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A Genetic Algorithm Approach for A Dynamic Cell Formation Problem Considering Machine Breakdown and Buffer Storage

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Abstract- *Cell formation problem mainly addresses how machines should be grouped and parts be processed in cells. In dynamic environments, product mix and demand are changed in each period of the planning horizon. Incorporating such assumption in the model increases flexibility of the system to meet customers' requirements. In this model, to ensure the reliability of the system in presence of unreliable machines, alternative routing process as well as buffer storage are considered to reduce detrimental effects of machine failure. This problem is presented by a nonlinear mixed integer programming model attempting to minimize the overall cost of the system. To solve the model in large scale for practical purposes, a genetic algorithm approach is adopted as the model belongs to NP-hard class of problems. Sensitivity analysis is used to show the validity of the proposed model. Besides, numerical examples are used both, for small-sized and large-sized instances to show the efficiency of the method in finding near optimal solution.*

Keywords: *Buffer storage, Dynamic cell formation problem, Genetic algorithm, Machine breakdown, Mathematical programming.*

I. INTRODUCTION

Group technology (GT) is a manufacturing philosophy by which similar parts are identified and dedicated to part families and machine groups into cells. One of the most dominant application of the GT is cellular manufacturing system (CMS) which has been identified as a hybrid system taking advantages of both job shop (flexibility) and mass production (efficient and high production rate) simultaneously (Papaioannou & Wilson, 2010). Cell formation (CF), cell layout, and intracellular machine sequencing are three steps adopted in the design of CMS (Chang et al., 2013). CF is the infrastructure of CM design where cells are formed according to machine groups and part family of similar characteristics so that a minimal inter-cell interaction can be obtained to satisfy market demand of various products. Because of product demand and mix fluctuations and extension of consumer goods in today's markets, dynamic cellular manufacturing systems (DCMS) are developed to meet the product demand requirements and overcome the probable disruptions of manufacturing organizations. Manufacturing cells reconfiguration is considered in DCMS, which is relocation of existing machines between cells, to take care of demand rate variations over multi-period planning horizon. "Machines are the key elements in the design of manufacturing systems" (JabalAmeli et al., 2008). Conventionally cell formation problems (CFP) assume that machines are completely reliable which is not the case in the manufacturing environments, moreover, absence of reliability consideration in CM design, expose system to vulnerable noise or failure in the manufacturing process. In addition machine breakdowns can dramatically affect system performance measures and lead to detrimental impact on due date performance as well as productivity of the overall

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system; hence, reliability considerations play an important role in the performance improvement of a system. Traditionally, CFP assume that each part has only one process plan which dramatically decreases flexibility of the entire system. Generalized cell formation problem (GCFP) is a modified version of CFP where a number of alternative process routings (APR) is considered for each part (Arkat et al., 2011). Adequate consideration of APR brings about additional flexibility, most reliable process plan selection, and performance improvement of the CMS design. Moreover, dealing with machine breakdowns, APR efficiently tackle disturbances of unreliable machines so that lower failure cost can be achieved.

In this paper a model is proposed concentrating on the integration of machine breakdown issues and CFP so that total cost of the system, such as inter-cell movement cost, machine failure cost, production time loss cost, production operation and etc. are minimized through a comprehensive model. To the best of the authors' knowledge this is the first mathematical model incorporating buffer storage problem as well as APR in CF design to increase system flexibility and reduce detrimental effects of unreliable machines on the performance of the system. A buffer is allocated to each machine to preserve work in process (WIP) inventory of products in every production stage. Buffer storage cost in this model is assumed to be dependent on part volume. This model attempts to present and optimize solution based on tradeoff between buffer storage cost and cost saving obtained through higher reliability of the system.

The remainder of this paper is organized as follows. Section II reviews the relevant literature. In section III the problem formulation of the proposed model is formulated. The developed genetic algorithm is elaborated in section IV. Section V provides numerical examples of the proposed model and illustrates the computational efficiency of the algorithm. Section VI presents a sensitivity analysis for model validation. Finally, conclusion and future research directions are given in section VII.

II. LITERATURE REVIEW

A. Cellular manufacturing systems

Literature body of CMS is quite extensive. Reviews and classifications of this issue can be found in (Wemmerlov & Hyer, 1986); (Kusiak & Chow 1988); (Mansouri et al., 2000); (Ghosh et al., 2011).

Other important works in this context can be found in (Nsakanda et al., 2006), where a comprehensive model for designing a cellular manufacturing system was presented. The model correlated several known problems in that it integrated the cell formation problem, the machine allocation problem, and the part routing problem. A solution methodology based on a combination of a genetic algorithm (GA) and large-scale optimization (LSO) techniques was developed for solving the presented model. The first particle swarm optimization (PSO) algorithm which was devoted to part-machine grouping is the one presented in (Carlos & Sebastia, 2006). The criterion used to group the machines in cells was based on the minimization of inter-cell movements. Also, a comprehensive model for the design of CMS was presented by (Ahkioon et al., 2009), where production planning and system reconfiguration decisions are incorporated in the presence of APR, operation sequence, duplicate machines, machine capacity and lot splitting via a mixed integer non-linear programing. (Won & Currie, 2006) adopted a new p-median formulation considering real-world production factors such as the operation sequences and production volumes for parts in order to organize machine cell/part family (MC/PF) formation in CMS design. Despite previous p-median models, which rely on the classic binary part-machine incidence matrix (PMIM), this one adopts a new similarity coefficient based on production factors that dramatically impact the MC/PF formation. (Safaei et al., 2008) developed a mixed-integer programming model to design CMS under a dynamic environment. They considered the batch inter/intra-cell material handling by considering the sequence of operations, considering alternative process plans for part types, as well as machine replication. An efficient hybrid meta-heuristic based on mean field annealing (MFA) and simulated annealing (SA) were used to solve the model. (Ghezavati & Saidi-Mehrabad , 2011) proposed a new version of stochastic model based on queuing theory towards CMS design, in which processing time of parts on machines and arrival time of parts to cells are described by a continuous distribution. The model was solved by a hybrid GA and SA algorithm where SA is a subordinate of GA. The proposed algorithm was validated compared with branch and bound algorithm and a benchmark algorithm existing in the literature. (Nouri & Hong, 2013) adopted the bacteria foraging optimization (BFO) algorithm to address CFP considering cell load variation and exceptional elements. The performance of BFO algorithm was compared with a number of commonly used algorithms from the literature such as K-mean clustering and C-link clustering.

