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Decision Support Mechanism for Cellular Production System – Application of NSGA-II Meta-heuristic and TOPSIS Ranking

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ABSTRACT

Cellular arrangement is considered beneficial for the distribution of heavy workload, resource utilization and fast paced production. In such mechanisms, machines, tools and product features are classified into different cells. Such arrangement impacts the overall performance of system in the form of productivity and throughput. In current study, serial, parallel and tubular systems have been analyzed with multiple variants of each production system. The objective is to select variants on the basis of optimal production time, least cost and higher productivity. Two methods have been used owing to the complex and combinatorial nature of the problem. Initially, a modified version of Non Sorting Genetic Algorithm (NSGA-II) has been used to provide Pareto fronts where possible candidates for optimum solution have been presented. A Multi Attribute Decision Making (MADM) approach of Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) criteria has been used to select the best compromise of optimal result. The results show that the objectives of cost, time and productivity are in conflict with each other and a global solution cannot be attained against the optimal values of all objectives. Also, an increased productivity can be assured by reducing the total time with an increase in cost.

1. Introduction

In modern manufacturing, enterprises are urged to simultaneously lower their costs/lead times, improve processes and provide optimal quality products. Such challenges are exacerbated by market competition and scarcity of resources. These resources such as, raw material, machines, personnel and space are considered a scarce commodity and their optimal use is imperative for sustainable production. The space constraint, in particular, impacts the performance of production as different machines can be arranged in several different ways in the available space [1]. For example, one of the classical arrangement of machines is serial line which ensures high throughput, however, it has been insignificant for smooth information flow. On the other hand, a U-shape assembly line although takes more time in transferring products, it has been considered viable for zero-defects strategy and information sharing. Normally, cells are formed by arranging machines in clusters using the approach of Group Technology (GT). The GT has attained more research attention as it helps in forming groups of machines/products on the basis of operational similarity [2]. Due to this similarity, maximum work can be performed using less number of machines by minimizing the capability overlap.

The Cellular Production System (CPS) is a type of GT which divides a production system into cells. Each cell contains multiple machines according to operational requirements. One of the motives behind the application of CPS is to reduce inter and intra cellular movement of equipment/material. It also helps in minimizing queue length, work-in-process time, waiting time and idleness of machines. Furthermore, such approaches are helpful in managing bottlenecks and dependency constraints. In inventory modeling problems, significant effect of GT has been demonstrated on material handling and lead times [3]. Similarly, cell formation problems have been considered more frequently in the concerned literature and these problems can be divided into products and machine variants. A cellular system designed on the basis of product is called *part family* system while machine arrangement is treated as *machine cells* [4]. The concept of GT is implemented in production by cellular arrangement, where GT is a philosophy for exploiting similar product features/processes. A fundamental issue is the determination of part families and machine cells. This issue is known as the Cell Formation (CF) problem which involves the decomposition of a production system into feasible cells. This study considers machine based cell formation problems in a typical Cellular Production System (CPS).

The rest of the study is organized as follows. Section 2 describes the literature and background of CPS and section 3 contains the solution approaches namely, NSGA-II and TOPSIS. Section 4 describes the relevant results while section 5 concludes the study.

2. Cellular Production System (CPS)

The concerned literature addresses a diverse range of problems related to cell formation. These problems have been solved using different techniques such as, mathematical modeling and algorithms. For example, Mak et al. [5] presented an approach of cell creation and scheduling by using a mathematical model and Ant Colony Optimization (ACO) approach. Instead of analyzing cellular systems on the

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single criterion of throughput, Shang and Tadikamalla [6] developed a multi-criteria approach. In particular, flow time, work-in-process and waiting time were used as performance criteria. The analysis was presented on the basis of Taguchi design and response surface methodology. In another study, Liu et al. [7] used a dynamic cellular system for presenting integrated issues of facility transfer and planning. A novel bacteria foraging algorithm (IBFA) was implemented to minimize the operation cost.

