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Reliability Consideration in the Design of Cellular Manufacturing Systems using Genetic Algorithm

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Reliability Consideration in the Design of Cellular Manufacturing Systems using Genetic Algorithm

By

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Reliability Consideration in the Design of Cellular Manufacturing Systems using Genetic Algorithm

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ABSTRACT

This thesis proposes a multi-objective, mixed integer, non-linear programming model of cellular manufacturing systems (CMS) design to maximize the system reliability and minimize the total system cost simultaneously. The model involves multiple machine types, multiple machines for each machine type, multiple part types, and alternative process routes for each part type. Each process route consists of a sequence of operations. System reliability associated with machines along process routes can be improved by increasing the number of parallel machines subject to acceptable cost. Assuming machine reliability to follow a lognormal distribution, the CMS design problem is to optimally decide the number of each machine type, assign machines to cells, and select, for each part type, the process route with the highest overall system reliability while minimizing the total cost. The total cost consists of the variable cost of manufacturing operations, the inter-cell material handling cost, the penalty cost of machine under-utilization, and machine annuity cost. Genetic algorithm (GA) is proposed as the solution procedure, and is applied to solve this practical-sized CMS design problem. It is shown that, with its characteristics of random selection, crossover, and mutation, GA is capable of finding a heuristic solution within a reasonable amount of computational time.

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CHAPTER 1

INTRODUCTION

In a cellular manufacturing system (CMS), machines are grouped into a limited number of cells. Compared with conventional manufacturing systems (job shops, flow shops, etc.), the techniques of part family and machine cell formation of CMS is advantageous in reducing set up times, throughput times and material handling cost, as well as enhancing production efficiency (Wemmerlov and Hyer, 1989; Wemmerlov and Johnson, 1997; Askin and Estrada, 1999) because each machine is capable of handling different operations for different parts. However, most research on CMS design in the past 30 years is subject to the assumption that machines are 100% reliable. System reliability is one of the major factors influencing the performance of CMS. Machine breakdowns result in higher production costs, longer production period (if the failed machine cannot be repaired/maintained within an expected time), and other manufacturing problems. Moreover, machine rerouting of parts to address the machine failure issue is not as easy in CMS as in job shops, even though each part may be processed using different machine routes. Unlike the parallel configuration of job shops, the series configuration of CMS requires intercellular transportation arrangement for rerouting. Therefore, system reliability is more important in the evaluation of CMS performance.

To overcome the challenges of machine breakdowns, Das *et al*. (2006) proposed an effective CMS design approach, which considers system reliability in the allocation of parts to available machine routes. In this thesis, their model is extended to consider, in addition to routing flexibility, the optimal number of machines allocated to increase the system reliability. More machines improve reliability; however, they increase the system cost as well. A CMS design study is thus developed in terms of both efficiency and cost-effectiveness.

The thesis proposes a multi-objective, mixed integer, non-linear programming model of CMS design to maximize the system reliability and minimize the total system cost. Different process plans are available for each part type. Each process plan consists of a sequence of operations, and each operation can be performed by different machines, which are configured as a series structure. Accordingly, the level of reliability for each process route is decided by the reliability of the machines along the route as well as the number of redundant machines.

It is known that reliability can be enhanced by increasing the number of parallel machines. However, this also increases the probability of incurring high penalty costs associated with machine under-utilization, as well as the associated annuity costs. In addition, different machines are assigned to different cells, so the inter-cell movement of parts between operations affects the cost performance. Using the concept of alternative process routes, reducing the inter-cell movements among the parts is another way to reduce the cost. The machine availability is taken into account to estimate the effective capacities of machines by allocating operations to machines.

The CMS design problem is thus how to optimally decide the number of each machine type, assign machines to cells, and select, for each part type, the process route with the highest overall system reliability, while minimizing the total cost.

In this thesis, genetic algorithm (GA) is proposed as the heuristic solution method to solve the model, and is applied to solve a practical-sized CMS design problem. With its characteristics of random selection, crossover and mutation, GA is capable of finding a heuristic optimal solution within a reasonable amount of computational time.

The thesis is organized as follows. Chapter 2 contains a review of the related literature, and provides the motivation of the thesis, and the extensions that are made compared to the model put forward by Das *et al.* (2006). In Chapter 3, machine availability is described. Assuming that machine reliability follows a lognormal distribution, the integration of the machine reliability into system objectives is developed in Chapter 3. The extended CMS model is described in detail in Chapter 4. The model is proposed to both maximize the system's reliability and minimize the total cost. The total cost consists of the variable cost of manufacturing operations, the inter-cell material handling cost, the penalty cost of machine under-utilization, and the machine annuity cost. The genetic algorithm used in the optimal search to solve this large practical-sized problem is described in Chapter 5. A numerical example with 24 part types, 14 machines, and 3 cells is given in Chapter 6 to demonstrate the application of the model and the genetic algorithm. Chapter 7 lists the result of the numerical example solved by the genetic algorithm. Based on the detailed data about system reliability and system's overall cost, the CMS performance is analyzed under various scenarios depending on the weights assigned to each objective. Chapter 8 gives the discussion and conclusions for this thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 Literature Survey

Machine reliability is an important factor influencing the expected output of the CMS. In the design of an effective CMS, two aspects of reliability planning are considered. First, parts are allocated to machine routes with the highest possible system reliability among the available machine routes. Second, in case of machine breakdown, parts can be rerouted flexibly to reduce the impact of machine failures. The enhancement of the performance in terms of reliability is often accompanied by an increase in the system cost. So, an effective CMS design needs to consider reliability and cost simultaneously.

In the past 30 years, effective CMS design models were developed by considering various costs and constraints (Wemmerlov and Hyer, 1986; Joines *et al*., 1996; Selim *et al*., 1998; Mansouri *et al*., 2000). However, since machine rerouting of parts to deal with machine failures is not as easy in CMS as in job shops, only a limited number of researchers have considered the effect of machine reliability in their design approaches. Although some CMS design models (Wicks and Reasor, 1999; Caux *et al*., 2000) used alternative machines routes to reduce costs and balance part flows, they did not take machine failure into account.

The importance of appropriate reliability planning on CMS output performance has been studied by a number of researchers. Logendran and Talkington (1997) compared both mean work in-process and mean throughput time in CMS and job shops considering machine breakdown. Their study indicated that performance on mean throughput time was better in CMS only when preventive maintenance was performed. So it was concluded that reliability is an important design factor in CMS. Seifoddini and Djassemi (2001) compared the performances of CMS and job shops considering different configurations. They pointed out that, compared with the parallel configuration of a job shop, the series configuration of CMS limits the flexibility of rerouting to handle machine failure. Their study demonstrated that the effect of machine reliability on system performance is more noticeable in CMS. Neither study developed a reliability-related design model.

In their work on cellular manufacturing systems, Jeon *et al*. (1998) focused on developing a cell configuration which works through alternative routes to deal with the problems caused by machine breakdowns. The proposed model minimized the inventory handling cost, penalty cost, and waiting cost. However, the research work did not take reliability into consideration explicitly. Diallo *et al*. (2001) pointed out the fact that machines are unreliable and attempted to develop a cell formation model to deal with machine breakdowns through alternative process plans. Moreover, the reduction of intercell interactions and the non-availability of machines were also discussed in their paper.

Recently, Das *et al.* (2006) focused on reliability considerations as well as the entire system cost when dealing with a CMS design model. Moreover, a reroute process plan was proposed to enhance system's efficiency. Simulated annealing (SA) and genetic algorithm (GA) were combined as a heuristic method to search the local optimal solution of the proposed model. Regarding the reliability consideration, both exponential distribution and Weibull distribution were used to model machine reliabilities, and the model results were compared under the both conditions (Das, 2008). Das *et al*. (2008) extended their previous work by integrating preventive maintenance planning with manufacturing system cost and machine system reliability in the CMS design model. The model also included an algorithm to determine effective preventive maintenance intervals for the CMS machines and minimize the maintenance costs subject to acceptable machine reliability. The results demonstrated that, compared to a CMS model without preventive maintenance planning, preventive maintenance improves the system reliability and decreases the total cost significantly.

2.2 Motivation

The CMS design research proposed in this thesis extends the work of Das *et al.* (2006) in four ways:

First, in the model of Das *et al.* (2006), only one unit of each machine type was assigned. If the machine fails, all the parts that are planned to be processed on this machine either have to be rerouted, or have to wait for the machine to be repaired if there is no option to reroute. In the proposed model, more than one unit of each machine type is available to assign. Multiple machines improve the availability and reliability of the machine type in question; however, the total cost increases as the number of machines increases. Therefore an optimal number of machines needs to be determined.

