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Minimizing makespan and flowtime in a parallel multi-stage cellular manufacturing company

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ABSTRACT

This study proposes a 3-phase solution approach for a multi-product parallel multi-stage cellular manufacturing company. The study focuses on a case study involving a shoe manufacturing plant in which products are produced according to their due dates. The investigated manufacturing process has three stages, namely lasting cells, rotary injection molding cells, finishing-packaging cells. System performance is measured based on total flowtime and makespan. We propose a 3-phase solution approach to tackle the problem; 1) the first phase of the proposed approach allocates manpower to operations in the lasting cells and finishing-packaging cells, independently. The objective is to maximize the production rates in these cells. 2) The second phase includes cell loading to determine product families based on a similarity coefficient using mathematical modeling and genetic algorithms (GA). The proposed GA algorithm for cell loading performs mutation prior to crossover, breaking from traditional genetic algorithm flow. The performance measures flow time and makespan are considered in this phase. 3) Flow shop scheduling is then performed to determine the product sequence in each (lasting, rotary injection molding, finishing-packaging) cell group. This 3-phase solution approached is repeated with alternative manpower level allocation to lasting and finishing-packaging cells where the total manpower level remains the same.

1. Introduction

The group technology (GT) philosophy focuses on bringing similar parts together through development of group scheduling and cellular manufacturing systems [1–3]. The cellular manufacturing system, developed as an alternative production approach that aims to combine the productivity advantages of mass production with the flexibility afforded by workshop-style production, employs different algorithms to group machines according to the similarities of parts. Production cells combine a machine, a material handling system, and a central control unit that manages them. Parts are classified into families based on similarities. These similarities can be features of the parts or processes required for the production of the part [4]. The goal of using GT concepts is to reduce non-value adding processes such as material handling, set-ups, and inventory [5]. Cellular manufacturing systems utilize group technology to form manufacturing cells. In a manufacturing system, a group technology philosophy is used to create manufacturing cell-part family pairs. This creates manufacturing cells with a small number of machines on which similar parts are processed to obtain certain benefits [6]. The benefits of cellular manufacturing systems can be summarized as follows: reductions in move distances/move times, lead times, response times to customer orders, work-in-process inventory, set-up times, finished goods inventory, and unit costs; improvements in part/product quality have also been cited [7,8].

This study focuses on a multi-stage cellular system where products cannot be completed in a single cell and instead they are processed on serially connected multiple cells due to nature of the manufacturing process. One of the main reasons is that too many operations are required to complete the product in just one cell. Furthermore, there is interruption in the flow of products from unit transfer in the cells to injection molding where process takes relatively longer time and batch processing occurs. This complicates the cellular control issues where not only cell loading and cell scheduling are necessary, but also balancing work force allocation in the serially formed manufacturing cells become important.

In the global supply chain, customer satisfaction levels are a very important point in the sustainability of a sector. This study analyzes a shoe manufacturing company that produces different volumes and

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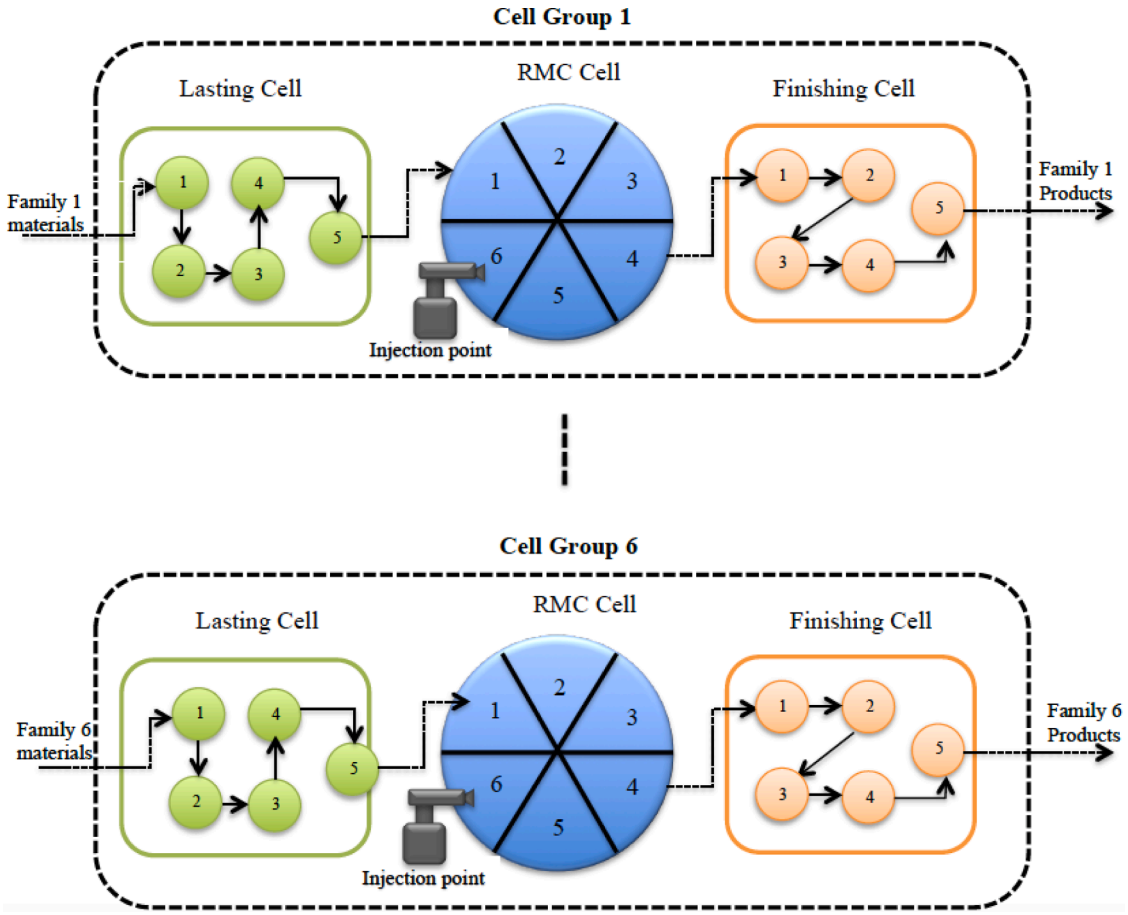


Fig. 1. Cell groups and configurations.

varieties of shoes for the market. The objective of the manufacturing company is to meet the scheduling and quality demands of the shoe sector while minimizing costs as much as possible; because of the large number of manufacturers and brands available in the sector, competition is intense. This company produces shoes in a variety of designs, colors, and materials. Each customer orders different models of shoes, each model in turn having different sole types [full shot (FS) and midsole (MS)], wearer gender, materials, colors, and sizes. The manufacturing company has six cell groups that each consist of a lasting cell group (LC), a rotary injection molding cell group (RMC), and a finishing and packaging cell group (FC). In the LC, shoes are prepared for rotary injection moulding in the RMC. The LC consists of sequential processes that are similar for all sole designs and shoe sizes. From the LC, shoes are transferred to the RMC, which has six pairs of stations, each of which can process one pair of shoes at a time. After injection moulding in the RMC, the shoes go to the FC, where extra material is removed from the shoe; afterwards, the shoes are finished and packed. The cell groups and configurations are explained in Fig. 1.

This is the first study that combines cell loading and flowshop scheduling in a multi-stage cellular manufacturing environment. First, products are assigned to cells considering available capacity during cell loading phase. Later, in the cell scheduling phase flowshop scheduling approach is used to consider multi-stage configuration of each cell. Furthermore, even though the total manpower for each cell is fixed, the allocation of manpower to two stages is not and therefore has to be evaluated as part of the overall scheduling system. All these characteristics make this scheduling problem very unique and also complicated. The allocation of manpower to stages affects the output rate from each stage and thus affect the processing times used in cell loading and flowshop scheduling. In short two different scheduling problems (cell loading and cell scheduling) and manpower allocation decisions are addressed simultaneously in this study.