It is important to specify the number of cells in advance in order to efficiently group machines. To do so, Mukattash et al. [8] used Sterling number to develop a 2-cell formation with unbounded size. An exact algorithm was applied to provide the system designer with flexibility of selection. In another study, Solimanpur et al. [9] performed the synthesis of inter-cell layout problem. The authors proposed an ant algorithm and the results were compared with different facility layout algorithms to prove its robustness.

A novel heuristic approach which combined Particle Swarm Optimization (PSO) with neural networks was applied by Mahmoodian et al. [10] to cell formation problem. The integrated approach provided improved results compared to the literature based findings. Similarly, Soto et al. [11] analyzed the cell formation problem by grouping machines into different cells. The goal was to identify organization of cells in order to minimize the transportation of parts between cells. A dynamic cellular problem was tackled by Rabbani et al. [12] by considering a multi-objective model. The problem consisted of part family formation and operators' assignment. The optimization of cost, labor utilization and variance of workload was carried out using linearly implemented GAMS, non-sorting genetic algorithm (NSGA-II) and multi-objective particle swarm optimization (MOPSO) approaches. In another study, Wang et al. [13] integrated the problems of cell formation and task scheduling. The model assigned available workers to appropriate machines/cells.

The cellular system offers multi-fold advantages, such as, minimization of set-up time, work-in-process inventory and delivery schedules. Asokan et al. [14] demonstrated that CPS is more effective in terms of simplified design of products, minimal tooling and improved human efficiency. A well-defined and integrated CPS system helps in improving production efficiency by using appropriate layout and material transportation between cells. Approximately 40-70% of overall production cost can be attributed to these factors [15]. The class of CPS problem considered here is related to facility layout which is defined as "identification of optimal location for arrangement of resources to utilize the space efficiently" [16]. In this study, three layouts (L_1: serial production line (SPL), L_2: parallel production line (PPL) and L_3: U-shape or tubular production line (TPL)) have been considered as shown in Table 1. Within each layout, three variants (CO_1, CO_2 & CO_3) have been analyzed and the difference between these variants is the production order as well as machine allocation. The problem complexity is enhanced by the fact that in each layout, different number of machines have been considered. For instance, 4, 6 and 7 machines have been used respectively in SPL, PPL and TPL.

A product with five (5) features has been considered for the analysis and its schematic is provided in Fig. 1. These features (F_{01}-F_{05}) require operations such as boring, drilling, finishing and contouring which are performed by different machines. Moreover, the operation precedence in each layout is changed to make it a dynamic layout problem. This makes the problem combinatorial and in literature, CFP's are widely considered as challenging problem sets. Also, they belong to non-polynomial hard (NP-hard) set of problems and computational time of such problems increases exponentially [17, 18]. The traditional optimization approaches, such as, linear programming cannot be used to solve such problem and rather, algorithms are used. A literature based relevance can be found in ref. [19], where simulated annealing algorithm has been used for layout analysis in order to minimize the material handling costs.

In most cases, fixed assembly line has been used for production with similar characteristics. Nonetheless, there is a product-oriented approach in literature as well where products with different characteristics are assembled. The line balancing approaches are adopted in such cases and associated tasks are performed on different machines. The classification of different tasks defined in Table 1 is provided in Fig. 2 where processing, turning, drilling, milling and finishing represents the set of five (5) processes. Adding to it, the relative importance of each task has also been provided by using the following nomenclature.

Table 1: Layout, product feature precedence and machine allocation.

Layout	Variants	Feature precedence	Machine order
L_1: SPL	CO_1	F_{01}- F_{02}- F_{03}- F_{04}- F_{05}	m_1- m_2- m_3- m_4
	CO_2	F_{01}- F_{03}- F_{04}- F_{02}- F_{05}	m_4- m_3- m_1- m_2
	CO_3	F_{03}- F_{05}- F_{02}- F_{04}- F_{01}	m_1- m_4- m_2- m_3
L_2: PPL	CO_1	F_{04}- F_{05}- F_{01}- F_{02}- F_{03}	m_3- m_4- m_5- m_1- m_2- m_6
	CO_2	F_{05}- F_{03}- F_{01}- F_{02}- F_{04}	m_2- m_3- m_4- m_6- m_1- m_5
	CO_3	F_{02}- F_{01}- F_{03}- F_{04}- F_{05}	m_6- m_1- m_2- m_4- m_3- m_5
L_3: TPL	CO_1	F_{04}- F_{02}- F_{03}- F_{01}- F_{05}	m_1- m_6- m_3- m_4- m_7- m_2- m_5
	CO_2	F_{01}- F_{05}- F_{02}- F_{04}- F_{03}	m_3- m_2- m_7- m_5- m_6- m_4- m_1
	CO_3	F_{05}- F_{02}- F_{03}- F_{04}- F_{01}	m_7- m_1- m_4- m_2- m_3- m_5- m_6

