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Stochastic Capacitated Cellular Manufacturing System Design with Hybrid Similarity Coefficient

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1. Introduction

Manufacturing system design is one of the most crucial steps of business processes. Several approaches have been proposed and implemented to increase productivity and profitability due to the change in customer characteristics, market condition and economy. Cellular Manufacturing (CM) is one of the approaches that emerged as an application of Group Technology in the late 70s due to the increase in product variety and demand variance. Group Technology (GT) is a product-oriented manufacturing approach to group similar products for smaller batch size production. As an application of GT, CM is the physical or virtual division of manufacturing facilities into manufacturing cells. A manufacturing cell is a small group of machines and/or workers ideally arranged in a flow layout to produce "similar items", in other words "product families".

Production volume and product variety have significant impact on the design of manufacturing system. Layout of the shop floor is generally used to classify the manufacturing systems. There are four well-known layout types; namely: fixed layout, product layout, process layout and cellular layout. A fixed layout consists of fixed parts and non-fixed resources which travel to parts to perform the operations. In product layout, resources are arranged based on the sequence of operations. This layout is very efficient to meet high volume demand when product variety is low. On the other hand, in process layout, similar resources thus processes are grouped together to meet low and medium volume demand and high product variety. Product layout is more efficient in terms of material flow, whereas process layout is more flexible to deal with high product variety. Cellular layout is a hybrid layout which includes the advantages of both product and process layouts. Cellular layout improves the manufacturing system performance from many aspects such as reduction in material handling, lead times, work-in-process inventory (WIP), re-work, scrap and efficient floor space usage (Wemmerlov U. & Johnson D. J., 1997).

Even though most of the cellular manufacturing system (CMS) design approaches work with deterministic data, uncertainty indeed significantly influences the CMS performance,

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especially in labor-intensive manufacturing cells. Therefore, the impact of such design parameters as variance in demand and variance in processing times should be taken into consideration during the CMS design. Moreover, most of the works in literature deals with the cell and family formation problem from only route-based similarity point of view. However, since the demand variance can have ruining impact on system performance, demand-based similarity should be also taken into consideration when building similarity matrix. In this chapter, a hybrid similarity matrix, which incorporates route-based and demand-based similarities, is proposed and a stochastic non-linear mathematical model is developed to design CMS considering uncertain demand and processing times. To validate the proposed model, simulation experiments are carried out. Finally, a Genetic Algorithm approach is proposed to deal with large problems.

2. Literature review

The literature is abundant with the works that include optimization methods. In addition to mathematical models, heuristics and meta-heuristics are used to tackle larger problems. The majority of works in literature address deterministic CMS design. However, uncertainty in some parameters such as demand and processing times brings probabilistic nature to design problems. While most of the studies in the literature have addressed the deterministic CMS design problem, less attention is paid to the problems that consider the probabilistic demand and processing times. The literature is reviewed in two sections, namely: deterministic design and stochastic design.

2.1 Deterministic CMS design

In deterministic case, mathematical optimization techniques are used to solve the cell formation problem. As a preliminary work, Purcheck (1974) developed a mathematical classification for the systematic analysis of process routes to group technology and cell formation problem (Purcheck, 1974). Kusiak (1987) provided a comparison of matrix and integer programming models, and discussed the impact of the models on the quality of process families and machine cells (Kusiak, 1987). Shtup (1989) proved the equivalency of cell formation problem to the Generalized Assignment Problem (GAP) (Shtubt, 1989). Rajamani, Singh and Aneja (1990) studied the impact of alternative process plans on the resource utilization and developed three integer programming models to analyze the effect of alternative process plans and simultaneous formation of part families and machine groups (Rajamani, Singh, & Aneja, 1990). Wei and Gaither (1990) developed an integer programming model for cell formation problem (Wei & Gaither, 1990). The objective was to minimize the cost of manufacturing exceptional parts outside the cellular system, subject to machine capacity constraints. Shafer and Rogers (1991) proposed a goal programming model to CMS design problem with the objectives: reducing setup times, minimizing intercellular movements of products and the investment in new equipment, and maintaining acceptable machine utilization levels (Shafer & Rogers, 1991). Kamrani, Parsaei and Leep (1995) developed a mathematical model and tested the performance of the model with simulation in four phases, namely: coding of parts, family formation, resource optimization, simulation (Kamrani, Parsaei, & Leep, 1995). Heragu and Chen (1998) applied a mathematical model to cell formation problem by considering three aspects; resource

utilization, alternate routings, and practical constraints (Heragu & J. Chen, 1998). Chen (1998) worked on designing a sustainable cellular manufacturing system in a dynamic environment and developed an integer programming model to minimize material handling and machine costs as well as cell reconfiguration cost for a multi-period planning horizon (Mingyuan Chen, 1998). Wang (1998) formulated a linear assignment model to the group formation problem (Wang, 1998). Sofianopolou (1999) proposed a mathematical model and a two-phased simulated annealing algorithm to solve the problem of grouping machines into cells and selecting a unique product process plan for each product to be produced (Sofianopoulou, 1999). The manufacturing systems considered include such features as replicate machines and several design requirements as well as operation sequence constraints. Akturk and Turkcan (2000) developed an integrated algorithm that considers the cell layout, part-family and cell formation problems simultaneously (Akturk M.S. & Turkcan A., 2000). Albadawi, Bashir and Mingyuan (2005) proposed a two-phased mathematical model for cell the formation problem (Albadawi, Bashir, & Mingyuan Chen, 2005). In the first phase, factor analysis is used to build similarity matrix and machine cells are identified. In the second phase, parts are assigned to the identified machine cells with an integer programming model.

Metaheuristics have also been used to deal with larger cell formation problems. The most commonly used ones are Genetic Algorithms (GA), Simulated Annealing (SA) and Tabu Search (TS). Genetic Algorithms is a random search technique which generates solutions by using techniques inspired by natural evolution. Simulated Annealing is another search based optimization technique which evolves by replacing the current solution by a random "nearby" solution to reach a near global optimum. Tabu Search is a local neighborhood search technique which improves the solution quality by modifying the neighborhood structure of each solution as the search progresses. Moon, Gen and Süer (1999) developed a GA model to minimize additional capital investment in manufacturing cell design (Moon, Gen, & Suer, 1999). Asokan, Prabhakaran and Kumar (2001) proposed two metaheuristics, GA and SA, for the cell formation problem with the objective of minimizing the total moves and minimizing the cell load variation (Asokan, Prabhakaran, & Satheesh Kumar, 2001). Süer, Pena and Vazquez (2003) developed an evolutionary algorithm and applied to three different problems with seven different cost schemes with the objective of minimizing the total machine investment cost (Suer, Pena, & Vazques, 2003). Cao and Chen (2004) formulated an integrated methodology, which consists of a mixed integer non-linear programming model and a TS algorithm for the NP-Hard Problems (Cao & M. Chen, 2004). Jayaswal and Adil (2004) added simulated annealing and local search heuristics to minimize the sum of costs of inter-cell moves, machine investment and machine operating costs (Jayaswal & Adil, 2004). Solimanpur, Vrat and Shankar (2004) modeled a multi-objective integer programming and GA with multiple fitness functions to the design of cellular manufacturing systems with independent cells (Solimanpur, Vrat, & Shankar, 2004).