Second, in addition to the operating and refixturing costs, the objective function also includes the purchase cost recovery component of the machine, i.e., the annuity cost charged to recover the initial purchase cost, which is often a significant part of the overall system cost.

Third, machine failures are assumed to follow a lognormal distribution, whereas Das *et al.* (2006) considered the failure distributions to be either exponential or Weibull. In this thesis, the system reliability is computed assuming the machines failure times are independent and identically distributed as lognormal. Like the hazard rate of a Weibull distribution, the hazard rate of a lognormal distribution is not always constant over time. Lognormal distributions can take on a variety of shapes with different shape and location parameters. It is also often observed that data fitting a Weibull distribution will also fit a lognormal distribution (Ebeling, 1997). Additionally, a lognormal distribution can deal with both increasing and decreasing failure rates. Further discussion in support of the use of a lognormal distribution is found in Section 3.2.5.

Fourth, the CMS design problem proposed in this thesis is expected to be a large, combinatorial model and difficult to solve exactly. Therefore, a Genetic Algorithm (GA)-based heuristic procedure is applied to solve the model. One of the advantages of GA is that it can avoid potentially wrong search directions that may lead the final solution far away from its optimum location. In each iteration, a set of chromosomes act to inherit advantageous characteristics in order to generate new chromosomes. The action of crossover tracks the search tendency and leads each generation of chromosome to be closer to the optimal solution. The action of mutation maintains the versatility of the chromosome to keep the final solution from being trapped in a local optimal area. Another advantage of GA is that, compared with traditional methods such as tabu searches and simulated annealing algorithms, it searches the final heurstic optimal solutions with a set of candidate solutions in parallel in each search step, not a single candidate solution; other heuristic algorithms search their answers through candidate solutions one by one (Mitsuo and Cheng., 1997). Therefore GA requires fewer iterations to search for an optimal solution. Also, GA does not require derivative information or other auxiliary knowledge; only objective functions, constraints, and the corresponding fitness levels influence the search direction of a GA. GA uses probabilistic transition rules, not deterministic ones. It works on an encoding of the parameter set rather than the parameter set itself, except where real-valued individuals are used (Zalzala and Fleming., 1997). Moreover, GA is easily extended and combined with other methodologies. In general, it tends to be particularly effective at exploring various parts of the feasible region and gradually evolving toward the best feasible solutions (Hillier and Lieberman, 2005).

2.3 Objectives

The objectives of the thesis are summarized as follows:

1. To develop a mathematic model of the CMS considering the reliability of machines, and considering the possibility of using more than one unit of a machine type. That is, the model involves multiple machine types, multiple machines for each machine type, multiple part types, and alternative process routes for each part type.

2. To investigate the application of lognormal distribution in the design of CMS. With different shape parameter, lognormal distributions can take on a variety of shapes to deal with both increasing and decreasing hazard rates.

3. To develop a GA solution for the model. Due to the non-linear nature of the proposed model, the genetic algorithm is applied as a solution procedure to solve a practical-sized CMS design problem.

CHAPTER 3

MACHINE RELIABILITY ANALYSIS

3.1 Machine availability consideration

In practice, no machine can be considered 100% reliable. A machine either performs functions when it is up, or waits for repair when it breaks down. “Availability is the probability that a machine performs its function at a given point in the time or over a stated period of time when the machine is operated or maintained in a prescribed manner.” (Ebeling, 1997). The point availability and interval availability expressions can be obtained as follows (Ebeling, 1997):

The point availability *A(t)*, i.e. the instantaneous availability at time $t \geq 0$, is the probability of machine functioning at time *t*.

The interval availability between t_1 and t_2, can be expressed as

$$A_{t_2 - t_1} = \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} A(t)dt \qquad (3\text{-}1)$$

In addition, the steady state availability, $A = \lim_{T \to \infty} A(T)$, can be defined as inherent availability

$$A_{inh} = \lim_{T \to \infty} A(T) = \frac{MTTF}{MTTF + MTTR} \qquad (3\text{-}2)$$

where *MTTF* is the mean time to failure and *MTTR* is the mean time to repair.

In this thesis, machine interval availability, computed using a lognormal distribution, is taken into account to estimate the effective machine capacity. Because inherent availability is based on both failure time and repair time distribution, a lognormal distribution was used to estimate machine availability.

Thus, availability of each machine type can be estimated from the following function:

$$A_j = \frac{MTTF_j}{MTTF_j + MTTR_j} \tag{3-3}$$

where A_j is the availability of machine type j, $MTTF_j$ and $MTTR_j$ are the mean time to failure and repair for machine type j, respectively.

The assumptions made are listed below.

1. For each machine type, the failure mode and repair mode are independent.
2. The information about MTTF and MTTR for each machine type is available from the maintenance files.
3. Machine breakdowns occur independently according to a lognormal distribution.
4. MTTF and MTTR do not change during the planning period.
5. Preventive maintenance is not considered.

3.2 Machine reliability consideration

3.2.1 The reliability function

The machine reliability function *r(t)* can be defined as the probability that the machine will perform its function over a given time period *t*. The reliability function is represented by:

$$r(t) = \Pr\{t \le T\} \tag{3-4}$$

where T is the continuous random variable representing the time to failure of the machine, $T \ge 0$, $r(t) \ge 0$, $r(0) = 1$, and $lim_{t \to \infty} r(t) = 0$. For a given value of *t*, $r(t)$ is the probability that the time to failure is greater than or equal to *t*.

3.2.2 Failure Distribution Function

If it is defined that

$$F(t) = 1 - r(t) = \Pr\{T < t\} \tag{3-5}$$

where *F(0)*=0 and $lim_{t \to \infty} F(t) = 1$, then *F(t)* is the probability that a machine failure occurs before a given time t, and *F(t)* is defined as the cumulative distribution function (CDF) of the failure times for machines. The probability density function (PDF) for the failure distribution is defined by:

$$f(t) = \frac{dF(t)}{dt} = -\frac{dr(t)}{dt} \tag{3-6}$$

where $f(t) \geq 0$ and $\int_0^{\infty} f(t)dt = 1$.

3.2.3 Reliability Function for Lognormal Distribution

The hazard rate of a lognormal distribution is not constant over time. Lognormal distributions may be used to model increasing, decreasing and even constant failure rates. The machine reliability function in the lognormal distribution is represented by the following equation:

$$r(t) = 1 - \Phi(\frac{1}{s} \ln \frac{t}{t_{med}}) \tag{3-7}$$

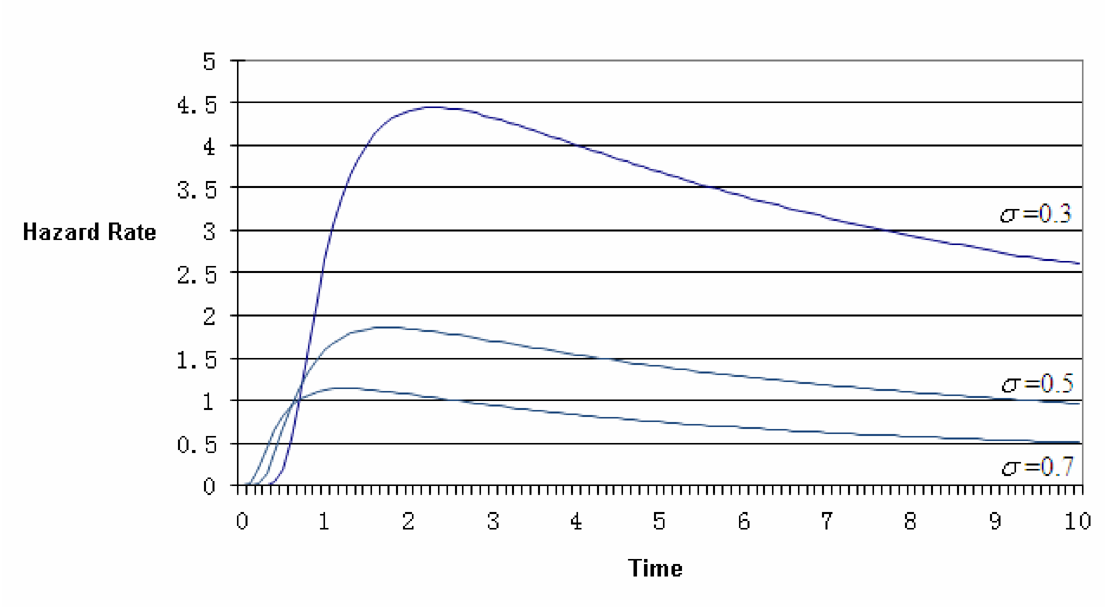
where s is the shape parameter and the location parameter t_{med} is the median time to failure.