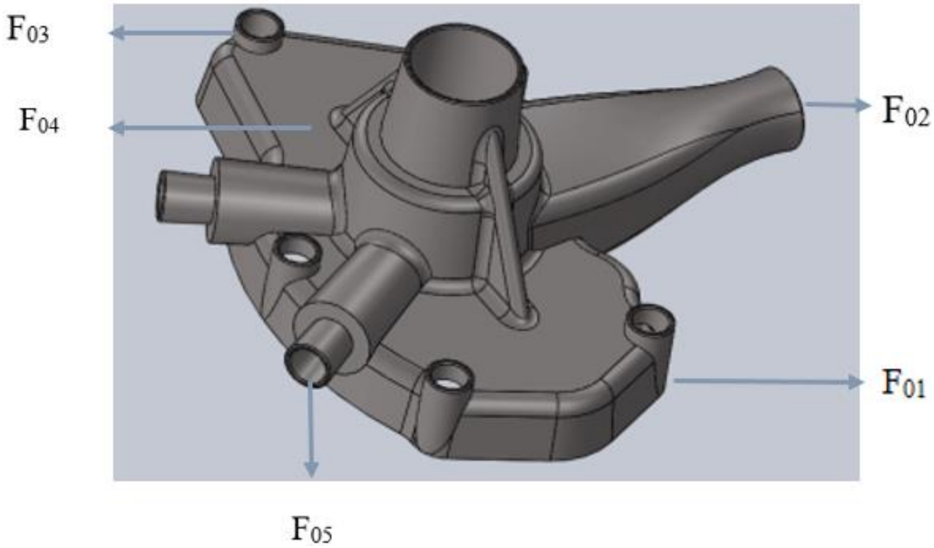

Fig. 1: Schematic of the case study.

A= Very important,

E= Exigent,

I= Important,

N= Neutral, and

U= Un-important.

This has been performed in order to take into account the closeness between tasks and machine allocation while changing the precedence. Similarly, if two tasks are consecutive then they will be assigned to machines according to their precedence relationship. The violation of this criterion can incur additional cost such as, waiting cost and an increase in stipulated queue time.

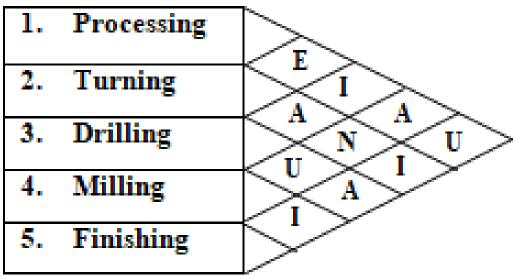

Fig. 2: Relative importance and closeness of tasks.

The cellular problems and assembly line approaches are of paramount importance as they provide analysis on the optimal ratio of throughput to cost. In majority of the studies, layout and machine allocation problems have been frequently discussed [19]. Three layouts have been considered (Fig. 3) and subsequently variability has been considered in the number of machines, precedence order and flow of goods between these layouts. The objectives of the study are;

1. To compare different layouts by taking into account the costs related to layout, setup, handling and processing,
2. To compare the layouts based on completion time and,
3. To compare the layouts on the basis of throughput. This objective is inversely related to the objectives of cost and time. An increase in the productivity results in a decrease in cost and time.

