Proceedings of the 2016 International Conference on Industrial Engineering and Operations Management
Kuala Lumpur, Malaysia, March 8-10, 2016

A Genetic Algorithm for Solving the Integrated Cell Formation, Layout and Scheduling Problem

Sherif A. Fahmy
Department of Industrial Engineering
American University of the Middle East, Egaila, Kuwait
On leave- Department of Mechanical Design and Production, Cairo University, Giza, Egypt
sherif.fahmy@aum.edu.kw

***Abstract*— Cellular manufacturing systems (CMS) typically comprise a number of manufacturing cells served by a centralized material handling system. Designing such systems includes three major decisions; cell formation (CF), group layout (GL), and group scheduling (GS). Traditionally, these three decisions have been dealt with separately, which has usually lead to less than optimal system performance. In a previous paper, a mixed integer linear programming (MILP) model was proposed for solving the integrated CF, GL and GS problem, to efficiently design and operate CMSs. In this paper, an efficient Genetic Algorithm (GA) is proposed to determine the optimal cell formation, layout of machines and schedule of parts on the machines in a job shop setting, simultaneously. The GA chromosome is designed to represent the three decisions in a way that allows maximum design and operational flexibility. The performance of the algorithm is tested by solving two problems previously introduced in the literature considering two objectives; minimizing the makespan and minimizing the mean flow time in the system. The proposed algorithm obtained the optimal solutions for the two problems in a few seconds.**

Keywords—cellular manufacturing systems; cell formation; group scheduling; group layout; genetic algorithm

I. INTRODUCTION

By the mid 1960's, it was realized that approximately 60-80% of the discrete products market demanded mid-variety and mid-quantity products. To cope with this shift in market behavior, the notion of Group Technology (GT) emerged. The basic idea was to divide the system capacity between groups of products, or product families, by dividing the system machines into a group of production cells, where each is dedicated for a product family; hence the paradigm of Cellular Manufacturing Systems (CMS). The design and efficient operation of a CMS typically involves four types of decisions [1]:

- Cell formation (CF): grouping similar parts into part families and machines into machine cells
- Group layout (GL): determining the locations of the cells in the shop floor and those of the machines within each cell
- Group scheduling (GS): determining the sequence of parts to visit each machine
- Resource assignment (RA): assigning labor, tools, materials, etc. to cells.

These types of decisions have received substantial attention by researchers in the past decades, especially the CF and GS problems. Traditionally, they have been dealt with either separately or sequentially [2]. It was proven however in [3] that operations sequence (GS) and machines layout (GL) have major effects on the CF decision. It was further shown in [4] and [5] that CF results have significant impacts on the GS decision, and that it is better to consider CF, GL and GS decisions simultaneously. Accordingly, in the past decade a number of studies have been proposed to model and solve all or combinations of these decisions, simultaneously. This integrated problem has usually been formulated as a non-linear model [5, 6, 7, 8] and has been frequently solved using Genetic Algorithms (GA) [4, 5, 8, 9].

In [10], a mixed integer linear programming model (MILP) was proposed for the integrated CF, GL, and GS problem. Because of the problem complexity, the MILP model can be used to obtain optimal solutions for small and fairly medium-sized problems only. In this paper, an efficient GA is proposed to solve the integrated problem. The algorithm takes into consideration intercellular and intracellular transportation times to determine the optimal cell formation, layout of machines and schedule of parts on the machines in a job shop setting, simultaneously. The GA chromosome is designed to represent the three decisions in a way that allows maximum design and operational flexibility. In Section 2, literature concerning the CMS design and operational decisions listed above is reviewed. In Section 3, the problem on hand is described along with the assumptions. In Section 4, the proposed GA is presented. In Section 5, the proposed algorithm is used to solve two problems earlier introduced in literature, followed by conclusions in Section 6.

II. LITERATURE REVIEW

The most important application of GT has been the utilization of CMSs in many discrete-product industries. Design of such system requires efficient solutions for the CF and GL problems to identify the cells, their locations and inner arrangements, while operational efficiency dictates the proper scheduling of parts on cell machines (GS) and assignment of resources to the formed cells (RA). In previous literature, the GL and RA decisions have been addressed, but the CF and GS problems have gained most of the attention from researchers. Traditionally, all such problems have been approached separately or sequentially. Because the CF problem is the first decision in a CMS design, it required no prior solution of the other three problems. However, solving the GS problem has always assumed that a CF solution is available [11, 12, 13]. Recently, the simultaneous consideration of two or more of the CF, GL, GS, and RA decisions has been proven to result in better design and operational performance of CMSs [3, 4, 5], and has been addressed in a number of studies.

