考慮不確定需求與機器故障下的線性製造單元設計

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摘 要

一般單元製造系統設計偏向在確定的環境下進行，忽略變動因素(例如產品組合、需求不確定、機器(可靠度)故障等)對其影響。本研究專注於直線式單元系統的設計，考慮工件途程彈性、需求不確定、和機器故障、機器佈置等因素，來建構單元群組的確定與不確定性數學模式，本研究重新定義變數和限制式，因此可以使數學模式線性化。本研究以極小化總操作成本和故障成本為目標，為了進一步了解不確定環境下的需求變動、故障率變動對於總成本的影響，因此本研究同時做了一連串的敏感性分析，務求單元設計成果可以符合動態環境下的需求。

關鍵詞：單元製造，不確定性，週期時間，可靠度

Flowline Manufacturing Cells Design Considering Demand Lot Size and Machine Breakdown Uncertainties

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ABSTRACT

This paper presents a stochastic model to deal with the designing of flowline cellular manufacturing systems considering uncertainty in machine reliability and demand lots size variation. The objective is to minimize the total cost consisting of operational cost and breakdown cost in the duration of cycle time. A new deterministic flowline cell formation model is established firstly, and then that is extended to a scenario-based stochastic model. Two index, the expected value of perfect information (EVPI) and the value of stochastic solution (VSS), are employed to evaluate the added-value of incorporating uncertainties into the models. An array of computational experiments is conducted for verifying the model's effectiveness. The experimental results show the proposed models are available and effective in finding optimal solutions in diverse scenarios, and the figures of EVPI and VSS are in a tendency of getting larger when the number of cells gains increasingly, which reveals the impact of uncertainties is getting more significant in larger scale of flowline manufacturing system than in smaller one. The proposed stochastic model incorporating uncertain issues is capable of designing flowline manufacturing cells which perform well under all possible situations rather than one that is optimal for one possible scenario but does poorly in other possible scenarios.

Key Words: cellular manufacturing system, uncertainty, stochastic, cycle time, reliability

1. Introduction

Cellular manufacturing has emerged as a promising alternative manufacturing system, where manufacturing cells are constructed by grouping the parts into part families and machines into cells; the machine cells are then dedicated to producing these part families. Manufacturing cells combine the advantages of flow shops and job shops with characteristics such as reduced cycle times compared to jobs shops and increased flexibility, and greater job satisfaction as compared to flow shops. Some of the other benefits include space reduction, quality improvement, labor cost reduction, and improved machine utilization (Wemmerlov and Hyer, 1989). The cell formation is a major design to construct cellular manufacturing system (CMS) and many methods of solving cell formation have been developed in past decades. General overviews on the methods of solving the cell formation problem can be found in Papaioannou and Wilson (2010), they review recent studies (1999-2008) of cell formation problem methodologies and provide the directions for future research. Ghosh et al. (2011) discuss various metaheuristic techniques such as evolutionary approach, ant colony optimization, simulated annealing, tabu search, and their applications to the vicinity of cell formation problem in cellular manufacturing. Moreover, they incorporate various prevailing issues such as open problems of meta-heuristic approaches, its usage, comparison, and hybridization to the future research. Balakrishnan and Cheng (2007) address cellular manufacturing under conditions of multi-period planning horizons with demand and resource uncertainties. They conduct a comprehensive review of presenting mathematical programming formulations as well as taxonomy of existing models, and they at last suggest some directions for future research. On the other hand, Bidanda et al. (2005) highlight the successful implementation of cellular manufacturing relies on focusing on technical issues such as cell formation design and human issues, simultaneously. They present an overview and evaluation of the diverse range of human issues involved in cellular manufacturing based on an extensive literature review.

Most of traditional cell formation problems model manufacturing cells in deterministic circumstances, ignoring any changes in demand’s lot size over time caused by product redesign, and uncertainties due to volume variation, part mix variation, and resource unreliability. Especially, in today’s business environment, shortened product life cycles and fluctuated demand volumes have become so normal challenges that managers cannot help to consider re-plotting the cell formation for adapting to successive variations. Moreover, machines are key elements in manufacturing systems and their breakdowns could dramatically affect system’s performance measures (Ameli et al., 2008). Machine failures usually cause the greatest impact on due dates and other performance criteria, even there have been existing alternatives of routing flexibility that make them possible to deal with the problems. Particularly, in the pattern of flow production that successively products parts in sequence, the impacts of machine failure are more critical than other patterns. The consideration of reliability levels for machines in the process of cell formation is benefit for selecting process routings of parts realistically. Without a doubt that incorporating practical operation factors into the modeling would toward a dilemma of making the cell formation problem more complex, but more realistic.

In this study, we present a flowline manufacturing cells design simultaneously taking into consideration some concerned issues such as demand's lot size variation, routing flexibility, machine reliability, and layout, where lot sizes changing and machine breakdown are in uncertainty. We defined that the manufacturing cells locate in a flowline layout and all the parts are processed by following their corresponding operations in sequence. A scenario-based model considering the minimization of total cost among the duration of cycle time is proposed for the flowline manufacturing cells design. The total cost consists of the operational cost of completing the demand of lot sizes and the breakdown cost of machine failures. In that way, it may hopefully have better opportunities to choose a manufacturing cell which perform well under all possible situations rather than one that is optimal for one possible scenario but does poorly in other possible scenarios.

The remainder of this study is organized as follows. In section 2 the relevant literature is reviewed. Section 3 describes the inspiration of designing the flowline manufacturing cells, and presents the mathematical formulation of deterministic and scenario-based models. Section 4 gives a verification of employing stochastic model to the flowline cell formation problem and its computational results. The conclusions are summarized in Section 5.

