Developing a Multi-Objective Model on Cell Formation and Operator Assignment Based on Reliability and Workload Planning

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Abstract:

Human resources and maintenance are two main issues to reduce production cost. To reduce machines' failures and repairing costs, they should be considered at the first stage of production planning. In many cases of cellular manufacturing system, designers assume that machines are always available but the failure time is a portion of machines' lifecycles. In the present research work, a multi-objective mixed integer non-linear programming (MINLP) model has been developed for solving the cell formation and operator assignment problem in which machine reliability and workload balance have been considered, simultaneously. Operators' selection and their assignment are also set based on the specified criteria and cross-training costs. The first level of objective function goes toward minimizing inter-intra cell movement, machines setup, operation, non-utilization, cross-training and operator's salaries costs. The second level of objective function maximizes the system reliability which is defined as the total parts processing route reliabilities. The third level of objective function also minimizes the summation of standard deviation of machines activities times to balance machines workloads. In order to validate the proposed model, NSGA-II algorithm is applied to solve the numerical examples, and the Analytical Network Process (ANP) is also utilized for determining the most preferred solution from the extracted Pareto set. The performance of the NSGA-II is compared to NRGA algorithms to solve the problem using SAW method. Results revealed that increasing production cost reduces lead time but parts processing routes reliability is increased when reliability and workload balance are simultaneously considered in planning.

Keywords:

Cell Formation, Worker Assignment, Cross-Training, Reliability, Lognormal Distribution

1. Introduction

Due to the competitive manufacturing environment, improving efficiency and productivity has become a main concern for industry owners to have a production system with low cost and high flexibility. Cellular manufacturing system (CMS), known as an application of group technology philosophy in industrial environments, uses adjacency among the parts features to reduce parts defect rates, throughput times, factory space requirements, material flows and machines setup times and costs. Therefore, many industries have recently shown great tendency to utilize CMS. CMS design problem is composed of five sub-problems including cell formation (CF), intra-cell layout, inter-cell layout, resource allocation (e.g., operators, equipment and materials) and finally operation scheduling [1-3]. In manufacturing environments, these problems are usually inter-linked and need to be developed in an integrated model. It is not guaranteed that optimal solution obtained by solving a problem includes all of the aforementioned factors. Although there are impressive favor results in CMS implementation, some of researches state some disadvantages for CMS [4-8].

Many existing CMS designed models assume that machines are totally reliable, while failure time is a portion of life cycle for each machine and parts are required to wait until the broken down machines to be repaired. Some engineers and managers believe that designing stage can be modified to achieve improved reliability, enhanced maintainability and maintenance resource requirements and so even eliminate the need for applying routine maintenance [9]. DAS [10] was handling this problem and suggested the selection routes with lowest failure probability for each part, also preparing the provision to reroute a part in case of any machine failure. Integration of the above points ensured due date fulfillment and improved the overall performance of CMS. Alternative routes and process plan are two well-known approaches for production route selection. For instance, table 1 shows process plan and alternative routes of part 4. Considering production route 412 selected for part 4 (means that work on part type 4, by process plan 1, and process route 2), machines 20, 17, 10 are required to apply to operational process. If machine 10 fails, the processing part uses machine 17 without any change in the scheduled process plan. Practically, all machines are categorized as unreliable or reliable. Machine reliability definition in a manufacturing situation is usually represented by its availability [10]. Machines reliability analysis using the exponential distribution to model failure is more popular because it is easier to understand, implement, tractability of approach and has been demonstrated in the literature to provide good approximations to machine failure distributions [11-13]. Other distribution functions have been also used such that Das [10] considered machines failure model using Wei-bull distribution function. In practical situations, all machines and plants have wear and tear effect and deteriorate with an increasing failure rate with increase in age, so one may analysis manufacturing machines relevant to CMS using an increasing failure rate. Since the exponential distribution function represents the constant failure rate behavior, Wei-bull distribution function also represents early failure characteristics.

Bruecker [14] defined criteria applied to operator selection, cross-training and allocation. NSGA-II algorithm has been also applied for solving the proposed multi-objective mathematical model, and an analytical network process (ANP) has been used to determine the preferred solution from the Pareto set. At the end of the proposed procedure, NSGA-II and NRGA algorithms' performances compared together in solving the developed MINLP model.

Table 1. *Alternative routes and process plan of sample part 4*

Part	Process plan	Operation				NO	Route	Alternative routes
		1	2	3	4			
4	1	18, 20	17	10	-	1	411	18-17-10
						2	412	20-17-10
	2	15	2, 7	5	8	3	413	15-7-5-8
						4	414	15-2-5-8

Cell formation problem is the first stage for designing CMS according to relevant studies can be found in the literature [15-19]. Balakrishnan and Cheng [20] state that operator allocation to machines is the key factor in efficiency of CMS. Cell formation and operator assignment was also [16] studied to extend the previous research work which is presented an approach with two phases, in which at the first; generating alternative operator levels, and second; finding the optimal operator and product assignments to the cells.Norman et al. [21] developed an MIP model to workers assignment in manufacturing cells, which maximize the productivity, output quality and minimizing training costs. In their proposed model worker assignments done based on the technical skills level and that be able to change with additional training. More investigation on the literature conducted on [22] introduced the eight human issues in cellular manufacturing systems include worker assignment strategies, communication, autonomy, reward/compensation systems, skill identification, cross-training, teamwork and conflict management.

Aryanezhad, et al. [23] proposed a dynamic cell formation and operator allocation problem simultaneously. They considered alternative processing routes, machine flexibilities and workers promotion from one skill level to another in which the objective functions is to inter-cell material, production and machine costs, salary, training, hiring and firing costs minimization. A multi-period cell formation and production planning was developed [24] considering worker assignment to minimizing the machine related costs, reconfiguration cost, inter-cell material handling cost, inventory holding and backorder costs, hiring, firing and salary costs. Ghotboddini, et al. [25] presented a multi-objective mixed-integer model, which considers dynamic cell formation and labor assignment simultaneously, which minimize the reassignment cost of human resource, over time cost of equipment and labors and maximization the utilization rate of human resource. They solved their model with the Benders' decomposition approach. An integrated fuzzy-DEA and fuzzy simulation to operator allocation was presented in learning effects by [26]. The main contribution of their work was taking into various operators layouts and learning effects using fuzzy-DEA and fuzzy simulation. To assess simulation alternatives, Fuzzy-DEA is utilized in various levels of uncertainty. The productivity of operators, machines and production rates maximized and lead times, waiting, operator number and costs minimized, done with Principle Component Analysis (PCA) to verification and validation of fuzzy-DEA results.