B. Dynamic cellular manufacturing systems

There is a considerable amount of literature devoted to newly designed CMS under dynamic situation referred to as dynamic cellular manufacturing system (DCMS). One of the most comprehensive with more integrated approach models in DCMSs was presented to generate manufacturing cells over multiple time periods by (Saxena & Jain, 2011). Additionally, important manufacturing attributes in existing model (e.g. alternative process plan and routing, machine breakdown effect, transfer batch size, system reconfiguration, machine in same cell constraint, system reconfiguration, sequence of operation and etc.) was compromised in the model. (Ahkioon et al., 2009) considered the design of DCMS with production factors including multi-period production planning, dynamic system reconfiguration, duplicate machine, machine capacity, and machine procurement flexibility considerations in addition to APR to overcome machine breakdown disruptions. A mixed integer programming approach was employed to deal with this problem. (Safaei et al., 2008) developed an integration of explicit uncertainty for a CFP with a dynamic condition in CMS. They utilized a fuzzy programming-based approach to solve an extended mixed-integer programming model of the DCFP. (Aramoon Bajestani et al., 2009) introduced a multi-objective DCMS where the total load variation and sum of the different costs such as machine cost, inter-cell material holding cost, and relocation cost are minimized simultaneously. A new multi-objective scatter search (MOSS) was employed because of the problem NP-hard nature. (Balakrishnan & Cheng , 2007) proposed a comprehensive mathematical programming model for an integrated dynamic cell formation and a multi-item multi-level capacitated lot sizing problem considering the impact of lot size on the product quality. A linear programming embedded GA was developed to solve the model owing to NP-complexity of the problem. Saidi-(Mehrabad & Safaei, 2007) proposed a new DCMS approach with the aim of minimizing the material handling cost. Dynamic production assumptions combined with alternative process plans and a sequence of operations was compromised in the proposed model. Due to the complexity of the model, a neural approach based on mean field theory (NAMFT) was applied to solve the desired model. (Rafiei & Ghodsi, 2013) incorporated human-related issues, which were mostly neglected in previous researches, in dynamic CFP. In that context they developed a new bi-objective mathematical model; the first objective function minimized the overall production costs (e.g. machine procurement cost, machine relocation cost an etc.), while the second objective function maximized labor utilization of the model. They proposed an ant colony optimization (ACO) meta-heuristic validated by randomly generated test problems to tackle with the problem. (Sakhaii et al., 2015) developed a robust optimization approach to cope with processing time uncertainty in DCMS. They considered different manufacturing issues consisting of machine reliability, production planning, APR and etc. (Renna & Ambrico, 2015) addressed CMS with reconfigurable machines to handle market changes. They developed three mathematical models concerning design, reconfiguration and scheduling of manufacturing systems. They also conducted simulations in several scenarios ranging from a steady demand and mix to a very dynamic environment in order to test the proposed algorithm.

C. Machine breakdowns and reliability consideration

Literature review on machine breakdowns and reliability considerations in CMS design reveals that only a small amount of efforts have been devoted to this case. The following is a brief review of researches taking machine breakdowns into account.

(JabalAmeli & Arkat , 2008) focused on the configuration of machine cells with respect to production volume and APR to address machine reliability. A pure integer linear programming (PLIP) was applied to formulate the situation. While, Chung & Chang (2010) proposed a tabu search (TS) algorithm other than PLIP based on a similarity coefficient to deal with APR and machine reliability considerations. Contrary to previous works in which reliability consideration was taken into account by using multiplying rules, (JabalAmeli et al., 2008) presented a new approach to handle reliability consideration. They modeled the effects of machine breakdown including cost and time-based effect to overcome the obstacles. A bi-objective linear programming was developed to deal with the proposed generalized CF problem. Model was solved through a numerical example using ε-constraint method. (Arkat et al., 2011) addressed machine reliability in GCF under stochastic situation. They used chance constrained programming (CCP) to model the problem other than expected value (EV) which is a straightforward procedure but incur some serious drawbacks (e.g. EV degrades the information of a probabilistic distribution to a single quantitative measure irrespective of inherent variation of the parameters). Compared with the traditional GCF model and the EV model, the superiority of the proposed model was revealed through some numerical examples. (Das et al., 2007) proposed a bi-objective mixed integer programming model of cellular manufacturing system (CMS) in which the total system cost is minimized and machine reliability is maximized along the selected process routes. The proposed approach yields, for each part, the process plans which have lower probabilities of machine failures. The most appropriate combination of cost and system reliability was obtained through the ε-constraint method with a range of solution to choose from. (Diallo et al., 2001) studied the design of cell reconfiguration for flexible manufacturing systems (FMS) in presence of unreliable machines. They utilized Markov chain model to address different states of system originated from availability or non-availability of unreliable machines and used them to build efficient cell reconfigurations. One of the important issues in terms of reliability considerations in CFP is preventive maintenance (PM) planning addressed in (Das et al., 2007) for the performance improvement of CMS. They determined a PM policy on each machine in such a way that the total maintenance cost and overall probabilities of machine failures are minimized simultaneously assuming that machine failure times follow a weibull distribution. To solve the model, a multi-objective approach was exploited to determine the PM interval by taking into account both the costs and the machine reliability. (Bagheri et al., 2015) proposed a mathematical model for DCMS by considering different production factors such as APR and machines reliability with stochastic arrival and service time. Due to the complexity of the given problem, a Benders' decomposition approach was applied to solve the problem efficiently. Then, the performance of the proposed approach was tested via some numerical examples generated randomly in hypothetical limits and solved by the proposed solution approach.

D. Buffer storage

Generally speaking, there are only few research works devoted to buffer storage problem in the presence of unreliable machines within a CMS. (Lee, 2000) proposed a buffer sizing problem with the purpose of prescribing a cost-based approach to determine the total buffer storage and the buffer allocation in the cellular manufacturing environment. They used a three-phase approach to handle the aforementioned problem. First, steady-state queuing statistics was served to determine approximate buffer size, which is then assigned to each machine. Then a one-dimensional, line-search based procedure was used to find the minimal cost buffer design. Finally, a local improvement method was utilized for the cost minimization.

Looking at Table I; where a brief review of last decade on CFP is reported, the lack of contribution for CMS design in terms of buffer storage as an instrument to hold WIP inventory and sustain the systems whenever breakdowns occur is clear. This characteristic of production environments for CMS design is tackled in the current work.

III. PROPOSED MODEL

In this section a mathematical model addressing DCFP is developed in which machines employed to process different parts are exposed to breaking down. To reduce the detrimental effect of machines breakdown, buffer storage is incorporated to the CMS model in addition to APR. A buffer is allocated to each machine in order to keep WIP inventory of different processing stages of each part. This assumption increases reliability of the production system and cope with the variability of breakdowns among different machines.

The overall objective is to minimize the system costs including inter-cell movements, system reconfiguration, machines operation, production loss time, part outsourcing, setup, part holding, machine repair, and machine procurement cost for the entire horizon.