2. Literature reviews

Manufacturing cells consist of a group of machines that are dedicated to producing a specific number of part families. A part family is a set of parts that have similar requirements in terms of tooling, setups and operations sequences. Often part families are assigned to a cell based on operation sequences so that materials flow and scheduling are simplified even though the part families produced by a cell may require different tooling. This process of manufacturing cell formation may result in each part family requiring the same set of machines where each part is processed on each machine in the same technological order. These manufacturing cells are called flow-shop manufacturing cells, which resemble the traditional flow shops except the existence of multiple part families (Schaller et al., 2000). Since parts are assigned to families based on sequencing or sequence-dependent orders, a flowline cells layout is usually accompanied with the implementation of cellular manufacturing. The examples of flowline can be observed in automotive fabrication, electronic components assembly, food package and consumer products manufacturing factories. Because of increasing employment in these industries, many of researches have embarked on the relevant issues such as cell formation using sequence data (Nair and Narendran, 1998; Jayaswal and Adil, 2004; Mahdavi and Mahadevan, 2008; Solimanpur and

Foroughi, 2011), cells layout considering linear flows (Chang et al., 2013; Chiang and Lee, 2004), operational issues focused on sequencing and scheduling (Taillard, 1990; Skorin-Kapov and Vakharia, 1993; Sridhar and Rajendran, 1993; Schaller et al., 2000), and performance evaluation (Akright and Kroll, 1998; Lee and Ahn, 2013).

Corresponding to flow-shop manufacturing cell formation problems, most of literatures solve these problems with minimizing the intra- and inter- cells movement cost or the voids, and only a handful of studies incorporate the aspect of line balancing into the construction of manufacturing cells. Mahesh and Srinivasn (2002) assert reducing cycle time to meet market quick response times is one of major advantages of flowline CMS and consider the cell formation problem with minimizing cycle time. They have all parts been transformed into an equivalent part of part family, in that way all parts are produced in a unidirectional flowline. A branch and bound technique and a heuristic approach based on a multistage programming approach are used to find the converged solutions. Their developed cell can be regarded as an incremental cell to the existing manufacturing system instead of performing the conversion of job shop to cellular manufacturing comprehensively. Mahdavi et al. (2006) solve the identical problem of Mahesh and Srinivasn (2002) by developing a heuristic method based on iterative set partitioning. At each iteration, the set of unassigned operations, which is arranged in the order of the given technological sequence, is decomposed into ordered subsets (or combinations) and each of them has a predetermined number of operations (combination size), wherein all the operations in a combination can be performed on the same common machine. Further, Mahesh and Srinivasan (2006) extended the previously study to multiple objectives problem considering the minimization of cycle time, unbalanced load, and total-work-content of an equivalent part, and then a lexicographic approach based on simulated annealing algorithm is developed and used to solve the problem.

The construction of flowline manufacturing cells not only have to consider the cycle time in the flow shop but also should think about how to sustain the prospective performance, not being affected by availability of system and machine reliability. Even though reselecting and replacing alterative routings, if the machine breakdowns, is a flexible way to overcome the loss of performance, but it may not be totally ensured to go through the subsequent operations because of fixtures setting. However, the consideration of machine's reliability in phase of the modeling makes the cell formation problem complex, but more realistic. Jeon et al. (1998) point out that machine failures must be taken into account during the designing of CMS for improving overall system performance. They considered both pre-decided minimum number of machine breakdowns and alternative routing of parts to decrease waiting cost and late finish cost. Esmailnezhad et al. (2015) present a new mathematical model to solve the cell formation problem in CMSs, where inter-arrival time, processing time and machine breakdown time are probabilistic. The aim is to maximize the number of operations of each part with more arrival rate within one cell. Two meta-heuristic algorithms, modified particle swarm optimization and genetic algorithm, are developed and used to solve the problem. The results indicate that considering the machine breakdown has significant effect on block structures of machine-part matrixes. Ameli and Arkat (2008) focus on the configuration of machine cells considering production volumes and process sequences of parts, and take alternative process routings for part types and machine reliability into considerations. Their experimental results show that the consideration of reliability has significant impacts on the final block diagonal form of machine-part matrixes. Chung et al. (2011) employ an efficient tabu search algorithm based on a similarity coefficient to solve the cell formation problem with consideration of alternative process routings and machine reliability. The goal seeks to the minimization of total cost of intercellular movement and machine breakdown. The breakdown cost is evaluated via Ameli et al. (2008)'s formulation that is achieved by dividing the production time by the mean time between failure (MTBF) and then multiplying this quantity by the unit machine breakdown cost. Das et al. (2006, 2007) develop a multi-objective mixed integer programming model for CMS design to minimize the total system costs and maximize the machine reliabilities along the selected processing routes. An approach that provides a flexible routing as alternative process routes in case of any machine failure is used to ensure high overall performance of the CMS. Seifoddini and Djassemi (2001) studied the effect of machine reliability on the application of quality index, regarding as a screening process for deciding the suitability of machine-part incidence matrix while converting manufacturing operations to CMS. They indicate that the use of quality index and machine reliability together can achieve the best performance in CMS, and for achieving the same performance level, the reliability requirement for individual machine is more critical in a CMS than in a job shop.