2.2 Stochastic CMS design

In contrast to abundant literature on deterministic CMS design, only a handful of works dealt with uncertainty. Such stochastic parameters as demand, processing time, capacity requirements are the driver of uncertainty in manufacturing environment. Seifoddini (1990)

dealt with the uncertainty of the product mix and developed a probabilistic model to minimize the expected intercell material handling costs of the system (Seifoddini, 1990). Harhalakis, Nagi and Proth (1998) studied minimizing the expected inter-cell material handling cost over the entire design horizon and developed a two-stage heuristic approach (Harhalakis, Nagi, & Proth, 1998). In the first stage, the production volumes are determined with respect to the joint probabilities for every feasible production mix; in the second stage, the cell formation is obtained via the heuristic method. Wicks and Reasor (1999) employed forecasting methods to determine product mix and the demand for products and solved the multi-period cell formation problem with GA (Wicks & Reasor, 1999). Saad (2003) addressed reconfiguration of manufacturing systems and developed following sub-modules; configuration and reconfiguration module, loading module, and simulation-based scheduling module (Saad, 2003).

Queuing theory is also applied to cell formation problem (Mehrabad and Ghezavati, 2009). Each machine is considered as server and each product is assumed as customer. The objective is to minimize the idleness costs for machines, the total cost of sub-contracting for exceptional elements and the cost of resource underutilization. Süer et al. (2010) proposed both deterministic and stochastic approaches in CMS design. Their stochastic approach considered uncertainty in both product demand and production rates (Suer, Huang, & Sripathi, 2010). In this approach, a layered cellular design concept is introduced to cell formation problem. Cells are identified as dedicated, shared and remainder cell to deal with the uncertainty and a product family can be assigned to more than one Cell. In their study, the generalized p-median model by (Kusiak, 1987) is modified to meet objectives as maximizing the utilization of cells and forming the most similar parts as families. However, cell formation model considers the capacity requirements as deterministic even though there is uncertainty in demand and production rates thus capacity requirements.

In this chapter, a stochastic capacitated p-median model is developed to deal with the probabilistic demand and production rates, thus capacity requirements based on the Süer et al.'s (2010) deterministic approach. A new similarity coefficient is defined to combine the demand and process similarity. A new Genetic Algorithm (GA) model is developed for the larger problems. The obtained cell configurations from stochastic mathematical model and GA are simulated with Arena Simulation Software.

3. The manufacturing system studied

The problem is derived from a jewelry company. There are thirty products and eighteen machines in the system. Each product has to be processed on several machines depending on its process route. Since each product's route represents a unidirectional flow, the cell configuration is flow shop. The machine with the maximum processing time among all machines on process route is the bottleneck machine.

Each cell in the system is allocated to only one product family. In other words, cells are independent and dedicated to one product family. Hence, inter-cell transfer of products is not allowed. Inter-cell transfer restrictions have been also used in several manufacturing systems such as pharmaceutical, medical device and food manufacturing. In some of these industries, independent cell configuration is inevitable since potential product mix up may cause serious problems. Each product can only be assigned to one cell (no product splitting

is allowed among cells). Since machine setup times are negligible, they are assumed to be zero in this study. Annual production capacity is taken as 2000 hours (50 weeks/yr * 40 hours/week). The annual demand and processing time for each product are random and follow normal distribution. The problem is the identification of product families and corresponding dedicated cells considering stochastic demand, stochastic processing times and hybrid similarity coefficient.

4. The proposed solution methodology: Stochastic CMS design

The proposed solution methodology is a hierarchical one and it consists of five steps, namely: identification of similarity coefficients, determining the bottleneck machine, and determining the probabilistic capacity requirements, stochastic non-linear mathematical model, and simulation. An example problem is solved to explain the methodology used.

4.1 Identification of similarities

In this section, identification of similarities is explained. Three types of similarity coefficients are used, namely: route-based, demand-based and hybrid similarity. Route- based similarity coefficient only considers the processing similarities of products in the manufacturing system. Demand-based similarity only considers the demand variation among products. Hybrid similarity is the combination of both similarity coefficients. Both of the similarity coefficients are explained in detail in the following sections.

4.1.1 Route-based similarity

The route-based similarity matrix is constructed based on the route similarities among products. Süer et al. (2010) modified the McAuley's (1972) similarity coefficient definition to find the similarities among products. The similarity coefficients are calculated via the suggested equation by Süer et al. (2010) as shown in equation 1. The route-based similarity (RB_{ij}) between products i and j is the ratio of number of common machines to total number of machines required.

$$RB_{ij} = \frac{No.of\ machines\ processing\ both\ parts\ i\ and\ j}{No.of\ machines\ processing\ parts\ either\ i\ or\ j} \quad (1)$$

4.1.2 Demand-based similarity

The main motivation of this similarity measure is to identify stable and unstable products. Stable products have lower variability and unstable products have higher variability. Assigning stable and unstable products to the same cell can cause turbulence in the cell. Even a single unstable product can complicate the operation control issues in a cell. Therefore stable products and unstable products are separated and allocated to different cells. By doing this; the turbulence in CMS is restricted to cells with unstable products only.

In this similarity coefficient, products' similarities are calculated based on the variability in demand (Equation 2). The variability in demand for product i (Vd_i) is obtained dividing mean demand (μd_i) by the variance of demand ($\sigma^2 d_i$) as shown in Equation 2 (Silver & Peterson, 1985). Firstly, the demand variability is calculated for all products.

$$Vd_i = \frac{\mu d_i}{\sigma^2 d_i} \tag{2}$$

Secondly, the absolute difference between each pair of products' variability values is obtained and entered in the difference matrix. Thirdly, the obtained difference values are scaled from 0 to 1 to be converted to demand-based similarity coefficients of pairs. In other words, the variability difference matrix is converted to variability dissimilarity matrix to be used as demand-based similarity matrix. The maximum difference that a pair has in difference matrix is assumed as the greatest dissimilarity. The scaling is applied assuming the maximum difference as 1. Fourthly, the dissimilarity matrix is converted to similarity matrix by subtracting dissimilarity values from 1.

4.1.3 Hybrid similarity

There is a need to strike a balance between route-based similarity vs demand-based similarity. Hybrid similarity coefficient is developed to cover both of previously explained similarities. Equation 3 represents the calculation of similarity coefficient. Beta (β) and (1- β) are the proportional impacts of route-based and demand-based similarities on the hybrid similarity coefficient, respectively. In this study, Hybrid Similarity Coefficient is used in CMS design.

$$H_{ij} = \beta * RB_{ij} + (1-\beta) * DB_{ij} \tag{3}$$

4.1.4 Hybrid similarity example

An example is derived to illustrate how the similarity concept is applied. Assume that there are five products with the following route, probabilistic demand and demand variability information shown in Table 1. According to the route information given in Table 1, route-based similarities are calculated by using Equation 1. The route-based similarity matrix is shown in Table 2. Demand-based similarity is the second step to calculate the hybrid similarity.