As discussed earlier, the stated problem is combinatorial and thus the use of NSGA-II [20] and multi-attribute decision making criteria called technique for order preference by similarity to ideal solution (TOPSIS) are proposed to solve the problem. The NSGA-II has been used to provide non-dominated Pareto-front of candidate solutions, whereas, TOPSIS has been used for hierarchical ranking.

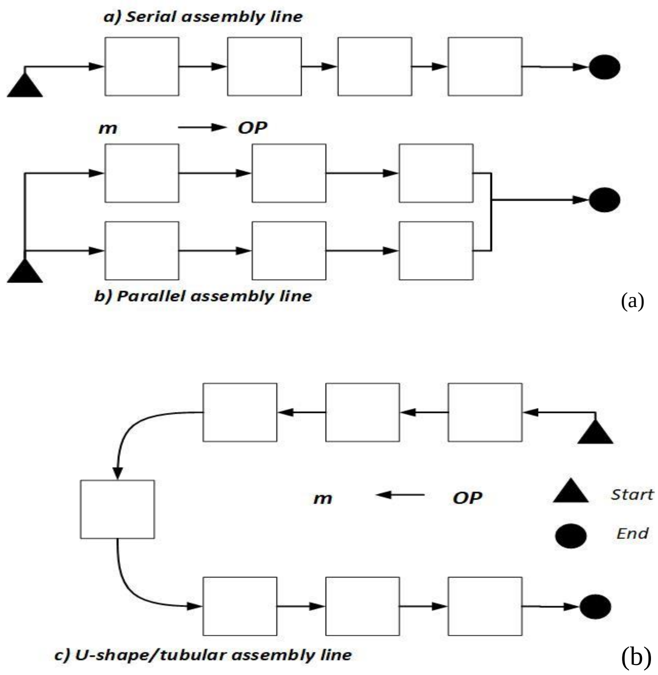

Fig. 3: a) Serial assembly line, b) parallel assembly line and c) tubular assembly line layout.

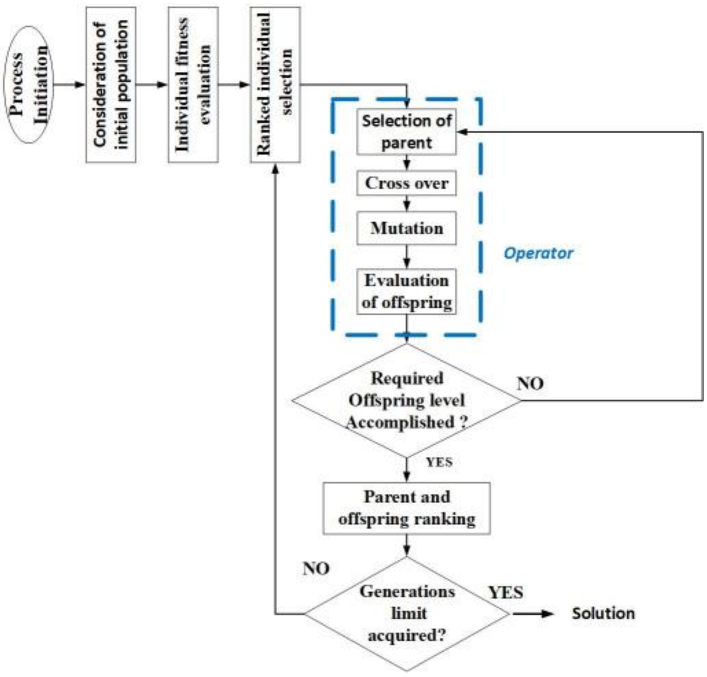

Fig. 4: Process flow of genetic algorithm.

3. Methods

3.1 Non-Sorting Genetic Algorithm (NSGA-II)

The Non-Sorting Genetic Algorithm is a non-domination based algorithm and it is based on the biological process of gene's evolution. In genetic algorithm, the chromosomes are used as proxies in the form of binary sequences to represent the candidate solution. Furthermore, a fitness function is employed to assess the potential of a chromosome against defined criteria (objective function). A list of chromosome is called population and periodic time based analysis of population is called generation. The process flow of NSGA-II is provided in Fig. 4 and it uses the genetic operators such as, reproduction, crossover and mutation.