The mean time to failure MTTF of the lognormal distribution is given by:

$$MTTF = t_{med} \exp(s^2 / 2) \tag{3-8}$$

Because it is time-dependent, the hazard rate of the lognormal distribution cannot be analyzed analytically but can be numerically calculated. The hazard rate of a lognormal distribution shows a pattern that increases to a maximum and then decreases to zero as time approaches infinity (Gupta and Lvin, 2005). Figure 3.1 shows the lognormal hazard rate at standard deviations σ =0.3, 0.5, 0.7 (Sweet, 1990).

Figure 3.1 Hazard rate of lognormal distribution (Sweet, 1990)



3.2.4 Machine Reliability Consideration in a Part-type Process-plan Route

To show how to correspond the machine reliability function to a part-type process-plan route, a small numerical example was developed as shown in Table 3.1. Each part type may be processed under two process plans. In each process plan, there are three operations which may be performed by different machines along different process routes. For example, part type 1 may be processed in any of the eight process routes shown in Table 3.2. Each route is represented by a 4-digit number where the first digit represents the part type, the second digit represents the process plan, and the

Table 3.1 A sample route for 4 part types and 5 machines

Part Type	Process Plan 1			Process Plan 2		
	Operation 1	Operation 2	Operation 3	Operation 1	Operation 2	Operation 3
1	M3 M2	M4 M5		M2 M4	M3	M1 M4
2	M2	M4 M5	M3	M1 M3	M2	M5
3	M1 M4	M3 M2	M2	M4 M5	M2 M4	M1 M3
4	M1 M3	M2 M4	M5	M4 M5	M1	M4

Table 3.2 Process routes for part type 1

Process Route	Machine Sequence
1101	M3 M4
1102	M3 M5
1103	M2 M4
1104	M2 M5
1201	M2 M3 M1
1202	M2 M3 M4
1203	M4 M3 M1
1204	M4 M3 M4

last two represent the route. For example, 1201 represents part type 1, process plan 2 and process route 01, which corresponds to the machine sequence M2-M3-M1 with a system's reliability:

$$\Re_{1201}(t) = R_1(t)R_2(t)R_3(t) \tag{3-9}$$

The machines of the same type in a cell are in parallel, with the corresponding machine reliability at time *t* given by:

$$R_j(t) = 1 - [1 - r_j(t)]^{m_j} \tag{3-10}$$

where $r_j(t)$ is the reliability of a machine type *j* at time *t*, and m_j is the number of machines of type *j*.

The reliability of each machine type *j* follows the lognormal distribution:

$$r_j(t) = 1 - \Phi(\frac{1}{s_j} \ln \frac{t}{t_{med\ j}}) \tag{3-11}$$

Then, system reliability along process route 1201 can be written as:

$$\Re_{1201}(t) = [1-\Phi(\frac{1}{s_1}\ln\frac{t}{t_{med1}})^{m_1}][1-\Phi(\frac{1}{s_2}\ln\frac{t}{t_{med2}})^{m_2}][1-\Phi(\frac{1}{s_3}\ln\frac{t}{t_{med3}})^{m_3}] \quad (3\text{-}12)$$

or,

$$\Re_{1201}(t) = \sum_{j=1,2,3}[1-\Phi(\frac{1}{s_j}\ln\frac{t}{t_{medj}})^{m_j}] \quad (3\text{-}13)$$

where we use $\Re_{1201}(t)$ to define system reliability corresponding to machine types 1, 2 and 3 for process (1201). The system reliability for other process routes is computed in the same way. Maximizing the reliability of each process route for parts by choosing appropriate process plans, machine types, and numbers leads to an optimal performance of the entire CMS system with the respect to reliability and cost.

3.2.5 Lognormal distribution in reliability studies

With different shape parameters, σ , and location parameters t_{med}, the lognormal distribution can take on a variety of shapes. With such characteristics, lognormal distributions are used for many types of life data, for example, semiconductor life, electrical insulation life, crack propagation, and metal fatigue (Ireson *et al*., 1996).

Jia *et al.* (1993) studied the fatigue design of machine tools by considering probabilistic reliability. In their model, machine tool fatigue lives are assumed to be lognormally distributed. They proposed a theoretical formula to calculate the equivalent fatigue load for reliability.

Because it is essential to collect and analyze field failure data for the purpose of assessing and improving the reliability of computerized numerical control (CNC) lathes, Wang *et al*. (1999) studied field failure data collection and collation. They analyzed the data by applying a lognormal distribution to calculate the time between successive failures (TBF) and by using the Kolmogorov-Smirnov test to verify the goodness of the fit of the data to a lognormal distribution.

Enginarlar *et al*. (2005) analyzed lean buffering in serial production lines with machine up-and-down time. Based on the consideration of Weibull, gamma, and lognormal distributions, they provided a method to select and study the lean level of buffering (LLB). They found that LLB mainly depended on the coefficients of the variation in machine up-and-down time distribution, and was sensitive to CV_{down} rather than CV_{up}.

It is pointed out by Mullen (1998) that the distribution of an event rate is lognormal because of the multiplicative processes in software systems; a lognormal distribution fits the empirical failure rates well. He proposed a model to analyze two series of failure data and the likelihood of data arising from lognormal based model and Log-Poisson based model. The results demonstrated that the lognormal based model fits a wide variety of reliability growth patterns.

Gokhale and Mullen (2008) gave an overview of the lognormal distribution. They discussed the emerging applications for lognormal distributions and summarized the evidence to confirm that it can be successfully applied to analyze problems in software reliability engineering.

CHAPTER 4

MATHEMATICAL MODEL

The following details are to describe the multi-objective model for cellular manufacturing systems.

4.1 Notations

Indices:

$k \in \{1, 2, .., K\}$	Cells
$j \in \{1, 2, .., J\}$	Machine types
$i \in \{1, 2, .., n\}$	Part types
$p \in \{1, 2, .., P(i)\}$	Process plans for part type *i*
(ip)	A combination of part type and process plan
$o \in \{1, 2, .., O(ip)\}$	Operations of *(ip)*
$J_{ipo} \in \{1, 2, .., J\}$	Set of machine types that can perform operation *o* of *(ip)*

Parameters:

A_j	Availability of machine type *j*

AN_j	Annuity cost of machine type *j*
b_j	Available capacity of machines type *j* cluster
$C_{oj}(ip)$	Operation and refixturing cost corresponding to operation *o* of *(ip)* on machine *j*
cp_j	Penalty cost of non- utilization of machine type *j*
d_i	Demand of part type *i*
$H_{ijk\hat{j}\hat{k}}$	Inter-cell transportation cost of moving part type *i* from machine *j* in cell *k* to machine $\hat{j}$ in cell $\hat{k}$ to perform the next operation
N	Number of years to recover the machine purchase cost
P_j	Present cost of machine type *j*
q	Interest rate per year
$r_j(t)$	Reliability of machine type *j* at time *t*
$R_j(t)$	Reliability of machine type *j* cluster at time *t*
s_j	Shape parameter of log normal distribution for machine type *j*
t_{medj}	Median time to failure of machine type *j*
$TF_{oj}(ip)$	Time to refixture for operation *o* of *(ip)* on machines type *j*
$TO_{oj}(ip)$	Time to perform operation *o* of *(ip)* on machines type *j*

UM Maximum number of machines in a cell

Decision Variables:

m_j Number of units of machine type *j* in the cluster

M_{jk} =1 if machine type *j* cluster is assigned to cell *k*,

=0 otherwise

$X_{ojk}(ip)$ =1 if operation *o* of *(ip)* is assigned to machine type *j* cluster in cell *k*,

=0 otherwise

$Z(ip)$ =1 if part type *i* is processed under process plan *p*,

=0 otherwise

4.2 Objective Functions

We assume that there is a set of machines types $j \in \{1, 2, .., J\}$ to process a set of part types $i \in \{1, 2, .., n\}$ with corresponding demands d_i during the planning time. A part type may be processed under any of the process plans $p \in \{1, 2, .., P(i)\}$. A combination of part type and process plan is expressed as (*ip*), and $o \in \{1, 2, .., O(ip)\}$ is the set of operations performed to process the (*ip*) combination. The machines that can perform operation *o* of (*ip*) is represented by the set $J_{ipo} \in \{1, 2, .., J\}$.