The remainder of this paper is organized as follows: First, a literature review is presented. Second, the problem statement and formulation are defined, and all three phases are explained. In addition, a genetic algorithm (GA) based approach is developed to solve the cell loading problem. Next section describes a case study designed to demonstrate how the proposed methodology is applied. Finally, conclusions and recommendations for future research are provided.

2. Review of current literature

In this paper, a three-phase manufacturing cell loading and manpower allocation problem for a multi-stage cellular structure is proposed. Süer et al. [9] extended cellular control research to multi-cell environments, which necessitates cell loading considerations. Aktürk and Wilson [10] applied cell loading problem by using aggregate production planning. Babayiğit [11] used a mathematical model and genetic algorithm to solve the problems of manpower allocation and cell loading, further extending previous works by Süer [12]. In Babayiğit's thesis, the research focused on single stage cells and models were developed to minimize the number of tardy jobs. Various different GA approaches were developed and tested. Data was generated theoretically and there was no case study involved.

Süer et al. [13] developed a mathematical model to decide the manpower level by minimizing makespan. This is also a multi-phase study where the focus is on cell loading in a multi-cell environment and then determining the product sequence in each cell. The first phase also starts with the optimal manpower allocation to operations in a cell. The cells are however single-stage cells and the overall objective of the

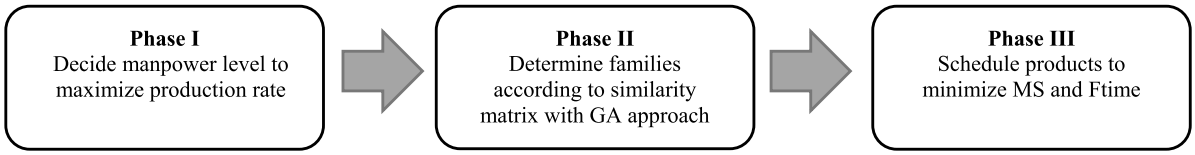


Fig. 2. Mathematical model application sequence.

study is to minimize intra-cell manpower transfers to smooth the operations and simplify control issues in the cells. Stnha and Hollier [14] determined that a desired level of throughput and optimum work-in-progress in a cell can be achieved through sequencing, reduced batch size, and period batch control. Gupta and Ho [15] solved the problem of scheduling jobs on two identical machines. The authors described an optimal schedule to minimize the makespan with subject to minimum total flowtimes. Gharbi and Haouari [16] considered the identical parallel machine scheduling problem to minimize makespan with constraints of release dates and delivery times.

Min and Cheng [17] developed a genetic algorithm to minimize makespan in identical machine scheduling problems. Chaudhry [18] used genetic algorithm approach to minimize total flowtime for identical parallel machines and to determine worker assignment. Huang et al. [19] considered a sequential genetic algorithm to find a schedule that minimizes makespan. Selen and Hott [20] determined mixed integer goal programming with the objective of minimizing makespan and total flowtime to solve m-machine flowshop-scheduling problems. Framinan et al. [21] developed a heuristic procedure to provide the decision maker with a good solution with respect to the objectives of makespan and flowtime minimization. Damodaran [22] solved scheduling problem with a batch-processing machine to minimize its makespan or completion time of the last batch of jobs by using simulated annealing approach. Manjeshwar et al. [23] also used simulated annealing approach to solve flow shop scheduling problem. Giannopoulos et al. [24] solved multi-objective flowshop-scheduling problems with the goal of minimizing makespan, maximum tardiness, and total flowtime.

Süer et al. [25] considered a three-phase methodology to perform cell loading and scheduling in a shoe manufacturing company. This research used three family definitions (sub-families, families, and superfamilies) in the cell loading process. These families allow the number of set-ups to be minimized. This paper focuses on cell loading and family scheduling issues in the same shoe manufacturing plant. However, manpower levels in lasting and finishing-packaging cells were assumed constant and therefore they were not considered as a factor in the solution methodology. Similarly, multi-stage connected cells were conveniently ignored. The performance measure was minimizing the maximum tardiness of jobs. This paper focuses on family sequencing and family splitting issues and particularly when jobs in the same family have different due dates. The tradeoff between individual due dates and running the products in the same family all together is investigated. Chang et al. [26] described a simulated annealing approach to minimize makespan in identical parallel batch-processing machines. Saraçoğlu and Süer [27] considered two objectives to minimize the total flow time and the makespan in order to generate non-dominated solution by using fuzzy mixed integer programming modeling. The minimization of makespan in the permutation flowshop scheduling problem with a position-based learning effect is considered by Muştu and Eren [28]. Gupta and Ruiz-Torres [29] sought to schedule n jobs on m identical machines in a way that minimized makespan, given that flow time was already minimized. This problem is an example of hierarchical multiple criteria scheduling. The authors proposed a heuristic and evaluated it against existing heuristics. Süer et al. [30] studied multi-objective scheduling problem considering three objectives, number of tardy jobs, total manpower, and average flow time. Saad et al. [31] proposed a multiple objective optimization technique to load and schedule cellular manufacturing systems by using goal programming formulation. Min et al. [32] developed multi-objective flow shop scheduling model with makespan and energy consumption by considering transportation constraint.

Three mathematical models are used to define and analyze the manufacturing system described in this paper. The first model seeks to allocate manpower in order to independently maximize the production rates in manufacturing cells. A similarity matrix is developed to describe the similarity between the various products based on the worker allocation levels acquired in the first model. This matrix is then used in the second model to perform cell loading to maximize the similarity of products in each cell. With production rates and part families defined in the first two models, the third model is used to schedule the products in their cells using the flow shop scheduling approach. A GA approach is developed for the cell loading phase.

3. Problem statement

The authors focus on a shoe manufacturing company that produces shoes in a variety of designs, sizes, and colors, using a variety of materials. There are parallel multi-stage cell groups and multi-processes in each cell.

The authors make the following assumptions in mathematically expressing our multi-product multi-stage manpower allocation, cell loading, and sequencing problem:

- There are two types of soles: FS and MS.
- All processing times are known and deterministic.
- There are multiple stages: LC, RMC, and FC.
- Set-up time is not allowed.
- All materials are ready in the beginning of the planning period. The ready time is zero.
- Demand data are known and deterministic.

Three phases are used to describe and evaluate this manufacturing system problem. The first phase decides the manpower allocation in the first cell and last cell and uses five sequential operations to maximize the production rate. In the second phase, a similarity coefficient matrix is calculated according to the manpower levels obtained in Phase I. In the same phase, a GA approach is applied to cell loading, using similar families in each cell group to maximize the utilization in each cell group. After all these decisions, in the third phase products are sequenced to minimize the makespan and flowtime separately. The structure used in this study is summarized in Fig. 2.

4. Solution methodology

4.1. Phase I: Manpower allocation

The problem is to formulate a model that maximizes the total production rate with constraints of worker levels and the operation times for each cell. The following notations are used to derive the integer linear programming (ILP) formulation of the proposed multi-product multi-stage cell loading problem developed by Süer et al. [13] is used in this study. The objective of this mathematical model is to optimally allocate manpower to maximize production rates. This model is run for each product at the various worker levels in the LC and FC. Eq. (1) shows

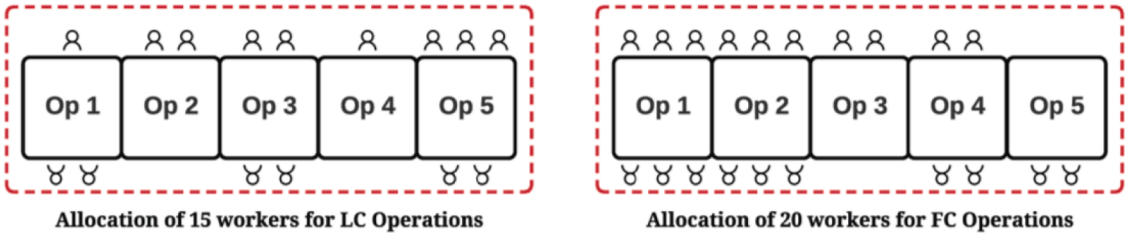


Fig. 3. Allocation manpower level for LC and FC operations.

the objective function of the mathematical model, which is to maximize the output rate. The relationship between the number of workers at station and the production rate is determined in Eq. (2). This relationship ensures that enough workers are assigned to each station to meet the desired output rate. An upper limit on the number of workers allowed for a station is established in Eq. (3). Eq. (4) ensures that the number of workers assigned to stations does not exceed the total number of workers in the system. Eq. (5) ensures the integer restrictions for the variables.