- Reproduction: This stage represents the selection of chromosomes according to fitness value. The result of this stage is used in the crossover and mutation stages. Also, individual population (parents) are selected in order to formulate the forthcoming generation of off-springs.
- Crossover: It is the exchange of portions between chromosomes. The parents from stage 1 are combined to produce children, similar to biologically inspired phenomena and resulted children shows resembling characteristics to their parents. The crossover operates by considering 2 chromosomes from a population and it results into new chromosome which exhibit different characteristics. There are different crossover operators in literature such as, single-point and uniform crossover.
- Mutation: It is the process of application of random modifications to a chromosome for producing improved offspring.

NSGA-II has been applied to different problems such as, work balancing problems and supply chain integration problems [21]. One of the advantages in using it is that the problem does not need to be expressed mathematically. The only requirement is to have an 'objective function' or 'fitness function' that can be evaluated numerically [22]. The pseudocode of NSGA-II algorithm is provided in Fig. 5.

NSGA-II Pseudocode

Input: $N^{''}$, g, $f_k(X)$> $N^{''}$ members evolved g generations to solve $f_k(X)$
Initialize Population $p^{''}$;
Generate random population- size $N^{''}$;
Evaluate Objective values;
Assign Rank (level) based on Pareto- *sort*;
Generate Child Population;
  Binary Tournament Selection;
  Recombination and Mutation;
for i= 1 to g **do**
  for *each parent and child in population* **do**
    Assign Rank (level) based on Pareto- *sort*;
    Generate sets of non-dominated solutions;
    Determine Crowding distance;
    Loop ; next solution starting from the first front until $N^{''}$ individuals;
  end
  Select points on the lower front with high crowding distance;
  Create next generation;
    Binary tournament selection;
    Recombination and mutation;
end

Fig. 5: Pseudocode of NSGA-II.

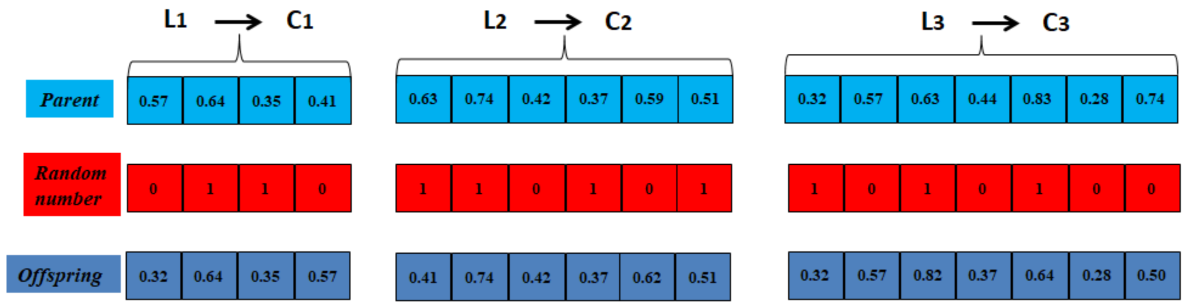

Fig. 6: Parent, offspring and random number assignment.

An example of the selected NSGA-II approach is demonstrated through Fig. 6 where a variant has been selected from each layout. In particular, we have selected first variant from the first layout, second variant from the second layout and last variant from the third layout. The row representing parent contains the number of machines in each layout such as, there are four (4), six (6) and seven (7) machines respectively, in the first, second and last variant. A real value between 0-1 is assigned to each of the parent member i.e. machine and correspondingly a random number (0/1) is associated to each member. The resulted off-springs after the crossover are provided in the last row. These results can be refined through multiple generations of mutation operator. As shown in Table 2, the considered population size is 40 and number of generations is 70. The selected operator is a binary number and probability values of crossover and mutation are 0.7 and 0.3, respectively.

Table 2: NSGA-II design parameters.