TABLE I. A brief review on CFP

Author	Certainty/Uncertainty				Factors									Modelling & Solution Procedure
	Determinist	Stochastic	Robust	Fuzzy	APR	Buffer Storage	DCMS	Production planning	Machine reliability	Operations sequence	Cell load variation	Exceptional elements	Scheduling	
Diallo et al. (2001)	✓						✓		✓					MCM
Lee (2000)	✓					✓								CBA
Won & Currie (2006)	✓									✓				p-median
Nsakanda et al. (2006)	✓				✓									GA & LSO
Carlos & Sebastia´n, (2006)														PSO
Balakrishnan & Cheng (2007)	✓						✓							LP & GA
Saidi-Mehrabad & Safaei (2007)	✓						✓			✓				NAMFT
Das et al. (2007a)	✓				✓				✓					BOMIP + ε-constraint
Das et al. (2007b)		✓							✓					MOHA
JabalAmeli & Arkat (2008)	✓				✓				✓					PLIP
JabalAmeli et al. (2008)	✓				✓				✓					BOLP + ε-constraint
Safaei et al. (2008a)				✓			✓							MIP
Safaei et al. (2008b)	✓						✓			✓				MFA & SA
Aramoon Bajestani et al. (2009)	✓						✓				✓			MOSS
Ahkioon et al. (2009a)	✓				✓		✓	✓		✓				MINLP
Ahkioon et al. (2009b)	✓				✓		✓	✓	✓					MIP
Chung & Chang (2010)	✓				✓				✓					TS
Ghezavati & Saidi-Mehrabad(2011)		✓												GA & SA
Saxena & Jain (2011)	✓				✓		✓	✓	✓	✓				MIP
Arkat et al. (2011)		✓			✓				✓					CCP
Nouri & Hong (2013)	✓										✓	✓		BFO
Rafiei & Ghodsi (2013)	✓						✓							ACO
Sakhaii et al. (2015)			✓		✓		✓	✓	✓					RO
Renna & Ambrico (2015)	✓						✓						✓	Simulation
Bagheri et al. (2015)		✓					✓		✓					BDA
Proposed model	✓				✓	✓	✓	✓	✓	✓				GA

Abbreviations equivalent: LSO, Large-scale optimization; MFA, Mean field annealing; BFO, Bacteria foraging optimization; MOSS, Multi-objective scatter search; NAMFT, Neural approach based on mean field theory; RO, Robust optimization; CCP, Chance constrained programming; MCM, Markov chain model; MOHA, Multi-objective heuristic approach; BDA, Benders' decomposition approach; CBA, Cost-based approach

A. Assumptions

The proposed model includes the following assumptions:

1. The demand for each part type per period is known.
2. The operating times for all part type operations on different machine types are known.
3. The manufacturing system is supposed to operate for a number of time periods.
4. The capability and capacity of each machine type is known and constant over the time period.
5. Machines can be replicated to meet capacity requirements.
6. All machines of type *m* can perform all part type *p* operations
7. Relocation cost of each machine type from one cell to another between periods is known.
8. Parts are moved between cells as batches.
9. Inter-cell batches have different costs and sizes for each part type regardless of traveled distance.
10. Procurement cost of each machine type is known in each period.
11. Maximum number of cells is constant over time.
12. The limitation and quantity of machines in each cell need to be specified in advance for each period of time.
13. Each machine type can perform one or more operations (machine flexibility). Likewise each operation can be done on one machine type with different times (routing flexibility).
14. Part inventory is assumed to have constant unit cost over the time period.
15. Backorders are not allowed. All demands must be satisfied in the given period.
16. No queuing in production is allowed.
17. Breakdown time for a machine type *m* is assumed to have an exponential distribution with a known failure rate of $\lambda(m)$, so mean time between failure (MTBF) is $1/\lambda(m)$.
18. Repair time for each machine follows an exponential distribution with a known failure rate of $\mu(m)$, so mean time to repair (MTTR) is $1/\mu(m)$.
19. Buffer storage is considered to handle production loss cost of unreliable machines.
20. Holding cost of work in process inventory kept in the buffer is considered in the model.
21. All work in process inventories are outsourced to an external supplier with specified capacity and production cost.

Assumptions (1-18) have been extensively considered by many researchers. However assumptions (19-21) are related to the novelty of the proposed model.

B. Indices

Time period index: $t=1, 2,\ldots, T$

Part type index: $p=1, 2, \ldots , P$

Index of operations of part *p*: $o=1, 2,\ldots,O_p$

Machine type index: $m=1, 2,\ldots, M$

Cell index: $c=1, 2,\ldots, C$.

C. Parameters

T	Number of planning periods
P	Number of part types
O_p	Number of operations for part type *p*
M	Number of machine types
C	Maximum number of cells that can be formed
$D_p(t)$	Demand of part type *p* during time period *t*
V_p^{inter}	Inter-cell movement cost per transfer batch of part type *p*
B_p^{inter}	Transfer batch size for inter-cell movement of part type *p*

B_p^p	Process batch size for part type *p*
$MTBF(m)$	Mean time between failures of machine type *m* in period *t*
$MTTR(m)$	Mean time to repair of machine type *m* in period *t*
R_m^+	Cost of installing one unit of type *m* machine
R_m^-	Cost of removing one unit of type *m* machine
$N_m(t)$	Maximum number of machine *m* that can be procured at time period *t*
C_m	Time capacity of machine type *m*
OS_p	Outsourcing cost of part type *p*
SC_{opm}	Setup cost for operation *o* of part type *p* on machine type *m*
OC_{opm}	Operating cost of operation *o* of part *p* processed on machine *m*
H_p	Unit inventory holding cost of part type *p*
BC_m	Machine repair cost of machine type *m* per hour
P_m	Procurement cost of machine type *m*
BH_{op}	Work in process inventory cost of operation *o* of part type *p* stored in the buffers.
P_{op}^{WIP}	Procurement cost for the work in process inventory of operation *o* of part *p*
C^{WIP}	Maximum capacity of work in process inventory that can be outsourced to a supplier
t_{opm}	Processing time of operation *o* of part type *p* on machine type *m*
L	A large positive number
$LB_c(t)$	Minimum number of machines in cell *c* at time period *t*.
$UB_c(t)$	Maximum number of machines in cell *c* at time period *t*.

D. Variables

Continuous

$X_{opmc}(t)$	Number of part type p processed by operation *o* on machine type *m* in cell *c* during time period *t*
$\overline{X_p(t)}$	Number of part type *p* to be outsourced at time period *t*.
$D_p^{\text{inter}}(t)$	Demand of part type *p* for internal production in time period *t*
$I_p(t)$	Number of part inventory of type *p* kept in time period *t* and carried over to period *(t+1)*
$WIP_{opmc}(t)$	Work in process inventory of stage *o* of part *p* available at the buffer *m* at cell *c* at time period *t*
$WIP_{opmc}^+(t)$	Work in process inventory of stage *o* of part *p* added to the buffer *m* at time period *t*
$WIP_{opmc}^-(t)$	Work in process inventory of stage *o* of part *p* removed from the buffer *m* due to machine failure at time period *t*

General integer

$Y_{mc}^+(t)$	Number of type *m* machines added to cell *c* at time period *t*
$Y_{mc}^-(t)$	Number of type *m* machines removed from cell *c* at time period *t*