In some studies, no actual sequences of parts on the machines were developed, as parts were treated as groups, but time (scheduling) data was used to improve the CF solution. In [14] a nonlinear model was proposed for the CF problem along with a hybrid GA and Simulated Annealing (SA) solution methodology. This work was extended in [15] by considering supply chain issues, and also the GL problem by considering the effect of machine positions on the CF solution. In [16], the CF problem was addressed while considering sequence of operations on machines, alternative processing routes, processing times, production volumes and others. A GA was proposed to solve the problem and identify the part families and manufacturing cells. In [17], similar factors were taken into consideration to solve the dynamic CF problem; reconfiguration of cells and reformation of part families. A SA algorithm was proposed to solve the problem. In [18], a two-phase procedure based on an improved similarity coefficient method was used to solve the CF problem taking into consideration aspects like alternative routing, machine capacity, and operation time. In phase 1, a similarity coefficient method was used to identify part families, and in phase 2 a mathematical model was used to assign machines to the formed part families.

The CF and RA problems have also been considered simultaneously in a number of studies. In [19], an integer linear programming (ILP) model for the CF problem considered multi-period production planning, system reconfiguration, machine capacities, as well as worker availability. The objective was to minimize total CF costs, including planning, reconfiguration and smoothing costs. In [20], a two stage heuristic approach was proposed for the CF and RA decision problems with focus on human resources. Factors like salary, hiring, firing, and cross-training were taken into consideration. In [21], this work was extended to simultaneously solve the CF and operator assignment problems, along with determining the intra-cell layout (GL problem) in a dynamic manufacturing environment.

Similarly, the integrated CF and GL problem has been approached in a number of studies. In [4], a non-linear integer programming (NLIP) model was formulated to capture the problem and a GA was proposed to solve it. In [22], a NLIP model was proposed to integrate the CF and GL decisions in a dynamic environment. A SA algorithm was proposed to solve the NP-hard problem. In [23], a two-stage NLIP model was proposed to model the CF and the intra-cellular machine sequencing problems. In the first stage, the CF problem is solved, and in the second, machines layout in each cell is determined based on the solution of the first stage. A two stage Tabu Search (TS) was also proposed to solve the integrated problem. The importance of including other decisions like parts scheduling in solving the integrated problem was also highlighted. In [24], the integrated CF and GL problem was formulated as a NLIP model considering operational decisions like alternative process routings, operations sequences, along with actual positions of machines in cells and aisle distances. The machines within cells were assumed to be arranged in a flow line (single line). A GA was also proposed to solve the problem due to its non-linearity and hardness.

As for parts scheduling, the GS problem has traditionally been solved as a second phase decision after solving the CF problem. In [6], and given a solution for the CF problem, the GS problem was modeled as a NLIP model. A scatter search approach was proposed to solve the non-linear hard model. In [25], an ILP model was developed for the GS problem, considering intercellular moves and sequence-dependent family setup times. An enhanced GA was also proposed to solve the problem. The work proposed in [6] was extended in [7] to simultaneously solve the CF and GS problems while neglecting intra-cell movement time. In [26], a mixed integer nonlinear programming model was further proposed for the CF and GS integrated problem, and a Lagrangian relaxation decomposition method with a heuristic was used to decompose the problem into CF and GS sub-problems. The CF sub-problem was linearized and solved, and a scatter search approach was developed to solve the GS sub-problem.

Finally, the simultaneous consideration of the CF, GL, and GS problems has been considered in very few studies. In [5], the work proposed in [4] was extended to include the GS decision along with the CF and GL decisions considering intercellular and intracellular transportation times. The problem was formulated as a NILP model and solved using a hierarchical GA algorithm with the objective of minimizing the makespan of all the parts. Because in [4] and [5], any of the machines can be assigned to any cell without considering its position in the shop floor, the resulting cells could physically be overlapping. To address this issue, a NLIP model was proposed [8, 9] for the integrated CF, GL, and GS problem taking into consideration the coordinates of the machines on the shop floor and imposing restrictions that prevent the formation of overlapping cells. Objectives considered were the minimization of the average completion time of parts [8] and minimization of makespan [9]. A GA was proposed to solve the problem, in which the sequence of parts on machines was developed and fixed for all machines (flow line setting).