In today’s business environment that product life cycles are shortened, and demand volumes and product mix vary frequently, and these phenomena are so highly uncertainty that they have to be dealt with at the design stage of flowline manufacturing cells. Thus, developing cell formation problem under stochastic scenarios might have been be a proper way to concretize the practicality of CMS. Forghani et al. (2013) present a new robust approach to handle demand uncertainty in cell formation and layout design process, where an interval approach is implemented to address data uncertainty for the part demands. Their objective is to minimize the total inter- and intra-cell material handling cost, and the experimental results reveal that when the level of conservatism is changed, the optimal layout can vary significantly. Marsh et al. (1997) found that layout changes could occur as soon as within six months of the start of the cell life cycle. Therefore, in the process of manufacturing cells design, both the changes of products and the uncertainties of demand should be accounted for. Jayakumar and Raju (2014) present a nonlinear mixed-integer mathematical model for the cell formation problem with uncertainty in product mix within a single period. The model contains lot of real-life parameters such as alternate routing, operation sequence, duplicate machines, uncertain product mix, uncertain product demand, batch size, processing time, machine capacity and various cost factors. A simulated annealing algorithm is used to find the best possible cell formations. Cao and Chen (2005) consider a system configuration problem with product demands in a number of probabilistic scenarios. An optimization model is formulated to minimize machine cost and expected inter-cell material handling cost. A two-stage Tabu search based on heuristic algorithm is developed to find the optimal or near optimal solutions to the NP-hard problem. Tavakkoli-Moghaddam et al. (2007) present a new mathematical model with stochastic demands for a facility layout problem in CMSs and for minimizing the total costs of inter and intra-cell movements. Due to different confidence levels of decision maker, the results demonstrate different scenarios of machine and cell layouts. As mentioned early that manufacturing industries are easily encountered with stochastic requirements due to the influences of customized products, shorter product life cycles and unpredictable patterns of demand, and that the production requirements (product mix and demand) is unlikely known at the beginning of manufacturing cells design at most of the time. Niakan et al. (2016) examine a new multi-objective cell formation mathematical model, where social criteria and uncertainty conditions are considered in dynamic environment. The first objective is to minimizes amounts of costs related to a machine such as machine fixed and variable costs, machine procurement and relocation costs, intra-cell and inter-cell movement costs and wages, while the second objective of social issues is to maximize the job opportunities. A meta-heuristic method using non-dominated sorting genetic algorithm is developed to find out the optimization. Jayakumar1 and Raju (2011) assume that a set of possible production requirements (scenarios) with certain probabilities are known at the design stage and propose a genetic algorithm in search of the best possible cell formation. Safaei et al. (2007) propose a fuzzy programming-based approach to the design of CMS under dynamic and uncertain conditions. The dynamic involved multi-period planning horizon and uncertain condition implicating to the imprecise nature of the part demand and to the availability of the manufacturing facilities in each period planning. An extended mixed-integer programming model is applied to determine the optimal cell configuration in each period with maximum satisfaction degree of the fuzzy objective. Saidi-Mehrabad and Ghezavati (2009) applied queuing theory to the CMS design problems that are associated with uncertainty issues, and their objective is to minimize the idleness costs for servers, the total cost of sub-contracting for exceptional elements, and the cost of resource underutilization. Süer et al., (2010) proposed an alternative CMS design approach, which is called layered manufacturing system, to deal with the uncertainty in product demand and production rates. The proposed layered CMS consists of three types of cells, named dedicated, shared and remainder cells. Fattahi et al. (2015) present a new nonlinear mathematical model to solve a cell formation problem under assumptions of processing time and inter-arrival time of parts are random variables. The cell formation problem is defined as a queue system and then are being optimized via queuing theory. Furthermore, two algorithms based on genetic and modified particle swarm optimization algorithms are developed to solve the cell formation problem due to the property of NP-Hard.

3. Problem description and formulation

A data transformation concept of an equivalent part of a part family, adopted from Thomopoulos (1970), identifies a combined set of operations to transform different parts in a part family into an equivalent single part. In that composite part, all the operations of a part family should be present but their sequence is immaterial, such that not only should all the operations of a part family exist in it, but also they should be processed in a unidirectional flow way. It is known that Mahesh and Srinivasan (2002) firstly adopt that transformed data to solve the incremental cell formation problem with minimizing cycle time in the unidirectional flow of CMS. The detailed processes of transforming an equivalent part of a part family can be referred to their study.

Table 1. The example of an equivalent part of a part family.

Sequence of operations	Alternative machines	Processing times
1	1, 2, 3	4, 5, 3
2	2, 3, 4	3, 5, 1
3	3, 4, 5	1, 2, 3
4	3, 4, 6	2, 3, 3
5	4, 6	2, 3

Table 2. Optimal solutions of example.

Optimal solutions	Location of workstation		
	1	2	3
1	(1-1)	(4-2,3,4)	(6-5)
2	(1-1)	(4-2,3)	(6-4,5)
3	(1-1)	(3-2,3)	(4-4,5)
4	(1-1)	(3-2,3)	(6-4,5)
5	(2-1)	(4-2,3)	(6-4,5)
6	(2-1)	(3-2,3)	(6-4,5)
7	(2-1)	(4-2,3,4)	(6-5)
8	(2-1)	(3-2,3)	(4-4,5)
9	(3-1)	(4-2,3,4)	(6-5)
10	(3-1)	(4-2,3)	(6-4,5)

Here a set of data, see table 1, has been transformed as an equivalent part of a part family. There are five operations in sequence and six available machines; each operation is associated with a set of alternative machines and their corresponding processing time, respectively. These operations have to be performed in cells following the order of sequence, namely produced the equivalent part of a part family in a unidirectional flow pattern. Originally, the incremental cell formation problem is to allocate all operations to specific numbers of cell for achieving the minimum cycle time. Table 2 lists all possible optimal solutions with minimum cycle time=6. Taking solution 1 for instance, the machine 1, 4, and 6 are selected out of six machines as three cells which are allocated in successive positions. The operation 1 is assigned to machine 1 (or cell 1), operation 2, 3, and 4 are assigned to machine 4, and so on. In that way, all operations are processed in a unidirectional flowline circumstances. The optimal solutions are comprised of selected machines and clustered operations, and the combination of both could cause different expenditures in operational cost and breakdown cost, even their cycle time are the same. Examining solutions listed in Table 2, these consequences make a dilemma to the decision makers who cannot choose an adequacy solution without additional criteria. Therefore, to remain the expected prospect of cell formation, additional criteria, such as machine reliability in the flowline production and workload variations through fluctuating demand of lot sizes have to be taken into consideration to assist decision makers choosing from. Figure 1 depicts the flowline layout of the illustrated solution 1.