A new mathematical model was proposed [3] for solving the cell formation, operator assignment and inter-cell layout problems and to validate that, a real case study in Iranian automobile industries of Saipa and Iran-Khodro companies.Mohammadi and Forghani [27] presented a new integrated approach for designing cellular manufacturing system and its inter- and intra-cell layouts. That is the first study which addresses all these design features, simultaneously. Park, et al. [28] presented a method to generation an operator allocation scenario which that combines of GA, simulation and DEA. In their integrated method genetic algorithm used to operator allocation scenarios. Scenario evaluation criteria determined by simulation and evaluation done by DEA. In their method feasible scenarios have additionally knowledge of worker assignment to machines.

Sakhaii, et al. [19] prepared a deterministic nonlinear mathematical model to solve a dynamic cellular manufacturing system (DCMS), which comprises cell formation, inter-cell layout design, production planning, operator assignment, machine reliability and alternative process routings, with the aim to minimizing the machine breakdown cost, inter/intra cell part trip costs, machines relocation cost, inventory holding and back order costs and also operator’s training and hiring costs. They applied robust optimization approach to the model as an optimization technique to cope with the product processing time uncertainty. By taking the product processing time uncertainty to solving linear model robust optimization approach applied. According to their study, to accede the CMS's benefits, system should be sustained in a reliable level. An integrated mathematical was developed [29] model for solving cell formation problem considering operator assignment, inter-cellular and intra-cellular layout problems and allowing duplicating machine in which two meta-heuristics algorithm namely multi-objective simulated annealing (MOSA) and multi-objective vibration damping optimization (MOVDO) present to solve the proposed model. Zohrevand, et al. [30] concluded that in studies two remarkable aspects, uncertainty and human-related issue have been significantly ignored. In order to compensate such a shortage, they developed a bi-objective stochastic model. The first objective function minimized the costs of machine procurement, machine relocation, inter-cell moves, overtime utilization, worker overtime cost, worker hiring/laying off cost, and worker assignment cost and the second objective function was to maximize the minimum labor ratio of system worker utilization. A dynamic mathematical model was also presented [31] to apply queuing theory in this field. Their objective function was defined in tow part, minimization of intra-cell part rips, system reconfiguration cost and maximization of all machines busy time. Mehdizadeh, et al. [32] a dynamic multi-objective model prepared, which seeks to determining production, inventory and subcontracting level for parts and worker optimum assignment to manufacturing cells. To solving mathematical model, they applied NSGA-II, NRGA and Multi-objective vibration-damping optimization (MOVDO), which the MOVDO had acceptable performance in compare with other algorithms. A investigation was also made [14] for whole workforce planning problems and presents a review and classification of the literature regarding to incorporating skills. They identified six different skill determinants and two different skill classifications. The skills of a person can be determined by the age/seniority, experience, degree of technical knowledge/capability, licenses/qualifications/job title, nurse grade, other.

One of the important factors in CMS design is the machines reliability. A few studies have noted machines breakdown issue in CMS design. Das [10] developed a MIP model to minimization the total system costs and maximize the machine reliabilities along the selected processing routes, which provide a flexible routing that ensures a high overall performance of the CMS. He applied exponential and Wei-bull distribution to approximation of machines failure rate and B&B algorithm used to solving the MIP model. His multi objective MIP model to be able change form in the event of breakdowns act based on process plan. Consequently, the machine's interactions are not constant, but process plans assignment make able to change it [11].

Chung, et al. [33] proposed an efficient combination of Tabu Search (TS) algorithm and similarity coefficient to solving the cell formation problem and machines reliability, which indicated that the reliability consideration has meaningful effects on the total system costs reduction. Rafiee, et al. [34] prepared a dynamic model to cellular manufacturing costs minimizing with integrate consideration of cell formation and inventory lot sizing problems and process deterioration and machine failures. They use Wei-bull distribution to machines failure rate for increasing the system reliabilities with preventive maintenance. Considering the cell formation problem and machine reliability in an MIP model was also another vision [35]. They assumed machine Breakdown rate with exponential distribution and minimized the breakdown cost.

In the present research work, a processing routes selection procedure has been proposed using process plan and Log-normal distribution function in which machines reliability distribution is considered for developing the model. To have an effective CMS model, a MINLP model has been developed in which cell formation and operator allocation cost and reliability are minimized simultaneously in the modeling process. Operator selection and cross-training as well as parts allocation are done based on six criteria introduced by Bruecker [14]. More discussion on solving process are presented in section 4 followed by describing on NSGA-II algorithm applied for solving the proposed multi-objective model and compared to NRGA algorithm. A multi-objective MINLP model has been prepared in which the first objective function consists of cell formation, operator salary and cross-training costs. The second objective function is to maximize system reliability by summation of each part processing routes reliabilities and the third one is also to minimize the standard deviation of machines activities time which reduces the unsuitable effect of reliability consideration and balanced of machines workload.

This paper is organized as follows. The problem description and required formulas presented in Section 2, then in the third section, NSGA-II algorithm as a solution approach described, then numerical examples solved and their results analyzed and compared with NSGA algorithm. Finally, a brief discussion of the main results and future research directions will be prepared in section 4.

2. Methodology

As said before, cell formation and human resource allocation problems with machines reliability and workload balance will be considered simultaneously. Consequently, the method of calculating the reliability and its assumptions are now described followed by descriptions of operator selection strategy and assumptions. Required parameters and variables are also discussed in this section.