From the above, it can be deduced that the simultaneous consideration of all or some of the CF, GL, GS, and RA problems leads to better results that treating each decision separately. Moreover, such integrated problems have usually been formulated as non-linear models and heuristics have been developed to solve these complex problems. Furthermore, in the very few studies that considered the integrated CF, GL and GS problem, GAs have been usually used to obtain a solution for the problem and a flow line setting has been assumed while solving the GS part of the problem.

III. Problem Description

In [10], the author proposed a MILP model for the integrated CF, GL, and GS problem. However, because of the hardness of solving the problem, especially for medium and large instances, the MILP model can only be used to obtain optimal solutions for small and fairly medium-sized problems only. Accordingly, in this paper, a GA is proposed to solve the integrated problem. In [5], because of the setting of the problem, resulting cells could physically be overlapping. To overcome this problem [8, 9], the coordinates of each candidate machine position was defined. This however has increased the complexity of the problem as the number of variables and decisions increased substantially. Furthermore, the chromosome design in [8, 9] fixed the sequence of parts that visit all the machines in the system; flow line setting. In the current work, this complexity is avoided and the following is assumed:

- Parts have different routing (process) plans through the system (job-shop setting).
- Once an operation starts on a machine, it cannot be interrupted before getting completed.
- The number of candidate cells (c) and the upper bound of cell capacity (R) are predefined.
- The layout is divided into a number of candidate empty cells, each with a pre-defined set of vacant positions for machines to be assigned (Fig. 1), and the total number of positions in the system is $p = c \text{ x } R$. This setting transforms the CF and GL problem into an assignment one, thus reducing its complexity [10].
- The distances between cells (d_c) and between vacant candidate machine positions (d_p) are known.

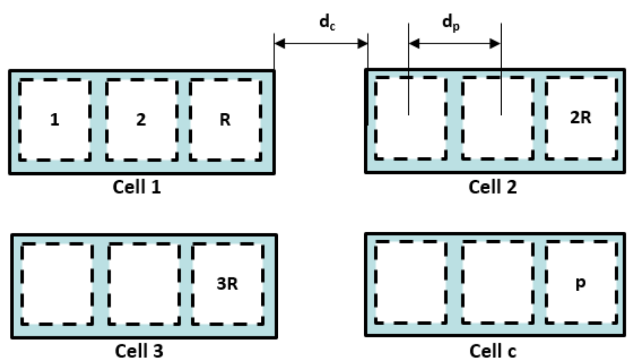


Fig. 1. Candidate cells with vacant positions

The above setting reduces the CF and GL problems into an assignment problem. By assigning each machine to a position in a cell, machines that share the same cell will form a production cell, and the parts whose most operations are conducted in that cell will constitute the corresponding part family.

IV. Proposed GA for the Intergated Problem

Genetic Algorithms (GAs) have proven to be an efficient methodology for solving the combined CF and GL problem [4], the job shop scheduling problem [25, 27, 28], and the integrated CF, GL, and GS problem [5, 8, 9]. GA is a type of evolutionary computation that starts with a set of initial solutions for the problem, and through a selection process and a number of genetic-inspired operators, it moves from one set of solutions to another until it stops at the best solution [29]. In GA, each solution is represented via a chromosome that carries the properties (attributes) of the solution, and each set of solutions is called a population. Natural selection is applied through a “survival of the fittest” strategy that preserves and reproduces new solutions (offspring) from the best solutions among the current set, based on a probability of selection. Finally, and to ensure diversity in the solutions to avoid getting trapped in a local optimal, GA uses operators like crossover –exchanging parts of chromosomes- and mutation –random change in a chromosome. The main aspects of the proposed GA are as follows:

A. Chromosome Representation

Since the proposed GA solves the CF, GL, and GS decisions simultaneously, they all have to be encoded in the chromosome. The chromosome is divided into two sections. The first section contains m genes equal to the number of machines in the system, and the alleles are the candidate machine positions. Thus, giving a value to any of these genes defines a specific position in a specific cell for the corresponding machine. Accordingly, the first section handles the CF and GL decisions of the problem. The second section is responsible for the GS decision and it is a permutation of the operations of all the parts visiting the system, representing the relative processing order on all machines [24]. Where n is the number of parts visiting the system and N_j is number of operations of part j, the overall length of the chromosome (Fig. 2) is thus $m + \sum_{j=1}^{n} N_j$.