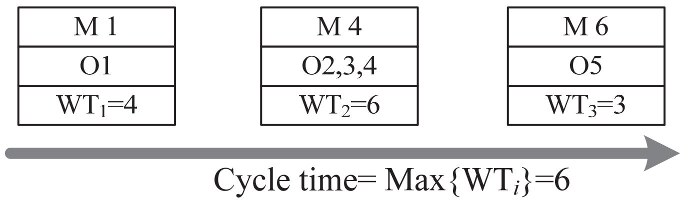

Figure 1. The layout of flowline manufacturing cells.

3.1 The deterministic model

The mathematical model of the flowline cell formation is now explained in detail below. As mentioned early, Mahesh and Srinivasan (2002) have allocated the precedent-constrained operations to specific cells for minimizing cycle time under flowline environments. However, insight of these converged solutions with the same value of objective, they are difficult to choose from due to lack of considering the characteristics of flowline cell manufacturing system. Therefore, in this paper we incorporate fluctuating demand of lot size and inevitable phenomenon of machine breakdown into the modeling. A compound objective considering the operational and breakdown cost is employed instead of purely cycle time. Some assumptions are considered as follows:

1. Duplicated machines are not accounted and only one machine can be allocated to each workstation.
2. Any number of operations has to carried out without violating precedent constraints such that the workflow of operations is unidirectional.
3. No operation is split across the workstations (or machines) and at least one operation should be carried out at each workstation (machine).
4. A set of common operations across the parts of a part family exists and sequence of operations in a part family does not contradict with one another.

In order to formulate the mathematical model, following notations were introduced.

i : index of operations to be carried out, i= 1, 2, …, I,

c : index of workstations required, c= 1, 2, …, C,

j : index of available machines, j= 1, 2, …, J,

t_{ij} : processing time of operation i performing on machine j,

CT : cycle time of flowline manufacturing cells,

PC_j : unit production cost for machine j,

BC_j : unit breakdown cost for machine j,

$MTBF_j$: mean time between failures for machine j,

y_{jc}: y_{jc} =1, if machine j is allocated to workstation c; =0, otherwise,

x_{ijc}: x_{ijc} =1, if operation i is assigned to machine j at workstation c; =0, otherwise.

The decision objective function computes from the total costs consisting of the operational cost of production (OP) and the penalty cost of machine breakdown (BC) within the duration of cycle time:

$$\text{Minimize objective function } = OP+BC \tag{1}$$

The CT is the maximum of workstation times, where workstation time is the sum of all processing times of operations at the same workstation. For the sake of native of hardly reaching line balancing which could decrease the utilization of machines, the OP is obtained by multiplying the CT by the number of selected machines, in that way the OP includes both operation time and idle time of machine's during the interval of CT. Given that the unit operational cost on machines is respectively. The OP is expressed as (2).

$$OP = CT\sum_{j=1}^{J}\sum_{c=1}^{C} PC_j y_{jc} \tag{2}$$

Amending machine breakdown needs to impose extra costs including those for machine repair or replacement. The machine failure is assumed to be mutually independent and the period of breakdown for a machine has an exponential distribution with a known failure rate λ. The reliability of a machine over its production times t is

$$R(t)= exp\ (-\lambda t) \tag{3}$$

A common way of dealing with machines reliability in a manufacturing system is using the evaluation of the quantities of the mean time between failures (MTBF). Then MTBF can be obtained by taking the reciprocal of λ, which is calculated as follows:

$$MTBF=1/\lambda \tag{4}$$

Obviously, the value of MTBF for machine j has known under the failure rate λ_j is known in advance. The breakdown is related to the availability of machine in the duration of CT so that defining r_j(t) is the ratio of breakdown for machine j at interval t, and it can be acquired by dividing the operational time by the MTBF, it can be referred to (5).

$$r_j(t)= \frac{t_j}{MTBF_j} \tag{5}$$

The production times t_j, in this study, is defined as the total operational time of machine j performing all assigned operations i during the interval of cycle time such that the t_j equals to $\sum_{i=1}^{I}\sum_{c=1}^{C} t_{ij}\, x_{ijc}$ for all machine j. Considering the individually unit breakdown cost, we can calculate the breakdown costs as below (6). The *BC* features the combination of machine types would cost differential expenditures, which could further affect the final decision making.

$$BC = \sum_{j=1}^{J} BC_j \frac{\sum_{i=1}^{I}\sum_{c=1}^{C} t_{ij} x_{ijc}}{MTBF_j} \quad (6)$$

The following constraints are considered.

$$\sum_{i=1}^{I}\sum_{c=1}^{C} t_{ij}\, x_{ijc} \le CT \qquad \forall\ j \qquad (7)$$

$$\sum_{j=1}^{J}\sum_{c=1}^{C} x_{ijc} = 1 \qquad \forall\, i \qquad (8)$$

$$\sum_{j=1}^{J} y_{jc} = 1 \qquad \forall\, c \qquad (9)$$

$$\sum_{c=1}^{C} y_{jc} \le 1 \qquad \forall\ j \qquad (10)$$

$$\sum_{i=1}^{I} x_{ijc} - y_{jc} \ge 0 \qquad \forall\ j, c \qquad (11.1)$$

$$\sum_{i=1}^{I} x_{ijc} - \alpha_j\, y_{jc} \le 0 \qquad \forall\ j, c \qquad (11,2)$$

$$\sum_{j=1}^{J}\sum_{c=1}^{C} c\, x_{ijc} \le \sum_{j=1}^{J}\sum_{c=1}^{C} c\, x_{(i+1)jc} \qquad \forall\, i \le I-1 \qquad (12)$$