Index:

j :	Operation index

Parameters:

t_j :	Unit operation time for operation j.
U_j :	Maximum number of operators available for operation j.
W :	Total number of workers available.
s :	Number of operations.

Decision Variables:

R :	Production rate.
m_j :	Number of operators assigned for operation j.

Objective Function:

$$Maximize\ Z = R \tag{1}$$

Subject to:

$$m_j\left(1 \,/\, t_j\right) - R \geq 0\ \forall j \tag{2}$$

$$m_j \leq U_j\ \forall j \tag{3}$$

$$\sum_{j=1}^{s} m_j \leq W\ \forall j \tag{4}$$

$$m_j \in \{0,1\}\ \forall j \tag{5}$$

According to the mathematical model, allocation manpower level is decided for each product, as an example the manpower level for 15 workers in LC operations and 20 workers in FC operations are shown in Fig. 3.

4.2. Phase II: Cell loading

4.2.1. Mathematical model for cell loading

This mathematical model assigns products to cells in order to maximize the similarity among products in the cells and to minimize the number of cells opened. Capacity restrictions ensure that cell utilization will not exceed 100%, and the number of opened cells is minimized by introducing a penalty to the objective function for each opened cell. Kusiak [33] developed p-median mathematical model used to identify product families and then cells are created accordingly. The similarity coefficient used in this model is calculated based on the machine-level-based similarity coefficient between products i and k ($SC_{i,k}$) and operations s developed by Süer and Ortega [34] and used in a study generated by Gannon and Süer [35]. Eq. (6) shows the formula used in the calculation of the similarity coefficient.

$$SC_{i,k} = \frac{\sum_{j=1}^{s} \min\left(m_{i,j}, m_{k,j}\right)}{\sum_{j=1}^{s} \max\left(m_{i,j}, m_{k,j}\right)}\ j = 1, \ldots, s,\ \forall i,\ \forall k \tag{6}$$

The objective, shown in Eq. (7), maximizes the similarity of products within cells, while enforcing a penalty for opening additional cells. The constraints expressed in Eqs. (8) and (9) require the utilization in each opened LC or FC to be no greater than 100%. Eq. (10) ensures that each product is assigned to a cell. Products cannot be assigned to a cell that has not already been opened. This constraint is enforced by Eq. (11). Eq. (12) ensures that the integer restrictions for all variables are used in the model.

Sets and Indices:

N :	Number of products, $i = 1, \ldots, N, k = 1, \ldots, N$

Parameters:

$SC_{i,k}$:	Similarity coefficient between product i and k.
u_i :	Capacity requirements for product i in cell 1.
w_i :	Capacity requirements for product i in cell 2.
p :	Penalty factor for opening a new cell.

Decision Variables:

x_{ik}: 1 if product i belongs to family k, 0 otherwise.

Objective Function:

$$Maximize\ Z = \sum_{i=1}^{n} \sum_{k=1}^{n} \left(SC_{i,k} x_{i,k}\right) - \sum_{k=1}^{n} \left(p x_{k,k}\right) \tag{7}$$

Subject to:

$$\sum_{i=1}^{n} u_i x_{i,k} \leq 1\ \forall k \tag{8}$$

$$\sum_{i=1}^{n} w_i x_{i,k} \leq 1\ \forall k \tag{9}$$

$$\sum_{k=1}^{n} x_{i,k} = 1\ \forall i \tag{10}$$

$$x_{i,k} \leq x_{k,k}\ \forall i,k \tag{11}$$

$$x_{i,k} \in \{0,1\}\ \text{for}\ \forall i,k \tag{12}$$

4.2.2. Proposed genetic algorithm approach for cell loading

A GA approach for cell loading is proposed in this section. GA is a stochastic search method proposed by Holland [36] that simulates the development process of biological systems based on Darwin's 'survival of the fittest' principle. The developed GA approach is used for cell loading in Phase II that is similar to the methodology used in a study performed by Gannon and Süer [35]. The chromosome initially is created by randomly ordering the products. The cells are then loaded

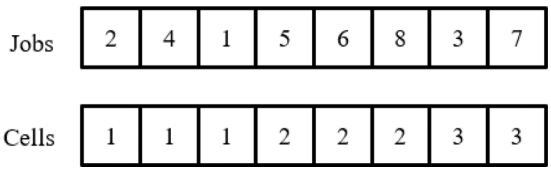


Fig. 4. Chromosome structure.

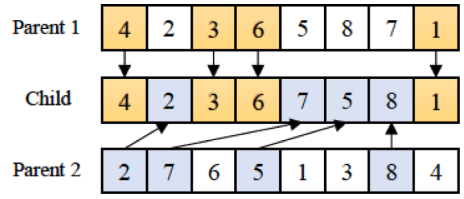


Fig. 5. Position-based crossover operator.

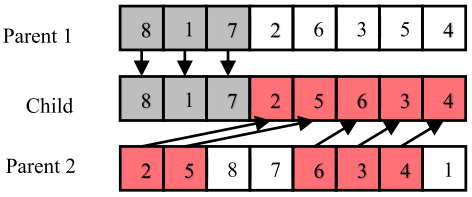


Fig. 6. Order-based crossover operator.

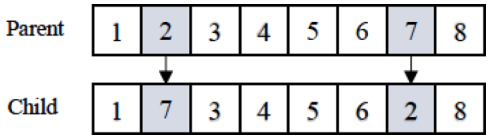


Fig. 7. Mutation operator.

sequentially from the randomly ordered list. When the utilization in either the LC or FC exceeds a maximum allowed utilization, that cell is closed, and the next cell is opened. This continues until all products are assigned to a cell. An example of the chromosome representation is shown in Fig. 4. The fitness function is calculated using Eq. (13), which is shown again below.

Order-based crossover is performed by selecting a string of genes from one parent and passing the string onto the child chromosome. The remaining genes are then filled in the order they appear in the other parent chromosome. Position-based crossover is performed by selecting a set of positions at random from one parent chromosome and passing the values at these positions to the child. The missing genes are then selected and filled in the child chromosome in the order they appear in the other parent chromosome. Examples of position-based crossover and order-based crossover are shown in Fig. 5 and Fig. 6. The arrows show how genes are passed from the parent chromosome to the child chromosome.

$$Fitness\ function = \sum_{i=1}^{n}\sum_{k=1}^{n}\left(SC_{i,k}x_{i,k}\right) - \sum_{k=1}^{n}\left(px_{k,k}\right) \tag{13}$$

The mutation strategy employed in this study is reciprocal exchange mutation, which is performed by using random numbers to select two positions in the chromosome and then swapping the values in these positions. An example of this mutation strategy is shown in Fig. 7. After crossover and mutation have been performed, products are reassigned to cells in the same manner as the original chromosome to ensure that the maximum utilizations are not exceeded. Selection involves selecting the top chromosomes from among the parent and child chromosomes to move onto the next generation.

This study also investigates the effect of performing mutation before crossover. Flow in classical GAs occurs by means of crossover before mutation. By reversing the traditional flow, it is possible that better parent chromosomes will be created and performing crossover with better parent chromosomes will result in improved offspring chromosomes. In this study, selection is performed by selecting the best ranked chromosomes from all the parent and offspring chromosomes for the next generation.

4.3. Phase III: Mathematical model for flow shop scheduling

The objective of this model is to schedule products in each cell group such that the selected performance measure is optimized. The objective is to complete the products so as to minimize either their makespan or flowtime. Let $ct_{i,j}$ be the time at which product j is completed in cell i. The makespan is the time of the last product completion in the last cell group, $max\{ct_{i,j}\}$, and the flowtime is the sum of the product completion times in the last cell group, $\sum_{j=1}^{n} ct_{i,j}$. Flow shop scheduling is conducted for each part family formed independently. Processing times for the rotary machine are determined based on the mold type, size, and gender of the intended wearer. This mathematical model is run independently for each family formed in the previous step.