2.1 Reliability of Parts Processing Route

In the present research work, processing routes selection with highest system reliability is proposed from process plan of each part type. An efficient approach to make the system robust has been provision for multiple routes for rerouting the parts, in the case of machines failure. Also, steady state availability is used for calculating the availability of each machine in system in the proposed MINLP model. To calculate the route's reliability of each part, reliability of machines on that route is applied. Lognormal distribution function has been utilized for analyzing machines reliability, because it is a versatile and life range distribution [36]. Suppose t is a random variable with lognormal distribution and (α, β) parameters, thus;

$$R(T)=\int_{T}^{\infty} f(t)dt=\int_{z\,(\ln(T))}^{\infty}\varphi(z)\,dz=1-\varphi(z)=1-\varphi\left(\frac{(ln(T)-\alpha)}{\beta}\right) \quad (1)$$

Note that α and β mean and standard deviation of the natural logarithm of collected data for the mean time to failures, respectively. Returning to table 1, suppose, part 4 selects process plan 1 and route 2 to production (include machines 20, 17 and 10), so reliability of this route is equal to where T_i is the activity time of each machine.

$$REL_{412}=\prod\nolimits_{i\in\{20,17,10\}}\int_{z_i\,(\ln(T_i))}^{\infty}\varphi(z_i)\,dz_i=\prod\nolimits_{i\in\{20,17,10\}}\left(1-\varphi\left(\frac{ln(T_i)-\alpha}{\beta}\right)\right) \quad (2)$$

2.2 Operator Assignment Strategy

Generally, in operator selection, training and assignment process of many criteria such as age, experience, initiative, physique, team work mood, skills, or effectiveness are based on the type of job their weight changed. So, to consider all criteria to develop an efficient operator selection, training and assignment, the criteria introduced by [14] have been used. In CMS, these criteria are described as follows:

Age/seniority: This criterion includes physique, morality, team work mentality, responsibility and so on.

Experience: This criterion includes all dependent and independent individual practical experience.

Degree of technical knowledge/capability: Education grade, dependence between job and technical knowledge, problem definition and solving, management, learning, ingenuity.

Licenses/qualifications/ job title: These criterions assess the individual legal permits.

Nurse grade: Dexterity in a task is a multi-level issue, may be a person being proficient or semi-proficient or novice.

Other: These criterions include job condition, type, risks, motivation, and annual leave and so on.

For each criterion give a weight (w_i) is defined based on type of job or machine. For each person give a score in interval $[0,w_i]$, for each criterion shown in Table 2 an instance. Person score is the summation of scores for all criterions. The relationship between operators and machines (jobs) represented by a matrix $O\times M$ called scores matrix, where O is the number of operators and M is the number of machines (jobs). The scores matrix (SK) shows the capability of operators on machines (jobs). For example, in operator 1, the score for working with machine 1 is 0.23 and for working with machine 2 is 0.75.Next, person's score is equal to the sum of his/her score for each machine (jobs). Rows with minimum summation are eliminated, while score matrix becomes a $M\times M$ matrix. If $O<M$, is considered as virtual row (person), the score matrix becomes an $M\times M$ matrix. This virtual row (person) scores for each machine (job) equal to 0. Yet, persons for assign to machines (jobs) determined. Now, operator training costs to assign calculate as follows while operator will be trained, while his/her score for assigned machine (job) is set as 1.

Table 2. *Criterions weights and person scores*

Criteria No.	**1**	**2**	**3**	**4**	**5**	**6**	**Score**
Weight	0.18	0.2	0.16	0.1	0.28	0.08	1
Interval	[0, 0.18]	[0, 0.20]	[0, 0.16]	[0, 0.10]	[0, 0.28]	[0, 0.08]	[0,1]
Person 1	0.15	0.12	0.10	0.09	0.21	0.05	0.72
Person 2	0.11	0.19	0.15	0.07	0.25	0.03	0.80

$$\mathrm{SK} = \begin{bmatrix} 0.23 & 0.75 & \dots & 0.45 \\ 0.39 & 0.89 & \dots & 0.68 \\ \dots & \dots & \dots & \dots \\ 0.15 & 0.27 & \dots & 0.50 \end{bmatrix} \quad (3)$$

$$\mathrm{traincost}_{wj} = (1 - \mathrm{SK}_{wj})\mathrm{TR}_j \quad (4)$$

2.3 Problem Description

Considering machines' reliabilities increase system costs while in some cases this occurs with greater intensity. In addition, Machine's failures disrupt production scheduling and system efficiency [37]. In CMS which increased with reliability consideration, the main concern is the most volume of WIP, that increased the non-utilization, repair and overtime costs and reduce the MTBF and increased orders lead time. In other words, machines' reliabilities and workloads balance should be considered simultaneously. A multi-objective MINLP that minimizes the system costs and maximizes the summation of processing routes reliability with log-normal distribution and minimizes the standard deviation of machines activities time, should be able to balance all machines' workloads. Here are some of the assumptions are required to develop mathematical model.

Total number of cells, demand of each part type, failure parameters of each machine, setup time and processing time of each operation on each machine are parameters.

Each part type has one process plan at least, which at most one can be set to produce that part type.

In each processing route for a part type, several operations on different machines are performed based on given sequence. In addition, in calculation of inter-cellular and intra-cellular material handling costs, the sequence of operations is important. To be more specific, the number of times a part either has to move between machines in different cells or between machines within the same cell is affected by the sequence of operation performed on each part. 1) Identical machines are not considered. 2) An operator can be assigned to only one machine. 3) An operator can be trained to operate with specific machine by spending a training cost. 4) Weight of each criterion for operator selection and determined by management.

2.4 Notations

Indices for developing mathematical model are defined as below:

Indices

I	part types index
J	Machines index
C	cells index

$p \in \{1,2,...,\mathrm{P(i)}\}$	Index set of process plan for part type *i*
$o \in \{1,2,...,\mathrm{O(ip)}\}$	Index set of operations for part type i under process plan p
$j \in \{1,2,...,\mathrm{J(ipo)}\}$	Index set of machines j that can perform operation o of part type i under process plan p
Parameters	
$H1_i$	Cost of moving part type i between cells
$H2_i$	Cost of moving part type i in the cells
RC_{oj}	Known cost for setup machine j to operation o
OC_{oj}	Known operations cost for operation o on machine j
OT_{oj}	Time for performing operation o on machine j
RT_{oj}	Time for setup machine j to operation o
U_c	Maximum number of machines in cell c
L_c	Minimum number of machines in cell c
D_i	Demand of part i
PC_j	Penalty cost for non-utilization proportion of machine j
b_j	Amount of time available on machine j during the planned manufacturing period
$A_j(t)$	Steady state availability of machine j
SA_{wj}	Cost of operator w for work with machine j
SK_{wj}	Row w and column j of score matrix
TR_j	Cross-training cost of machine j
Variables	
R_{ip}	1 if part type *i* is processed under process plan p, 0 otherwise
Z_{jc}	1 if machine j is assigned to cell c, 0 otherwise
$X_{ojc(ip)}$	1 if operation o is performed on machine j in cell c for the combination (ip) of part type i and process plan p, 0 otherwise
Y_{wjc}	1 if operator w is assigned to machine j in cell c, 0 otherwise

2.5 Mathematic Model

In the first objective function (Z), equations (5) and (6) respectively calculates the cost of moving parts between cells and the cost of moving parts within the cells. Equation (7) calculates the setup costs and operation costs and equation (8) calculates the non-utilization costs. Equation (9) calculates the operator's total cost and equation (10) calculates the operators training costs.