There are two objective functions in this model. The first objective function, defined as objective function 1, calculates the overall system reliability through all part-type process-plan routes:

$$\text{Maximize objective function 1} = \prod_{i=1}^{n}\prod_{p=1}^{P(i)} R_{ip} \tag{4-1}$$

$$\text{where } R_{ip} = \prod_{o=1}^{O(ip)} \sum_{j \in J_{ipo}} R_j(t) \sum_{k=1}^{K} X_{ojk}(ip) \qquad \forall i, p \tag{4-2}$$

Equation (4-2) generates a composite expression by adding up the machine reliability along all the feasible process routes for each (*ip*) combination. During the optimization process, the operation allocation variable $X_{ojk}(ip)$ is compelled to assign only one machine to each operation of the (*ip*) in order to comply with constraints (4-9) and (4-10), which are noted in Section 4.3. Consequently, for each (*ip*) combination, the solution will include the reliabilities of the machines for only one selected process route.

The first objective function is searched to select the appropriate sets of part-type process-plan routes and machine types with its numbers to maximize the entire reliability of the system.

The second objective function, defined as objective function 2, computes the total system cost, which consists of the variable cost of manufacturing operations (*VCM*), the inter-cell material handling cost (*MHC*), the penalty cost of machine under-utilization (*MNC*) and machine annuity cost (*MAC*).

$$\text{Minimize objective function 2} = VCM + MHC + MNC + MAC \tag{4-3}$$

The various components of this objective function are computed as follows.

The variable cost of manufacturing operations *VCM* computes the operation and refixturing costs $C_{oj}(ip)$:

$$VCM = \sum_{i=1}^{n} d_i \sum_{p=1}^{P(i)} \sum_{o=1}^{O(ip)} \sum_{j \in J_{ipo}} C_{oj}(ip) \sum_{k=1}^{K} X_{ojk}(ip) \tag{4-4}$$

$X_{ojk}(ip)$ is a binary variable which is equal to 1 when operation o of (*ip*) is performed on a machine of type *j* in cell *k*, and zero otherwise. d_i is the demand of part type *i*.

The inter-cell material handling cost *MHC* computes the total inter-cell transportation cost of the parts as they move from machine *j* in cell *k* to machine $\hat{j}$ in cell $\hat{k}$ to perform the next operations (*o*+1):

$$MHC = \sum_{i=1}^{n} d_i \sum_{p=1}^{P(i)} \sum_{o=1}^{O(ip)-1} \sum_{j \in J_{ipo}} \sum_{\hat{j} \in J_{ip(o+1)}} \sum_{1 \le k, \hat{k} \le K} H_{ijk\hat{j}\hat{k}} X_{ojk}(ip) X_{(o+1)\hat{j}\hat{k}}(ip) \tag{4-5}$$

$H_{ijk\hat{j}\hat{k}}$ is the cost of moving a unit of part type *i* from machine *j* in cell *k* to machine $\hat{j}$ in cell $\hat{k}$ to perform the next operations (*o*+1).

The penalty cost of machine under-utilization *MNC* computes a penalty on the portion of a machine's capacity that is not utilized:

$$MNC = \sum_{j=1}^{J} cp_j \left[1 - \sum_{i=1}^{n} d_i \sum_{p=1}^{P(i)} \sum_{o=1}^{O(ip)} \frac{TO_{oj}(ip) + TF_{oj}(ip)}{[1-(1-A_j)^{m_j}] \cdot b_j} \sum_{k=1}^{K} X_{ojk}(ip) \right] \tag{4-6}$$

where cp_j is the penalty cost of non- utilization of machine type *j*. $TO_{oj}(ip)$ is the Time to perform operation *o* of *(ip)* on machines type *j* and $TF_{oj}(ip)$ is the time to refixture for operation *o* of *(ip)* on machines type *j*. A_j is the availability of machines type *j*, and b_j is the available capacity of machine type *j*. The expression $[1-(1-A_j)^{m_j}]\cdot b_j$ is the effective capacity of machine type *j* cluster.

Finally, the machine annuity cost *MAC* computes the annualized cost of recovering the machine purchase cost:

$$MAC = \sum_{j=1}^{J} AN_j m_j \tag{4-7}$$

where $AN_j = P_j \dfrac{q(1+q)^N}{(1+q)^N - 1}$ (4-8)

AN_j is the annuity cost of machine type *j*, m_j is the number of machines of type *j*, P_j is the present cost of machine type *j*, *q* is the interest rate, and N is the number of years to recover the machine purchase cost.

The second objective function is searched to select the appropriate sets of part-type process-plan routes and machine types with its numbers to minimize the overall cost of the system.

4.3 Constraints

$$\sum_{p=1}^{P(i)} Z(ip) = 1 \qquad \forall i \tag{4-9}$$

This constraint ensures that a part type *i* is processed under a single process plan. $Z(ip)$ equals to 1 if part type *i* is processed under process plan *p*, and zero otherwise.

$$\sum_{j \in J_{ipo}} \sum_{k=1}^{K} X_{ojk}(ip) = Z(ip) \qquad \forall i, p, o \tag{4-10}$$

This constraint establishes a correspondence between the selections of a process plan for a part type *i*, and assigns the operations of that part to machines in cells where they have been allocated.

$$\sum_{k=1}^{K} M_{jk} = 1 \qquad \forall j \tag{4-11}$$

This constraint ensures that machine type *j* is allocated to cell *k*. It is pointed out that 'machine type *j*' infers a machine cluster which consists of m_j units in parallel. M_{jk} equals to 1 if machine type *j* cluster is assigned to cell *k*, and zero otherwise.

$$\sum_{j=1}^{J} M_{jk} \le UM \qquad \forall k \tag{4-12}$$

The above constraint limits the total number of machines of each type in a cell.

$$\sum_{i=1}^{n} \sum_{p=1}^{P(i)} \sum_{o=1}^{O(ip)} X_{ojk}(ip) \ge M_{jk} \qquad \forall j, k \tag{4-13}$$

This constraint ensures that, before assigning operations to a machine type *j*, it has to be placed in a cell *k*.

$$\sum_{i=1}^{n} d_i \sum_{p=1}^{P(i)} \sum_{o=1}^{O(ip)} [TO_{oj}(ip) + TF_{oj}(ip)] X_{ojk}(ip) \le b_j M_{jk} [1 - (1 - A_j)^{m_j}] \qquad \forall j, k \tag{4-14}$$

This constraint ensures that the capacity of a machine cluster is not exceeded while allocating operations to it.

$X_{ojk}(ip), Z(ip), M_{jk}$ are binary variables $\qquad \forall i, p, o, j, k$

Finally, this constraint identifies the variables as 0-1 integer.

4.4 Model Summary

$$\text{Maximize objective function 1} = \prod_{i=1}^{n}\prod_{p=1}^{P(i)} R_{ip} \tag{4-1}$$

where $R_{ip} = \prod_{o=1}^{O(ip)} \sum_{j \in J_{ipo}} R_j(t) \sum_{k=1}^{K} X_{ojk}(ip) \quad \forall i, p$. (4-2)

$$\text{Minimize objective function 2} = VCM + MHC + MNC + MAC \tag{4-3}$$

where

$$VCM = \sum_{i=1}^{n} d_i \sum_{p=1}^{P(i)} \sum_{o=1}^{O(ip)} \sum_{j \in J_{ipo}} C_{oj}(ip) \sum_{k=1}^{K} X_{ojk}(ip) \tag{4-4}$$

$$MHC = \sum_{i=1}^{n} d_i \sum_{p=1}^{P(i)} \sum_{o=1}^{O(ip)-1} \sum_{j \in J_{ipo}} \sum_{\hat{j} \in J_{ip(o+1)}} \sum_{1 \le k, \hat{k} \le K} H_{ijk\hat{j}\hat{k}} X_{ojk}(ip) X_{(o+1)\hat{j}\hat{k}}(ip) \tag{4-5}$$

$$MNC = \sum_{j=1}^{J} cp_j \left[1 - \sum_{i=1}^{n} d_i \sum_{p=1}^{P(i)} \sum_{o=1}^{O(ip)} \frac{TO_{oj}(ip) + TF_{oj}(ip)}{[1-(1-A_j)^{m_j}] \cdot b_j} \sum_{k=1}^{K} X_{ojk}(ip) \right] \tag{4-6}$$

$$MAC = \sum_{j=1}^{J} AN_j m_j \tag{4-7}$$

where $AN_j = P_j \dfrac{q(1+q)^N}{(1+q)^N - 1}$ (4-8)