The objective function is designed to minimize the makespan, and is given in Eq. (14). Constraint (15) establishes the relationship between the product's completion time and its makespan, ensuring that the makespan is equal to the completion time of the last product in the last cell group. Constraint (16) asserts that a product must finish processing in its current cell before it can begin in the following cell. In a similar manner, Constraint (17) ensures that a product must complete processing in the final cell before it can be labeled complete. The relationship between completion times, due dates, and tardiness is described in Constraint (18). Constraint (19) ensures that the total tardiness is equal to the summation of tardiness values of all products. According to the relations given in Constraint (20), if product j is processed before product k in cell i, then Constraint (21) is implied, if product j is not processed before product k in cell i. Constraints (22) and (23) ensure that the integer restrictions for all variables are used in the model. Constraint (24) specifies that all variables will be positive.

Sets and Indices:

C :	Number of cells, $i = 1,\ldots,C$
N :	Number of products, $j = 1,\ldots,N$, $k = 1,\ldots,N$

Parameters:

$p_{i,j}$:	Processing time of product j in cell i.
d_j :	Due date of product j.
$r_{i,j}$:	Ready time of product j in cell i.
ε :	A positive small number.
M :	A positive large number.

Decision variables:

$y_{i,j}$	Start time of product j in cell i.
$ct_{i,j}$	Completion time of product j in cell i.
t_j	Tardiness of product j.
tt	Total tardiness.
$z_{i,j,k}$	Binary variable: equal to one if the product j is processed before product k in cell i, and zero if the product j is not processed before product k in cell i.
MS	Makespan
$Ftime$	Total flowtime

Model I:

Objective Function:

$$min\ Z = MS \tag{14}$$

Subject to:

Table 1
Input data for Phase I.

Products	Type	Demand	LC Operations Time (min)					RMC time (min)	FC Operations Time (min)				
			1	2	3	4	5		1	2	3	4	5
1	FS	1863	1.41	1.36	0.76	0.65	0.39	0.33	0.44	0.41	1.49	0.54	1.15
2	MS	2147	0.8	0.78	0.85	0.76	0.59	0.27	1.23	1.1	0.32	0.63	1.17
3	FS	2291	0.79	1.45	1.13	1.98	0.53	0.33	1.07	0.43	0.91	1.21	1.12
4	FS	1328	0.31	0.54	2.79	0.66	0.95	0.33	0.77	0.99	0.95	1.47	0.33
5	FS	2300	1.26	0.43	1.39	1.28	1.4	0.33	0.58	0.68	1.49	0.28	0.4
6	FS	1627	0.73	0.57	1.04	0.78	0.94	0.33	2.18	0.43	0.42	1.72	0.23
7	MS	1389	0.57	0.78	1.23	0.19	0.36	0.27	0.6	0.44	1.12	0.81	1
8	FS	2010	0.43	1.42	1.07	0.25	0.79	0.33	1.64	2.05	0.7	0.31	2.55
9	FS	1601	0.87	0.61	1.04	0.87	0.68	0.33	0.48	0.59	0.26	0.15	0.41
10	MS	1409	1.98	0.62	1.25	1.25	0.8	0.27	1.39	2.1	0.62	0.63	1.17
11	MS	2271	1.38	1.86	1.24	0.6	0.34	0.27	0.7	0.88	1.3	1.4	0.6
12	FS	2259	1.68	1.38	0.55	1.21	0.81	0.33	0.86	1.09	1.65	0.25	0.25
13	MS	1680	1.65	2.12	0.73	0.34	1.53	0.27	0.99	1.05	0.89	0.67	1.24
14	MS	2021	0.89	1.25	0.81	1.69	0.32	0.27	0.99	1.46	3.1	1.57	2.05
15	FS	2036	1.15	1.24	1.24	0.48	1.12	0.33	0.23	1.21	0.93	0.37	0.7
16	MS	1919	1.01	0.96	0.79	0.21	1.68	0.27	0.52	0.66	0.68	0.7	0.79
17	MS	1495	0.38	0.25	0.58	0.16	0.76	0.27	0.87	0.79	0.17	0.44	0.27
18	MS	2032	0.59	0.7	0.87	0.85	0.94	0.27	0.22	1.36	1.29	1.69	0.32
19	MS	2005	0.37	0.48	1.18	0.81	1.39	0.27	0.97	1.47	0.23	1.01	1.88
20	FS	1446	1.87	1	2.9	0.41	0.24	0.33	0.78	0.38	0.95	0.49	0.96

$$ct_{i,j} \leq MS$$

$$i = C,\ \forall j \tag{15}$$

$$y_{i+1,j} - y_{i,j} \geq p_{i,j}$$

$$i = 1, \ldots,\ C,\ \forall j \backslash \{C\} \tag{16}$$

$$ct_{i,j} - y_{i,j} \geq p_{i,j}$$

$$i = 1, \ldots,\ C,\ \forall j \tag{17}$$

$$ct_{i,j} - t_j \leq d_j$$

$$i = C,\ \forall j \tag{18}$$

$$tt - \sum_{j=1}^{N} t_j = 0\ \forall j \tag{19}$$

$$M.z_{i,j,k} + \left(y_{i,j} - y_{i,k}\right) \geq p_{i,k}$$

$$i = 1, \ldots,\ C,\ j = 1, \ldots, N-1,\ \forall k \tag{20}$$

$$M.\left(1 - z_{i,j,k}\right) + \left(y_{i,k} - y_{i,j}\right) \geq p_{i,j}$$

$$i = 1, \ldots,\ C,\ j = 1, \ldots, N-1,\ \forall k \tag{21}$$

$$z_{i,j,k} \in \{0,1\}\ \forall i,j,k \tag{22}$$

$$w_j \in \{0,1\}\ \forall j \tag{23}$$

$$MS \geq 0,\ ct_{i,j} \geq 0\ for\ \forall i,j,\ y_{i,j} \geq 0\ for\ \forall i,j \tag{24}$$

Objective function (14) can be formulated again by adding total tardiness and total flowtime constraints in order to justify the total flowtime and total tardiness values. Objective function (25) ensures that the makespan is minimized and that flowtime is minimized simultaneously by adding an infinitesimally small number, ε. Constraint (26) is added after being defined in the mixed integer linear programming model (MILP). The small number, ε, is added to the objective function to ensure that the optimal solution has the minimal amount of total flowtime among solutions with optimal total tardiness.

Model II:

$$min\ Z = MS + \varepsilon.\ \sum_{j=1}^{N} t_j + \varepsilon.Ftime \tag{25}$$

Subject to:
Constraint sets (15)-(24) of the Model I

$$Ftime = \sum_{j=1}^{N} \left(ct_{i,j} - r_{i,j}\right) \tag{26}$$

In this study, two objective functions are applied to measure the performance of the manufacturing system. The makespan objective function is defined beforehand. The other objective function is designed to minimize the total flowtime that defines the total completion times of all products in the last cell. While makespan is calculated according to the maximum completion time of the last cell, flowtime is calculated according to the total of the completion times in the last cell. To minimize the total flowtime, the objective function is changed by using Eq. (27). Model II, which minimizes the total flowtime, is obtained by using objective function (27) and all the constraints (16) – (24) used in Model I.

$$min\ Z = Ftime + \varepsilon.\ \sum_{j=1}^{N} t_j \tag{27}$$

5. Case study of a shoe manufacturing company

The company analyzed in this study is a shoe manufacturing firm that produces different sizes and models of shoes. The manufacturing plant has six cell groups; each cell has three stages, and 20 products are processed in every stage. Each entry of a customer order becomes a job. All jobs are assumed to have the same due date at the end of the planning period. The planning period is organized as a weekly period that comprises 40 hours. The rotary machine cell (RMC) is the bottleneck of the manufacturing cell. The injection times for FS and MS are calculated as 0.33 min and 0.27 min, respectively.