M_1 M_2 ……. M_m	o_{11} o_{12} …… o_{1N1} o_{21} o_{22} ……… o_{2N2} …………………. o_{n1} o_{n2} …… o_{nNn}

Fig. 2. Chromosome structure

B. Initialization, fitness function and selection

The initial population is randomly generated, while ensuring a feasible schedule for each solution (chromosome). To ensure the feasibility of the generated schedule, the values assigned to the genes that belong to the same part are re-arranged to respect the processing route of that part. The objective function for the integrated CF, GL, and GS problem is a scheduling one [10], and assuming it is a minimization function (makespan or mean flow time), the fitness function $f(x)$ of any chromosome x is equal to $g_{max} - g(x)$, where $g(x)$ is the objective value of solution x, and g_{max} is its maximum value among all chromosomes of the current population. To determine the value of the objective function for a given chromosome, the generated machine positions (first section of chromosome) are used to calculate the transportation times (inter and intra-cellular) of parts between any two machines, and the relative order of operations (second section of chromosome) determines the sequence of parts to visit each machine in the system. To ensure that the schedule is generated smartly, the operations are inserted into the schedule according to their relative order while making use of any earlier available time slots on the corresponding machines, without violating the processing order of the corresponding part. The elitist chromosome is always carried to the next population and the worst is discarded instead. The Roulette wheel approach is finally used for selecting the parent chromosomes, with a selection probability proportionate to the value of the fitness function.

C. Crossover and Mutation

In the proposed GA, and because the values of the alleles cannot be repeated in any of the two sections of the chromosome, Partially-Mapped Crossover (PMX) is used for both sections. This ensures exploring different schedules for the same cell formation and layout, and vice versa. In PMX, two different crossing points enclosing a matching section in the two parent chromosomes are randomly chosen. This matching section is exchanged between the two parent chromosomes to create the offspring.

As for the mutation operator, again and according to the mutation probability, two positions are randomly selected; one in each section of the chromosome. The value in the selected position (gene) is exchanged with another gene in the corresponding section to explore different cell formations and layout (first section), and different schedules as well (second section).

V. ILLUSTRATIVE EXAMPLES

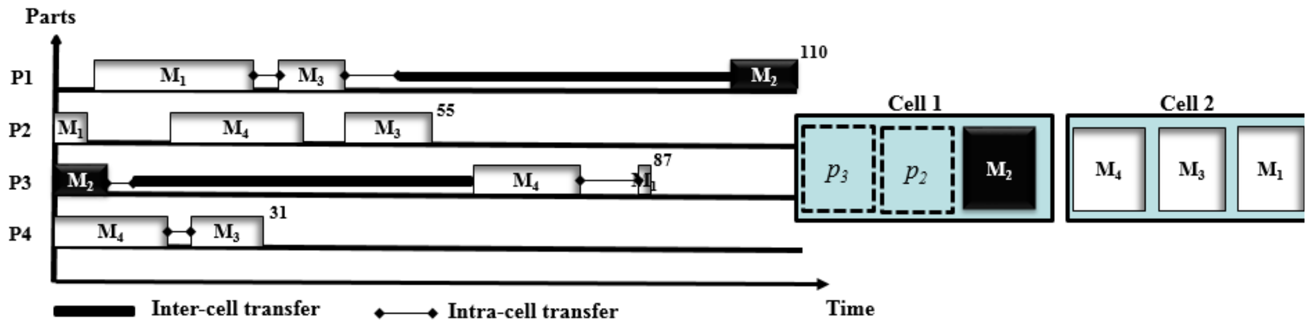
In this section, the proposed GA is used to solve two problems that were earlier introduced in literature. The problems are modified to fit the current problem description and assumptions. The algorithm is coded using MATLAB™ on a 3.40-GHz personal computer with 4.00 GB of RAM. For all problems, a population size of 50, 100 generations a crossover rate of 0.75 and a mutation rate of 0.01 were used.