Subject to constrains as follows:

$$\sum_{p=1}^{P(i)} Z(ip) = 1 \qquad \forall i \tag{6-9}$$

$$\sum_{j \in J_{ipo}} \sum_{k=1}^{K} X_{ojk}(ip) = Z(ip) \qquad \forall i, p, o \tag{6-10}$$

$$\sum_{k=1}^{K} M_{jk} = 1 \qquad \forall j \tag{4-11}$$

$$\sum_{j=1}^{J} M_{jk} \leq UM \qquad \forall k \tag{4-12}$$

$$\sum_{i=1}^{n} \sum_{p=1}^{P(i)} \sum_{o=1}^{O(ip)} X_{ojk}(ip) \geq M_{jk} \qquad \forall j, k \tag{4-13}$$

$$\sum_{i=1}^{n} d_i \sum_{p=1}^{P(i)} \sum_{o=1}^{O(ip)} [TO_{oj}(ip) + TF_{oj}(ip)] X_{ojk}(ip) \leq b_j M_{jk} [1 - (1 - A_j)^{m_j}] \qquad \forall j, k \tag{4-14}$$

$X_{ojk}(ip), Z(ip), M_{jk}$ are binary variables $\qquad \forall i, p, o, j, k$

CHAPTER 5

A HEURISTIC SOLUTION METHOD BASES ON GENETIC ALGORITHM

The idea of a genetic algorithm (GA) emanates from the biological theory of evolution which was proposed by Charles Darwin in the middle of 1800s. Being a stochastic global search method, GA begins with a population of random trial solutions. In each generation, it evaluates the “fitness” of each chromosome as a candidate solution, select better chromosomes to randomly modify and combine, generates new chromosomes, and then proceeds to next iteration. In this thesis, the “fitness” is measured by the objective functions (4-1) and (4-3). In addition, occasional mutation is used to help the genetic algorithm explore perhaps better chromosomes than previously explored. Lastly, iteration is terminated when the stopping criterion is satisfied, e.g., a given number of iterations or a given tolerance is reached. Then the chromosome with the fittest value is closest to the optimal solution.

Given the example presented in Table 3.1, a chromosome sample is represented by 14 genes. Genes 1 to 5 represent the optimal numbers of machines of each type. Genes 6 to 10 denote the cell number, to which the machine group of a given type is allocated. The Genes 11 to 14 represent the process routes assigned to part types. Consider the example, S=(2 1 2 2 2) (1 2 2 1 2) (1201 2201 3102 4101). It identifies that 2 machines of type 1, one machine of type 2, and 2 machines of type 3, 4 and 5, respectively, are chosen; two machines of type 1 and two machines of type 4 are allocated to cell 1, while machines of type 2, type 3 and type 5 are allocated to cell 2;

part type 1 is processed in process route 01 under process plan 2, part type 2 is processed in process route 01 under process plan 2, and so on.

The first step of genetic algorithm is to generate a set of chromosomes randomly. Then GA evaluates these chromosomes by a fitness function. In this thesis, evaluation is performed by ranking the chromosomes in terms of their values of the objective function. After evaluation, the chromosomes with a higher ranking are selected to perform the crossover and mutation operations. The new chromosomes generated by the crossover operation inherit the 'excellent' features of the old chromosomes; the mutation operation induces a new chromosome with new features that are not inherited from the old chromosomes.

To illustrate how crossover and mutation work, we consider an example with two chromosomes (initial solutions).

(**1 2 1 2 2**):(**1 2 2 1 2**):(**1201,2201,3101,**:**4201**)

(2 2 1 1 2):(2 1 2 2 1):(1101,2102,3202,:4101)

The interchange between the two chromosomes occurs around the crossover point and generates a new chromosome with potentially better solutions.

(2 2 1 1 2):(**1 2 2 1 2**):(1101,2102,3202,:**4201**)

(**1 2 1 2 2**):(2 1 2 2 1):(**1201,2201,3101,**:4101)

On the other hand, mutation changes one or more genes in one chromosome to result in a new chromosome.

(1 2 1 2 2):(**1 2 2 1 2**):(1201,**2201**,3101,:4201)   (before mutation)

(1 2 1 2 2):(**1 2 1 1 1**):(1201,**2102**,3101,:4201)   (after mutation)

In this case, the crossover point and mutation point are chosen randomly. After a series of extensive experiments by setting different probability values, it was found that the genetic algorithm corresponding to this model converges well when the probability of crossover and the probability of mutation are set at 0.9 and 0.01, respectively.

After crossover and mutation, a new population is generated. Again, the newly-born chromosomes are evaluated and ranked by fitness function, and selected to be the candidate chromosomes for processing crossover and mutation to generate the next, new population. In each iteration, the process of candidate chromosomes follows the steps: evaluation, selection, crossover and mutation. Iterations continue until a heuristic optimal solution is reached based on the defined stopping criterion. In this case, the stopping criterion is a given number of iterations.

CHAPTER 6

A NUMERICAL EXAMPLE

A numerical example with 14 machine types is employed to show how the model works. There are 2 units of each machine type available to be allocated to 3 cells. There are 24 part types, each having more than one operation that may be performed on 2 or 3 alternative machines. For example, as Table 6.1 indicates, part type 1 can be processed under either process plan 1 or process plan 2. Process plan 1 will perform 3 operations, while process plan 2 will perform 2 operations. In process plan 1, operation 1 can be performed by machine type 4, operation 2 can be performed by machine type 1 or type 5, and operation 3 can be performed by machine type 7. Thus, the machine sequence for part type 1 through process plan 1 is M4-M1-M7 or M4-M5-M7. Similarly, it is evident that each part type has several process routes to execute the corresponding operations. The number of cells is 3 and the maximum number of machine types in each cell is assumed to be 5.

For each machine type, the *MTTF* and *MTTR* is generated randomly following the uniform distributions U(160,360) and U(8,48), respectively, to satisfy the requirement that the machine availability may fluctuate between 80% and 95% (Askin *et al.*, 1997). The parameter T_{med} must be selected to be less than *MTTF* due to the definite positive characteristics of the lognormal distribution.

Transportation cost among the machines within a cell is assumed to be \$1 per unit. Inter-cell transportation cost is assumed to be \$3 per unit. The planning period T is 75 hours. It is expected that the machine costs will be recovered in three years at an interest rate of 10% per year.

Table 6.1 indicates part demands, processing times and costs of operations for the given parts performed by given machines, and the alternative process routes for the numerical example with 14 machine types and 24 parts.

Information regarding the parameters of each machine type is shown in Table 6.2, including *MTTF, MTTR*, T_{med}, penalty costs for machine non-utilization, machine capacities, and present costs.

The input data in both Table 6.1 and Table 6.2 are the same as the data used by Das *et al.* (2006). Due to the following two reasons, however, the results in this thesis cannot be compared to Das's results. First, the results obtained in this thesis are based on the lognormal distribution, whereas in Das *et al.* (2006), the Weibull distribution is used to represent machine reliability. Second, the model developed in this thesis is nonlinear; that is, the objective function includes a non-linear term, and one constraint (Equation 4-14) is also non-linear. The model in Das *et al.* (2006) is a linear integer model.