$$x_{ijc}, y_{jc} \in \{0, 1\} \qquad \forall\, i, j, c \qquad (13)$$

The first constraint (7) ensures that workstation time does not exceed the cycle time. The constraint (8) limits an operation can only be allocated to one type of machine and its correspondent workstation. The constraint (9) and (10) ensures that each workstation contains only one type of machine, and vice versa. The constraint (11.1, 11.2) ensures if one machine is allocated to its unique workstation, at least one operation is allocated to each workstation (or machine). The variable y_{jc} in the model can be either 0 when $\sum_{i=1}^{I} x_{ijc} = 0, \forall j,\ c$, or 1 when $\sum_{i=1}^{I} x_{ijc} \ge 1, \forall j,\ c$. The constraint requires that one of these two conditions must be hold. To model this situation, it is necessary that $\sum_{i=1}^{I} x_{ijc}, \forall j,\ c$ be bounded above in the problem; i.e., there must exist an upper bound such that $\sum_{i=1}^{I} x_{ijc}, \forall j,\ c$ is $\le$ it at all feasible solutions to the problem $\sum_{i=1}^{I} x_{ijc}, \forall j,\ c$. Let α_j be such an upper bound for $\sum_{i=1}^{I} x_{ijc}, \forall j,\ c$ at all feasible solutions to the problem. The constraint that $\sum_{i=1}^{I} x_{ijc}, \forall j,\ c$ is either 0, or $\ge$ 1 is then equivalent to (11.1) and (11.2), respectively. The upper bound, α_j, can be determined by *J*-*C*+1, the maximal number of operations that can be allocated at one workstation. The constraint (12) is precedence constraints among the operation of parts, ensuring (i+1)th operation is to be assigned to a cell *c* after precedence *i*th operation has been allocated to that cell. The last constraint (13) illustrates that the proposed model is a binary integer model.

3.2 An extension to scenario-based model

Mostly parameters have their own uncertain characteristics in practice. Fluctuant changeover of demands is the major uncertainty in CMS, and unexpected breakdown of machines in flowline production will accompany with reparations or alternatives-reassigned. To construct an adapting flowline manufacturing cells satisfying the need of robust environments, it is worthy to consider uncertainty issues in the phase of modeling. The uncertainty in parameters can be modeled via stochastic programming. The goal of stochastic programming is to discover a solution that would perform well under any possible realizations of uncertainty. The uncertain parameters can be defined as continuous values or discrete scenarios (Snyder, 2006). In this paper, a scenario-based analysis is utilized to the consideration of uncertainty. For more information, it can refer to Birge and Louveaux (1997).

To formulate the cell formation under uncertainty, new sets, parameters, and variables are added to the previous definitions.

u : index of scenarios, u= 1, 2, …, U,

p^u : probability of scenario u,

t_{ij}^u : processing time of operation i performing on machine j under scenario u,

$MTBF^u_j$: mean time between failures for machine j under scenario u,

CT^u : cycle time of manufacturing cells under scenario u,

The scenario-based stochastic mathematical model can be described as:

$$\text{Minimize objective function} = \sum_{u=1}^{U} p^u(OP^u + BC^u) \tag{14}$$

where the changeover of OP^u is associated with the cycle time which is found at each scenario.

$$OP^u = CT^u \sum_{j=1}^{J} \sum_{c=1}^{C} PC_j y_{jc} \tag{15}$$

The values of BC^u vary from scenario to scenario and are associated with the combination of total demands that are processed on corresponding selected machine and MTBF. Under the assumption of routings of all distinct parts are transformed as part of a part family in advance, the processing time of an operation related to equivalent part of a part family is calculated by summation up the volume of parts multiplies its respective processing time. Thus, the processing time of operations in an equivalent part family is varied from the demand lot size of parts. In this study, we use the uncertain processing time (i.e., t_{ij}^u) instead of the variation of demand lots size. The BC^u can be described as:

$$BC^u = \sum_{j=1}^{J} BC_j \frac{\sum_{i=1}^{I}\sum_{c=1}^{C} t_{ij}^u x_{ijc}}{MTBF_j^u} \tag{16}$$

The following constraints are considered on the stochastic models.

$$\sum_{i=1}^{I}\sum_{c=1}^{C} t_{ij}^u x_{ijc} \le CT^u \qquad \forall\, j,u \tag{17}$$

and constraints (8) -(13)

4. Computational experiments

To measure the impact of uncertainty to the cell formation's decision, an illustrated example modified from literature is generated for experimentation. Table 3 and 4 shows the data in details. The illustrated example contains one routing of equivalent parts of a part family, which has 10 distinct machines and 12 precedent-constrained operations. There are five scenarios associated with the operations' alterative machines and corresponding processing times, and three scenarios are presumed on MTBF of machines. In that way, totally 15 combinations, where {(a, b) |a=1...,5, b=1...,3}, are computed for comparison. The processing times at first scenario (t^1_{ij}, u=1) is obtained from a uniform function of interval [1, 10] and that of the succeeding scenarios are generated from interval [t^1_{ij}, $u\ t^1_{ij}$] randomly, so the demands variation is getting more increasingly expanding. Similarly, the value of MTBFs at first scenario is obtained from random numbers between [250, 400] and increasingly reducing at ratio of 0.2 related to secondary scenario, and 0.4 related to the third scenario, representing the failure rate is getting higher and higher. Other parameters such as unit cost are generated from random interval as well. Table 5 is given the changeover probabilities of scenarios and they are subsequently used to conduct a sensitivity analysis.

To examination of whether the scenarios and stages are well defined and the solution of stochastic model is justified, two index, the expected value of perfect information (EVPI) and the value of stochastic solution (VSS), are employed to evaluate the value-added of incorporating uncertainty in the phase of modeling. The EVPI measures the loss of profit due to the presence of uncertainty that is also denoted the maximum amount the decision maker is willing to pay for getting accurate information in the future. The EVPI can be defined as EVPI= SS- WS that is the difference between the stochastic solution (SS), that is obtained by solving stochastic model under uncertainty, and the average of objective functions obtained by solving deterministic models, having the perfect information in prediction. A solution based on perfect information would yield optimal first stage decisions for each scenario, the expected value of these decisions is known as wait-and-see (WS). On the other hand, the

Table 3. Experiment data included operations, alternative machines, and corresponding processing times.