Design Parameter	Assigned value
Size of population	40
Generations specification	70
Selection operator	Binary
Probability of cross-over	0.7
Probability of mutation	0.3

3.2 TOPSIS

The Technique for Order of Preference by Similarity to Ideal Situation (TOPSIS) is a frequently used ranking tool and it has been discussed in literature as a Multi-Criteria Decision Making (MCDM) approach. It was introduced for the first time by Hwang et al. [23] to solve problems requiring selection of optimal result from given Pareto fronts. Its application can be found in supply chain resilience and risk management [24], renewable energy analysis for electricity production [25] and artificial intelligence based product failure analysis [26].

The logic behind its application is to select an alternate on the basis of minimum distance from positive ideal solution and maximum distance from negative ideal solution. The positive solution is based on maximization of benefits (such as values and profit) while negative solution enhances the cost and minimizes the beneficial outcome. To summarize, the positive-ideal solution is composed of all best values attainable of criteria, and the negative-ideal solution consists of all the worst values attainable of criteria. A single value based integration of performance criteria is made to implement in a diverse optimization environment. Various performance ratings are assigned on the basis of weights allocation to alternatives [27].

A matrix is used by TOPSIS for comparing pairs of elements and relative priorities are assigned to each pair, as shown in the matrix below.

$$\begin{bmatrix} l_{11} & l_{12} & l_{1t} \\ l_{21} & l_{22} & l_{2t} \\ l_{z1} & l_{z2} & l_{zt} \end{bmatrix}$$

Where,

ℓ_{ij}; $i = 1, \ldots .. z$; $j = 1, \ldots .. t$; F_j; $j = 1, \ldots \ldots, t$ represents the fuzzy numbers;

$$\ell_{ij} = (k_{ij}, l_{ij}, m_{ij}) \tag{1}$$

$$F_j = (k_{j1}, l_{j2}, m_{j3}) \tag{2}$$

$$F = [F_1 \;\; F_2 \ldots\ldots F_t] \tag{3}$$

The normalized matrix N is represented by;

$$N = [r_{ij}]_{z\times t} \tag{4}$$

The decision matrix, on the basis of weighted normalized fuzzy criteria, is provided by;

$$V = \begin{bmatrix} V_{11} & V_{12} & \cdots & V_{1t} \\ V_{21} & V_{22} & \cdots & V_{2t} \\ \vdots & \vdots & & \vdots \\ V_{z1} & V_{z2} & \cdots & V_{zt} \end{bmatrix} = \begin{bmatrix} F_1 r_{11} & F_2 r_{12} & \cdots & F_t r_{1t} \\ F_1 r_{21} & F_2 r_{22} & \cdots & F_t r_{2t} \\ \vdots & \vdots & & \vdots \\ F_1 r_{z1} & F_2 r_{z2} & \cdots & F_t r_{zt} \end{bmatrix}$$

The process flow of TOPSIS is explained through Fig. 7 which starts with identification of the problem such as, to select optimal solution from Pareto-fronts provided by NSGA-II. The second step is to determine alternates such as, layouts, variants and operation precedence. A criterion is then outlined on the basis of subjective assignment of different weights. Finally, the solution alternates are ranked as a result of implementing TOPSIS.

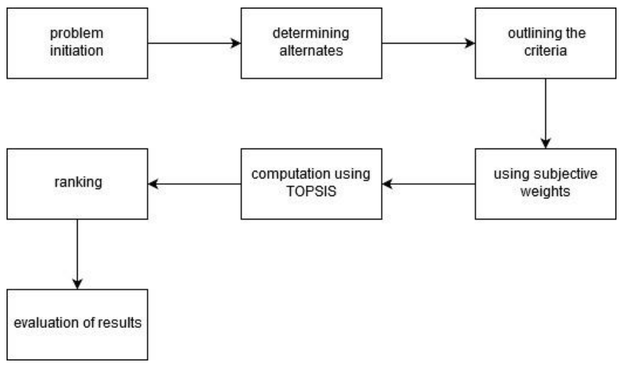

Fig. 7: Process flow of TOPSIS.