Table 6.1 Demand, operation time, cost and process routes for part types

Part Type	Demand	Data	Process Plan 1				Process Plan 2		
			Operation 1	Operation 2	Operation 3	Operation 4	Operation 1	Operation 2	Operation 3
1	20	Machine	M4	M1 M5	M7		M1	M7 M13	
		Time (hrs)	5	6 8	4		3	6 5	
		Cost ($)	9	7 7	8		8	4 6	
2	10	Machine	M4 M5	M6 M7			M1 M4	M5	M12 M13
		Time (hrs)	7 8	6 7			9 7	4	8 6
		Cost ($)	8 7	8 9			8 9	8	5 9
3	30	Machine	M2	M3	M10		M2 M3 M3	M11 M13	
		Time (hrs)	8	3	6		6 7 10	9 7	
		Cost ($)	6	4	8		2 3 9	8 7	
4	40	Machine	M2	M3 M5	M11 M13		M2	M10 M12	M5 M11
		Time (hrs)	9	5 6	11 9		6	7 6	7 8
		Cost ($)	5	4 7	7 4		8	4 4	9 4
5	10	Machine	M8	M9	M11		M6 M12	M9 M11	M14
		Time (hrs)	4	7	5		8 9	5 4	7
		Cost ($)	9	7	7		6 12	9 9	6
6	50	Machine	M1	M13			M4 M7	M5 M9	M12
		Time (hrs)	6	6			7 8	5 6	7
		Cost ($)	5	5			5 4	8 7	4
7	20	Machine	M3	M7	M10 M12	M13	M3 M4	M5	M11 M12
		Time (hrs)	3	6	7 5	5	7 6	8	9 8
		Cost ($)	6	6	6 4	5	9 6	7	9 6
8	30	Machine	M12	M13			M4 M5	M7 M8	
		Time (hrs)	5	7			9 10	4 4	
		Cost ($)	6	8			7 8	6 4	

Table 6.1 Cont'd

Part Type	Demand	Data	Process Plan 1				Process Plan 2		
			Operation 1	Operation 2	Operation 3	Operation 4	Operation 1	Operation 2	Operation 3
9	40	Machine	M6 M8	M8	M9 M11	M13 M14	M2	M8 M11	M14
		Time (hrs)	5 7	4	8 6	6 5	5	5 4	7
		Cost ($)	5 5	6	6 7	8 8	5	9 6	6
10	10	Machine	M6 M10	M9 M9			M9	M12	M14
		Time (hrs)	4 5	7 6			9	7	6
		Cost ($)	5 7	6 7			7	6	6
11	20	Machine	M6 M9	M12	M12 M14		M7 M9	M10 M14	
		Time (hrs)	5 6	6	6 4		5 6	7 6	
		Cost ($)	6 7	8	7 6		7 5	6 7	
12	10	Machine	M6	M8 M12	M9 M14		M8 M12	M10 M14	
		Time (hrs)	6	7 5	5 6		8 4	7 6	
		Cost ($)	6	9 9	5 4		6 8	4 6	
13	10	Machine	M9 M12	M13 M14			M6 M10	M8 M13	
		Time (hrs)	9 7	7 8			7 8	6 5	
		Cost ($)	5 5	9 7			9 4	9 8	
14	50	Machine	M6 M8	M9 M13			M9 M12	M13 M14	
		Time (hrs)	6 5	8 9			6 7	6 5	
		Cost ($)	8 5	5 4			6 8	7 5	
15	30	Machine	M6 M10	M8	M9 M13		M1 M3 M14	M8 M10	M14
		Time (hrs)	5 6	9	4 3		9 7 4	8 7	6
		Cost ($)	6 4	7	8 7		7 4 8	6 8	5
16	50	Machine	M6 M9	M8 M13			M9 M12	M5 M14	
		Time (hrs)	8 6	7 8			6 5	6 7	
		Cost ($)	4 9	7 4			9 8	4 8	

Table 6.1 Cont'd

Part Type	Demand	Data	Process Plan 1								Process Plan 2					
			Operation 1		Operation 2		Operation 3		Operation 4		Operation 1		Operation 2		Operation 3	
17	20	Machine	M1	M4	M5	M8	M7	M13			M1		M10	M12	M13	M14
		Time (hrs)	6	4	5	4	5	6			3		6	7	8	9
		Cost ($)	9	4	4	5	3	8			8		7	9	7	9
18	30	Machine	M4	M13	M12	M14					M1	M13	M6	M10		
		Time (hrs)	4	8	6	5					5	7	4	6		
		Cost ($)	9	7	6	6					5	8	6	7		
19	40	Machine	M4	M7							M1	M13	M5	M9		
		Time (hrs)	7	6							9	8	6	7		
		Cost ($)	4	7							7	5	7	7		
20	10	Machine	M4	M7	M5	M9	M7				M1	M4	M12	M14	M9	M13
		Time (hrs)	6	5	3	4	3				5	6	5	6	3	4
		Cost ($)	3	5	4	5	3				6	8	7	6	3	5
21	20	Machine	M3	M7	M11	M14					M2	M6	M10	M12		
		Time (hrs)	7	6	8	7					7	6	7	5		
		Cost ($)	7	5	5	7					7	7	8	6		
22	30	Machine	M6	M10	M8	M13					M9	M13	M5	M14		
		Time (hrs)	6	5	6	7					6	7	6	8		
		Cost ($)	3	7	9	4					7	7	7	8		
23	50	Machine	M4	M13	M5		M11	M13			M1		M6	M9	M11	M13
		Time (hrs)	7	7	5		8	9			8		4	5	6	7
		Cost ($)	9	9	5		5	6			8		5	7	5	6
24	10	Machine	M10	M13	M11	M12					M2	M10	M3	M13		
		Time (hrs)	5	6	7	8					7	8	5	6		
		Cost ($)	8	5	5	7					5	7	4	6		

Table 6.2 Machine data for numerical example

Machine Type	MTTF (hrs)	MTTR (hrs)	T_{med} (hrs)	Capacity (hrs)	Penalty Cost for non-utilization ($)	Present Cost ($)
1	282	35	234	1000	425	8500
2	288	24	226	1000	470	7500
3	190	37	177	700	408	6000
4	198	24	185	1000	319	9600
5	241	18	203	700	375	5500
6	207	10	191	2000	490	4900
7	312	30	270	700	485	5700
8	311	35	259	1800	430	8300
9	175	15	163	1000	472	8000
10	200	27	179	1000	336	8900
11	191	20	170	1000	419	7400
12	168	30	155	1000	470	4500
13	346	40	280	2000	452	6600
14	217	40	189	1000	444	7800

CHAPTER 7

RESULTS

The algorithm is coded in MATLAB 7.1 and run on a PC (1.6GHZ, 1 GB of RAM) to solve the numerical example with 14 machine types, 3 cells and 24 part types. The heuristic optimal solutions provide the best options for the number of units of each machine type, the machine-cell assignments and the selected process routes.

The solutions are obtained using the genetic algorithm which optimizes the following composite objective function:

$$\text{Max ObjV=W1*Obj1-W2*Obj2} \tag{7-1}$$

subject to the constraints described in section 6. Obj1 represents objective function 1 (system reliability as considered in equation(4-2)), and Obj2 represents objective function 2 (the total cost as considered in equation(4-3)). W1 and W2 are the weights assigned to objective functions 1 and 2, respectively. The weights are specifically chosen so as to reflect the relative importance of Obj1 and Obj2 in the composite objective ObjV. The model is solved using various combinations of W1 and W2.

The model is first used to solve two extreme cases: (W1:W2)=(1:0) and (W1:W2)=(0:1). In the case of (W1:W2)=(1:0), only the reliability function (Obj1) is maximized, regardless of the cost, to obtain the highest reliability associated with the heuristic solution; that is, an upper bound is determined on the reliability function. In contrast, in the case of (W1:W2)=(0:1), only the total cost function (Obj2) is minimized, regardless of the reliability, to obtain the lowest total cost achievable, i.e., a lower bound on the total cost function is determined. Next, gradually increasing weights are assigned to the reliability function, ranging from W1=100 to W1=1,000,000, (while keeping W2 =1), representing a total of 16 test cases. The model is solved in each case, and the results are summarized in Tables 7.1-7.4.

Table 7.1 summarizes the objective function values for the 16 test cases, and Table 7.2 lists the corresponding cell assignments. The first case corresponds to (W1:W2) =(1:0). Here, the algorithm starts with 10 randomly selected chromosomes as a set of initial solutions, which results in the highest reliability function value of only 0.5432, and the corresponding chromosome:

(2 2 1 1 1 1 2 2 2 2 2 2 1 2) (1 3 1 1 2 2 2 3 2 3 3 1 3 1) (1201 2202 3205 4202 5202 6204 7201 8204 9103 10201 11102 12101 13202 14101 15206 16203 17105 18201 19201 20203 21102 22103 23103 24103)

The chromosome consists of three parts. The first part has 14 genes, each representing the number of units of each machine type. The second part has 14 genes which show the assignment of machines to cells. The last part has 24 genes denoting the process route for each part type.