Operation	Alternative Machines	Processing time at scenarios				
		1	2	3	4	5
1	1,3,6,7,9,10	3,7,6,8,7,5	5,7,12,15,8,7	5,13,17,9,7,8	9,11,24,16,13,17	10,18,14,35,33,16
2	1,4,9,10	3,3,2,3	6,4,4,3	4,9,2,6	5,3,5,5	7,12,9,3
3	1,4,6,7,10	6,8,4,7,2	6,8,4,7,2	12,15,9,16,2	12,28,4,8,3	9,32,13,31,5
4	2,4,6,10	10,4,2,3	13,6,4,4	28,8,6,5	22,8,7,6	42,7,2,7
5	1,2,3,4,5,6,9,10	6,2,10,7,1,4,7,6	11,3,19,8,1,5,12,12	15,3,26,18,3,6,19,6	21,2,15,16,2,16,18,19	13,3,10,18,2,20,17,29
6	2,4,6,8,10	6,3,3,1,2	11,6,6,1,4	6,4,5,2,5	18,4,7,1,3	19,10,15,4,6
7	3,5,7,10	5,8,8,10	5,8,13,12	5,24,9,24	20,8,22,18	13,17,33,35
8	1,3,5,7,9	4,3,3,2,3	6,3,6,4,3	12,9,9,4,4	8,6,6,6,10	14,6,11,7,7
9	1,4,6,8,10	9,4,3,7,6,1	16,6,6,9,6,2	23,12,7,19,6,3	18,4,11,22,16,3	27,20,6,30,6,1
10	1,2,6,8,9,10	1,8,7,6,7,9	2,15,9,10,12,18	1,23,12,8,20,20	1,27,21,16,19,34	4,30,21,12,14,16
11	2,4,6,8	4,3,7,3	8,6,8,5	6,9,7,5	5,9,17,3	14,9,19,7
12	1,2,5,7,9	5,10,4,9,7	10,18,6,9,11	14,25,11,17,7	12,33,14,35,10	23,17,15,27,26

Table 4. Experiment data included MTBF and unit cost.

Individual data	MTBF and unit cost on machine j									
	1	2	3	4	5	6	7	8	9	10
MTBF at scenario 1	240	465	386	306	403	240	303	351	388	447
MTBF at scenario 2	193	398	377	271	397	209	274	287	328	413
MTBF at scenario 3	156	303	344	191	328	163	179	256	245	361
PC_j	144	189	154	124	147	142	174	116	198	131
BC_j	2300	3200	2800	2600	3100	2200	3100	3500	2700	3200

Table 5. The changeover of probability under scenarios.

Scenarios	(1,1)	(1,2)	(1,3)	(2,1)	(2,2)	(2,3)	(3,1)	(3,2)	(3,3)	(4,1)	(4,2)	(4,3)	(5,1)	(5,2)	(5,3)
Case 1	0.0135	0.0299	0.0408	0.0376	0.054	0.0649	0.0537	0.0701	0.081	0.0698	0.0862	0.0971	0.0859	0.1023	0.1132
Case 2	0.0667	0.0667	0.0667	0.0667	0.0667	0.0667	0.0667	0.0667	0.0667	0.0667	0.0667	0.0667	0.0667	0.0667	0.0667
Case 3	0.1132	0.1023	0.0859	0.0971	0.0862	0.0698	0.081	0.0701	0.0537	0.0649	0.054	0.0376	0.0408	0.0299	0.0135

VSS can be interpreted either as the benefit you gain if you use stochastic modeling that has taken uncertainty into account, or as the benefit you lost if you opt deterministic modeling that has used the average of stochastic parameters instead of scenario variables. The value EEV denotes the expected result of using the solution of the deterministic model EV, the one obtained by replacing all random variables by their expected values; The VSS can be expressed as VSS = EEV- SS that is the difference between the averaged solution of the expected value problem and the stochastic solution.

Therefore, three models combining different data and solution approaches are conducted in the process of computational experimentation. The first one is the deterministic model, which adopts the individual data listed in table 3 and 4 and the deterministic model listed in section 3.1 to solve each of 15 scenarios and find their respectively optimal TC, and then the average of all optimal TCs leads to the value of WS. The stochastic model, the second one, is used to find the value of SS, where the individual data listed in table 3 and 4 and the scenario-based model listed in section 3.2 are employed under the circumstance of occurrence probability of all scenarios is equal. Furthermore, the last one, averaged model substitutes stochastic data with their expected values, and then bringing them into scenario-based model for solution of EEV.

The problems are solved by LINGO 10 and performed on Intel core2 platform with windows XP OS. The computational experiments of deterministic model are conducted at different cell sizes. Table 6 shows the results of solving deterministic model under scenario (1, 1). Observing the tendency of total cost, it does not keep decreasing as the number of cells growing. That is mainly affected by the operational cost, where once the number of cell sizes is increasingly growing the decreasing span of CT is shrinking, so that the reduced cost caused from decreased CT might be dominated by the incremental cost of a newly cell. While the breakdown cost of machines remains decreasingly downward due to the number of cell sizes growing. The cell size c=6 has the minimum total cost. Moreover, the result of optimal number of cells varies from scenario to scenario and Figure 2 depicts the experimental results when cell size changes from 3 to 8 at different scenarios (a, 1), a=1..., 5, where the demand variation getting more increasingly expanding.

Table 6. the solutions of deterministic model under scenario (1, 1) and different cell sizes.