4. Results and Discussion

As discussed in the previous sections, main objective of current study is to select a layout which provides optimal values of cost, time and productivity. Initially, NSGA-II was applied using binary coder to ascertain Pareto-optimal values for defined objectives. Table 3 contains the result of genetic algorithm for different feature precedence and machine orders. As can be observed, a global solution cannot be attained which provides optimal value against all three indices of cost, process time and number of products. For instance, minimal cost value is $5842 which is against the first variant of serial production layout, however, process time and number of product values are not optimal in this case. The process time value is minimum for the case of first variant of parallel layout as it has more machines and hence a high throughput results in less process time. It does not, however, provide an optimal value of productivity and rather the highest production quantity is 136 which is against first variant of tubular layout.

It can be observed that if minimal cost values are chosen, they will represent local optimal, instead of holistic/global solution. A solution will provide global optimal value of one variable with sub-optimal values of other variables. It is clearly a case of conflict where a trade-off decision can be made only. In order to avoid such circumstances, we call all solutions as Pareto-fronts and thereby consider TOPSIS to provide the ranked solutions. The ranked solutions will assist decision maker to select the best compromise. The weighting criteria is defined in Table 4 for order preferences and three weights, Low (L), Medium (M) and High (H) have been identified with set scores and alternate scores represented as the vertices of a triangle. The alternate scores have been multiplied by 10 to magnify the initial set values.

Table 3: NSGA-II results against objective functions.

Feature precedence	Machine order	{cost, total. time}	Productivity
F_{01}- F_{02}- F_{03}- F_{04}- F_{05}	m_1- m_2- m_3- m_4	{5842, 376}	112
F_{01}- F_{03}- F_{04}- F_{02}- F_{05}	m_4- m_3- m_1- m_2	{6102, 348}	95
F_{03}- F_{05}- F_{02}- F_{04}- F_{01}	m_1- m_4- m_2- m_3	{5978, 416}	104
F_{04}- F_{05}- F_{01}- F_{02}- F_{03}	m_3- m_4- m_5- m_1- m_2- m_6	{7344, 292}	84
F_{05}- F_{03}- F_{01}- F_{02}- F_{04}	m_2- m_3- m_4- m_6- m_1- m_5	{6788, 345}	109
F_{02}- F_{01}- F_{03}- F_{04}- F_{05}	m_6- m_1- m_2- m_4- m_3- m_5	{5964, 366}	98
F_{04}- F_{02}- F_{03}- F_{01}- F_{05}	m_1- m_6- m_3- m_4- m_7- m_2- m_5	{8671, 408}	136
F_{01}- F_{05}- F_{02}- F_{04}- F_{03}	m_3- m_2- m_7- m_5- m_6- m_4- m_1	{7298, 388}	117
F_{05}- F_{02}- F_{03}- F_{04}- F_{01}	m_7- m_1- m_4- m_2- m_3- m_5- m_6	{6346, 320}	104

Table 4: Weighting criteria.

Weights	Set value	Alternate scores
Low (L)	(0,0,0.1)	(0,0, 1)
Medium (M)	(0.5,0.6,0.8)	(5,6,8)
High (H)	(0.6,0.8, 1)	(6,8, 10)

Table 5: TOPSIS scores and ranking result.

Layout	Conf.	Alt. values	Fuzzy matrix	Normalized score	Weighted score	# Ranking
L_1	CO_1	H	(6,8,10)	(0.6,0.8, 1)	(0.36,0.47,1)	2
	CO_2	L	(0,0,1)	(0,0,0.1)	(0.6,0.6,0.27)	5
	CO_3	M	(5,6,8)	(0.5,0.6,0.8)	(0.25,0.36,0.47)	6
L_2	CO_1	M	(5,6,8)	(0.5,0.6,0.8)	(0.25,0.36,0.47)	7
	CO_2	H	(6,8,10)	(0.6,0.8, 1)	(0.54,0.63,1)	1
	CO_3	M	(5,6,8)	(0.5,0.6,0.8)	(0.25,0.36,0.47)	9
L_3	CO_1	L	(0,0,1)	(0,0,0.1)	(0.6,0.6,0.27)	3
	CO_2	H	(6,8,10)	(0.6,0.8, 1)	(0.36,0.47,1)	4
	CO_3	L	(0,0,1)	(0,0,0.1)	(0.6,0.6,0.27)	8

The computation results of TOPSIS ranking on the basis of subjective weights assignment are provided in Table 5. The last column provides ranking of variants according to weighted scores. For instance, the second variant of parallel layout with alternate value assigned as high (H) has been ranked one (1).