In the second objective function (REL), equations (11) and (12) calculate the summation of route's reliability and reliability of each route, respectively. In the third objective function (DEV), equations (13), (14) and (15) respectively represent the summation of standard deviation and mean of machine's activities time and activities time of each machine (s_j). Constraint set (16) assigns each part to a single process plan. By constraint set (17), when a process plan for a part type is selected, each operation of process plan is assigned to one of the available machines in one cell. Constraint set (18) ensures that machine j is assigned to at most one of the cells. Constraints set (19) and (20) respectively enforce lower limit and upper limit on the number of machines allowed in each cell. The lower and upper limits are determined by CMS user. The next constraint set (21) ensures that a machine j is assigned to cell c before any operation allocated to the assigned machine. Constraint set (22) ensures that allocated operations do not overload a machine beyond its effective capacity. Constraint set (23) assigns each operator to a single machine. Constraint set (24) assigns each machine to a single operator. Constraints set (25) ensure that each operator or machine is allocated to only one cell. Constraint set (26) defines the integrality requirements. Objective function Z and REL with all constraint as model 1 and Objective function Z and REL and DEV with all constraint as model 2 considered.All equations are tabulated as follows:

$$\sum_{i=1}^{N}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)-1}\sum_{j\in J(ip(o+1))}\sum_{j\prime\in J(ip(o+1))}\sum_{c=1}^{C}\sum_{c'=1}^{C} H1_i\, D_i X_{ojc(ip)} X_{(o+1)j'c'(ip),c\neq c\prime} + \tag{5}$$

$$\sum_{i=1}^{N}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)-1}\sum_{j\in J(ip(o+1))}\sum_{j\prime\in J(ip(o+1))}\sum_{c=1}^{C}\sum_{c'=1}^{C} H2_i\, D_i X_{ojc(ip)} X_{(o+1)j'c'(ip),c=c\prime} + \tag{6}$$

$$\sum_{i=1}^{N}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)}\sum_{j\in J(ipo)}\sum_{c=1}^{C}(RC_{oj}+OC_{oj})D_i X_{ojc(ip)} + \tag{7}$$

$$\sum_{i=1}^{N}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)}\sum_{j\in J(ipo)}\sum_{c=1}^{C} PC_j((A_j(t)b_j) + D_i(OT_{oj}+RT_{oj}))X_{ojc(ip)} + \tag{8}$$

$$\sum_{i=1}^{N}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)}\sum_{j\in J(ipo)}\sum_{c=1}^{C}\sum_{w=1}^{W}(D_i(OT_{oj}+RT_{oj}))SA_{wj}Y_{wjc} \tag{9}$$

$$\sum_{j=1}^{J}\sum_{c=1}^{C}\sum_{w=1}^{W}(1-SK_{wj})TR_j Y_{wj} \tag{10}$$

$$Max\ REL = \sum_{i=1}^{N}\sum_{p=1}^{P} LIR_{ip} \tag{11}$$

$$LIR_{ip} = \prod_{c=1}^{C}\prod_{o=1}^{O}(\prod_{j\in J(ipo)}\left(\int_{\left(\frac{\ln(S_j)-\alpha}{\beta}\right)}^{\infty}\varphi(z)dz\right))X_{ojc(ip)} \qquad \forall i,p \tag{12}$$

$$Min\ DEV = \left(\frac{\sum_{j=1}^{J}(S_j)^2}{J}\right) - (\overline{S})^2 \tag{13}$$

$$S_j = \sum_{i=1}^{N}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)}\sum_{c=1}^{C}(D_i(RT_{oj}+OT_{oj}))X_{ojc(ip)} \qquad \forall j \tag{14}$$

$$\bar{S} = \frac{\sum_{j=1}^{J}\sum_{i=1}^{N}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)}\sum_{c=1}^{C}(D_i(RT_{oj}+OT_{oj}))X_{ojc(ip)}}{J} \tag{15}$$

S.t:

$$\sum_{p=1}^{P(i)} R_{ip} = 1 \qquad \forall i \tag{16}$$

$$\sum_{j\in J(ipo)}\sum_{c=1}^{C} X_{ojc(ip)} = R_{ip} \qquad \forall i,p,o \tag{17}$$

$$\sum_{c=1}^{C} Z_{jc} \leq 1 \qquad \forall\, j \tag{18}$$

$$\sum_{j=1}^{J} Z_{jc} \geq L_c \qquad \forall\, c \tag{19}$$

$$\sum_{j=1}^{J} Z_{jc} \leq U_c \qquad \forall\, c \tag{20}$$

$$\sum_{i=1}^{N}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)} X_{ojc(ip)} \geq Z_{jc} \qquad \forall j\,,c \tag{21}$$

$$\sum_{i=1}^{N}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)} D_i\left(OT_{oj}+RT_{oj}\right)X_{ojc(ip)} \le b_j A_j(t) Z_{jc} \qquad \forall j\,,c \qquad (22)$$

$$\sum_{j=1}^{J}\sum_{c=1}^{C} Y_{wjc} = 1 \qquad \forall w \qquad (23)$$

$$\sum_{j=1}^{J}\sum_{c=1}^{C} Y_{wjc} = 1 \qquad \forall j \qquad (24)$$

$$\sum_{w=1}^{W} Y_{wjc} = Z_{jc} \qquad \forall j\,,c \qquad (25)$$

$$\forall\ \mathrm{i,p,o},j\,,c \qquad X_{ipo(ip)}, Z_{jc}, R_{ip} \in \{0,1\} \qquad (26)$$

3. Solution Approaches

There are several difficulties in solving the presented model; these are non-linear, multi objective and complicated and NP-hard nature of problems. In this case, we have to use evolutionary algorithms for solving proposed model. Among MOEA (multi objective evolutionary algorithms), NSGA-II is popular, also is able in solving the proposed problems, and to validate the obtained results NRGA employed. At the end of this section, the parameters tuning procedure of algorithms expounded.