To build demand-based similarity matrix, first of all the difference between the mean demand/variance of demand ratios (Vd_i) are calculated for all pairs and shown in Table 3. The maximum difference is 4.757 and the minimum difference is 0. These values are scaled to 0-1 range as shown in Table 4. These values are then subtracted from 1 and thus the dissimilarity matrix given in Table 4 is converted to demand-based similarity matrix given in Table 5.

Product	Opr. 1	Opr. 2	Opr. 3	Mean Demand	Variance of Demand	Vd_i
1	A	B	C	2999	1284	2.336
2	A	C		4297	2604	1.650
3	A	C	D	2217	346	6.408
4	B	C	E	1255	359	3.496
5	D	F		2463	454	5.425

Table 1. Operational routes and demand information

Product \ Product	1	2	3	4	5
1	-	0.67	0.5	0.5	0
2	0.67	-	0.67	0.25	0
3	0.5	0.67	-	0.2	0.25
4	0.5	0.25	0.2	-	0
5	0	0	0.25	0	-

Table 2. Route-based similarity matrix

Product \ Product	1	2	3	4	5
1	0.000	0.686	4.072	1.160	3.089
2	0.686	0.000	4.757	1.846	3.775
3	4.072	4.757	0.000	2.912	0.982
4	1.160	1.846	2.912	0.000	1.929
5	3.089	3.775	0.982	1.929	0.000

Table 3. Vd_i Difference Matrix

Scaled Matrix	1	2	3	4	5
1	-	0.144	0.856	0.244	0.649
2	0.144	-	1	0.388	0.793
3	0.856	1	-	0.612	0.207
4	0.244	0.388	0.612	-	0.406
5	0.649	0.793	0.207	0.612	-

Table 4. Scaled Difference Matrix

Product \ Product	1	2	3	4	5
1	-	0.856	0.144	0.756	0.351
2	0.856	-	0.000	0.612	0.207
3	0.144	0	-	0.388	0.793
4	0.756	0.612	0.388	-	0.594
5	0.351	0.207	0.793	0.594	-

Table 5. Demand-based similarity matrix

After both route-based and demand-based similarity matrices are built, hybrid similarity matrix is developed by using Equation 3. In this example, β is taken as 0.5. The developed hybrid similarity matrix is shown in Table 6.

Product \ Product	1	2	3	4	5
1	-	0.763	0.322	0.628	0.175
2	0.763	-	0.335	0.431	0.103
3	0.322	0.335	-	0.294	0.522
4	0.628	0.431	0.294	-	0.297
5	0.175	0.103	0.522	0.297	-

Table 6. Hybrid similarity matrix

4.2 Bottleneck machine identification

In this case, the definition of bottleneck machine is modified since processing times are probabilistic. An example is given in Table 7 to illustrate the situation for product *i*.

Product *i*	Opr. – 1 on M/C 1	Opr. – 2 on M/C 2
Mean (μ)	5 min	4 min
Standard Deviation (σ)	1.2	1.6
Process Time Estimate based on 2 Sigma (ε=2)	7.4 min	7.2 min
Process Time Estimate based on 3 Sigma (ε=3)	8.6 min	8.8 min

Table 7. Bottleneck machine identification

Assume that product *i* requires two operations and the mean processing times for operations 1 and 2 are 5 min and 4 min, respectively. Also assume that standard deviation of processing time for operation 1 is 1.2 and for operation 2 is 1.6 minutes. If only mean values are to be considered, machine 1 would be regarded as the bottleneck machine. If processing times are estimated based on 2 sigma (ε= 2) using Equation (4), then processing time estimates will be 7.4 min and 7.2 min, respectively and machine 1 will still be the bottleneck machine. However, if the processing times are estimated based on 3 sigma (ε= 3), then the bottleneck operation will shift to machine 2. In this paper, we have considered the processing time estimate based on 3-sigma level as the basis for the bottleneck machine identification. The reason for this is that the probability that actual processing time will exceed the estimate based on 3-sigma value is very small.

$$\boldsymbol{p}_{ik}^{e} = \mu_{ik} + \boldsymbol{\varepsilon} * \boldsymbol{\sigma}_{ik} \tag{4}$$

where, $\boldsymbol{p}_{ik}^{e}$ is the processing time estimate, μ_{ik} is the mean processing time, σ_{ik} is the standard deviation of processing time for operation k of product *i* and ε is the coefficient of standard deviation.

4.3 Capacity requirements in the presence of stochastic demand and processing times

In the deterministic case, the capacity requirement of a product is calculated via multiplying its demand with processing time. However, in the stochastic case, since both demand and processing time are probabilistic, the product of these two random variables becomes

probabilistic and requires statistical analysis to find the probability density functions (pdf) of the capacity requirements. To find the fitted distribution (pdf) of the capacity requirement of product *i*, statistical analysis is performed with Arena Input Analyzer software.

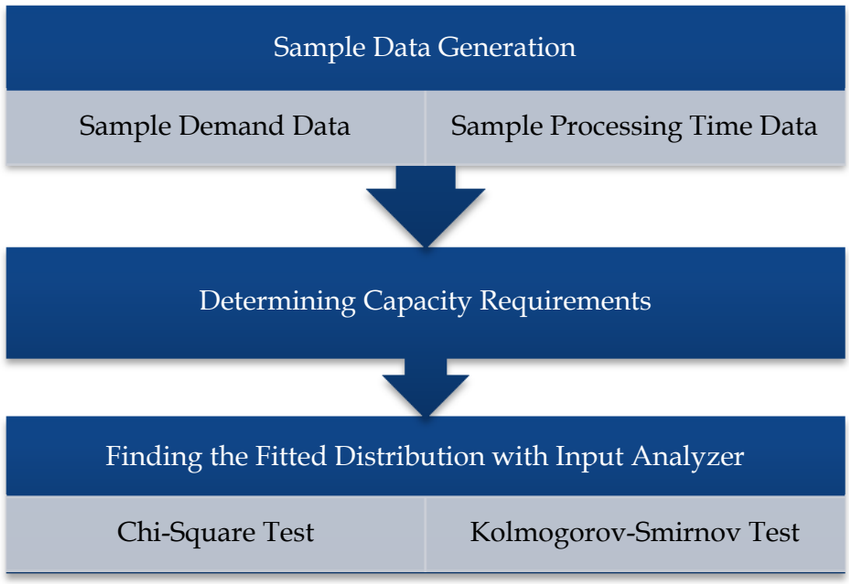

Fig. 1. The Framework of Input Analysis

The framework of the analysis is illustrated in Figure 1. Sample probabilistic demand and processing time data are generated. Capacity requirements are determined from the samples. The fitted distributions for capacity requirements are obtained from Input Analyzer software with respect to test results.