In the first phase, the manpower allocation problem is solved by using the data given in Table 1. The worker allocation performed in this study assumes that 35 workers are available to be divided between the LC and FC for each cell group. The LC and FC both consist of five sequential manual operations requiring simple tools. Owing to the different shoe sizes and types, the processing times vary for the operations.

When workers are allocated to the LC or FC, they are also allocated to

Table 2
Manpower level and production rates for 15/20 manpower level.

Products	LC Operations manpower level					LC Production Rates (unit/ min)	FC Operations manpower level					FC Production Rates (unit/ min)
	1	2	3	4	5		1	2	3	4	5	
1	4	4	3	2	2	2.84	2	2	7	3	6	4.55
2	3	3	3	3	3	3.53	5	5	2	3	5	4.07
3	2	3	3	5	2	2.07	4	2	4	5	5	3.74
4	1	2	7	2	3	2.51	4	4	4	6	2	4.04
5	3	1	4	3	4	2.33	3	4	8	2	3	5.17
6	3	2	4	3	3	3.19	8	2	2	7	1	3.67
7	3	4	5	1	2	4.07	3	2	6	4	5	4.55
8	2	5	4	1	3	3.52	4	6	2	1	7	2.44
9	3	2	4	3	3	3.28	5	6	3	2	4	9.76
10	5	2	3	3	2	2.07	5	7	2	2	4	3.17
11	4	5	3	2	1	2.42	3	4	5	5	3	3.57
12	4	4	2	3	2	2.38	4	5	7	2	2	4.24
13	4	5	2	1	3	1.96	4	4	4	3	5	3.81
14	3	4	2	5	1	2.47	2	3	7	4	4	1.95
15	3	3	3	2	3	2.42	2	7	5	2	4	5.38
16	3	3	3	1	5	2.97	3	4	4	4	5	5.71
17	3	2	4	1	5	6.25	6	6	2	4	2	6.90
18	2	3	3	3	4	3.39	1	5	5	7	2	3.68
19	2	2	4	3	4	2.88	4	5	1	4	6	3.19
20	4	3	6	1	1	2.07	5	2	5	3	5	5.21

Table 3
Similarity matrix for 15/20 worker combination level.

Products	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1		.76	.67	.50	.58	.67	.76	.67	.67	.76	.88	.88	.76	.67	.81	.67	.58	.67	.58	.67
2			.76	.58	.76	.88	.67	.67	.88	.76	.67	.76	.67	.67	.93	.76	.67	.88	.76	.58
3				.50	.58	.67	.58	.58	.67	.67	.58	.67	.50	.76	.71	.58	.50	.76	.67	.50
4					.58	.67	.58	.58	.67	.50	.43	.43	.43	.36	.61	.50	.58	.58	.67	.58
5						.88	.58	.58	.88	.67	.50	.58	.50	.50	.71	.67	.76	.76	.88	.50
6							.67	.67	1.0	.76	.58	.67	.58	.58	.81	.67	.76	.76	.88	.58
7								.76	.67	.58	.67	.67	.67	.58	.71	.67	.67	.58	.58	.76
8									.67	.50	.67	.58	.76	.50	.71	.67	.67	.67	.67	.58
9										.76	.58	.67	.58	.58	.81	.67	.76	.76	.88	.58
10											.67	.76	.58	.58	.71	.58	.58	.67	.67	.58
11												.76	.76	.67	.71	.58	.50	.58	.50	.67
12													.76	.76	.71	.58	.50	.67	.58	.58
13														.58	.71	.67	.58	.58	.50	.58
14															.61	.50	.43	.58	.50	.50
15																.81	.71	.81	.71	.61
16																	.88	.76	.67	.58
17																		.67	.76	.58
18																			.88	.50
19																				.50
20																				

an operation within the cell. Because the processing times vary on these operations from shoe to shoe, the worker allocation to operations within the cell also varies from shoe to shoe. Six worker level combinations were evaluated: 15/20, 16/19, 17/18, 18/17, 19/16, and 20/15, where the first number represents the workers assigned to the LC and the second number represents the workers assigned to the FC. In the first model, $W = 35$ workers are specified for 15/20 configurations; for all operations, a maximum worker level of 15 is used for solving the manpower allocation problem. All three mathematical models and the GA are used to solve the problems of manpower allocation, cell loading, and flow shop scheduling for 20 products.

For all worker combinations and for all products, Phase I's model is run separately and then maximum production rates and manpower levels for each product are obtained. Table 2 shows the manpower level and production rates for LC and FC operations at the 15/20 worker level combination. Similarity coefficient matrices are calculated according to the results of the first phase. A similarity coefficient matrix is obtained separately for each of the six worker combinations. Table 3 shows the similarity matrix for 20 products at the 15/20 worker combination level. In Phase II, according to the similarity coefficient matrix, families are determined by using the GA described before in order to maximize the utilization for all cell groups.

5.1. Parameter optimization

The GA has two crossover strategies and the option to perform mutation before crossover. This creates four general strategies: order-based crossover before mutation (GA1), position-based crossover before mutation (GA2), order-based crossover after mutation (GA3), and position-based crossover after mutation (GA4). Within each of the four general strategies, ten combinations of crossover probability and mutation probability were tested. Five trials were performed for each crossover and mutation probability combination in each of the general strategies. The crossover/mutation combinations evaluated were 0.45/0.01, 0.45/05, 0.45/10, and 0.45/0.20. A Tukey test was done to compare all possible pairs of probability combinations and determine if a significant difference exists between the probability combinations. Both 0.45/0.10 and 0.45/0.20 produced significantly different results from 0.45/0.01, and 0.45/0.20 produced significantly different results from 0.45/0.05.

In addition to showing the part family assignments, GA strategies were carried out using MATLAB version 8.6 (R2015b) in a reasonable timeframe, employing all GA strategies shown in Table 4. Flow shop

Table 4
Phase II cell loading results for all manpower level and all models.

Worker Level	Model	Cell Loading					
		Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6
15/20	ILP	8,12,13	1,11,14	2,10,15	4,6,9,16,17	5,18,19	3,7,20
	GA1	8,19,9,2	20,7,3	15,13,16	11,14,1	10,6,17,5	18,12,4
	GA2	13,12,8	17,5,19,9	1,14,11	6,16,4,18	7,3,20	2,15,10
	GA3	12,8,13	10,15,2	16,9,17,4,6	14,1,11	3,20,7	18,19,5
	GA4	7,3,20	5,17,16,6	11,14,1	2,15,10	19,9,18,4	13,8,12
16/19	ILP	2,6,8,9	5,12	13,15,16	10,17,18,19	4,7,11,20	1,3,14
	GA1	7,20,11	3,14,1	12,18,4	2,6,9,8	5,10,17,19	16,15,13
	GA2	19,5,10,17	20,11,7	14,3,1	13,15,16	4,18,12	2,6,9,8
	GA3	13,15,16	20,4,11,7	17,18,19,10	14,3,1	5,12	2,8,6,9
	GA4	19,8,19,9	16,15,13	12,5	14,3,1	10,17,6,2	11,4,20,7
17/18	ILP	2,5,9	1,3,14	10,12,15	8,17,19	7,13,16,20	4,6,11,18
	GA1	12,13,11	20,7,10,16	14,3,1	15,6,4,18	9,2,5	19,17,8
	GA2	19,10,8,17	7,20,16	5,2,9	4,15,6,18	11,13,12	3,1,14
	GA3	1,14,3	8,17,19,10	18,15,6	5,9,2	16,7,20,4	12,11,13
	GA4	14,3,1	20,7,4,16	10,15,2	9,11,12	13,18,5	6,8,17,19
18/17	ILP	5,8,9,10	1,12,14	3,6,15,18	4,13,16,17,19	2,7,11,20	NO
	GA1	12,15,18,6	8,9,5,10	11,2,7,13,17	19,1,16,4	14,20,3	NO
	GA2	20,16,2,6,7	1,14,12	8,5,9,10	11,4,18,15	3,19,13,17	NO
	GA3	17,19,8	16,13,15	11,7,20,1	6,18,4,12	9,10,2,5	3,14
	GA4	1,13,2,16	20,14,3	9,11,17,19,4	18,10,6,12	7,5,15,8	NO
19/16	ILP	2,5,9,10	12,14	3,13,16	4,6,15,18	8,17,19	1,7,11,20
	GA1	13,8,12	2,9,5,10	6,19,17,16	3,14	18,15,11,4	1,20,7
	GA2	4,15,18,6	12,14	1,20,11,7	3,13,16	5,10,2,9	19,8,17
	GA3	9,10,2,5	11,15,18,4	12,13,8	16,17,19,6	14,3	20,7,1
	GA4	3,16,13	8,17,19	7,1,20,11	12,14	15,18,6,4	5,10,2,9
20/15	ILP	2,5,6,9	3,14	11,13,15,16	4,12,18	8,17,19	1,7,10,20
	GA1	1,7,11,20	17,8,19	9,5,2,10	13,3,16	18,6,4,15	14,12
	GA2	5,10,2,9	11,7,1,20	6,15,18,4	14,12	8,19,17	16,13,3
	GA3	7,1,12,20	13,11,16	14,3	4,18,15,6	8,17,19	10,2,5,9
	GA4	12,14	4,6,15,18	16,13,8	7,3,20,1	9,2,10,5	11,19,17

