\right)\right]\right)\left(1-\frac{U_{ee}}{\sum_{k=1}^{c}U_{cell}^{k}}\right)}{U_{plant}} \tag{20}$$

$$U_{cell}^{k} = \left\{\sum_{i=1}^{mic}\sum_{j=1}^{pic} u_{ij}\right\}^{k} \tag{21}$$

$$U_{ee} = \sum_{i=1}^{moc}\sum_{j=1}^{poc} u_{ij} \tag{22}$$

$$U_{plant} = \sum_{i=1}^{mtp}\sum_{j=1}^{ptp} u_{ij} \tag{23}$$

c: number of cells
m: number of parts
p: number of machines
k: index of cell $\{k=1,2,\ldots c\}$
i: index of machines $\{i=1,2,\ldots m\}$
j: index of parts $\{i=1,2,\ldots p\}$
U_{cell}^{k}: Total utilization of k^{th} cell
U_{plant}: Total utilization of plant

U_{ee}: Total utilization outside the block diagonal cell structure
u_{ij} = utilization of machine i induced by part j; $1 \leq i \leq q$ and $1 \leq j \leq n$
V_k: Total number of voids in cell k $\{k=1,2,\ldots c\}$
E_k: Total number of elements in cell k $\{k=1,2,\ldots c\}$
mic: number of machines in cell
pic: number of parts in cell
moc: number of machines outside of cells
poc: number of parts outside of cells
mtp: Total number of machines in plant
ptp: Total number of parts in plant

4. Computational Results

In order to verify the proposed mathematical model, real valued datasets are required. Therefore required utilization based datasets are generated using the data generating algorithm described in section #2. The proposed model is programmed in AMPL IBM ILOG CPLEX tool using an Intel 2.4 GHz i3 computer. Eighteen datasets of small to medium sizes ranging from 4×7 to 20×35 are tested and the solutions obtained are shown to be competitive.

The results are displayed in Table 1. Computational time is not a focus area of this research rather it is essential to obtain optimal or near optimal solutions. CPLEX uses branch-&-bound (B&B) algorithm to find near-optimal solutions for all problems considered. B&B algorithm was introduced in 1960. [39] For interested readers, the detailed B&B algorithm is portrayed in Appendix B. For small size problems (#1 to #6) CPLEX obtains solutions within trivial time, whereas the medium size problems (#7 to #18) CPLEX runs for infinite time to achieve the near-optimal solutions and the execution is terminated after permissible computing time (25 minutes) to reduce the usage of computer resources. This infinite execution happens due to the increasing complexity of the problems, which are NP hard in nature. [12] Larger the problem size, bigger the number of variables and constraints and higher the complexity.

Table 1 reveals few significant aspects related to the objective function and performance measure. For test problem no. 1 and 3 both CPLEX yields global best solution. For test problem no. 8, 12, 16, 17 the B&B algorithm of CPLEX gives near best solutions. However influence of voids count is trivial, instead TCU and TEU have greater impact on the design of UGE. Thus, the solutions attained sometime depicts more number of voids than usual. It is often observed in Table 1 that the objective function values are greatly influenced by the number of voids present in the solutions. The reason is the values assigned to the weight factors of Eq. (11). Since all the three weight factors are equally treated thus, the count of voids receives similar importance in the design of objective function of the problem. Therefore, the objective values are reduced with an improved UGE. This fact indicates the requirement of a systematic procedure to assign weights to the weight factors of Eq. (11). For an example $w1=0.4$, $w2=0.4$ and $w3=0.2$ would show consistent changes in objective values obtained.

Another insight is the dependency of UGE on exceptional elements and voids. For an example, for the test problem no. 8, the CPLEX B&B technique obtains a good UGE value but CPLEX B&B solution has less exceptional element. Further, the CPLEX B&B solution of problem no. 12 again shows improvement in UGE score but the solution has same number of exceptional elements (ee) while less number of voids.