$N_{mc}(t)$ Number of machine type m in cell c during period t

Binary variables

$\alpha_{opc}(t)=1,$ If operation o for part type p is carried out in cell c

$=0,$ Otherwise

$\beta_p(t)=1,$ If part p is produced in time period t

$=0,$ Otherwise

E. Model formulation

The mathematical formulation for the proposed cell formation problem is presented as follows:

$$\text{Minimize } Z= \frac{1}{2}\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{o=1}^{O_p-1} V^{\text{inter}} \cdot \frac{X_{opmc}(t)}{B_p^{\text{inter}}}\left|\alpha_{(o+1)pc}(t)-\alpha_{opc}(t)\right| \tag{1}$$
$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\left(R_m^{+}.Y_{mc}^{+}(t)+R_m^{-}.Y_{mc}^{-}(t)\right)$$
$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{o=1}^{O_p}\left(X_{opmc}(t)+\left(X_{opmc}(t)-WIP_{opmc}^{-}(t).\frac{MTTR(m)}{MTBF(m)}\right)\right)t_{opm}.OC_{opm}$$
$$+\sum_{t=1}^{T}\sum_{p=1}^{P}OS_p.\overline{X_p(t)}+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{o=1}^{O_p}\frac{X_{opmc}(t)}{B_p^{p}}.SC_{opm}$$
$$+\sum_{t=1}^{T}\sum_{p=1}^{P}H_p.I_p(t)+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{o=1}^{O_p}\frac{X_{opmc}(t).t_{opm}}{MTBF(m)}.BC_m$$
$$+\sum_{m=1}^{M}P_m\left(\sum_{c=1}^{C}N_{mc}(T)-\sum_{c=1}^{C}N_{mc}(0)\right)$$
$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{o=1}^{O_p}P_{op}^{WIP}(t).WIP_{opmc}^{+}(t)$$
$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{o=1}^{O_p}BH_{op}(t).WIP_{opmc}(t)$$

Subject to:

$$\sum_{c=1}^{C}\alpha_{opc}(t)=\beta_p(t) \qquad \forall(o,p,m,c,t) \tag{2}$$

$$X_{opmc}(t)\le L.\beta_p(t) \qquad \forall(o,p,m,c,t) \tag{3}$$

$$D_p^{\,i}(t)=\sum_{c=1}^{C}\sum_{m=1}^{M}\left(X_{opmc}(t)+WIP_{opmc}(t)\right) \qquad \forall(o,p,t) \tag{4}$$

$$D_p^{\,i}(t)+I_p(t-1)-I_p(t)+\overline{X_p(t)}=D_p(t) \qquad \forall(p,t) \tag{5}$$

$$\sum_{c=1}^{C}N_{mc}(t)-\sum_{c=1}^{C}N_{mc}(t-1)\le N_m(t) \qquad \forall(m,t) \tag{6}$$

$$\sum_{p=1}^{P}\sum_{o=1}^{O_p}X_{opmc}(t).t_{opm}\le C_m.N_{mc}(t) \qquad \forall(m,c,t) \tag{7}$$

$$\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{o=1}^{O_p}WIP_{opmc}(t)\le C^{WIP} \qquad \forall(t) \tag{8}$$

$$N_{mc}(t)=N_{mc}(t-1)+Y_{mc}^{+}(t)-Y_{mc}^{-}(t) \qquad \forall(m,c,t) \tag{9}$$

$$LB_c(t)\le\sum_{m=1}^{M}N_{mc}(t)\le UB_c(t) \qquad \forall(c,t) \tag{10}$$

$$\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{o=1}^{O_p}X_{opmc}(t).t_{opm}\ge\frac{q}{c}\left(\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{o=1}^{O_p}X_{opmc}(t).t_{opm}\right) \qquad \forall(c,t) \tag{11}$$

$$\sum_{c=1}^{C}\sum_{m=1}^{M}X_{(o+1)pmc}(t)=\sum_{c=1}^{C}\sum_{m=1}^{M}\left(X_{opmc}(t)+WIP_{opmc}(t)\right) \qquad \forall(o,p,t) \qquad (12)$$

$$WIP_{opmc}(t)=WIP_{opmc}(t-1)+WIP^{+}_{opmc}(t)-WIP^{-}_{opmc}(t) \qquad \forall(o,p,m,c,t) \qquad (13)$$

$$Y_{mc}{}^{+}(t),Y_{mc}{}^{+}(t),N_{mc}(t)\in\{0,1,2,..\} \qquad \forall(o,p,m,c,t) \qquad (14)$$

$$X_{opmc}(t),\overline{X_{p}(t)},D_{p}{}^{i}(t),I_{p}(t),WIP_{opmc}(t),WIP^{+}_{opmc}(t),WIP^{-}_{opmc}(t)\geq 0 \qquad \forall(o,p,m,c,t) \qquad (15)$$

$$\alpha_{opmc}(t),\beta_{mc}(t)\in\{0,1\} \qquad \forall(o,p,m,c,t) \qquad (16)$$

F. Model objective function

The objective function given in Eq. (1) is utilized to minimize the overall cost of the proposed model. The first term of the objective function represents inter-cell movement cost. Machine relocation cost is expressed by the second term. The first part of the third term represents machines operation cost and the second part illustrates production loss time cost of the broken machines. The forth term is part outsourcing cost. The fifth, sixth, seventh and eighth terms are machine setup cost, part holding cost, machine repair cost and machine procurement cost respectively. The ninth term represents work in process holding cost. Finally the last term of the objective function is the procurement cost of work in process inventories. It is noticeable that terms 4, 9 and 10 of the objective function is due to buffer storage assumption as considered in this paper.

G. Model constraints

Eqs. (2) and (3) show that the number of part produced internally can be positive when part type *p* is produced internally by operation *o* on machine type *m* in cell *c*. Eq. (4) indicates that the number of part type *p* produced internally can be required by the sum of all cells and machines adopted to perform operation type *o*. Eq. (5) is related to inventory balance constraint. The maximum numbers of machines type *m* in access to process operate at the beginning of time period *t* are expressed in Eq. (6). Eq. (7) ensures that the production time of parts do not exceed maximum capacity of the machines. Capacity in access to procure WIP of different stages of products which should be added to buffers at the beginning of each period is expressed in Eq. (8). Eq. (9) implies that the number of machines type *m* in current period is equal to the number of machines in the previous period, adding the number of machines moved in and subtracting the number of machines moved out of the cell *c*. Eq. (10) specifies the lower and upper bounds on size of cells. Workload balance among cells is enforced in Eq. (11). Eq. (12) is adopted to incorporate material flow conservations in the model. Eq. (13) is related to work in process inventory balancing kept in the buffer of machine type *m* in cell *c*. Eqs. (14), (15) and (16) are integrality constraints. Equations (8), (11), (12) and (13) are constraints related to the buffer storage assumptions as considered in this paper. While, other constraints have been developed by other researchers.