Table 5
Results for all models and objectives.

		Mspan objective				Ftime objective			
Model	Schedule	Mspan	Ftime	Status	Distance	Mspan	Ftime	Status	Distance
ILP	S1	57.75	177.12	Dominated	0.68	61.5	171.82	Dominated	0.74
	S2	56.9	171.59	Non-dominant	0.56	6.31	157.63	Dominated	0.44
	S3	57.74	169.97	Non-dominant	0.54	59.4	155.5	Dominated	0.37
	S4	61.42	193.77	Dominated	1.19	64.05	18.25	Dominated	0.99
	S5	58.4	168.47	Non-dominant	0.54	58.66	151.07	Non-dominant	0.28
	S6	64	18.9	Dominated	1.25	64	17.27	Dominated	0.82
GA1	S1	61.24	187.16	Dominated	1.06	64.16	187.16	Dominated	1.11
	S2	58.3	189.08	Non-dominant	0.93	6.31	171.59	Dominated	0.70
	S3	58.45	164.08	Non-dominant	0.46	61.59	152.55	Non-dominant	0.41
	S4	61.2	193.77	Dominated	1.17	62.67	182.09	Dominated	0.97
	S5	63.03	168.47	Dominated	0.99	63.03	161.57	Dominated	0.63
	S6	59.15	166.31	Dominated	0.55	59.15	153.47	Non-dominant	0.33
GA2	S1	57.39	162.58	Non-dominant	0.38	61.5	153	Dominated	0.41
	S2	58.3	189.08	Dominated	0.93	6.31	157.63	Dominated	0.44
	S3	58.45	164.08	Dominated	0.46	61.59	152.55	Dominated	0.41
	S4	59.94	193.77	Dominated	1.09	61.41	187.51	Dominated	1.03
	S5	58.4	168.47	Dominated	0.54	58.66	151.07	Non-dominant	0.28
	S6	59.15	166.31	Dominated	0.55	59.15	153.47	Dominated	0.33
GA3	S1	57.75	177.12	Dominated	0.68	61.5	171.82	Dominated	0.74
	S2	56.9	171.59	Non-dominant	0.56	6.31	157.63	Dominated	0.44
	S3	58.45	15.36	Non-dominant	0.25	61.59	141.1	Non-dominant	0.28
	S4	59.41	182.8	Dominated	0.86	6.01	156.84	Non-dominant	0.41
	S5	63.03	168.47	Dominated	0.99	69.52	161.57	Dominated	1.11
	S6	64	166.31	Dominated	1.10	64	153.47	Dominated	0.59
GA4	S1	57.39	165.98	Dominated	0.45	61.5	152.66	Dominated	0.41
	S2	56.9	182.66	Non-dominant	0.78	61.16	164.23	Dominated	0.59
	S3	57.02	143.79	Non-dominant	0.02	59.4	136.9	Non-dominant	0.07
	S4	59.8	191.54	Dominated	1.04	61.93	177.25	Dominated	0.85
	S5	58.4	168.47	Dominated	0.54	58.66	151.07	Non-dominant	0.28
	S6	59.15	166.31	Dominated	0.55	6.18	153.47	Dominated	0.36

scheduling is performed in Phase III. The scheduling mathematical model was executed for each part family in each worker combination level by using LINGO 17.60 on an Intel Core i7–4790 PC @3.60 GHz processor with 16.0 GB of RAM. All alternative models were applied to 20 products and six cell groups by separately using two objective functions, and makespan measurements, flowtime measurements, and product sequences were obtained. The results are shown in Table 5. All models were compared with each other to determine dominance in the

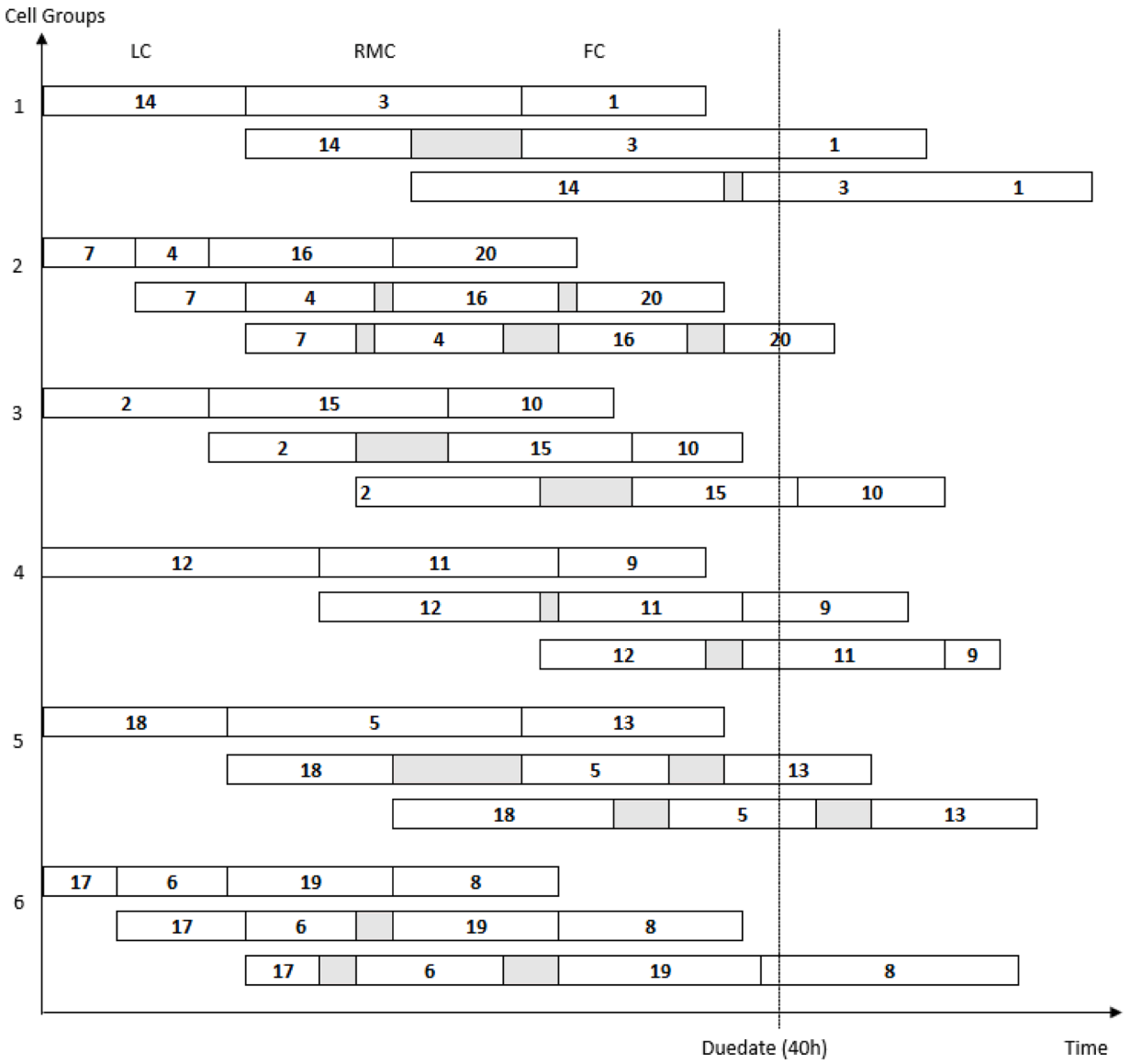


Fig. 8. Gantt Chart for scheduling solution with objective of makespan.

scheduling. There are three results in the non-dominated set, which includes S2, S3, and S5, according to the Mspan objective in the ILP model. On the other hand, S1, S4, and S6 results are shown in the dominated results. However, if the flowtime objective is used for the scheduling problem, only S5 shows as a non-dominated result. Thus, a decision must be made to determine which results should be used.