Table 1. Computational Results of CPLEX B&B

#	*Size*	*Cell#*	*Obj*	*UGE*	*TCU*	*TEU*	*EE and Voids*	*CPU Time*
1	4×7	2	-0.1691	55.02	2.5191	0.5579	ee=5; voids=2	< 10 Sec.
2	6×8	2	**-0.0745**	39.59	3.7429	1.106	ee=5; voids=7	< 10 Sec.
3	7×10	2	-0.1412	46.65	4.6167	1.2737	ee=15; voids=6	< 30 Sec.
4	8×15	2	**-0.0831**	46.45	5.9656	0.973	ee=13; voids=29	< 30 Sec.
5	8×22	2	**-0.0812**	50.63	6.6895	0.7214	ee=15; voids=52	< 2 Min.
6	10×10	3	**-0.1158**	49.82	6.639	1.0831	ee=8; voids=14	< 2 Min.
7	10×25	3	**-0.0251**	28.06	6.4909	2.4918	ee=30; voids=31	>25 Min.
8	12×24	3	**0.0272**	**21.19**	7.3996	3.2919	ee=38; voids=42	>25 Min.
9	12×29	3	**0.0205**	24.79	7.5357	2.9084	ee=35; voids=50	>25 Min.
10	14×30	3	**0.0267**	24.17	8.8611	3.3628	ee=49; voids=69	>25 Min.
11	14×35	3	**0.0345**	18.99	8.2919	4.2342	ee=56; voids=60	>25 Min.
12	16×32	3	**0.0546**	**17.7**	9.3968	4.8189	ee=66; voids=78	>25 Min.
13	17×27	3	**0.0649**	20.39	10.1567	4.4513	ee=46; voids=74	>25 Min.
14	18×35	3	**0.0576**	16.57	10.6621	5.6094	ee=90; voids=97	>25 Min.
15	18×35	3	**0.0632**	17.69	11.156	5.4751	ee=78; voids=97	>25 Min.
16	18×35	3	**0.0547**	**14.07**	10.18	6.0911	ee=91; voids=88	>25 Min.
17	20×20	4	**0.0072**	**15.97**	10.5876	6.3779	ee=72; voids=37	>25 Min.
18	20×35	4	**0.0473**	8.08	10.3456	8.0896	ee=116; voids=63	>25 Min.

Thus, it can be concluded that the count of exceptional elements has a greater influence than the number of voids but number of voids also shows some significance when the number of exceptional elements are not differentiable. This fact indicates a careful tradeoff in the design for the utilization based problems.

5. Conclusions

A novel utilization based cell formation problem is presented in this paper. Ratio data is widely practiced as 'processing time', which is proved to be 'utilization percentage of machines'. Naming this as 'processing time' could be completely unscientific. Owing to this confusion of nomenclature most of the researchers are more inclined to produce the 'processing time' based incidence matrix using real valued random number generation method which is irrational and improper from the view of 'utilization percentage of machines'. Therefore, a new data generation algorithm is proposed. Hence, availability of datasets is no longer an issue to the researchers for the problems based on ratio data. Henceforth a novel multi-objective mathematical formulation is proposed which minimizes TEU and number of voids and maximizes TCU. This multi-objective utilization based problem is linearized and solved using B&B method of IBM ILOG CPLEX. Eighteen datasets are generated of sizes ranging from 4×7 to 20×35, using the novel data generation algorithm. UGE is used as the performance measure, which is an appropriate measure of efficiency for the utilization based problems. The CPLEX B&B algorithm show to yield good results.

Appendix A. AMPL code for utilization based model

```
### SCALAR PARAMETERS ###
param q:=4; param p:=7; param c:=2;

### ARRAY PARAMETERS ###
param u {1..q,1..p}; param a {1..q,1..p};

### VARIABLES ###
var x {1..q,1..c} binary; var y {1..p,1..c} binary;

### OBJECTIVE ###
Minimize obj_function:
0.33*((0.5 * sum{k in 1..c} sum{j in 1..p} sum{i in 1..q} (x[i,k]-y[j,k])*(x[i,k]-
y[j,k])*u[i,j])/(sum{j in 1..p} sum{i in 1..q} u[i,j])
-(sum{k in 1..c} sum{j in 1..p} sum{i in 1..q} x[i,k]*y[j,k]*u[i,j])/(sum{j in 1..p} sum{i in
1..q} u[i,j])
+(sum{k in 1..c} sum{j in 1..p} sum{i in 1..q} (1-a[i,j])*x[i,k]*y[j,k])/(sum{j in 1..p}
sum{i in 1..q} a[i,j]));

### CONSTRAINTS ###
Subject to constr1{i in 1..q}: sum{k in 1..c} x[i,k] = 1;
Subject to constr2{j in 1..p}: sum{k in 1..c} y[j,k] = 1;
Subject to constr3{k in 1..c}: sum{i in 1..q} x[i,k] >= 1;
Subject to constr4{k in 1..c}: sum{j in 1..p} y[j,k] >= 1;
```