F. Linearization of the model

As exact solutions of small-sized instances for the proposed model are calculated using GAMS-CPLEX mathematical programming software to validate the proposed GA, linearization of the model seems to be crucial. Linearization reduces complexity of solving the model by CPLEX solver to validate the proposed model. Also, optimal solutions are compared with those of the same size solutions obtained by the GA to verify the performance of the developed algorithm. The presented model is a nonlinear integer programming due to the first term of the objective function. To transform the non-linear term $X_{opmc}(t).\left|\alpha_{(o+1)pc}(t)-\alpha_{opc}(t)\right|$ into a linear one, binary variable $Z_{opc}(t)$ is introduced and term of $X_{opmc}(t).\left|\alpha_{(o+1)pc}(t)-\alpha_{opc}(t)\right|$ is replaced with the quadratic term of $X_{opmc}(t).Z_{opc}(t)$. In the next step, $X_{opmc}(t).Z_{opc}(t)$ is replaced by a continuous variable $T_{opmc}(t)$ with additional constraints given below.

$$\alpha_{(0+1)pc}(t) - \alpha_{opc}(t) \le Z_{opc}(t) \qquad \forall(o,p,c,t) \qquad (17)$$

$$-\alpha_{(0+1)pc}(t) + \alpha_{opc}(t) \le Z_{opc}(t) \qquad \forall(o,p,c,t) \qquad (18)$$

$$T_{opmc}(t) \ge X_{opmc}(t) + L.Z_{opc}(t) - L \qquad \forall(o,p,m,c,t) \qquad (19)$$

$$T_{opmc}(t) \le X_{opmc}(t) \qquad \forall(o,p,m,c,t) \qquad (20)$$

$$T_{opmc}(t) \le L.Z_{opc}(t) \qquad \forall(o,p,m,c,t) \qquad (21)$$

$$Z_{opc}(t) \in \{0,1,2,...\}, T_{opmc}(t) \ge 0 \qquad \forall(o,p,m,c,t) \qquad (22)$$

Equations (17)-(22) are added to the proposed nonlinear model and a mixed integer linear programming is obtained. The linearization procedure utilized in this paper, is adopted from (Defersha & Chen, 2008).

IV. SOLUTION METHODOLOGY

Biologically motivated approaches has gained increasing popularity in solving complex optimization problem in the last decades. GA which was first introduced in 1970s by (Holland, 1975) is one of the optimization approaches constructed based on evolutionary processes occurring in the natural systems. GA strives to synthesize the good features of different individuals within a population to create individuals who are better suited. For this purpose, GA operators such as crossover, mutation, and selection are utilized to evolve individuals in order to reach desired solutions. In contrary to other stochastic searches, GA encompasses noticeable features, such as implicit parallelism, population-based search and flexibility to be hybridized with domain-dependent heuristics which make researchers prefer it over traditional heuristics.

GAs have been widely used to solve the CFP. (Venugopal & Narendran, 1992) applied GA to tackle CFP based on the minimization of total cell load variation. Uddin & Shanker (2002) formulated generalized grouping problem as an integer programming problem and used GA as a solution methodology. (Mahdavi et al., 2009) utilized GA for the CFP aiming at minimization of voids and exceptional elements.

A. Chromosome representation

The chromosome representation or encoding of a solution is the first task when utilizing a genetic algorithm. Each chromosome referred to an initial population represents a solution to the problem. To encode the proposed model, independent chromosomes are defined involving variables:

$X_{opmc}(t)$, $\overline{X_p(t)}$, $WIP^{+}_{opmc}(t)$, $WIP^{-}_{opmc}(t)$, $\mathrm{N}_{mc}(t)$, $\beta_p(t)$ and C_{op}. A five dimensional matrix of size $o \times p \times m \times c \times t$ is defined for each continuous variable excluding $\overline{X_{p(t)}}$ which is encoded by a chromosome of size $p \times t$. A three dimensional matrix of size $m \times c \times t$ corresponding to $N_{mc}(t)$ is defined in which each gene takes a positive integer number representing the number of machines type m installed in cell c in period t. The other chromosome is a matrix of size $p \times t$ related to the binary variable $\beta_p(t)$ which takes an integer value in {0,1} to show whether part p is produced in period t. Finally a chromosome of size $o \times p$ is represented in which the gene C_{op} takes the value in $\{1,2,...,C\}$ to show the index of cell in which operation o of part p is to be produced.

B. Chromosome decoding

The values of all continuous variables and integer variables $N_{mc}(t)$, $\beta_p(t)$ are directly obtained from the chromosome, while the variable $\alpha_{opc}(t)$ is specified by Eq. (23). From this equation, it is clear that the constraint in Eq. (2) is satisfied by any randomly generated solution as illustrated in Eq. (24).

$$\alpha_{opc}(t) = \begin{cases} \beta_p(t) \; If \; \text{the subscript } c = C_{op} \\ 0; \quad \text{otherwise} \end{cases} \tag{23}$$

$$\sum_{c=1}^{C} \alpha_{opc}(t) = \left(\sum_{\forall c \neq C_{op}} \alpha_{opc}(t)\right) + \beta_p(t) = 0 + \beta_p(t) \tag{24}$$

C. Fitness function

The fitness function is calculated to evaluate the candidate solutions in the population with respect to the objective function and constraints of the model. For a given solution, the fitness value of the proposed model, which is given in Eq. (25) is calculated by the sum of model objective function and the penalty term defined to prevent constraint violation of Eq. (10). Also the factor W_c is used to scale the penalty term, which is determined by trial and error.

$$F = \text{Model objective function} + W_c . \sum_{t=1}^{T} \sum_{c=1}^{C} \max\left\{0, LB_c - \sum_{m=1}^{M} N_{mc}(t), \sum_{m=1}^{M} N_{mc}(t) - UB_c\right\} \tag{25}$$

D. Genetic operators

Genetic operators are employed to create better solution and replace them with those which existed in initial population to obtain near optimum solution. Generally, genetic operators are classified as selection, crossover and mutation. In the proposed genetic algorithm roulette wheel operator is used to probabilistically select the parents within the initial population to construct new children. The main operator of the GA is crossover which reproduces individuals by combining the information of randomly selected parents such that created offsprings share the characteristics of both parents. These offsprings are compared with respect to fitness function and passed onto the next generation. The crossover operator used in the proposed GA is uniform crossover. For integer variables, a binary chromosome namely α with the same size of corresponding integer variable is generated. Offspring1 adopts those genes of parent1 whose corresponding genes of α take value of 1 and adopts the rest of genes from parent2. The reverse procedure is applied to create offspring2. For continuous variables however, α is a value randomly selected between [ε,1+ε]. The equations of uniform crossover are given as follows.

$$offspring1 = \alpha \times Parent1 + (1-\alpha) \times Parent2 \tag{26}$$

$$offspring2 = \alpha \times Parent2 + (1-\alpha) \times Parent1 \tag{27}$$

The other genetic operator is mutation. This operator is mainly used to avoid local optimization by randomly changing individual genes and increasing the search space. In this study binary operator for mutation process. This operator is applied to the randomly selected individual as follows: parameter μ is defined between [0,1] and the number of genes within the selected parent that should be replaced to create new offspring is obtained as follows:

Number of replaced genes=[μ×Number of genes within a chromosome] + 1 (28)

Then the number of genes specified above are randomly selected from the parent and replaced with an appropriate random integer with respect to the chromosome type.

V. EXPERIMENTAL RESULTS

In this section the performance of the proposed GA is evaluated through numerical examples. Table II includes the parameters of the model, which are randomly generated to perform the test problems. In this regard, the algorithm was run on a computer with Intel® Core 5 CPU, 2.67 GHz speed and 4 GB RAM. The experiments were implemented in two categories; firstly for small-sized instances and secondly for large-sized instances.