Cell sizes	TC	OP	BC	solutions	CT
c=3	14836.43	14384	452.43	(10-1,2,3,4,5,6,7) (1-8,9,10) (2-11,12)	31
c=4	11740.41	11298	442.41	(10-1,2,3,4,5,6) (5-7,8) (8-9,10,11) (1-12)	21
c=5	10386.62	9898	488.62	(10-1,2,3,4) (4-5,6) (5-7,8) (8-9,10) (2-11,12)	14
c=6	8493.76	8110	383.76	(10-1,2,3) (6-4,5,6) (3-7,8) (4-9) (8-10,11) (1-12)	10
c=7	8981.57	8622	359.57	(1-1) (10-2,3) (6-4,5,6) (3-7,8) (4-9) (8-10,11) (5-12)	9
c=8	9421.57	9056	365.57	(7-1) (10-2,3,4) (6-5,6) (3-7,8) (4-9) (1-10) (8-11) (5-12)	8

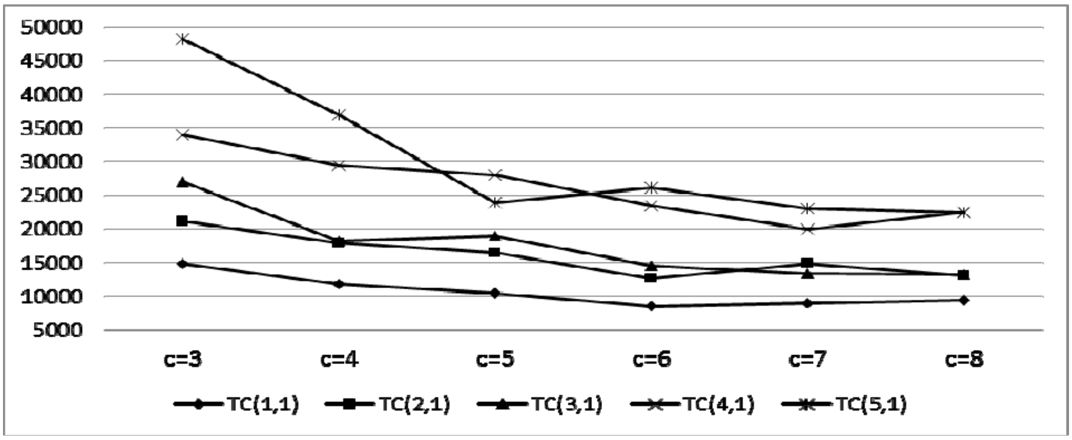

Figure 2. The tendency of total cost under different scenarios and cell sizes.

Table 7. The comparison of related cost under c=5.

Scenario	Deterministic model		Stochastic model		Averaged model	
	Optimal TC	CT	Stochastic TC	CT	Expected TC	CT
(1,1)	10386.620	14	10784.074	14	10386.621	14
(1,2)	10451.660	14	10833.910	14	10451.661	14
(1,3)	10578.910	14	10959.302	14	10578.914	14
(2,1)	16471.850	23	19847.952	26	19091.571	26
(2,2)	16552.880	23	19924.645	26	19190.361	26
(2,3)	16746.590	23	20114.562	26	19381.074	26
(3,1)	18881.320	26	23766.318	31	24404.674	33
(3,2)	18985.340	26	23867.007	31	24540.979	33
(3,3)	19202.460	26	24123.414	31	24825.050	33
(4,1)	28005.970	38	29255.298	38	28005.974	38
(4,2)	28176.340	38	29387.549	38	28176.338	38
(4,3)	28466.210	38	29711.893	38	28466.212	38
(5,1)	23859.050	31	23998.490	31	31001.354	42
(5,2)	23983.920	31	24123.399	31	31182.910	42
(5,3)	24335.390	31	24442.405	31	31516.190	42
Expected	WS=19672.30		SS=21676.01		EEV=22746.64	

Table 8. The ANOVA of SS solution.

Source	SS	*df*	MS	F	*P*-value	Critical value
SS_MTBF	306607.8	2	153303.9	40.38039	6.6E-05	4.45897
SS_Demand	5.75E+08	4	1.44E+08	37878.94	3.88E-17	3.837853
SSE	30371.95	8	3796.494			
Total	5.76E+08	14				

Table 7 reveals the computational results when c=5. The solutions of stochastic model, (10-1,2,3,4), (4-5,6), (3-7,8), (6-9,10), and (2-11,12), are applied to all over the scenarios, while that of averaged model are (10-1,2,3,4), (4-5,6), (5-7,8), (8-9,10), and (2-11,12). As mentioned early, using single criteria of minimizing cycle time is hard to choose from an adequate solution unless incorporating additional decision variables. Taking scenarios (1, b), b=1, 2, and 3 at Table 7 for example, the cycle time of both averaged and stochastic model are the same, but the final solutions, in terms of the combination of machines and operations, are different, and that turn out differentially in total cost. Looking at Table 7 results of the WS=19672.30 and the SS=21676.01, hence EVPI=2003.71, representing the maximum amount that the decision maker is willing to pay to get accurate information, while EEV=22746.64 which lead to VSS=1070.63, the saving value of using the proposed stochastic model instead of averaged model. Such that the improved cost is about 4.707% (= VSS/EEV). Furthermore, due to ignore the uncertainty and without considering the variation of demand, the cycle time converged from the averaged model is larger than that of other two, implying more total cost needs to be paid in the future. Table 8 shows the testing results of two factors ANOVA of SS solutions. It reveals the fluctuation of uncertainties, demand lots size and MTBF has significantly impacts on total cost. Especially, the effect of demand lots size is more significant than that of MTBF. The results make a hint of it is worthily taking both into account in the design of flowline manufacturing cell system.