Appendix B. Branch & Bound (B&B) Algorithm

B&B algorithm is a global optimization technique for discrete optimization problems, such as integer programming (IP), mixed integer programming (MIP) etc., which are known as NP-hard problem. The algorithm is depicted in Fig. 1. In this technique, the relaxed problem is considered. Thereafter the partial solutions are identified. B&B algorithm would create branches for each discrete variables. B&B divide each node (variable) into two new sub-nodes. This procedure would split the solution space into small subsets with specific upper and lower bound. An NP-hard problem could possibly have a large number of solutions, which increases with the size of the problems.

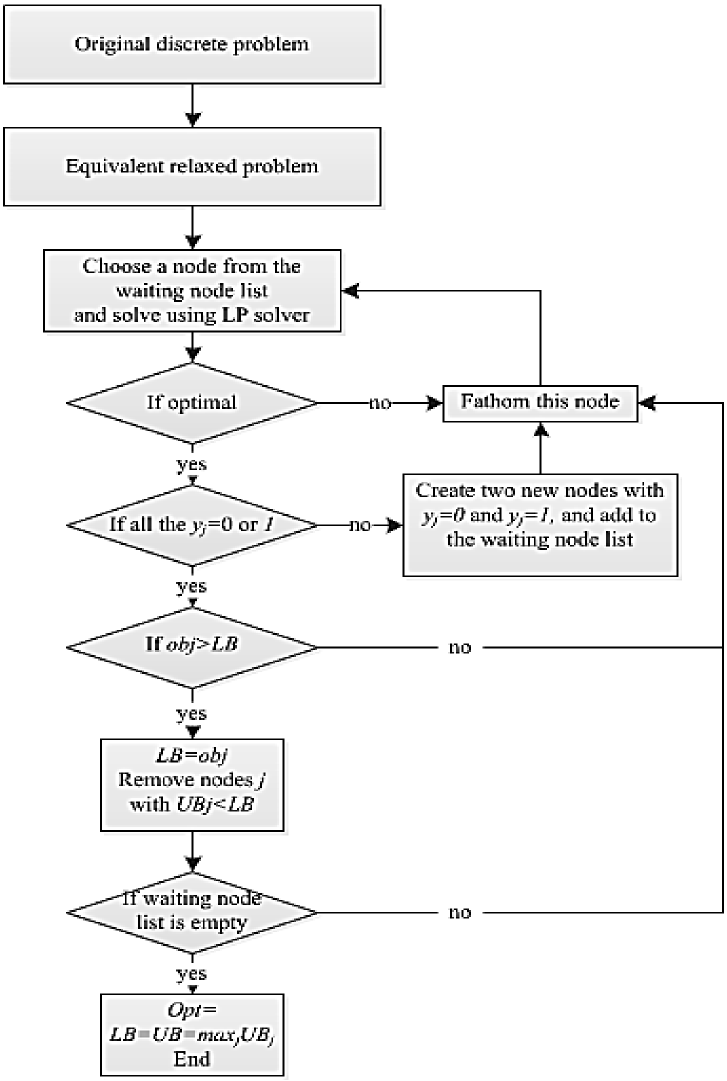

Fig. 1. B&B Flowchart
(https://optimization.mccormick.northwestern.edu/index.php/File:BB.png)

Therefore, the bounds for the objective functions are coupled with the value of the local best solution for exploitative search. Branching could be done on, (1) the existing node or (2) the newly created node with the smallest bound. The former, would generally investigate minimum sub-problems, which saves computation time with high memory. The later, would utilize less memory intensive and higher computational time.

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