A. Small-sized problems

The first set of experiments are carried out on 10 small-sized instances. Here, small-sized instances are referred to problems which are solvable optimally in GAMS software using CPLEX solver in reasonable CPU time. The solutions obtained from the GA, which is coded in MATLAB software, are compared with optimal solutions of these instances to verify the efficiency of the proposed algorithm.

Based on trial and error, the population size of GA and total number of generations are set to 75 and 50 respectively. Table III represents the data for the test problems and a comparison between exact solutions obtained from the GAMS and those resulted from the proposed GA approach in terms objective function values. Table IV includes the optimal cell configuration of the small-sized problems. The reasonable gap of the optimal solution and GA solution presented in Table III permits us to generalize the proposed algorithm for large-sized instances which are not solvable optimally by the CPLEX solver.

TABLE II. Randomly generated data

Parameter	Cost	Parameter	Cost
V^{inter}	[25 50]	OS_p	[4000 5000]
B_p^{inter}	[25 50]	SC_{opm}	[100 250]
B_p^p	[100 150]	OC_{opm}	[30 50]
$MTBF(m)$	[4000 5000]	H_p	[500 600]
$MTTR(m)$	[200 350]	BC_m	[1500 2000]
R_m^+	[650 750]	BH_{op}	[50 120]
R_m^-	[650 750]	Pm	[1300 1600]
C_m	[5000 8000]	P_{op}^{WIP}	[50 120]
D_{pt}	[1500 2500]	t_{opm}	[20 35]

TABLE III. Small-sized test problems

Problem No.	O×P×M×C×T	Exact Solution	GA Solution	Gap (%)
1	3×4×4×2×2	78540342	79474972	1.19
2	3×5×5×2×2	82706141	84624923	2.32
3	3×5×4×2×3	105167848	107344822	2.07
4	3×7×8×3×2	131509601	136072984	3.47
5	3×6×5×2×3	148409845	161173091	1.86
6	3×6×6×3×3	169629549	175821028	3.65
7	4×7×7×3×2	181580872	190950445	5.16
8	4×7×6×3×3	194186340	203662633	4.88
9	4×8×8×3×2	187540389	192603980	2.70
10	4×8×8×3×3	207569320	219047903	5.53

B. Large-sized problem

Another set of experiments are performed for large-sized instances. Since the authenticity of GA procedure was proven in previous section. To establish the desired experiments, 6 large-sized instances, as presented in Table V, are designed and implemented in MATLAB software. In accordance with enhancement of problem sizes, we increase the population size of GA and total number of generations to 200 and 150 respectively. Results consisting objective function values are presented in Table V. Besides, column III of Table V represents the objective values of large-sized instances after running for an hour in GAMS-CPLEX solver as a lower bound of GA solutions. The gap of every pair of solutions reported in column V of Table V proves the efficiency of the proposed GA for large-sized instances. Also, cell configurations of the large-sized problems, obtained from GA procedure, are indicated in Table VI.

VI. SENSITIVITY ANALYSIS AND MODEL VALIDATION

In this section, the validation of the proposed model is examined by changing model parameters to see if model is reasonably sensitive to the changes of parameters. Besides the performance of WIP inventory and buffer storage concept in CMS is analyzed.

TABLE IV. Cell configuration of small-sized instances

Problem No.	H=1			H=2			H=3		
	C=1	C=2	C=3	C=1	C=2	C=3	C=1	C=2	C=3
1	1,2	3,4		2	1,3,4				
2	2,4,5	1,2,3,4		2,4,5	1,4,5				
3	2,3	1,4		1,2	3,4		1,2	3,4	
4	2,3,7	1,4,5,6	3,5,7	4,5,6	1,3,7	2,3,5,6			
5	2,4	1,3,5		2,3,4	1,5		4,5	1,2,3	
6	1,4,6	3,4,5	1,2,5,6	1,5,6	3,4,6	2,3,5	2,3,5	1,2,4,5	1,3,6
7	2,4,7	1,3	5,6	2,5	1,3	4,6,7			
8	3,5	1,4,7	2,6	2,4,7	1,6	3,5	4,6,7	2,5	1,3
9	2,8	3,4,7	1,5,6	1,7	3,5,8	2,4,6			
10	2,6,7	4,8	1,3,5	3,4	1,2,6	5,7,8	1,2,5	6,8	3,4,7

TABLE V. Large-sized test problems

Problem No.	O×P×M×C×T	Lower bound after an hour	GA Solution	GAP (%)
1	4×10×8×3×3	330492763	334789169	1.30
2	4×10×10×3×3	321834748	328110526	1.95
3	5×15×10×4×2	804146778	822802984	2.32
4	5×15×12×4×3	1421492358	1451201549	2.09
5	5×20×15×4×3	2440900805	2510710568	2.86
6	5×25×20×4×3	4132889013	4253982661	2.93

TABLE VI. Cell configuration of larged-sized instances

Problem No.	**H=1**				**H=2**				**H=3**			
	C=1	**C=2**	**C=3**	**C=4**	**C=1**	**C=2**	**C=3**	**C=4**	**C=1**	**C=2**	**C=3**	**C=4**
1	1,3,4,6	4,7,8	2,3,5,7		1,5,8	4,6,7	2,3,4,8		3,5,6,7 8	2,3,6,7	1,4,5,8	
2	3,7,8	2,5,9	1,4,5,6 10		4,7,8,10	2,3,5,6 9	1,4,6,10		1,6,9	5,8,10	1,4,7,8	
3	4,6,7	1,5,6,8 10	3,5,6,9	4,6,7,8 10	2,5,7,	4,7,8,9	1,3,5,8 10	2,4,6,9 10				
4	4,7,10 11	3,5,8 10,11	5,6,8,9 12	1,4,6,7 9,11,12	8,9,11	2,5,7 10	4,6,8,9	2,5,6,7 11	5,8,9 12	1,2,6,8 10,12	3,4,6 11	4,9,10 12
5	3,8,10 11,14	6,9,12 13	4,6,7,10 14,15	1,5,8,12 13	2,5,7,8,10 12,13	1,7,9,10 11,12,15	3,7,10 14	1,2,4,6,9 11,13	4,5,8 10,12	1,3,9 15	3,4,6,7 9,10,13	5,6,9 11,15
6	1,4,7,11 14,15 17	2,5,9,12 13,16 19	2,6,8,11 16,20	1,5,9,13 14,17 19	2,5,7,10 15,18	4,8,14 17,20	3,6,7,9 13,15,19	4,5,6,10 12,13,17 18,20	1,6,7 10,14 15,16 20	2,3,7,9 11,12 19	1,5,6,8 10,13 15,16 17,18	3,4,8 10,14 16,19 20

In this regard, the proposed model is compared to the classic CMS model in terms of objective function values. To acquire classic CMS model, new assumptions added in this paper (assumptions (19-21)) are omitted. Subsequently, the ninth and tenth terms of objective function and Eq. 1 are omitted and the rest of objective terms and constraints are modified by omitting variables; $WIP_{opmc}(t)$, $WIP^{+}_{opmc}(t)$ and $WIP^{-}_{opmc}(t)$.