4.4 Stochastic capacitated non-linear cell formation

A stochastic non-linear mathematical model is developed by modifying Süer et al.'s (2010) deterministic model. The proposed model considers the variation of capacity requirements along with the mean capacity requirements. Product families and cell formations are determined with respect to available cell capacity and similarity coefficients. The indices, parameters and decision variables are listed as follows.

Indices:

i Product index
j Product index and family/cell index

Parameters:

S_{ij} Similarity coefficient between product i and j
μ_{CR_i} Mean capacity requirement for product i
σ_{CRi}^2 Variance of capacity requirement for product i
n Number of products
TU Upper limit for cell capacity
α Design factor

Decision Variables:

X_{ij} 1, if product i is assigned to family j ; 0, otherwise

Objective Function:

$$\max Z = \sum_{i=1}^{n}\sum_{j=1}^{n} S_{ij} * X_{ij} - \sum_{j=1}^{n} X_{jj} \tag{5}$$

Subject to:

$$p\left(Z_{nj} \le \frac{\left(TU - \sum_{i=1}^{n} \mu_{CR_i} * X_{ij} \right)}{\sqrt{\sum_{i=1}^{n} \sigma_{CRi}{}^{2} * X_{ij}}} \right) \ge (1-\alpha) \quad \text{j} = 1,2,\ldots,\text{n} \tag{6}$$

$$\sum_{j=1}^{n} X_{ij} = 1 \qquad i = 1,\ldots,n \tag{7}$$

$$X_{ij} \le X_{jj} \qquad j = 1,\ldots,n \; and \; i = 1,\ldots,n \tag{8}$$

$$X_{ij} \in [0,1]; X_{ij} \; integer \tag{9}$$

The objective function is shown in equation 5. It maximizes the total similarity among products that are formed as families to be produced in dedicated cells, while minimizing the total number of cells. Equation 6 is the non-linear constraint which limits the cell utilization up to the cell capacity by considering mean and variance of capacity requirements based on a factor, α, which indicates the maximum acceptable probability that capacity requirements will exceed the capacity available. Equation 7 forces all products to be assigned to a cell. Equation 8 guarantees the assignment of each product to only one of the cells that are open. Equation 9 determines whether product *i* is assigned to cell *j* or not.

4.5 Simulation

In this study, the proposed solution methodology is validated with a simulation model. Even though, the CMS design literature is abundant with several mathematical models, model validation is considered in only a handful of works. Indeed, model validation is one of the significant requirements of any model-based solution methodology. Especially in a system where demand, processing times and capacity requirements are probabilistic, it is a must to validate the proposed approach. The type of model proposed in the study is white-box (causal descriptive) according to the Barlas's classification (Barlas, 1996). Therefore, it is expected that the model reproduces the behavior of the system studied. The behavior of the system is analyzed with respect to four measures, namely: cell utilization, WIP, waiting time and the number waiting. The hierarchical framework followed through the validation is shown in Figure 2.

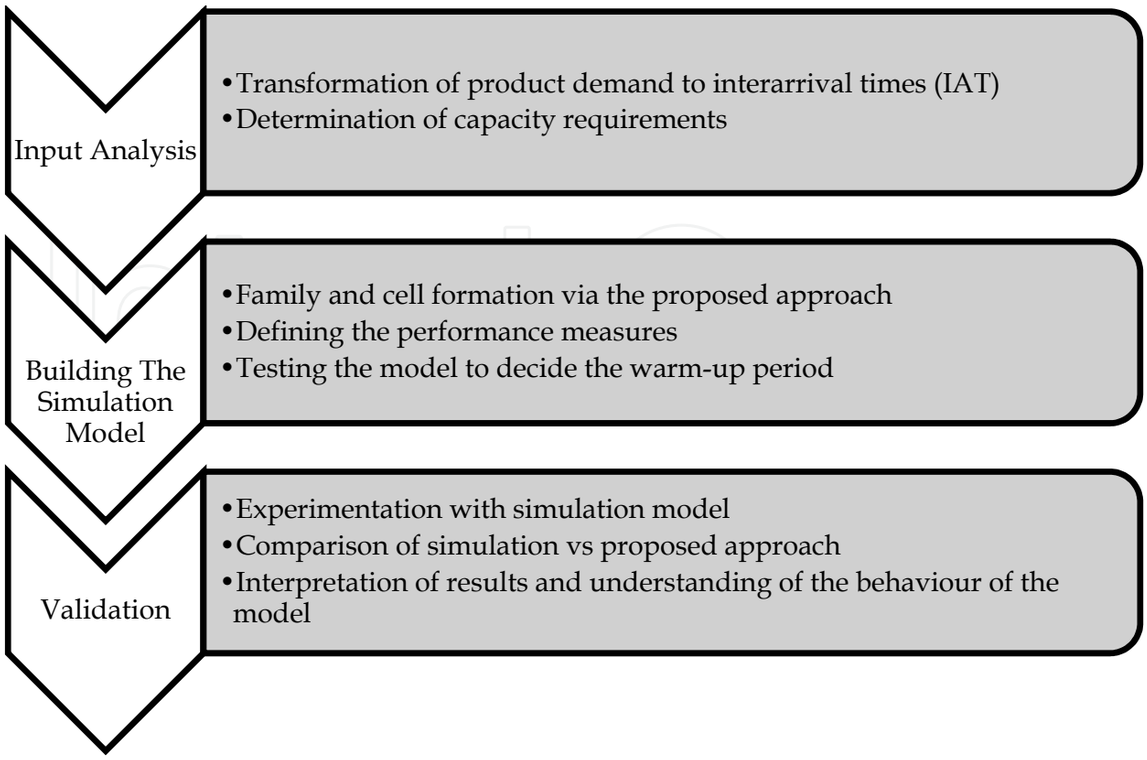

Fig. 2. The hierarchical framework

4.6 Example problem

An example problem is derived to explain the solution methodology (Please refer to the first 10 parts of part-machine matrix in Süer et al., 2010). There are 10 products in the system. The hybrid similarity matrix is shown in Table 8 and probabilistic capacity requirements are shown in Table 9. The capacity of a cell is considered as 800 hours for the example problem.