After 1000 iterations, the genetic algorithm reached the following heuristic solution:

(2 2 2 2 1 2 2 2 2 2 2 1 2 2) (3 3 2 2 1 1 1 3 2 3 3 1 1 2) (1201 2102 3204 4102 5201 6101 7101 8201 9101 10102 11201 12101 13201 14101 15101 16101 17107 18204 19101 20102 21203 22101 23202 24203)

with a composite objective function (ObjV) value of 0.9760, which is derived from

ObjV= W1*Obj1 - W2*Obj2

=1*0.9760 - 0*90,060

=0.9760.

Table 7.1 Performance summary

Test Case	W1	W2	Obj1	Obj2	ObjV	CPU Time (seconds)
1	1	0	0.9760	90,060	0.9760	67.953
2	0	1	0.1953	51,024	-51,024	59.547
3	100	1	0.2021	51,139	-51,118	58.844
4	1,000	1	0.2053	51,222	-51,017	54.750
5	10,000	1	0.2941	51,720	-48,779	58.609
6	25,000	1	0.3015	51,667	-44,130	62.719
7	50,000	1	0.8180	65,919	-25,017	59.516
8	75,000	1	0.9401	78,190	-7,683.5	60.297
9	100,000	1	0.9466	81,907	12,755	58.406
10	250,000	1	0.9685	83,939	158,190	58.719
11	500,000	1	0.9745	84,387	402,840	51.750
12	600,000	1	0.9746	86,308	498,470	62.813
13	700,000	1	0.9759	86,519	596,630	61.609
14	800,000	1	0.9759	86,360	694,380	53.422
15	900,000	1	0.9759	86,192	792,140	66.938
16	1,000,000	1	0.9759	85,811	890,080	55.373

Table 7.2 Machines assignments to cells

Test Case	Cell1	Cell2	Cell3
1	M5+2 M6+2 M7+M12+2 M13	2 M3+2 M4+2 M9+2 M14	2 M1+2 M2+2 M8+2 M10+2 M11
2	M1+M6+M7+M8+M13	M2+M9+M11+M12+M14	M3+M4+M5+M10
3	M4+M5+M7+M12+M13	M3+M9+M10+M14	M1+M2+M6+M8+M11
4	M1+M2+M3+M5+M11	M4+M6+M8+M12	M7+M9+M10+M13+M14
5	M1+M2+M3+M6+M13	M4+M5+M8+M9+M12	M7+M10+M11+M14
6	M1+M2+M6+M7+M11	M4+M5+M12+M14	M3+M8+M9+M10+M13
7	M1+M4+M10+M11	2 M2+2 M5+2 M12+2 M13+2 M14	M3+M6+M7+M8+M9
8	2 M2+M8+2 M10+M11+2 M12	2 M1+M3+M4+M6	2 M5+2 M7+2 M9+2 M13+2 M14
9	M6+2 M7+2 M9+M11+2 M13	2 M1+2 M2+2 M5+2 M12	M3+M4+2 M8+2 M10+2 M14
10	M4+2 M5+2 M8+2 M9+M11	2 M1+2 M2+2 M3+2 M6+2 M13	2 M7+2 M10+M12+2 M14
11	2 M1+M5+2 M7+M10	2 M2+2 M3+2 M6+2 M8+2 M13	2 M4+2 M9+M11+2 M12+2 M14
12	2 M1+2 M2+2 M7+2 M14	2 M3+2 M4+M5+2 M9	2 M6+2 M8+2 M10+M12+2 M13
13	2 M1+2 M8+2 M9+2 M4	2 M2+M5+2 M6+M11+M12	2 M3+2 M4+2 M7+ 2M10+2 M3
14	2 M2+2 M3+2 M4+M5+M11	2 M6+2 M7+2 M8+2 M10+M12	2 M1+2 M9+2 M3+2 M4
15	2 M3+2 M10+M12+2 M13	2 M4+2 M6+2 M8+2 M9+M11	2 M1+2 M2+2 M5+2 M7+2 M14
16	2 M1+2 M4+2 M7+2 M10+M12	2 M2+ 2M3+2 M11+2 M14	2 M5+2 M6+2 M8+2 M9+2 M13

This value indicates that the reliability function has improved from 0.5432 to 0.9760.

The cell assignments in this case are shown in Table 7.2, and are as follows:

Cell 1: M5, 2 of M6, 2 of M7, M12, 2 of M13

Cell 2: 2 of M3, 2 of M4, 2 of M9, 2 of M14

Cell 3: 2 of M1, 2 of M2, 2 of M8, 2 of M10, 2 of M11

In the second test case, when only the total cost function is considered, i.e., when W1:W2 =0:1, the heuristic solution is:

(1 1 1 1 1 1 1 1 1 1 1 1 1 1) (1 2 3 3 3 1 1 1 2 3 2 2 1 2) (1201 2104 3201 4102 5204 6101 7202 8204 9202 10101 11204 12202 13102 14104 15204 16102 17105 18201 19101 20101 21103 22202 23201 24201)

with a composite objective function (ObjV) value of -51,024, which is derived from

ObjV=W1*Objective function 1+W2* objective function 2

=W1*Obj1-W2*Obj2

=0*(0.9760) - 1*(-51,024)

= -51,024.

Because the emphasis in this case is on minimizing the total cost regardless of the reliability, the model assigns only one unit of each machine type to the cells, as shown in the following cell assignment (table 7.2):

Cell 1: M1, M6, M7, M8, M13

Cell 2: M2, M9, M11, M12, M14

Cell 3: M3, M4, M5, M10

It may be of interest to note that system reliability in this case is only 0.1953. The first two cases, therefore, establish an upper bound on reliability of 0.9765, and a lower bound on the total cost of 51,024.

In a similar manner, the other test cases corresponding to various weight combinations (W1 and W2) are evaluated as shown in Tables 7.1 and 7.2. The optimization process in essence generates a set of Pareto ‘optimal’ solutions, striking a balance between the two objectives depending on the importance attached to each; as the weight assigned to the reliability objective (Obj1) increases, the model attempts to generate solutions with higher system reliabilities, which is possible by increasing the number of parallel machines in each cluster, thus increasing the total costs.

In test cases 3 to 13, the weight of objective function 2 remains as 1 (W2=1), but the weight of objective function 1 gradually varies from 100 to 700,000. As a result, the objective function 1 value is increased from 0.2021 to 0.9759, whereas, the importance of the total cost (objective function 2) diminishes correspondingly; the value of objective function 2 increases from 51,139 to 86,519.

In test cases 14 to 16, as the weight of objective function 1 increases to 1,000,000, the value of the objective function 1 remains unchanged at 0.9759, the upper bound on system reliability. On the other hand, the performance of the total cost function improves; the value of objective function 2 decreases from 86,360 to 85,811.

The performance values of the reliability function (Obj1) and the total cost function (Obj2) are illustrated in Figures 7.1 and 7.2, respectively. It is observed that the reliability function (Obj1) improves dramatically when the weights (W1:W2) change from (100:1) to (75,000:1), improves very slowly up to (W1:W2) = (75,000:1), and