For the analysis mentioned above, test problem number 5 of small-sized instance is selected. For the model without new assumptions, by setting number of parts (P) from 3 to 8. However, for the proposed model, in addition to P, procurement cost of WIP inventories (P_{op}^{WIP}) is set in four different values; P_{op}^{WIP} , $2P_{op}^{WIP}$ $3P_{op}^{WIP}$ and $4P_{op}^{WIP}$. Then, objective function values of two models are used as the base of the comparison.

Eq. (27) calculates the change in the objective function for a given combination, where $OFV_w(P)$ is the objective function value for the model without new assumptions with P parts and $OFV_p(P, P_{op}^{WIP})$ is the objective function value for the proposed model with P parts in P_{op}^{WIP} level of WIP inventory procurement cost.

$$\sigma\% = \frac{OFV_w(P) - OFV_p(P, P_{op}^{WIP})}{OFV_p(P, P_{op}^{WIP})} \times 100 \tag{27}$$

Table VII shows the values of OFV_w, OFV_p and σ% for different combinations of P and P_{op}^{WIP} .Also, results are illustrated in different plots of figure 1, where the *x*-axis is number of parts and *y*-axis is objective function value of models in different levels of P_{op}^{WIP} .

It is inferred from figure 1 that the proposed model is reasonably sensitive to the change of number of parts. In other words OFV_p increases as the result of increase in P . Hence, the model is validated. Besides, It is obvious that the proposed model is preferred to the model without new added assumptions of this paper, as it results in lower cost in all levels of P_{op}^{WIP} , while approaching to the former model as P_{op}^{WIP} level increases. The proximity of the proposed model with the classic model in higher level of P_{op}^{WIP} indicates that the efficiency of the model decreases facing of machine failure costs in higher level of P_{op}^{WIP} .

TABLE VII. Sensitivity analysis results

Number of parts	OFV_w	OFV_p $(\sigma\%)$			
		WIP procurement cost level			
		P_{op}^{WIP}	$2P_{op}^{WIP}$	$3P_{op}^{WIP}$	$4P_{op}^{WIP}$
3	84196031	90617436 (7.63)	88901468 (5.58)	87134507 (3.49)	85997826 (2.14)
4	99361298	107957614 (8.65)	105198401 (5.87)	102649214 (3.31)	101279368 (1.93)
5	125167848	134734091 (7.64)	131914675 (5.39)	129174095 (3.20)	128153226 (2.39)
6	148409845	159285618 (7.32)	156101692 (5.18)	153681996 (3.55)	151926965 (2.37)
7	165398765	178863023 (8.14)	176402058 (6.65)	171375106 (3.61)	169660271 (2.58)
8	180273610	195965177 (8.70)	191852913 (6.42)	186923922 (3.68)	185143673 (2.70)

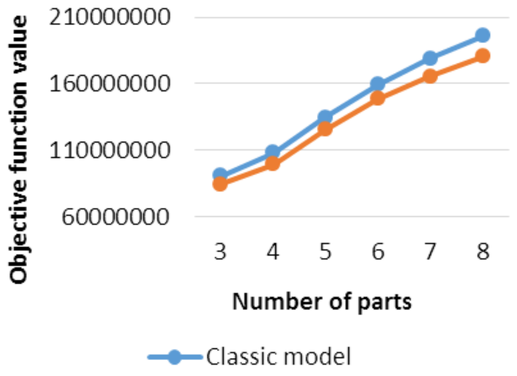

Fig. 1.1. WIP procurement cost level = P_{op}^{WIP}

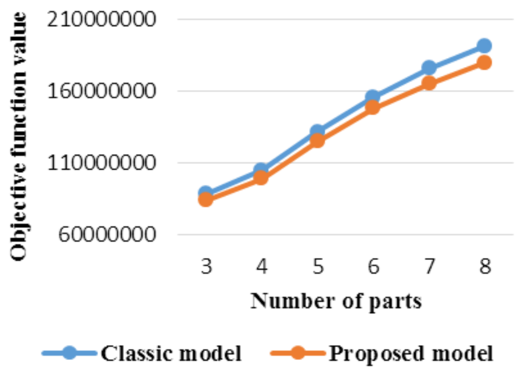

Fig. 1.2. WIP procurement cost level = $2P_{op}^{WIP}$

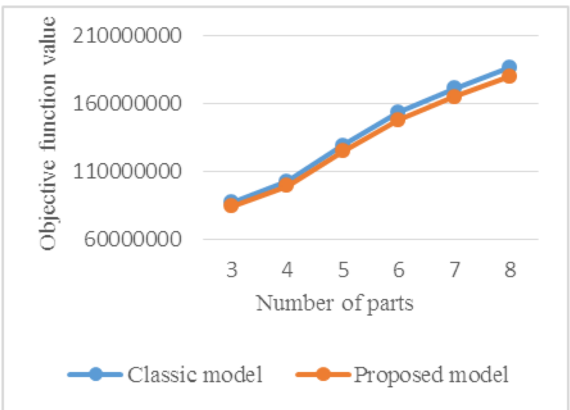

Fig. 1.3. WIP procurement cost level = $3P_{op}^{WIP}$

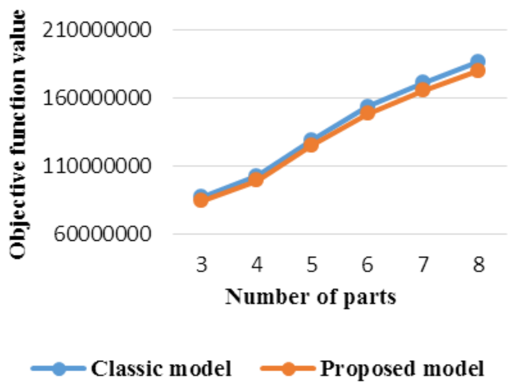

Fig. 1.4. WIP procurement cost level = $4P_{op}^{WIP}$

Fig. 1. Sensitivity analysis results

VII. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

We presented a new approach to dynamic cell formation problem in which a comprehensive model consisting of different aspects of the cell formation problem is proposed to minimize the overall costs of the system such as machine repairing cost, inter-cell movement cost, work in process inventory cost, machine relocation cost and etc. The model encompasses alternative routing process and buffer storage to heighten the reliability of the system. Work in process inventory of each production stage are kept in the buffers to prevent the fraction of production flow. Other attributes and practical constraints include workload balancing, dynamic system reconfiguration, cell size limit and etc. were considered. It is obvious that the mathematical programming model for manufacturing cell problem is NP-hard. Hence, a genetic algorithm is utilized to solve the problem. 10 small-sized instances as well as 6 large-sized instances have designed and implemented and the performance of the genetic algorithm to reach near optimum solutions has been verified. Also, the validation of the proposed model as well as the applicability of new assumptions are proven by sensitivity analysis. To continue the current research directions, developing a simulation optimization based approach might be of great interest. Also, it is highly recommended to consider queuing in production as a novel assumption in CFP context as a related future work.

REFERENCES

1. Ahkioon, S., Bulgak, A.A. & Bektas, T. (2009a). Cellular manufacturing systems design with routing flexibility, machine procurement, production planning and dynamic system reconfiguration. *International Journal of Production Research*, *47*, 1573–1600.