Part \ Part	1	2	3	4	5	6	7	8	9	10
1	1	0.808	0.765	0.555	0.849	0.561	0.75	0.68	0.712	0.636
2	0.808	1	0.685	0.718	0.747	0.59	0.677	0.775	0.631	0.597
3	0.765	0.685	1	0.545	0.794	0.569	0.703	0.597	0.751	0.627
4	0.555	0.718	0.545	1	0.539	0.562	0.545	0.681	0.477	0.636
5	0.849	0.747	0.794	0.539	1	0.605	0.692	0.65	0.656	0.611
6	0.561	0.59	0.569	0.562	0.605	1	0.499	0.69	0.507	0.656
7	0.75	0.677	0.703	0.545	0.692	0.499	1	0.583	0.855	0.542
8	0.68	0.775	0.597	0.681	0.65	0.69	0.583	1	0.534	0.715
9	0.712	0.631	0.751	0.477	0.656	0.507	0.855	0.534	1	0.499
10	0.636	0.597	0.627	0.636	0.611	0.656	0.542	0.715	0.499	1

Table 8. Hybrid similarity matrix

Part	1	2	3	4	5	6	7	8	9	10
Mean	154	153	494	93.9	106	500	138	45.6	439	135
Variance	231.04	262.44	5745.64	88.92	136.89	5343.61	187.69	25.1	6052.84	222.01

Table 9. Probabilistic capacity requirements (hrs)

Cell Formation	Cell 1 / Family 1	Cell 2 / Family 2	Cell 3 / Family 3	Cell 4 / Family 4
Product Family	Products (1,2,4,8)	Products (3, 5)	Products (6, 10)	Products (7, 9)
Resource Requirements	M/C (1-7,9,10,18)	M/C (1-4,8,10-12,18)	M/C (4,6,9,10,12,14,16, 18)	M/C (1,2,3,11,13,17, 18)
Expected Utilization	447	600	635	577
Util. w.r.t. 10 % risk	478 (60 %)	698 (87 %)	730 (91 %)	678 (85 %)

Table 10. Solution of example problem

The example problem is solved with the proposed non-linear mathematical model. The results are shown in Table 10. Products are formed as four families thus four cells are required where each is dedicated to one product family. Cell and family formations are the same since independent dedicated cells are assumed and intercell movements are not allowed.

5. Alternative solution methodology: Genetic algorithms

Genetic Algorithms (GA) is one of the most powerful metaheuristics used to solve NP-hard problems. It is usually used for solving large size problems where mathematical models run into computational and memory problems. The framework of GA is shown in Figure 3. This framework also represents the one cycle evolutionary process of GA.

GA consists of following steps (Süer, Mese, & Eğilmez, 2011):

1. Initial population of n chromosomes is formed randomly.
2. Mates are determined using the mating strategy to perform crossover.
3. The crossover and mutation operations are performed to generate offspring.
4. For selection, parents are added to the selection pool along with offspring.
5. The next generation is selected from this pool based on their fitness function values.
6. These steps are repeated until the number of the generations specified by the user is reached.
7. Finally, the best chromosome obtained during the entire evolutionary process is taken as the final solution.

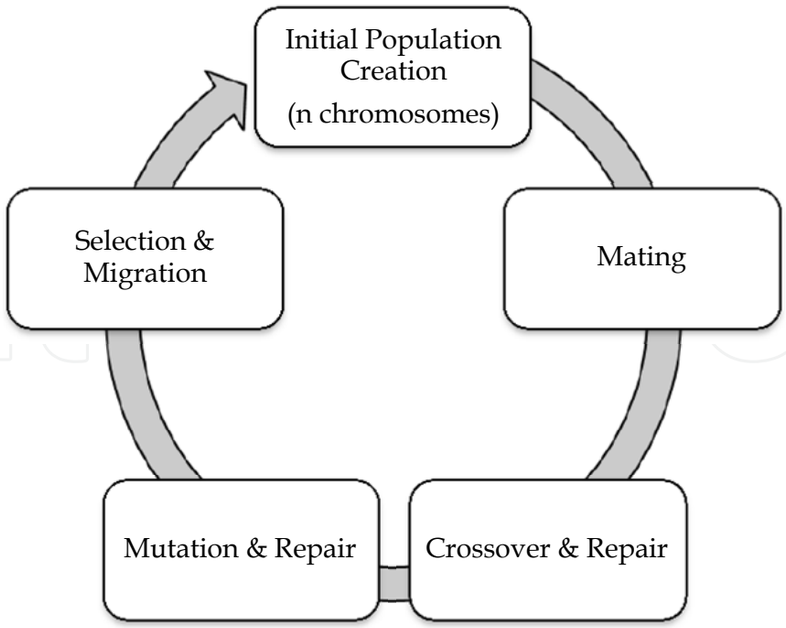

Fig. 3. Illustration of one generation

5.1 Initial population generation

Initial population is randomly generated based on the pre-defined number of chromosomes to form the population. Chromosome represents a candidate solution to the problem. In the proposed GA, the chromosome representation is designed to include product and cell numbers. An example chromosome is shown in Figures 4a and 4b. Each gene carries two types of information: part number and cell number. When generating chromosome, the product numbers are randomly assigned to genes as shown in Figure 4a. Once the assignment is finished the allocation of cells is done with respect to available capacity as shown in Figure 4b. The final chromosome representation is given in Figure 4b.

Cells are matched with products from left to right. First of all, cell 1 is opened and products are assigned to cell 1 as long as the cell capacity is available. If a product is going to result in overutilization, a new cell is opened. Product and cell allocation are illustrated in Table 11.

For example, after the assignment of products 1, 2 and 4 to cell 1, the total expected utilization of cell 1 is 400.9 hours and the standard deviation is 24.13. Under 10 % of risk (z=1.28), the upper bound of utilization is 400.9 + 1.28*24.13 = 431.79. If part 3 were to be assigned to cell 1, the total expected utilization would be 894.9 and variance would be 6328.04. The utilization under 10 % is equal to 894.9 + 1.28 * 79.55 = 996.72 hours > 800 hours. Since the cell is over utilized, a new cell is opened and product 3 is assigned to cell 2. The fitness function of a chromosome is the total similarity of cells. The similarity of cell is calculated via summing the similarities of products within the cell. The resulted cell formation and utilizations are shown in Table 11.

1	2	4	3	5	10	7	9	6	8

Fig. 4a. Example chromosome after product assignment

1,1	2,1	4,1	3,2	5,2	10,2	7,3	9,3	6,4	8,4

Fig. 4b. Example chromosome after cell allocation

	Cell 1			**Cell 2**	
Part	μ	σ^2	Part	μ	σ^2
1	154	231.04	3	494	5745.64
2	153	262.44	5	106	136.89
4	93.9	88.92	10	135	222.01
Total	400.9	582.40	Total	735	6104.54
	Cell 3			Cell 4	
Part	μ	σ^2	Part	μ	σ^2
7	138	187.69	6	500	5343.61
9	439	6052.84	8	45.6	25.10
Total	577	6240.53	Total	545.6	5368.71

Table 11. Cell utilization (hrs)

5.2 Mating strategy

Random Mating Strategy is used in mating. Firstly, the reproduction probabilities of the chromosomes are calculated according to their fitness function. Each chromosome in the population is mated with a randomly selected partner and they produce one offspring. The partner is selected using reproduction probability based on Roulette Wheel approach.