3.1. NSGA-II Algorithm

NSGA-II proposed 2002 [38], is one of the most efficient and famous multi-objective evolutionary algorithms, which use the fast non-dominated sorting technique and crowding distance to ranking and selecting the population fronts. Then, the algorithm applies standard bimodal crossover and mutation operators to combine the current population and its offspring generated as next generation. The best individuals in terms of non-dominance and diversity are selected as the solution. NSGA-II outlined by the below algorithm.

1. [Start] create a random population of N chromosomes (suitable solutions for the problem).

2. [Fitness] Evaluate the multi-objective fitness of each chromosome x in the population.

3. [Rank] Rank population by following steps:

3.1. [Domination Rank] dominated and Non-dominated chromosome determined.

3.2. [Crowding Distance] Calculate the crowding distance of chromosomes.

3.3 [sorting] population sorted based on rank and crowding distance.

4. [New population] generate a new population by repeating the following steps until it is complete.

4.1. [Selection] choose two parent chromosomes from a population based on the binary tournament selection.

4.2. [Crossover] with a crossover chance, crossover the parents to form new offspring.

4.3. [Mutation] with a mutation chance mutate new offspring at each locus.

4.4. [Accepting] new offspring added to old population and new population determined.

5. [Replace] Use new generated population for further run of the algorithm.

6. [Test] If the end condition is satisfied (e.g. reaches an established number of generations in this paper), stop, and return the best solution in current population else go to Step 2.

3.2. NRGA

NRGA works similar to NSGA-II, with exception in their selection approach to choose the parents and copying them in mating pool. More specifically, NRGA first introduced by [39], they combined a ranked-based Roulette Wheel selection operator and Pareto-based population-ranking algorithm, which one of the fronts selected by applying based roulette wheel selection operator firstly. Then, one solution within candidate front is selected by the same procedure. Therefore, the belonging solutions to the best non-dominated set of the first front have the largest probabilities to be chosen, as the solutions within a set of the second front are selected with less probability and so on.

3.3. Chromosome Representation

Proper chromosome-representation can lead to more efficient and effective performance of a MOEA. A CMS with 5 machines, 5 operators, 5 parts and 3 cells consider. Chromosome consists of four section include machine, part, operator and operation sections (figure 1). The machine section indicates the assignment of machines to the cells, for example, in figure 1, machine 1 assigned to cell 3. The part section indicates the assignment of process plan for parts, for example, in figure 1, part 1assign to process plan 2. The operator section indicates the assignment of operators to the machines, for example, in figure 1, operator 1 assigned to machine 4. The operation section indicates the assignment of machines to the operations, for example, in figure 1,machine 4 assigned to operation 2 of part 1 and machine 3 assigned to operation 4 of part 5.

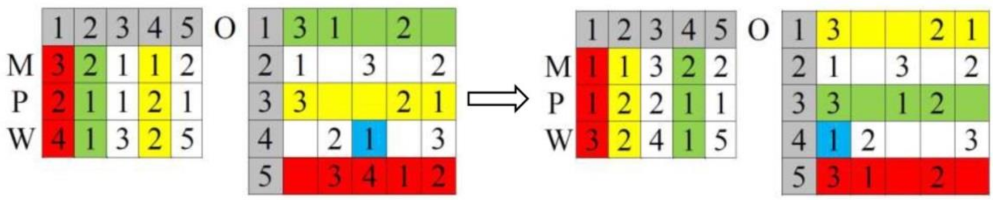

Figure 1. *Chromosome representation and mutation operator*

3.4. Crossover

Crossover operator explores a new solution space and provides the possibility of generating new solutions called offspring through mating pairs of chromosomes. In this study, due to the chromosome structure, both one-point crossover and two-point crossover are used in all sections. For this goal, cut points randomly selected within the length of sections M, P and W, also within the dimension of section of chromosome. It should be mentioned that the proposed crossover operators are performed on child chromosomes with equal chance.

3.5. Mutation

Mutation designed to improve diversity in population and explore new solutions space. Mutation is usually carried out on child chromosomes with a low probability of occurrence. In the proposed NSGA-II, two types of mutations are performed, general mutation and heuristic mutation. Two various operators are applied in the general mutation, including:

(1)Change operator: In this operator, value of the mutated gene is altered randomly. For instance, in figure 1, the value of gene 1 in machine section (M) is 3 so altered to 1; or in figure 1, the value of gene 5 in operation section (O) is altered from 0-3-4-1-2 to 3-1-0-2-0.(Red in figure 1)

(2)Exchange operator: This operator exchanges the contents of two cells. For example, in figure 1, in part section the content of gene 2 (route 1 of part 2) are exchanged with gen4 (route 2 of part 4), (green and yellow colors in figure 1).

Note that each of those operators considered as a general mutation and performed with equal chances to each gene. Beside of general mutation, to increase the efficiency of algorithm a heuristic mutation applied on child chromosomes. It should be noted that the proposed heuristic mutation is performed on all child chromosomes. In the proposed heuristic mutation, operation o which processed by machine jin the operation section (O) considered. If exist machine j', which can be processed operation o, this operation value changed to machine j' (colored in blue shown in figure 1).

3.6. Stopping Criteria

Many researchers showed that the convergence to an absolute optimum solution is not an inherent property of a MOEA, but it is possible to consider specific conditions. As there is no guarantee to improve solutions obtained during a new generation using mutation and crossover operators, a MOEA can be assumed to converge to a set of Pareto optimal solutions when a stopping criterion is met. In the proposed procedure, a pre-specified maximum number of iterations (N) are considered to stop the algorithms.

3.7. Parameters Tuning and Comparison of Algorithms

Three metrics have been adapted for performance measures to compare solutions set obtained from NSGA-II and NRGA algorithms and parameters' specifications. These metrics are the average distance, the number of the non-dominated solutions and the ratio of the non-dominated solution. For more information please refer to [40, 41].