2. Ahkioon, S., Bulgak, A.A. & Bektas, T. (2009b). Integrated cellular manufacturing systems design with production planning and dynamic system reconfiguration. *European Journal of Operational Research*, *192*, 414 – 428.

3. Aramoon Bajestani, M. Rabbani, M. Rahimi-Vahed, A.R. & Baharian, G.K. (2009). A multi-objective scatter search for a dynamic cell formation problem. *Computers & Operations Research*, *36*, 777 – 794.

4. Arkat, J., Naseri, F. & Ahmadizar, F. (2011). A stochastic model for the generalized cell formation problem considering machine reliability. *International Journal of Computer Integrated Manufacturing, 24*, 1095 – 1102.

5. Balakrishnan, J. & Cheng, C. H. (2007). Multi-period planning and uncertainty issues in cellular manufacturing: a review and future directions. *European Journal of Operational Research, 177*, 281-309.

6. Chang, C. C., Wu, T. H. & Wu, C. W. (2013). An efficient approach to determine cell formation, cell Layout and intracellular machine sequence in cellular manufacturing systems. *Computers & Industrial Engineering, 66*, 438 – 450.

7. Carlos, A. & Sebastia´n, L. (2006). A particle swarm optimization algorithm for part–machine grouping. *Robotics and Computer-Integrated Manufacturing, 22*, 468 – 474.

8. Chung, S.H. & Chang, C.C. (2010). An efficient tabu search algorithm to the cell formation problem with alternative routings and machine reliability considerations. *Computers & Industrial Engineering, 60*, 7-15.

9. Das, K., Lashkari, R. S. & Sengupta, S. (2007a). Reliability consideration in the design and analysis of cellular manufacturing systems. *International Journal of Production Economics, 105*, 243-262

10. Das, K., Lashkari, R. S. & Sengupta, S. (2007b). Machine reliability and preventive maintenance planning for cellular manufacturing systems. *European Journal of Operational Research, 183*, 162-180.

11. Defersha, F. H. & Chen, M. (2008). A linear programming embedded genetic algorithm for an integrated cell formation and lot sizing considering product quality. *European Journal of Operational Research, 187*, 46-69.

12. Diallo, M., Pierreval, H. & Quilliot, A. (2001). Manufacturing cells design with flexible routing capability in presence of unreliable machines. *International Journal of production economics, 74,* 175 – 182.

13. Ghezavati, V. R., & Saidi-Mehrabad, M. (2011). An efficient hybrid self-learning method for stochastic cellular manufacturing problem: A queuing-based analysis. *Expert Systems with Applications, 38*, 1326 – 1335.

14. Ghosh, T., Sengupta, S., Chattopadhyay, M., & Dan, P. (2011). Meta-heuristics in cellular manufacturing: A state-of-the-art review. *International Journal of Industrial Engineering Computations, 2*, 87-122.

15. JabalAmeli, M.S., Arkat, J. & Barzinpour, F. (2008). Modelling the effects of machine breakdowns in the generalized cell formation problem. *International Journal of Advanced Manufacturing Technology, 39*, 838 – 850.

16. JabalAmeli, M.S. & Arkat, J. (2008). Cell formation with alternative process routings and machine reliability consideration. *International Journal of Advanced Manufacturing Technology, 35*, 761 – 768.

17. Kusiak, A. & Chow, W.S. (1988). Decomposition of manufacturing systems. *IEEE Journal of Robotics and Automation, 4*, 457 – 471.

18. Lee, S.D. (2000). Buffer sizing in complex cellular manufacturing systems. *International Journal of Systems Science, 31*, 937 – 948.

19. Mahdavi, I., Paydar, M. M., Solimanpur, M., & Heidarzade, A. (2009). Genetic algorithm approach for solving a cell formation problem in cellular manufacturing. *Expert Systems with Applications, 36*, 6598 – 6604.

20. Mansouri, S.A., Husseini, S.M.M. & Newman, S.T. (2000). A review of modern approaches to multi-criteria cell design. *International Journal of Production Research, 38*, 1201 – 1218.

21. Nsakanda, A. L., Diaby, M. & Price, W. L. (2006). Hybrid genetic approach for solving large-scale capacitated cell formation problems with multiple routings. *European Journal of Operational Research, 171*, 1051 – 1070.

22. Nouri, H., & Hong, T. S. (2013). Development of bacteria foraging optimization algorithm for cell formation in cellular manufacturing system considering cell load variations. *Journal of Manufacturing Systems, 32*, 20 – 31.

23. Papaioannou, G. & Wilson, J. M. (2010). The evolution of cell formation problem methodologies based on recent studies (1997–2008): Review and directions for future research. *European Journal of Operational Research, 206*, 509 – 521.

24. Rafiei, H., & Ghodsi, R. (2013). A bi-objective mathematical model toward dynamic cell formation considering labor utilization. *Applied Mathematical Modelling, 37*, 2308 – 2316.

25. Renna, P., & Ambrico, M. (2015). Design and reconfiguration models for dynamic cellular manufacturing to handle market changes. *International Journal of Computer Integrated Manufacturing*, *28*, 170 – 186.

26. Safaei, N., Saidi-Mehrabad, M., Tavakkoli-Moghaddam, R. & Sassani, F. (2008a). A fuzzy programming approach for a cell formation problem with dynamic and uncertain conditions. *Fuzzy Sets and Systems, 159*, 215 – 236.

27. Safaei, N., Saidi-Mehrabad, M. & JabalAmeli, M. S. (2008b). A hybrid simulated annealing for solving an extended model of dynamic cellular manufacturing system. *European Journal of Operational Research, 185*, 563 – 592.

28. Saidi-Mehrabad, M. & Safaei, N. (2007). A new model of dynamic cell formation by a neural approach. *International Journal of Advanced Manufacturing Technology, 33*, 1001 – 1009.

29. Sakhaii, M., Tavakkoli-Moghaddam, R., Bagheri, M., & Vatani, B. (2015). A robust optimization approach for an integrated dynamic cellular manufacturing system and production planning with unreliable machines. *Applied Mathematical Modelling*, doi:10.1016/j.apm.2015.05.005.

30. Saxena, L.K. & Jain, P.K. (2011). Dynamic cellular manufacturing systems design—a comprehensive model. *International Journal of Advanced Manufacturing Technology, 53*, 11 – 34.

31. Uddin, M. K., & Shanker, K. (2002). Grouping of parts and machines in presence of alternative process routes by genetic algorithm. *International Journal of Production Economics*, *76*, 219 – 228.

32. Venugopal, V., & Narendran, T. T. (1992). A genetic algorithm approach to the machine-component grouping problem with multiple objectives. *Computers & Industrial Engineering, 22*, 469 – 480.

33. Wemmerlov, U. & Hyer, N.L. (1986). Procedures for the part family machine group identification problem in cellular manufacturing. *Journal of Operations Management, 6*, 125 – 147.

34. Won, Y. & Currie, K.R. (2006). An Effective P-median Model Considering Production Factors in Machine Cell/Part Family Formation. *Journal of Manufacturing Systems*, *25*, 58 – 64.