5.3 Crossover operation and repair

A modified order crossover method is employed for the problem studied. In the order crossover as represented in Figure 5, a random number between 1 and the maximum number of cells (4, in the example given in Figure 5) is drawn. Assume that 2 is drawn. This is to decide how many cells from parent 1 are going to be kept in offspring. Then, the two cells are randomly selected and copied to offspring. The remaining genes are filled from parent 2 based on the order of remaining products in parent 2's chromosome. Finally, cell numbers of products that are obtained from parent 2 are assigned based on the availability of cell capacity. As long as the cell capacity is available, products from left to the right are assigned to the same cell. If a capacity violation occurs, a new cell is opened.

5.4 Mutation operation and repair

Mutation is only applied to part numbers and after the mutation operation, same repair operation as in crossover strategy is employed to re-identify cell formation based on

available cell capacity. Each gene is mutated subject to a mutation probability. If a mutation occurs in a gene, a random part number is replaced with an existing part number in a particular cell.

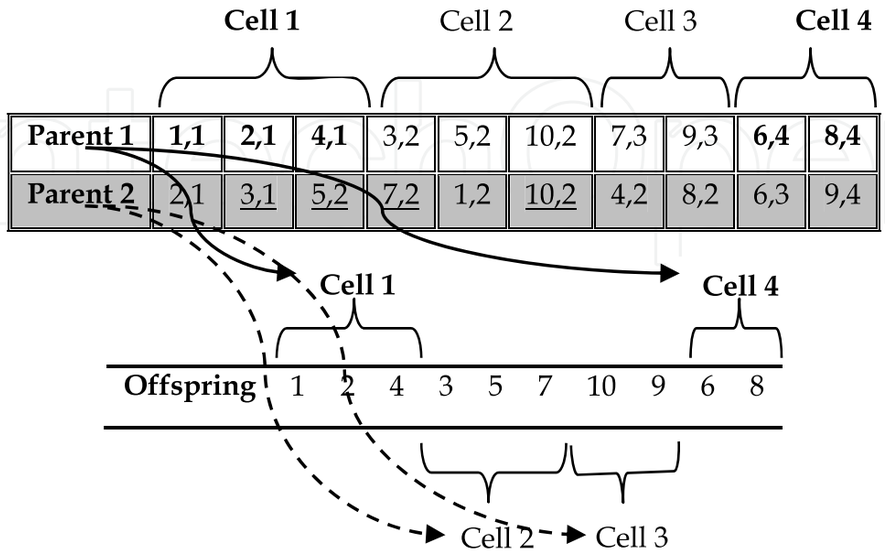

Fig. 5. Cell-Based Order Crossover (CBOC)

5.5 Selection and migration

Selection pool consists of all offspring and parents. The best chromosome is selected as the best solution for the particular generation. After each generation, a predetermined portion of existing generation is advanced to the next generation. Assume that x is the desired percentage of selection pool advancing to the next generation. X is basically an experimentation parameter. When generating next generation, the remaining positions are filled with randomly generated chromosomes (thus the term migration).

6. Experimentation and results

Experimentation consists of two sections. In the first section, the proposed stochastic non-linear mathematical model is compared with Süer et al.'s (2010) deterministic model. The results of both approaches are compared with respect to the obtained cell formation and simulation results. In the second section, proposed alternative solution methodology (GA) is compared with the non-linear mathematical model. Five different problems are considered, namely: 10, 20, 30, 45 and 60 parts. In the first section, the 30-part problem is used for the comparison and simulation runs. For the comparison of non-linear mathematical model with GA, all five problems are used with respect to the solution quality and execution time.

6.1 Data generation

The part-machine matrix (30x18) is obtained from a jewelry manufacturing company. Processing times are generated from uniform distribution with (15, 25) minutes. Each cell is

independent, i.e. part undergoes all the operations in only one cell and comes out as a final product. Therefore, intercell movement of parts is not allowed. Independent cells are used in certain systems where intercell movement of parts is either not possible (pharmaceutical manufacturing) or may cause serious problems due to product mix up. One piece flow principle is assumed for the entire cellular manufacturing system. Set-up times for the parts are assumed as zero.

Demand Category	Annual Uniform Demand Distribution	
	Lower Bound	Upper Bound
1	250	750
2	751	1250
3	1251	1750
4	1751	2250
5	2251	2750

Table 12. Annual Uniform Demand Data Generation

Cell capacity is assumed as 2000 hours (50 weeks x 40 hrs per week) per year. Remaining two weeks is allocated to compensate for unexpected system breakdowns and plant shutdowns. Demand for each product is assumed to follow normal distribution. The mean demand is generated from uniform distribution from five categories. Each product is assigned randomly to a category (see Table 12). The standard deviation of demand is generated via multiplying the mean demand with a factor. The factor is obtained randomly via uniform distribution (0.1, 0.5).

6.2 Comparison of Süer et al.'s (2010) model with the proposed stochastic approach

In this section, the results of Süer et al.'s (2010) deterministic approach (see Figure 6) and the proposed stochastic approach (see Figure 7) are provided. The deterministic model grouped the products into 10 families/cells based on the hybrid similarity matrix. Simulation experiment resulted in 100% utilization in cell number 5 and second highest utilization is observed in cell number 2. Since deterministic model only considers mean capacity requirements of products, some of the cells are utilized over 95% when deterministic mathematical model is used. However, these high utilization rates resulted in the same or lower utilization with simulation experimentation. The overall trend of utilization obtained from simulation is observed as similar to the result of mathematical model.

According to the results of the proposed stochastic non-linear approach (Figure 7), products are formed as 13 families/cells. The proposed approach increased the number of cells by 3 and the number of machines by 18%. A similar trend between the result of mathematical model and simulation is also observed with the stochastic approach. In contrast to very high utilization observed on 2 cells in the deterministic approach, the highest utilization is obtained as 82% with the stochastic approach (from simulation). Simulation model resulted in 1% to 7% less utilization of cells than mathematical model's results. There is no overutilization observed in any cell with simulation since the proposed approach considers variance of capacity requirements in addition to similarities during the cell formation.

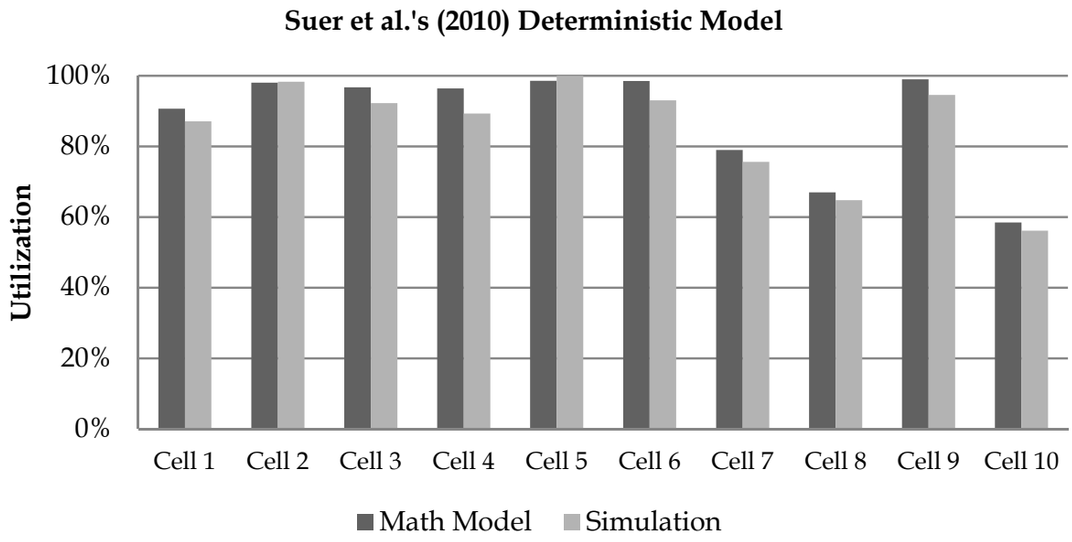

Fig. 6. Utilization Results of Deterministic Model by Süer et al. (2010)