Table 9. The experiment results under cell numbers changed from 3 to 8.

no. of cell	EEV	SS	WS	EVPI	VSS	IM%	OP%
3	29189.17	29189.17	29189.17	0.00	0	0.000%	0.000%
4	24017.02	23087.02	22992.51	94.51	930	3.872%	0.411%
5	22746.64	21676.01	19672.30	2003.71	1070.63	4.707%	10.185%
6	21235.04	18593.87	17174.84	1419.03	2641.17	12.438%	8.262%
7	20658.02	18052.72	16160.25	1892.47	2605.30	12.612%	11.711%
8	22883.70	19673.47	16279.09	3394.38	3210.23	14.028%	20.851%

Table 9 reveals the computational results under cell numbers change from 3 to 8. A special and rear case has happened in c=3. Whatever models were solved, they find the identical solutions (10-1, 2, 3, 4, 5, 6, 7), (1-8, 9,10) and (2-11,12), which leads to the same value of EEV, SS and WS. Hence both, EVPI and VSS, are equal to zero. The figures of both EVPI and VSS in Table 8 are getting larger when the number of cells is increasing that reveals the impact of uncertainties is getting more significant in larger scale of flowline manufacturing system than in smaller one.

Let the IM% denotes the improved percentage of cost-reduced by using stochastic model instead of averaged model, and IM=VSS/EEV; OP% represents the tolerance percentage of optimality that uses stochastic model instead of deterministic model, and OP=EVPI/WS. The results in Table 9 reveal that the values of IM% are increasing as the number of cells increased. However, as the number of cells increasing, the span of margin of OP% reaches up among 8% to 20%, while the average is 12.75%. Ideally, a stochastic model is expected to find the values of objective which is as closer as that of deterministic model, if so, the stochastic model would be capable of being an evaluator in the uncertainty environments.

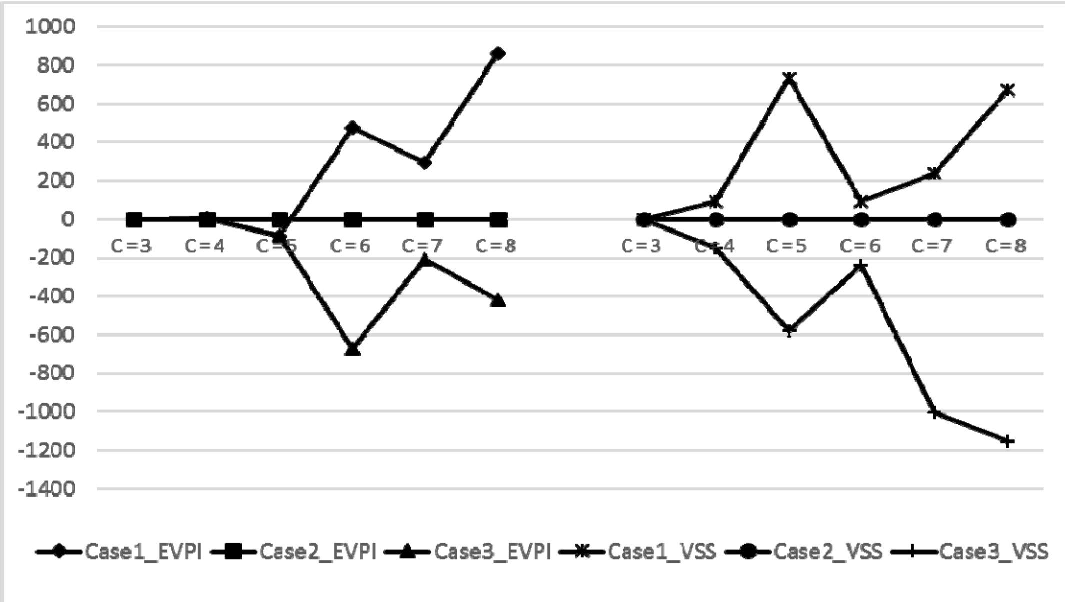

Figure 3. The results of sensitivity analysis.

A sensitivity analysis is conducted via adjusting the probability of scenarios, see Table 5, where case 2 is regarded as a referenced (regret) scenario. By contrasting to case 1 that increases the probability of higher variation scenarios, while to case 3 that oppositely decreases the probability of higher ones. For comparison, setting the value of EVPI (VSS) in case 2 as referenced value so that all EVPI (VSS) in case 2 must have been equaled to zero. While the differences related to case 1 and case 3 can be calculated by individually subtracting the referenced value to their original EVPI (VSS). Figure 3 depicts the computational results. As the probability of higher variation scenario (case 1) is rising, the value of EVPI and VSS is increasing too, oppositely the EVPI and VSS in case 3 decrease as the probability of higher variation scenario down. This result reveals the impact of uncertainty is stronger in case 1 than case 3. Furthermore, observing the tendency of the difference of EVPI and VSS, it is more significant as the number of cells increasingly, revealing the impact of uncertainty is more intensified as well.

5 Concluding Remarks and future work

This study presented a new model for the design of flowline manufacturing cells by considering uncertainty in machine reliability and demand lot size variation within an optimization framework and aimed to minimize the total cost of operation and machine breakdown. Both deterministic and stochastic model are developed to experiment for comparison and to conduct a sensitivity analysis on uncertainty as well. Comparing to the literature, the proposed model has several advantages in offering many information such as EVPI, EEV and VSS; in designing robust model that take into consideration of many practical factors such as demand variation, machine failure and multi-flow production data; in overcoming the decision problem that cannot easily choose from because of converged duplication solutions. The proposed model can find better flowline manufacturing cells which perform well under all possible situations rather than one that is optimal for one possible scenario but does poorly in other possible scenarios. Nevertheless, some issues need to be further explored such as the impact of different MTBF distribution function on the proposed model; instead of solving the proposed model via optimization software, redeveloping heuristic algorithms using meta-heuristic methodologies to solve the large-scale problems are recommended. Further, a multiple-stage stochastic model that considers adding periodic level of demands to the existing one is well worth to try out for finding better stochastic solution that could approximate to wait-and-see solution.

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