The Fig. 8 provides three dimensional results of cost, time and number of products. There are multiple candidates for local optima in two-dimensional space whereas aim of the study was to identify the global optimal in a three-dimensional space (cost, time and productivity) starting from implementing genetic algorithm followed by TOPSIS ranking criteria. The objective function values have been multiplied with a big number M to make the graph leagible.

5. Conclusions

The production systems are constantly urged to be more sustainable in their approaches due to scarcity of resources. This study considered the problem of space utilization and layout; the analysis was performed using different combination of machines and order of operations. A multi-objective assessment was conducted for optimizing cost, process time and productivity. The combinatorial problem was solved using non-sorting genetic algorithm (NSGA-II) and the non-dominated solutions were ranked using TOPSIS.

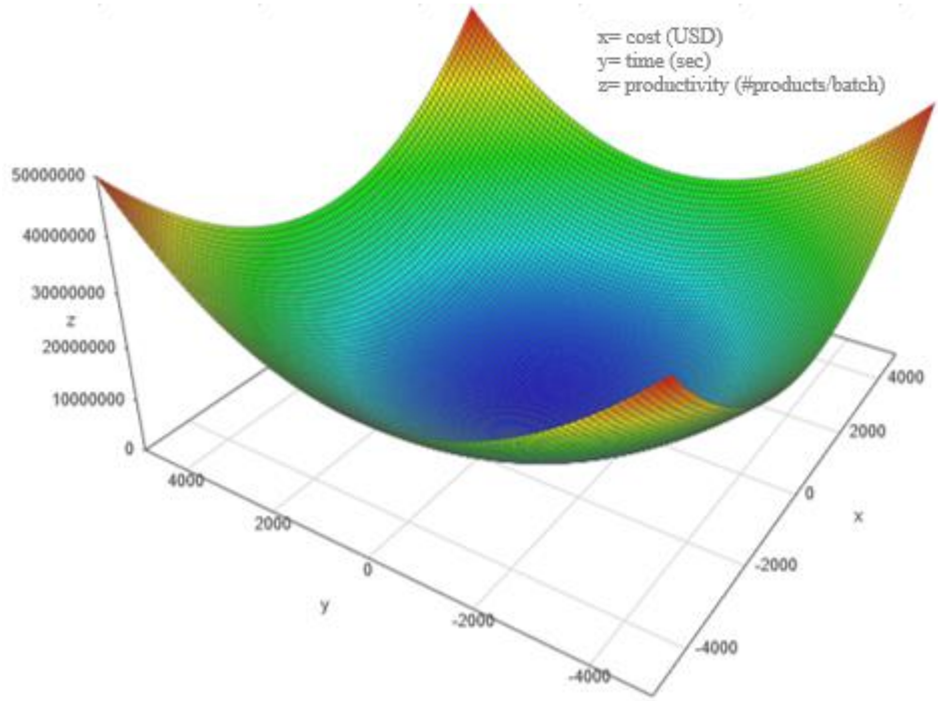

Fig. 8: Results for cost (x), time (y) and productivity (z).

The study contains following limitations. The time between changing layouts was assumed zero which is not possible to sustain in real environments. Similarly, push production strategy was considered which means that production is irrespective of demand. Future study can model this problem considering fixed or dynamic demand environment. Similarly, in all layouts, different number of machines were used. Intuitively, different number of machines will require different number of operators which can potentially affect the objectives such as, cost and completion time. Although the number of operators was not accounted for in current study, it can be taken into consideration as operators directly impacts cost, productivity and process time in each layout. Lastly, future studies can compare the findings by using other algorithms such as, ant colony optimization and multi-objective particle swarm optimization.

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