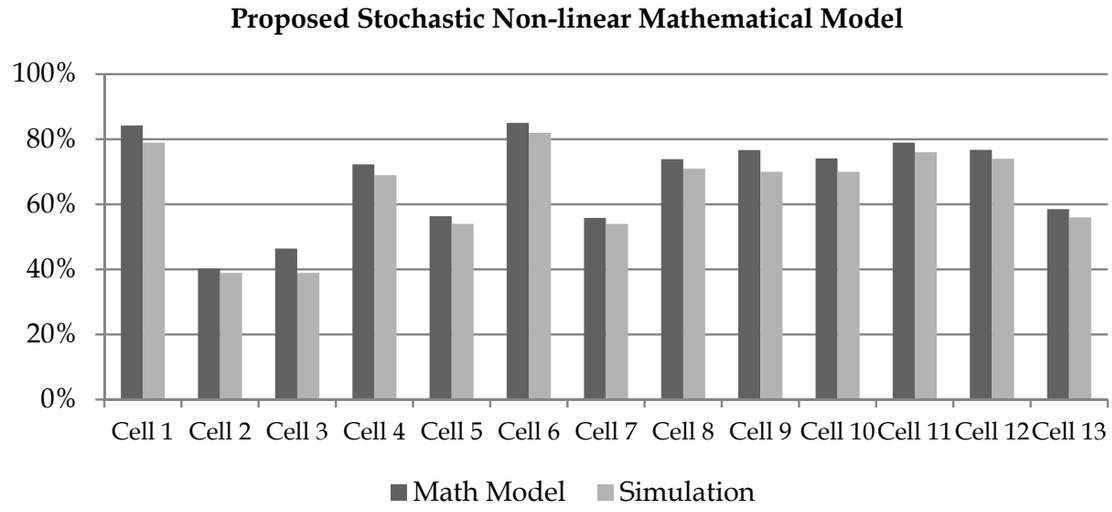

Fig. 7. Utilization Results of the Proposed Stochastic Model

Utilization-based comparison is important to observe the model validation with simulation experiments. However, the behavior of model is also important in model validation. Therefore, system performance is also included in comparison. The performance measures considered are 1) cell utilization, 2) the number of machines, 3) work-in-process (WIP) inventory, 4) average waiting time and 5) average number waiting. The results obtained from both approaches are shown in Table 13.

According to the system performance comparison (Table 13), WIP, average waiting time and average number of waiting decreased significantly since there is no overutilization occurred with stochastic approach. However, the number of machines increased from 94 to 111.

Deterministic Approach (Süer et al., 2010)					Proposed Stochastic Approach				
Cell	# M/C	WIP	Av. Waiting Time	Av. Number Waiting	Cell	# M/C	WIP	Av. Waiting Time	Av. Number Waiting
1	10	6.06	18.8	1.22	1	17	3.53	11.73	0.44
2	13	7.84	12.17	1.05	2	10	2.27	2.09	0.06
3	10	6.06	19.11	1.09	3	9	1.64	2.72	0.11
4	12	6.62	17.57	0.97	4	8	1.72	2.50	0.14
5	13	298.46	6256.56	294.30	5	7	5.00	5.42	0.18
6	12	6.83	18.45	1.03	6	11	6.02	9.90	0.43
7	4	2.52	1.04	0.03	7	11	5.53	4.73	0.22
8	8	3.9	0.39	0.01	8	6	4.37	3.98	0.30
9	8	5.72	21.37	1	9	8	2.95	5.24	0.26
10	4	1.94	0.07	0	10	9	7.60	7.90	0.42
Total	94	345.97	6365.53	300.71	11	4	1.90	1.02	0.03
					12	7	3.86	7.52	0.30
					13	4	1.95	0.07	0.00
					Total	111	48.34	64.82	2.90

Table 13. System Performance Based Comparison

6.3 Comparison of the proposed stochastic non-linear mathematical model with GA

The problem studied is NP-Hard. Therefore, it is important to provide alternative solution approaches that are providing near optimal solution in faster times when dealing with larger problems. In this section, proposed mathematical model and genetic algorithms are compared. The comparison is made in two ways: 1) system performance and 2) solution quality and execution time. Five datasets are used consisting of 10, 20, 30, 45 and 60 parts. Mathematical model could only provide global optimal solutions for the first 4 datasets. To be able to analyze system performance, both solutions for dataset with 30 parts obtained from mathematical model and GA are simulated. The simulation results are shown in Table 14. According to the results, both approaches formed 30 products as 13 families and opened 13 dedicated cells. The utilizations of cells vary from 39% to 82%. In terms of total number of machines, GA resulted in 10 less machines. Even though, there is parallelism between WIP and average number waiting results, in terms of average waiting times, GAs solution provided more than 50% lower average waiting time. However, both mathematical model and GA results showed better performance than Süer et al.'s (2010) deterministic model.

Secondly, both approaches are compared based on the solution quality and execution time. The optimal solution of mathematical model, and best and average solution of GA, execution times and the average % distance (gap) GA's solution from mathematical model and parameter set used in GA are shown in Table 15. Mathematical model provided global optimal solution for the first 4 datasets. On the other hand, GA provided the optimal solution with 100% frequency with 10 parts dataset. With the datasets: 20, 30 and 45 parts; GA provided near optimal solutions with great improvements in execution times. Since the solutions of 30 parts dataset provided by GA and mathematical models are compared in detail in Table 14, it can be concluded that near optimal solutions with respect to similarity coefficient can still provide good or even better system performance. However, system performance should always be assessed with validation methods e.g. simulation.