In this case, Euclidian distance is applied according to two performance measures and the best results [37,38]. In order to avoid any problem arising from the criteria scale differences, the authors normalize the values by using this formula for the ith scheduling solution: $S^N_{ijk} = (S_{ijk} - \min\{S_{ijk}\})/(\max\{S_{ijk}\} - \min\{S_{ijk}\})$, where S_{ijk} denotes the value of the jth objective function and kth performance measure, and $k = 1$ for makespan and $k = 2$ for flowtime. Euclidian distances are calculated by the following formula:

$$d_{ij} = \sqrt{\sum_{k=1}^{2} \left(S^N_{ijk} - min\left\{S^N_{ijk}\right\}\right)^2}$$

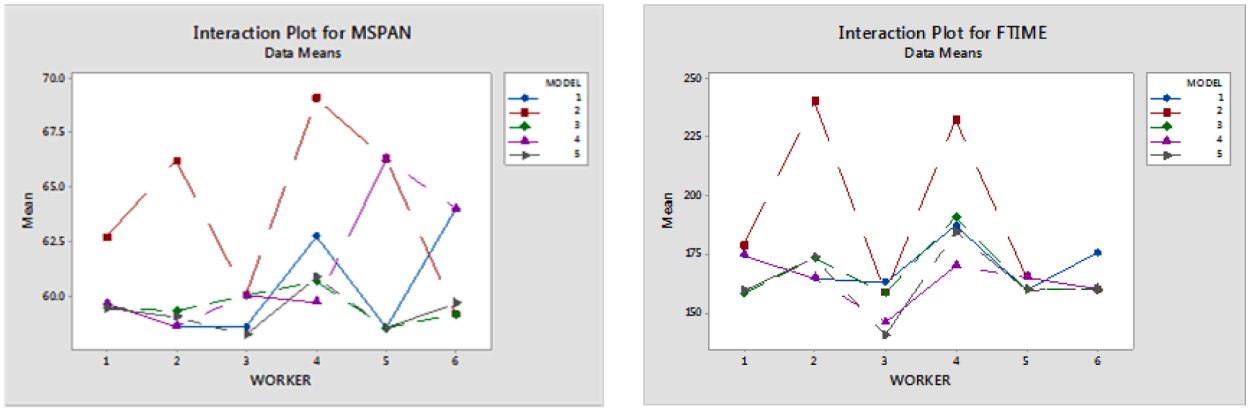
$$i = 1, \ldots, n,\ j = 1, \ldots, m \tag{29}$$

and the minimum distance, which is used to select best results, is given as

$$d^*_{ij} = min\left\{d_{ij} \mid i = 1, 2, \ldots, n\right\} \tag{30}$$

According to the distance values in Table 5, S5 has the minimum distance compared to the other non-dominated and dominated solutions, and was selected as the best solution in the ILP model. On the other hand, all the solutions obtained from all the models show that the best solution is composed of S3 scheduling based on the GA4 approach. In the shoe manufacturing company scheduling and loading problem, the products will be sequenced for six cell groups by using 17 workers for LC and 18 workers for FC, and using makespan objective function Model I {(14,3,1), (7,4,16,20), (2,15,10), (12,11,9), (18,5,3), (17,6,19,8)}. In this solution, the optimal makespan is 57.02, and the corresponding sum of flow times is 143.79. Eleven products will be tardy and the total tardiness and maximum tardiness values are 101.95 and 17.02, respectively. Gantt charts for the 20 products, six cell groups, and three stages are shown in Fig. 8.

Analysis of Variance (ANOVA) is conducted in order to explore the relative significance of individual factors in terms of their main effects on the objective function. At a significant level of 5%, worker level, objective function, and applied different models are effective on the



(a) (b)

Fig. 9. (a). Interaction plot for Makespan response for worker and models; (b). Interaction plot for Flowtime response for worker and models.

results of makespan and total flowtime. On the other hand, there is also interaction effect on the results by using worker level and models. The interaction plots in Fig. 9 (a-b) show the parameters' interaction effects on the makespan and flowtime results. As seen in Fig. 9, when the third worker level combination (17/18) was utilised, the best solution is found by using cell loading solutions of GA4 strategies in ILP.

6. Conclusion

In this study, the authors solved a real-life shoe manufacturing scheduling problem. The authors formulated a three-phase solution methodology to solve a multi-product parallel multi-stage cellular manufacturing system problem, with the objective of minimizing the makespan and flowtime. The first model allocates manpower to maximize the production rate in the lasting and packing cells independently. A similarity matrix between the various products was obtained based on the worker allocation levels acquired in the first model. In order to maximize the similarity of products in each cell, the second model was applied to allocate products. Four different GA approaches were developed for cell loading in Phase II. Different cell loading results were obtained from the GA approaches and the ILP model. All cell loading results were applied to find the scheduling that obtained the optimal makespan and flowtime response. The model and the solution technique were found to be an effective approach in solving cell loading and scheduling problems encountered in cellular manufacturing systems.

Cellular manufacturing continues to be important and relevant in the manufacturing industry today. Production activity has been only increasing in the world due to increasing population and wealth and buying power in every corner of the world. More countries are taking part in this economic development and competition is tough and widespread. In countries where labor-intensive manufacturing is dominant, the approach discussed in this paper can be extensively adapted and used to gain any economic advantage as a result of higher manpower utilization in cells. Other examples of industries can be listed as electromechanical industry, medical device industry, and bicycle industry.

In future research, this model can be further generalized to include a multi-objective programming model in order to consider all objectives in one model, and a Pareto approach to solve the non-dominant solution. All phases discussed in this paper can be solved simultaneously as well and we will attempt this in the future works. Because of the complexity and exponentially execution time for larger problems, meta-heuristics methods can also be considered for solving this problem in a reasonable time. In addition, the authors will develop a model with stochastic demand for all types of products. The authors also plan to validate our system by applying it to manufacturing systems problems through simulation.