A. Problem 1: 4 Parts x 4 Machines x 2 Cells

The first problem was introduced and solved in [8] considering the combined CF, GL and GS decision. It constitutes 4 parts and 4 machines. The problem is to divide the four machines into two manufacturing cells and obtain the optimal schedule for the parts. To fit the problem description presented in this study, it is assumed that the two cells have 3 empty positions each, to accommodate the machines. The distance between each two adjacent positions is assumed to be 2 units of distance and the distance between cells is 10 units. The intracellular and intercellular unit transfer times are 2 and 5 time units, respectively. This problem was solved twice in [10] using MILP, and the optimal mean flow time was 70.75 time units and optimal makespan was 102 time units. Using the proposed GA, the optimal mean flow time and optimal makespan solutions are obtained in less than 4 seconds, and are shown along with the corresponding chromosomes in Fig. 3 and Fig. 4, respectively.

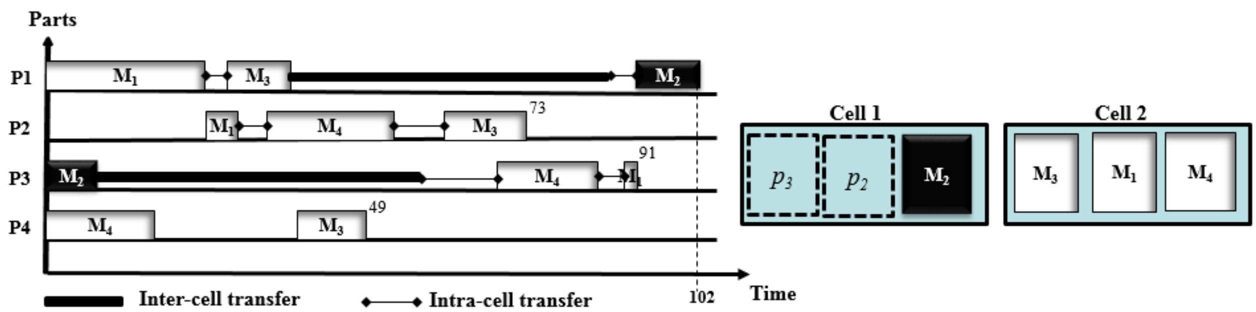
B. Problem 2: 8 Parts x 7 Machines x 3 Cells

The second problem is adapted from [6], in which only the combined CF and GS decision was considered; the layout of machines within the cells was not considered. The problem constituted 8 parts and 7 machines and an intercellular transfer time of 2.5 seconds between all cells. The problem is to divide the 7 machines into three cells and obtain the optimal schedule for the parts. It was solved in [10] and the optimal solution had a mean flow time of 6.3125 seconds. Using the proposed GA, a different solution was obtained in 6.8 seconds with the same optimal mean flow time of 6.3125 seconds as shown in Fig. 5.



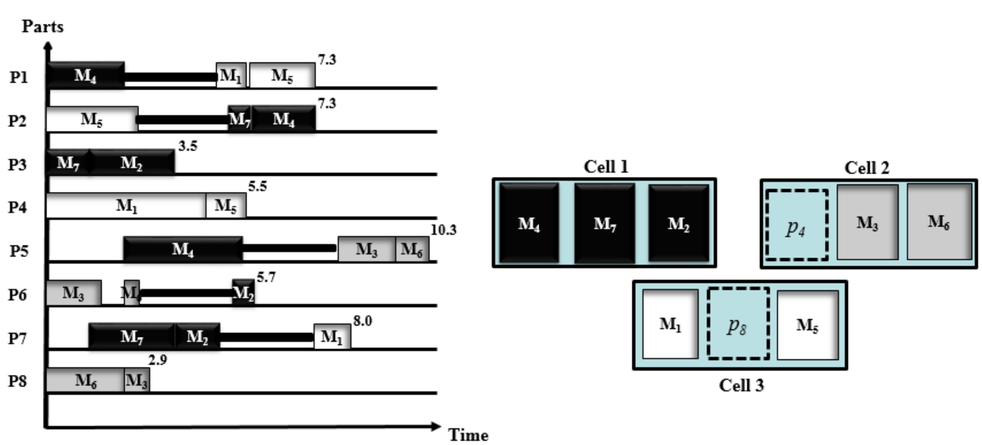
M1	M2	M3	M4	o11	o12	o13	o21	o22	o23	o31	o32	o33	o41	o42
6	1	5	4	5	6	9	1	8	10	2	4	11	3	7

Fig. 3. Solution for problem 1: optimal mean flow time



M1	M2	M3	M4	o11	o12	o13	o21	o22	o23	o31	o32	o33	o41	o42
5	1	4	6	2	3	10	4	8	11	1	6	7	5	9