	Stochastic Non-linear Mathematical Model				**Genetic Algorithms**			
Cell	# M/C	WIP	Av. Waiting Time	Av. Number Waiting	# M/C	WIP	Av. Waiting Time	Av. Number Waiting
1	17	3.53	11.73	0.44	8	0.94	2.93	0.11
2	10	2.27	2.09	0.06	6	2.39	2.03	0.15
3	9	1.64	2.72	0.11	5	2.46	1.85	0.11
4	8	1.72	2.50	0.14	5	0.13	0.04	0.00
5	7	5.00	5.42	0.18	4	1.41	0.51	0.02
6	11	6.02	9.90	0.43	8	0.28	0.03	0.00
7	11	5.53	4.73	0.22	10	1.92	3.00	0.12
8	6	4.37	3.98	0.30	14	6.15	5.43	0.34
9	8	2.95	5.24	0.26	8	4.57	1.48	0.11
10	9	7.60	7.90	0.42	6	5.48	0.46	0.02
11	4	1.90	1.02	0.03	7	1.87	0.20	0.01
12	7	3.86	7.52	0.30	12	14.54	3.58	0.15
13	4	1.95	0.07	0.00	8	5.73	4.25	0.20
Total	**111**	**48.34**	**64.82**	**2.90**	**101**	**47.86**	**25.79**	**1.34**

Table 14. System Performance Comparison of Mathematical Model and GA

Problem Size	Stochastic Non-linear Mathematical Model		Genetic Algorithms				
	Optimal Solution	Sol. Time (Sec)	Best Solution	Avr. Solution	Avr. % Gap	Avr. Exe. Time (Sec)	Parameter Set (IP,NOG,CP,MP,MR)
10	4.606	145	4.606	4.606	0%	9.70	(100, 200, 0.7-0.9, 0.01, 10-20%)
20	10.87	1522	10.57	10.11	7%	16.90	(500, 100, 0.7-0.9, 0.01, 10-20%)
30	12.29	40836	11.80	11.53	6%	32.93	(1000, 1000, 0.7-0.9, 0.01, 10-20%)
45	20.064	198662	17.024	16.315	19%	78.13	(1000, 2000, 0.7-0.9, 0.01, 10-20%)
60	N/A	N/A	26.855	25.164	-	114.31	(1000, 2000, 0.7-0.9, 0.01, 10-20%)

IP: Initial population, NOG: Number of generations, CP: Crossover probability, MP: Mutation probability, MR: Migration rate

Table 15. Comparison Based on Solution Quality and Execution Time

7. Conclusion

In this study, the impact of probabilistic demand and processing times on cell formation is addressed. The uncertainty in demand and processing times is one of the most common problems of manufacturing world. Manufacturing system design is also directly influenced by such factors which may result in million dollars of wrong investment on machines and equipments. Majority of literature on cell formation and manufacturing system design either neglects the uncertainty in demand and processing times or assumes the impact as limited. Süer et al. (2010) proposed two approaches; deterministic and stochastic. Deterministic model used in their study formed the cells based on the expected (mean) capacity requirements. On the other hand, stochastic approach proposed a layered manufacturing system design to deal with uncertainty in demand and processing times. They allowed a family to have more than one cell to deal with uncertainty. In this study, each family is restricted to one cell and the impact of variance is included in the proposed approach. A hierarchical methodology is used to solve the problem. First of all a new similarity coefficient is introduced which incorporates the route and demand similarity in one similarity coefficient, "hybrid similarity coefficient". Hybrid similarity matrix is built based on the data obtained from a jewelry manufacturing company where the operations are labor intensive. To deal with the cell and family formation under the impact of

uncertain demand and processing times, a stochastic non-linear mathematical model is developed.

The proposed model and Suer et al.'s (2010) deterministic model are experimented with 30x18 (part x machine) dataset. During the modeling and experimentation phases, independent cell and family formation is considered. Therefore, intercell movement of parts is not allowed. Each formed product family is assumed to be produced by a dedicated cell. In addition to solving the cell and family formation problem with mathematical optimization, model validation is also considered. To validate the designed cellular manufacturing system, simulation models are developed for both proposed stochastic and Süer et al's (2010) deterministic approaches. According to the simulation results, similar cell utilization patterns are obtained between the mathematical model and simulation results for both proposed and Suer et al.'s (2010) deterministic approaches. In the further analysis, both approaches are compared based on the system performance. Five performance indicators are considered in comparison, namely: cell utilization, the number of machines, WIP, average waiting time, average number waiting. According to the results, the proposed approach resulted in more number of cells and more machines, but it performed better with respect to all other performance measures.

Even though, the proposed non-linear stochastic model with respect to hybrid similarity coefficient guarantees the optimal solution, solution time increases exponentially as the number of parts increases due to the NP-hardness of problem studied. Metaheuristics are usually employed to deal with NP-hard problems. Therefore, a Genetic Algorithm (GA) model is also developed to deal with the medium and large scaled problems. The probabilistic parameters are also reflected in GA. Experimentation is performed with five datasets, namely 10, 20, 30, 45 and 60 parts. All other datasets are generated as a portion or random replication of 30 parts datasets. First of all, the solution obtained from GA for 30 parts is simulated. Both stochastic non-linear mathematical model and GA's simulation results are compared. According to the simulation results, GA performed better in terms of all performance measures. In addition, both GA and mathematical model resulted in better performance than the deterministic model. Secondly, remaining datasets are also experimented with both proposed mathematical model and GA. According to the results, GA found the optimal solution with 100% frequency for the first dataset (10 parts). For the larger datasets 20, 30 and 45 parts, GA provided 6% to 19% distant solution than the optimal solution. The largest (60 parts) dataset can only be solved by GA. Besides, GA significantly outperformed the mathematical model in all datasets in terms of execution time. Another important conclusion is that the optimal solution with respect to similarity does not guarantee that system performance will be better. The proposed CMS is required to be validated with simulation.

Even though GA provided good and faster solutions and to the best knowledge of authors there has not been any GA approach including stochastic components proposed for the problem studied in literature yet, the proposed GA is planned to include alternative genetic operators to be able to increase the solution quality. In addition, the problem studied can be extended to include other features of CMS design such as allowance of intercell movement of parts, system implementation costs, setup times etc. The impact of variance on system

design is another potential important side of the problem which may affect the solution significantly. Moreover, identification of the bottleneck machine in systems where bottleneck machine shifts is also another important potential future work. Finally, in addition to genetic algorithms, other meta-heuristics such as Simulated Annealing, Tabu Search can be considered to cope with the larger problems.

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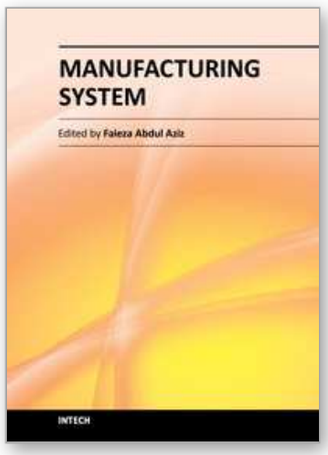

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This book attempts to bring together selected recent advances, tools, application and new ideas in manufacturing systems. Manufacturing system comprise of equipment, products, people, information, control and support functions for the competitive development to satisfy market needs. It provides a comprehensive collection of papers on the latest fundamental and applied industrial research. The book will be of great interest to those involved in manufacturing engineering, systems and management and those involved in manufacturing research.

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