3.8. ANP Method

Generally, MOEA algorithm a set of Pareto optimal solutions estimate, which requires choosing one of them to implement. Moreover, experts' preferences are applied to choice a solution of Pareto optimal solutions set. From a decision maker's perspective, the choice of a solution from Pareto optimal solutions set called a posteriori approach, which acting based on all relevant attributes. Multiple attribute decision-making (MADM) techniques are generally employed in posterior evaluation of Pareto-optimal solutions set to choose the best one among them. Large number of methods has been developed for selecting best compromise solution in multiple attribute or multiple criteria problems. In this paper, due to dependent between objective functions, Analytic Network Process (ANP) applied to find the best Pareto solution. Due to interactions and dependencies between criteria, many decision making problems cannot be structured in a hierarchal way. In this case, the structure of the problem should be built in the form of a network. ANP is general form of Analytic Hierarchy Process (AHP), and can help in solving the complex decision making problems with dependencies and interactions between criteria [42]. In figure 2, objective functions, criteria and Pareto solutions are considered as alternatives. In this method, priority of objective function for alternative is equal ($w_1 = w_2 = w_3$). The above mentioned weights are defined based on decision maker points of view and problem type.

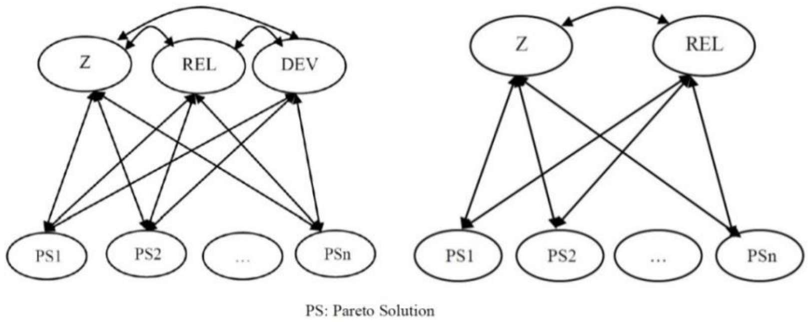

Figure 2. *Network structure of ANP for selection the best Pareto solution*

4. Illustrative Examples

Five numerical examples adopted from literature are used for comparisons and illustrate the proposed model. Table 3 shows the dimension of the problems (Machine (M), part (P), cell (C), operator (O)). Incomplete data such as Log-normal distribution parameters, MTBF and MTTR, operating and setup times, operating and setup costs, etc are randomly generated using the uniform distribution.

Table 3. *Generated problem instances size*

Problem No	$M \times P \times C \times O$	**L**	**U**	**planning time period**
1	11×8×3×11	2	5	25000
2	10×10×3×10	2	5	10000
3	18×13×6×18	3	6	15000
4	15×17×6×15	3	6	24000
5	20×23×6×20	2	5	12000

Table 4 shows the intervals of uniform distribution to generating parameters for each problem. The proposed mathematical model based on log-normal distribution has been solved utilizing NSGA-II. NSGA-II parameters are: population size (pop), maximum number of iterations (ITER), crossover rate (CRO), and mutation rate (MUT), the value of each parameter is chosen from a set of pre-defined values given in table 5 for model 1and in table 6 for model 2. It should be noted that these sets have been obtained via pilot tests and the results of similar studies. Instance 2, is also used to parameters tuning. NSGA-II algorithm parameters final value showed in table 7.

Table 4. *Generated problem instances parameters*

Parameters	Problem 1	Problem 2	Problem 3	Problem 4	Problem 5
α	[5,8]	[4.5, 7]	[4, 8]	[4.5, 9]	[5.5, 8]
β	[1, 2]	[0.9, 1.5]	[0.7, 1.3]	[0.5, 1.5]	[0.7, 2]
RT	[3, 9]	[1, 5]	[1, 9]	[2, 8]	[1, 5]
OT	[12, 20]	[8,15]	[15,25]	[12,20]	[8, 15]
RC	[1, 5]	[3, 8]	[1, 5]	[1, 5]	[2,6]
OC	[10,20]	[15,17]	[10,30]	[10,25]	[15,30]
$MTBF$	[1500,3000]	[500, 900]	[700, 1500]	[700,1500]	[500,900]
$MTTR$	[100,400]	[50,200]	[100,400]	[100,700]	[50,250]
PC	[5,15]	[2000,4000]	[5,15]	[5,15]	[1,4]
D	[200,400]	[80,130]	[80,250]	[100,200]	[80,130]
$H2$	[10,15]	[5,15]	[5,15]	[10,20]	[5,15]
$H1$	[25,35]	[20,40]	[15,40]	[25,35]	[20,40]
DI	[2,5]	[2,7]	[1,6]	[2,7]	[2,6]
OS	[8,12]	[15,20]	[10,15]	[9,15]	[10,15]
SA	[3,8]	[5,15]	[5,10]	[3,8]	[3,10]
SK	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
TC	1	[0.2,1]	[1,3]	1	[1,2]
TR	[1200,1800]	[600,1100]	[1000,1500]	[700,1500]	[500,1200]

Table5. *Parameters tuning of NSGA-II to model 1*

POP	ITER	N_{NDS}	DI_R	R_{NDS}	MUT	CRO	N_{NDS}	DI_R	R_{NDS}
100	100	6	0.0298	1	0.05	0.65	7	0.0256	1
100	125	7	0.0288	1	0.05	0.70	7	0.0258	1
100	150	2	0.12	1	0.05	0.75	7	0.0195	1
150	100	7	0.0342	1	0.1	0.65	4	0.0282	1
150	125	4	0.0371	1	0.1	0.70	5	0.034	1
150	150	4	0.0381	1	0.1	0.75	5	0.0304	1
200	100	3	0.068	1	0.15	0.65	7	0.0288	1
200	125	4	0.059	1	0.15	0.70	5	0.0358	1
200	150	5	0.027	1	0.15	0.75	6	0.0287	1