Fig. 4. Solution for problem 1: optimal makespan



M 1	M 2	M 3	M 4	M 5	M 6	M 7	O 11	O 12	O 13	O 21	O 22	O 23	O 31	O 32	O 41	O 42	O 51	O 52	O 53	O 61	O 62	O 63	O 71	O 72	O 73	O 81	O 82
7	1	5	3	9	6	2	5	16	19	1	11	21	2	10	3	17	6	9	14	4	15	20	7	8	13	12	18

Fig. 5. Solution for problem 2: optimal mean flow time

VI. Conclusions

In this paper, a new GA is proposed to solve the combined CF, GL, and GS decision problem to determine the optimal cell formation, layout of machines and schedule of parts on the machines, simultaneously. The algorithm takes into consideration intercellular and intracellular transfer times, candidate positions for machines within the cells, and the distances between these positions and between the cells. In its current form, it can handle any time related scheduling objective, and it can also be modified to handle traditional cell formation objectives, like minimizing the number of exceptional parts.

Compared to previous literature, the novelty of the proposed algorithm lies in producing non-overlapping manufacturing cells, with optimal/near optimal positions for the machines within each cell, and optimal/near optimal production schedules in a job-shop setting. The performance of the proposed algorithm was tested by solving two problems that were earlier introduced in literature; a small and a medium-sized problem. Optimal solutions for the two problems were obtained considering different objectives in a few seconds. In the future, numerical experiments will be conducted to measure the performance of the algorithm against that of the MLIP model proposed in [10].

References

[1] F. Khaksar-Haghani, R. Kia, I. Mahadvi, and M. Kazemi, "A genetic algorithm for solving a multi-floor layout design model of a cellular manufacturing system with alternative process routings and flexible configuration," Int. J. Adv. Manuf. Technol., vol. 66, pp. 845-865, 2013.

[2] F. Chan, K. Lau, L. Chan, and V. Lo, "Cell formation problem with consideration of both intracellular and intercellular movements," Int. J. Prod. Res., vol. 46, pp. 2589-2620, 2008.

[3] R. Logendran, "Impact of sequence of operations and layout of cells in cellular manufacturing," Int. J. Prod. Res., vol. 29, pp. 375–390, 1991.

[4] X. Wu, C.-H. Chu, Y. Wang, and W. Yan, "Concurrent design of cellular manufacturing systems: a genetic algorithm approach," Int. J. Prod. Res., vol. 44, pp. 1217–1241, 2006.

[5] X. Wu, C.-H. Chu, Y. Wang, and D. Yue, "Genetic algorithms for integrating cell formation with machine layout and scheduling," Comput. Ind. Eng., vol. 53, pp. 277-289, 2007.

[6] J. Tang, X. Wang, I. Kaku, and K.-L. Yung, "Optimization of parts scheduling in multiple cells considering intercell move using scatter search approach," J. Intell. Manuf., vol. 21, pp. 525-537, 2010.

[7] X. Wang, J. Tang, and K.-L. Yung, "A scatter search approach with dispatching rules for a joint decision of cell formation and parts scheduling in batches," Int. J. Prod. Res., vol. 48, pp. 3513-3534, 2010.

[8] J. Arkat, M. H. Farahani, and L. Hosseini, "Integrating cell formation with cellular layout and operations scheduling," Int. J. Adv. Manuf. Technol., vol. 61, pp. 637-647, 2012.

[9] J. Arkat, M. Farahani, and F. Ahmadizar, "Multi-objective genetic algorithm for cell formation problem considering cellular layout and operations scheduling," Comput. Int. Manuf., vol. 25, pp. 625-635, 2012.

[10] S. Fahmy, "Mixed integer linear programming model for integrating cell formation, group layout and group scheduling,' IEEE Int. Conf. Ind. Tech., pp. 2403 – 2408, 2015.

[11] A. Elmi, M. Solimanpur, S. Topaloglu, and A. Elmi, "A simulated annealing algorithm for the job shop cell scheduling problem with intercellular moves and reentrant parts," Comput. Ind. Eng., vol. 61, pp. 171-178, 2011.

[12] M. Solimanpur and A. Elmi, "A tabu search approach for cell scheduling problem with makespan criterion," Int. J. Prod. Econ., vol. 141, pp. 639-645, 2013.