Declaration of Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] P. Gu, A. Monid, Design of cellular manufacturing systems-An industrial case study, Robot. Comput. Integr. Manuf. 10 (1993) 147–151, https://doi.org/10.1016/0736-5845(93)90037-K.
[2] S.S. Heragu, Group Technology and Cellular Manufacturing, IEEE Trans. Syst. Man Cybern. 24 (1994) 203–215, https://doi.org/10.1109/21.281420.
[3] I. Mahdavi, B. Mahadevan, CLASS: an algorithm for cellular manufacturing system and layout design using sequence data, Robot. Comput. Integr. Manuf. 24 (2008) 488–497, https://doi.org/10.1016/j.rcim.2007.07.011.
[4] S. Lozano, D. Canca, F. Guerrero, J.M. García, Machine grouping using sequence-based similarity coefficients and neural networks, Robot. Comput. Integr. Manuf. 17 (2001) 399–404, https://doi.org/10.1016/S0736-5845(01)00015-1.
[5] R.G. Askin, C.R. Standridge, Modeling and analysis of manufacturing systems, Eur. J. Eng. Educ. (1994), https://doi.org/10.1080/03043799408928348.
[6] N. Hyer, U. Wemmerlov, Reorganizing the Factory: Competing through Cellular Manufacturing, Productivity Press, 2002.
[7] T.J. Greene, R.P. Sadowski, A review of cellular manufacturing assumptions, advantages and design techniques, J. Oper. Manag. 4 (1984) 85–97, https://doi.org/10.1016/0272-6963(84)90025-1.
[8] R.G. Askin, Contributions to the design and analysis of cellular manufacturing systems, Int. J. Prod. Res. 51 (2013) 6778–6787, https://doi.org/10.1080/00207543.2013.825745.
[9] G.A. Süer, M. Saiz, C. Dagli, W. Gonzalez, Manufacturing cell loading rules and algorithms for connected cells, Manuf. Res. Technol. 24 (1995) 97–127, https://doi.org/10.1016/S1572-4417(06)80038-0.
[10] M.S. Akturk, G.R. Wilson, A hierarchical model for the cell loading problem of cellular manufacturing systems, Int. J. Prod. Res. 36 (1998) 2005–2023, https://doi.org/10.1080/002075498193084.
[11] C. Babayigit, Genetic Algorithms and Mathematical Models in Manpower Allocation and Cell Loading Problem, 2003.
[12] G.A. Süer, I.S. Bera, Optimal operator assignment and cell loading when lot-splitting is allowed, Comput. Ind. Eng. 35 (1998) 431–434, https://doi.org/10.1016/s0360-8352(98)00126-0.
[13] G.A. Süer, J. Cosner, A. Patten, Models for cell loading and product sequencing in labor-intensive cells, Comput. Ind. Eng. 56 (2009) 97–105, https://doi.org/10.1016/j.cie.2008.04.002.
[14] R.K. Stnha, R.H. Hollier, A review of production control problems in cellular manufacture, Int. J. Prod. Res. 22 (1984) 773–789, https://doi.org/10.1080/00207548408942498.
[15] J.N.D. Gupta, J.C. Ho, Minimizing makespan subject to minimum flowtime on two identical parallel machines, Comput. Oper. Res. 28 (2001) 705–717, https://doi.org/10.1016/S0305-0548(99)00083-0.
[16] A. Gharbi, M. Haouari, Minimizing makespan on parallel machines subject to release dates and delivery times, J. Sched. 5 (2002) 329–355, https://doi.org/10.1002/jos.103.
[17] L. Min, W. Cheng, A genetic algorithm for minimizing the makespan in the case of scheduling identical parallel machines, Artif. Intell. Eng. 13 (1999) 399–403, https://doi.org/10.1016/S0954-1810(99)00021-7.

[18] I.A. Chaudhry, Minimizing flow time for the worker assignment problem in identical parallel machine models using GA, Int. J. Adv. Manuf. Technol. 48 (2010) 747–760, https://doi.org/10.1007/s00170-009-2323-1.
[19] J. Huang, G.A. Süer, S.B.R. Urs, Genetic algorithm for rotary machine scheduling with dependent processing times, J. Intell. Manuf. 23 (2012) 1931–1948, https://doi.org/10.1007/s10845-011-0521-9.
[20] W.J. Selen, D.D. Hott, A Mixed-Integer Goal-Programming Formulation of the Standard Flow-Shop Scheduling Problem Published by : Palgrave Macmillan Journals on behalf of the Operational Research Society Stable, 37, 1986, pp. 1121–1128. URL : http://www.jstor.org/stable/2582302. REFERENCES Linked reference.
[21] J.M. Framinan, R. Leisten, R. Ruiz-Usano, Efficient heuristics for flowshop sequencing with the objectives of makespan and flowtime minimisation, Eur. J. Oper. Res. 141 (2002) 559–569, https://doi.org/10.1016/S0377-2217(01)00278-8.
[22] P. Damodaran, K. Srihari, S.S. Lam, Scheduling a capacitated batch-processing machine to minimize makespan, Robot. Comput. Integr. Manuf. 23 (2007) 208–216, https://doi.org/10.1016/j.rcim.2006.02.012.
[23] P. Kumar Manjeshwar, P. Damodaran, K. Srihari, Minimizing makespan in a flow shop with two batch-processing machines using simulated annealing, Robot. Comput. Integr. Manuf. 25 (2009) 667–679, https://doi.org/10.1016/j.rcim.2008.05.003.
[24] N. Giannopoulos, V.C. Moulianitis, A.C. Nearchou, Multi-objective optimization with fuzzy measures and its application to flow-shop scheduling, Eng. Appl. Artif. Intell. 25 (2012) 1381–1394, https://doi.org/10.1016/j.engappai.2012.06.011.
[25] G.A. Süer, O.K. Ates, E.M. Mese, Cell loading and family scheduling for jobs with individual due dates to minimise maximum tardiness, Int. J. Prod. Res. 52 (2014) 5656–5674, https://doi.org/10.1080/00207543.2014.903343.
[26] P.Y. Chang, P. Damodaran, S. Melouk, Minimizing makespan on parallel batch processing machines, Int. J. Prod. Res. 42 (2004) 4211–4220, https://doi.org/10.1080/00207540410001711863.
[27] I. Saraçoğlu, G.A. Süer, Multi-objective fuzzy flow shop scheduling model in a manufacturing company, Procedia Manuf 17 (2018) 214–221, https://doi.org/10.1016/j.promfg.2018.10.039.
[28] S. Mușțu, T. Eren, Maximum completion time under a learning effect in the permutation flowshop scheduling problem, Int. J. Ind. Eng. Theory Appl. Pract. 25 (2018) 156–174.
[29] J.N.D. Gupta, A.J. Ruiz-Torres, Minimizing makespan subject to minimum total flow-time on identical parallel machines, Eur. J. Oper. Res. 125 (2000) 370–380, https://doi.org/10.1016/S0377-2217(99)00386-0.
[30] G. Süer, N. Almasarwah, O. Alhawari, C. Davis, Multi-objective scheduling in labor-intensive manufacturing systems, J. Manuf. Syst. 57 (2020) 469–483, https://doi.org/10.1016/j.jmsy.2020.08.014.
[31] S.M. Saad, A. Baykasoglu, N.N.Z. Gindy, A new integrated system for loading and scheduling in cellular manufacturing, Int. J. Comput. Integr. Manuf. 15 (2002) 37–49, https://doi.org/10.1080/09511920110035012.
[32] M. Dai, D. Tang, A. Giret, M.A. Salido, Multi-objective optimization for energy-efficient flexible job shop scheduling problem with transportation constraints, Robot. Comput. Integr. Manuf. 59 (2019) 143–157, https://doi.org/10.1016/j.rcim.2019.04.006.
[33] A. Kusiak, The generalized group technology concept, Int. J. Prod. Res. 25 (1987) 561–569, https://doi.org/10.1080/00207548708919861.
[34] G. Süer, M. Ortega, A machine level based-similarity coefficient for.pdf, Comput. Ind. Eng. 27 (1994) 67–70, https://doi.org/10.1016/0360-8352(94)90239-9.
[35] P. Gannon, G.A. Süer, A Genetic Algorithm approach for loading cells with flow shop configuration, Proc. Elev. Int. Conf. Manag. Sci. Eng. Manag. (2018) 559–576, https://doi.org/10.1007/978-3-319-59280-0_46.
[36] J.H. Holland, Genetic algorithms and the optimal allocation of trials, SIAM J. Comput. 2 (1973) 88–105, https://doi.org/10.1137/0202009.
[37] S. Wang, X. Wang, J. Yu, S. Ma, M. Liu, Bi-objective identical parallel machine scheduling to minimize total energy consumption and makespan, J. Clean. Prod. 193 (2018) 424–440, https://doi.org/10.1016/j.jclepro.2018.05.056.
[38] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Trans. Evol. Comput. 6 (2002) 182–197, https://doi.org/10.1109/4235.996017.