Table 6. *Parameters tuning of NSGA-II in model 2*

POP	ITER	N_{NDS}	DI_R	R_{NDS}	MUT	CRO	N_{NDS}	DI_R	R_{NDS}
100	100	16	0.153	1	0.05	0.65	9	0.184	1
100	125	15	0.152	1	0.05	0.70	16	0.166	1
100	150	9	0.196	1	0.05	0.75	18	0.155	1
150	100	16	0.136	1	0.1	0.65	26	0.12	1
150	125	10	0.183	1	0.1	0.70	15	0.149	1
150	150	12	0.181	1	0.1	0.75	7	0.189	1
200	100	16	0.158	1	0.15	0.65	14	0.163	1
200	125	13	0.157	1	0.15	0.70	9	0.215	1
200	150	17	0.164	1	0.15	0.75	14	0.194	1

Table 7. *NSGA-II parameters*

	NSGA-II algorithm	
	Model 1	**Model 2**
POP	100	150
ITER	125	100
CRO	0.75	0.65
MUT	0.05	0.1

4.1 Model Capability

The Analytical Network Process (ANP) results to determine the preferred Pareto solution from the NSGA-II Pareto solutions set, illustrated in table 8. (Pareto Solution Number (PSN), first objective function (Z), second objective function (REL), third objective function (DEV), operator salaries (Wage), machines minimum activities time (TL), machines maximum activities time (TU)). As shown in table 8, Pareto Solution Number (PSN) in model 2 is better than model 1. Problem 1 is a small size numerical problem. According to table 8, in problem 1, with considering workload balance, CMS total costs is decreased in which operators total salaries costs in model 2 is increased. Based on table 10, workload disperses between all machines in system, machines with minor reliability or machines with small time efficiency utilized. Illustrated workload balance decreases the accumulation of operating costs include inter and intra cell movement, machines setup and processing and non-utilization costs, in CMS. In contrast, due to difference between machines operations processing time, machines maximum activities time (orders lead time) increased from 27130 to 25370, but machines minimum activities time increased from 4750 to 11800. Due to workloads disperse in model 2, reliability of processing routes in model 2 less than model 1 and value of third objective function in model 2 less than of model 1.

Problem 2 is a small size numerical instance. According to table 8, in problem 2, considering minimization of machines standard deviation of activities time summation, CMS total costs increased, but operator salaries in model 2 more than model 1. Which indicate the CMS total operating costs in model 2 is less than model 1. In this problem machines maximum activities time in both model equal. But due to NSGA-II algorithm prepared Pareto solutions, machines minimum activities time in model 1 is 3100 but in model 2 is 1120. Also, reliability of processing routes in model 2 more than model 1, in contrast, value of third objective function in model 1 less than of model 2.

Problem 3 is a medium size numerical instance. In this problem, CMS total costs in Model 2 less than model 1and third objective functions value in this model 2 less than model 1. This can be indicating the interaction between workload balance and reliability of processing routes. In this problem, due to workload disperse processing routes reliability in model 2 less than model 1 also orders lead times from 18080 to 16320 decreased, also machines minimum activities time in model 1 equal to 2970, but in model 2 equal 0, which in table 10 machine 16 activities time in model 1 equal 3360 and in model 2 is idle. It could be due to low reliability and high cost.

Problem 4 is a small size numerical instance. CMS total costs in model 2 increased, and processing routes reliability and summation of standard deviation activities time in model 2 extremely lowed in this problem. However, based on table 10 in model 2 idle machine utilized but orders lead time increased. Problem 5 is a big size numerical instance. In model 2, CMS total costs increased, but processing routes reliability increased and summation of standard deviation activities time decreased.

Table 10 show machines activities time in models 1 and 2. In problem 1, due to machine 6 reliabilities high, activities time in model 1 is 24340, while its activities time in model 2 is 11800, because in system exist machines with same operation ability. In contrast, machine 11 has low reliability and activities time in model 1 is 4750 but due to workload disperse activities time in model 2 is 14630.

In problem 3, machine 16 has low reliability, so activities time in model 1 is 3360. In model 2, due to high operation cost and low reliability is idle and assigned operator should fire. In contrast, due to low reliability of machine 15 of problem 4, in model 1 is idle, but it has low operation costs, so its activities time is 12600, in model 2. Table 9 shows the results of model 1 and 2 for machines assign to cells, parts processing routes selection and operators assign to machines of problem 4. Also table 10 showed the operation assign to machines. These both table 9 and 10 confirms the machines reliability and workload balance considering effects on machines assignment, routes selection and operator assign and operation scheduling problems of CMS design.

Table 8. *ANP results and compare models*

		Problem 1	**Problem 2**	**Problem 3**	**Problem 4**	**Problem 5**
Model1	PSN	6	7	7	4	2
	Z	207528967	176361894	685722089	3845178841	926183223
	REL	0.000285	8.248e-8	0.002841	0.00602	1.897e-11
	DEV	60787	14630	72384	49093	46909
	Wage	1159940	733340	1135630	890059	767550
	TL	4750	3100	2970	0	1235
	TU	25370	8990	18080	18855	9840
Model2	PSN	12	26	15	15	28
	Z	207025421	176350135	685681397	385635827	926244716
	REL	0.000176	2.2244e-7	0.001683	0.001531	1.6347e-10
	DEV	47445	20216	71496	21471	36495
	Wage	1642630	869970	1190320	1026264	768640
	TL	11800	1120	0	2640	3015
	TU	27130	8990	16320	19645	9840

Table 9. *Machines assignment, routes selection and operator assign in model 1 and 2 with NSGA-II algorithm*

NO	**Machines assignment**		**Routes selection**		**Operator selection**	
	Model1	Model2	Model1	Model2	Model1	Model2
1	6	6	1	2	9	7
2	2	5	1	1	8	9
3	5	1	1	1	7	13
4	5	3	1	1	6	3
5	3	1	1	1	12	4
6	1	1	2	2	11	15
7	4	2	1	1	1	12
8	1	1	2	2	13	5
9	3	4	1	1	14	11
10	6	6	2	2	10	10
11	4	3	1	1	15	8
12	3	4	1	1	5	14
13	6	5	2	2	4	6
14	6	1	1	2	2	1
15	2	2	2	2	3	2
16			1	1		
17			1	1		

According to the above mentioned results: 1) Reliability and workload balance consideration in the CMS increased the operator salaries, inter/intra cell movement, non-utilization, set up and operation costs. 2) Reliability consideration on the CMS generally changed the part processing routes. 3) Workload balance consideration on the CMS generally changed the part processing routes. 4) Workload balance consideration on the CMS generally reduces the routes reliability. 5) Reliability and workload balance consideration on the CMS design changed on cell formation and operator assignments.