[13] W. Zuberek, "Optimal schedules of manufacturing cells-modeling and analysis using timed Petri nets," Proceed. of the IEEE Int. Symp. on Ind. Elec.(ISIE), vol. 2, pp. 1055-1060, 1996.

[14] V. Ghezavati and M. Saidi-Mehrabad, "Designing integrated cellular manufacturing systems with scheduling considering stochastic processing time," Int. J. Adv. Manuf. Technol., vol. 48, pp. 701-717, 2010.

[15] V. Ghezavati, "A new stochastic mixed integer programming to design integrated cellular manufacturing system: A supply chain framework," Int. J. Ind. Eng. Comput., vol. 2, pp. 563-574, 2011.

[16] M. Solimanpur and A. Foroughi, "A new approach to the cell formation problem with alternative processing routes and operation sequence," Int. J. Prod. Res., vol. 49, pp. 5833-5849, 2011.

[17] R. Tavakkoli-Moghaddam, N. Safaei, and F. Sassani, "A new solution for a dynamic cell formation problem with alternative routing and machine costs using simulated annealing," J. Oper. Res. Soc., vol. 59, pp. 443-454, 2008.

[18] L. Wu and S. Suzuki, "Cell formation design with improved similarity coefficient method and decomposed mathematical model," Int. J. Adv. Manuf. Technol., vol. 79, pp. 1335–1352, 2015.

[19] I. Mahadvi, A. Aalaei, M. Paydar, and M. Solimanpour, "Designing a mathematical model for dynamic cellular manufacturing systems considering production planning and worker assignment," Comput. Math. Appl., vol. 60, pp. 1014-1025, 2010.

[20] M. Bashiri and M. Bagheri, "A two stage heuristic solution approach for resource assignment during a cell formation problem," IJE Trans., vol. 26, p. 943-954, 2013.

[21] M. Bashiri and M. Bagheri, "A new mathematical model towards the integration of cell formation with operator assignment and inter-cell layout problems in a dynamic environment," Appl. Math. Mod, vol. 38, pp. 1237-1254, 2014.

[22] R. Kia, A. Baboli, N. Javadian, R. Tavakkoli-Moghaddam, M. Kazemi, and J. Khorramil, "Solving a group layout design model of a dynamic cellular manufacturing system with alternative process routings, lot splitting and flexible reconfiguration by simulated annealing," Comput. Oper. Res., vol 39, pp. 2642-2658, 2012.

[23] C.-C. Chang, T.-H. Wu, and C.-W. Wu, "An efficient approach to determine cell formation, cell layout and intracellular machine sequence in cellular manufacturing systems," Comput. Ind. Eng., vol. 66, pp. 438-450, 2013.

[24] M. Mohammadi and K. Forghani, "A novel approach for considering layout problem in cellular manufacturing systems with alternative processing routings and subcontracting approach," Appl. Math. Mod., vol. 38, pp. 3624-3640, 2014.

[25] K. Halat and R. Bashirzadeh, "Concurrent scheduling of manufacturing cells considering sequence-dependent family setup times and intercellular transportation times," Int. J. Adv. Manuf. Technol., vol. 77, pp. 1907–1915, 2015.

[26] J. Tang, C. Yan, X. Wang, and C. Zeng, "Using Lagrangian relaxation decomposition with heuristic to integrate the decisions of cell formation and parts scheduling considering intercell moves," IEEE Trans. Auto. Sci. & Eng., vol. 11, pp. 1110-1121, 2014.

[27] I. Moon, S. Lee, and H. Bae, "Genetic algorithms for job shop scheduling problems with alternative routings," Int. J. Prod. Res., vol. 10, pp. 2695-2705, 2008.

[28] Z. Jia, X. Lu, J. Yang, and D. Jia, "Research on job-shop scheduling problem based on genetic algorithm," Int. J. Prod. Res., vol. 12, pp. 3585-3604, 2011.

[29] M. Melanie, "An Introduction to Genetic Algorithms," The MIT Press, 1999.

BIOGRAPHY

Sherif Fahmy is an Assistant Professor of Industrial Engineering at the American University of the Middle East (AUM), Kuwait. He earned B.Sc. and M.Sc. in Mechanical Design & Production Engineering from Cairo University, Egypt, and Ph.D. in Mechanical & Manufacturing Engineering from University of Manitoba, Winnipeg, Canada. He worked in healthcare improvement and in innovation management. He has published journal and conference papers in the areas of automated manufacturing systems, optimization, scheduling, and supply chain management.