Based on the above mentioned, reliability and workload balance consideration at the design stage of CMS to arrive the ideal cellular manufacturing system is not enough, and applying of production and maintenance planning in utilizing stage is also an essential issue. In other words workload balance and reliability consideration in the design stage and applying in utilizing stage are complementary, and are pieces of a unique puzzle.

4.2. NSGA-II and NRGA Results Comparing

Numerical instance 2 has been investigated to the NRGA algorithm parameters tuning. These parameters for model 2 are tabulated in table 11. In five problem instance, the results obtained using NSGA-II are compared to the ones obtained by NRGA based on three indicators (N_{NDS} , DI_R , R_{NDS}) which have been calculated by implementing the algorithms on different problems shown in table 12.

Table 10. *Machine activities time in model 1 and 2 with NSGA-II algorithm*

	Problem 1		**Problem 2**		**Problem 3**		**Problem 4**		**Problem 5**	
	model1	**model2**	**model1**	**model2**	**model1**	**model2**	**model1**	**model2**	**model1**	**model2**
1	14850	9600	7990	8320	4960	3410	14660	14850	5420	8320
2	15300	19620	5700	3705	7520	12140	11880	10800	5005	3705
3	14050	20310	8590	5745	15520	9970	12564	10670	5745	5745
4	17240	24840	5980	7135	5520	10320	16590	13590	8760	7135
5	25370	27130	6950	7840	10890	7410	18855	19645	8315	7840
6	24340	11800	6200	3015	2970	2970	13280	9540	1235	3015
7	11990	16340	4650	7200	4860	10390	8640	10350	5260	7200
8	12600	13000	3100	4220	18080	15120	11560	12640	4085	4220
9	24360	14830	8990	7840	7700	11660	15700	15725	8895	7840
10	21320	22800	7740	4645	4400	16320	6820	2640	2695	4645
11	4750	14630			13400	13400	13300	16720	7415	8565
12					11090	11090	15230	15230	9840	9840
13					11790	12310	11222	7622	3695	5055
14					6360	4560	16010	16010	8810	9110
15					13670	5400	0	12600	9490	3930
16					3360	0			8380	6870
17					3480	3600			3500	4300
18					11610	6480			7250	5040
19									2050	3570
20									3490	7000

As a set of Pareto-optimal solutions obtained in each simulation run, ANP results have been considered for comparison. MADM methods called simple additive weighting (SAW) methods are used for comparing two algorithms (Hwang & Yoon, 1981). This method was employed to determine which algorithm is preferable. In this paper, we have 2 alternatives and 3 indices and weight of indices is equal (w1=w2=w3=1/3). SAW method starts with normalizing a decision matrix based on the linear method, in which a decision matrix has 2 rows and 3 columns. In the next step, an un-scaled weight matrix is made in weights. Then, total sum of each row is computed. At the end, an algorithm with largest total sum of weights, select for each of the problem instances. Table 12 also shows the applicability of each algorithm in all problems. Based on the results obtained from that table, NRGA is the better algorithm for four problems, while NSGA-II is the better algorithm for one problem, so it can be concluded that NRGA algorithm work satisfactorily to optimize the reliability and workload balance in CMS design problem.

Table 11. *Parameters tuning of NRGA algorithm 2*

POP	ITER	N_{NDS}	DI_R	R_{NDS}	MUT	CRO	N_{NDS}	DI_R	R_{NDS}
100	100	13	0.019	1	0.05	0.65	14	0.0105	1
100	125	9	0.04	1	0.05	0.70	20	0.0078	1
100	150	15	0.05	1	0.05	0.75	9	0.021	1
150	100	14	0.0113	1	0.1	0.65	8	0.0269	1
150	125	16	0.019	1	0.1	0.70	14	0.0099	1
150	150	13	0.026	1	0.1	0.75	16	0.013	1
200	100	14	0.011	1	0.15	0.65	10	0.0145	1
200	125	12	0.01	1	0.15	0.70	15	0.0125	1
200	150	17	0.009	1	0.15	0.75	7	0.0165	1

Table 12. *NSGA-II and NRGA algorithms comparison results*

	NSGA-II			NRGA			After SAW method		
	N_{NDS}	DI_R	R_{NDS}	N_{NDS}	DI_R	R_{NDS}	NSGA-II	NRGA	Applicability
1	12	0.0099121	1	19	0.0043104	1	0.688	0.999	NRGA
2	26	0.0088555	1	8	0.0348	1	0.333	0.174	NSGA-II
3	15	0.014828	1	18	0.0068265	1	0.763	0.999	NRGA
4	15	0.0058306	1	23	0.0077664	1	0.883	0.912	NRGA
5	28	0.0075986	1	31	0.0069313	1	0.312	0.333	NRGA

5. Conclusions and Recommendations for Future Studies

In this paper, a multi objective model for cell formation and operator assignment with machine reliability and workload balance has been developed. A method for operator selection and training and assignment has been proposed as well. In the proposed MINLP model, the reliability of machines with log-normal distribution is calculated and cumulative of routes reliabilities maximized. In order to balance machines workload, the summation of standard deviation of machines activities time is minimized. The proposed model confirms that considering machines reliability and workload balance effects in cell formation, operator assignment and operation scheduling problems of CMS design. Results of running the proposed procedure showed that increasing in production costs reduces lead time as well as parts processing routes reliability is also increased. In addition, machines with high reliability can be dispersing workloads, so lead time is sequentially decreased. In other words, reliability and workload balance should be considered, simultaneously.

Moreover, applicability of NSGA-II and NRGA in solving the reliability and CMS problem have been compared in which NRGA algorithm is more satisfactorily working. Interaction between objectives in ANP method used to determine the preferred solution from the Pareto set, and SAW method with three criteria (average distance, the number of the non-dominated solutions and the ratio of the non-dominated solutions) used to compare the algorithms performance. For future studies, authors are recommended to consider other model features such as production planning and operation scheduling as attractive and challenging aspects of the reliability problem.

Conflicts of Interest

Authors declare that no funding or financial support has been gained from scholarship, fellowship or any organizations to conduct this research work, so there is no conflict of interest regarding the publication of this paper.

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