Figure 7.1 System reliability corresponding to test cases 2-16

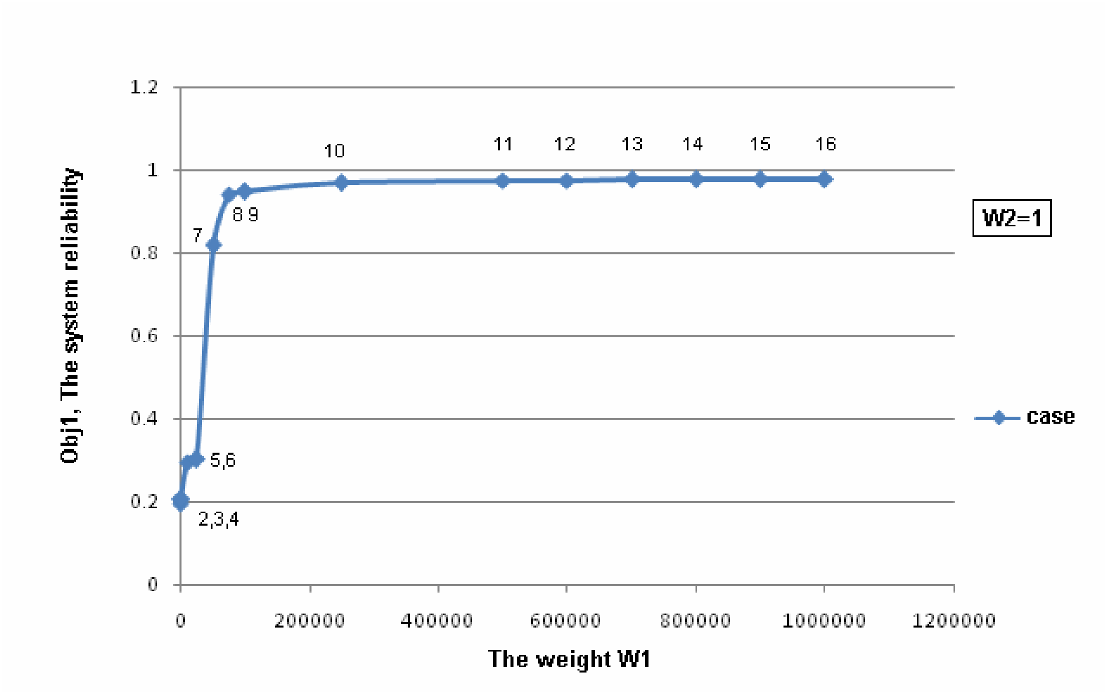
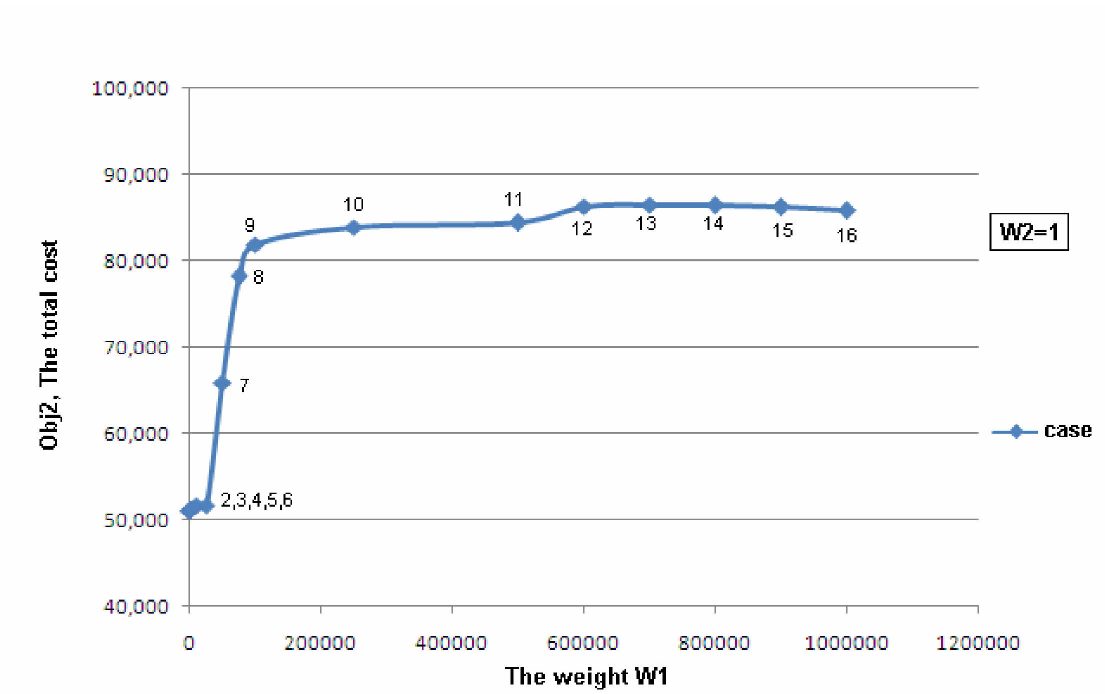


Figure 7.2 Total cost corresponding to test cases 2-16



remains relatively stable beyond that point. Similarly, when the weights (W1:W2) change from (25,000:1) to (75,000:1), the total cost function increases significantly. At (W1:W2) =(700,000:1), it reaches its highest value, and thereafter, it slightly decreases. The selection of the ‘best’ solution is left to the decision-maker (i.e., producers) to strike a balance between reliability and costs.

Table 7.3 displays the process routes selected for each part type in each test case. Thus, in test case 1, part type 1 is processed using process route 1201, which prescribes that operation 1 will be performed on machine M1, and operation 2 on machine M7. The other entries in the table are interpreted in a similar fashion.

Finally, Table 7.4 displays the ‘optimal’ number of the units of each machine type in each case. We can see from Tables 7.3 and 7.4 that, for cases 13-16, the number of the units of each machine type as well as the process routes for each part type in each case remain the same, indicating that the genetic algorithm converges to a heuristic solution which is fairly stable in terms of the system reliability.

Table 7.3 Process routes for each part type

Part Type	Case 1		Case 2		Case 3		Case 4	
	Process Route	Machine Sequence	Process Route	Machine Sequence	Process Route	Machine Sequence	Process Route	Machine Sequence
1	1201	M1-M7	1201	M1-M7	1201	M1-M7	1201	M1-M7
2	2102	M4-M7	2104	M5-M7	2104	M5-M7	2104	M5-M7
3	3204	M3-M13	3201	M2-M11	3201	M2-M11	3201	M2-M11
4	4102	M2-M3-M13	4102	M2-M3-M13	4102	M2-M3-M13	4101	M2-M3-M11
5	5201	M6-M9-M14	5204	M12-M11-M14	5203	M12-M9-M14	5203	M12-M9-M14
6	6101	M1-M13	6101	M1-M13	6101	M1-M13	6101	M1-M13
7	7101	M1-M7-M10-M13	7202	M3-M5-M12	7204	M4-M5-M12	7201	M3-M5-M11
8	8201	M4-M7	8204	M5-M8	8201	M4-M7	8202	M4-M8
9	9101	M6-M8-M9-M13	9202	M2-M12-M14	9202	M2-M12-M14	9202	M2-M12-M14
10	10102	M6-M9	10101	M6-M8	10101	M6-M8	10101	M6-M8
11	11201	M7-M10	11204	M9-M14	11203	M9-M10	11203	M9-M10
12	12101	M6-M8-M9	12202	M6-M12-M14	12102	M6-M8-M14	12201	M6-M12-M9
13	13201	M6-M8	13102	M9-M14	13102	M9-M14	13102	M9-M14
14	14101	M6-M8	14104	M8-M13	14202	M9-M14	14202	M9-M14
15	15101	M6-M8-M9	15204	M3-M10-M14	15204	M3-M10-M14	15204	M3-M10-M14
16	16101	M6-M8	16102	M6-M13	16203	M12-M5	16102	M6-M13
17	17107	M4-M8-M7	17105	M4-M5-M7	17105	M4-M5-M7	17105	M4-M5-M7
18	18204	M13-M9	18201	M1-M5	18201	M1-M5	18201	M1-M5
19	19101	M4	19101	M4	19101	M4	19101	M4
20	20102	M4-M9-M7	20101	M4-M5-M7	20103	M7-M5-M7	20104	M7-M9-M7
21	21203	M6-M10	21103	M7-M11	21103	M7-M11	21101	M3-M11
22	22101	M6-M9	22202	M9-M14	22202	M9-M14	22202	M9-M14
23	23202	M1-M6-M13	23201	M1-M6-M11	23201	M1-M6-M11	23101	M4-M5-M11
24	24203	M10-M3	24201	M2-M3	24201	M2-M3	24201	M2-M3

Table 7.3 Cont'd

Part Type	Case 5		Case 6		Case 7		Case 8	
	Process Route	Machine Sequence	Process Route	Machine Sequence	Process Route	Machine Sequence	Process Route	Machine Sequence
1	1201	M1-M7	1201	M1-M7	1102	M4-M5-M7	1201	M1-M7
2	2102	M4-M7	2101	M4-M6	2104	M5-M7	2104	M5-M7
3	3204	M3-M13	3204	M3-M13	3202	M2-M13	3206	M10-M13
4	4102	M2-M3-M13	4102	M2-M3-M13	4104	M2-M5-M13	4203	M2-M12-M5
5	5201	M6-M9-M14	5201	M6-M9-M14	5203	M12-M9-M14	5203	M12-M9-M14
6	6101	M1-M13	6101	M1-M13	6201	M4-M5-M12	6101	M1-M13
7	7204	M4-M5-M12	7204	M4-M5-M12	7204	M4-M5-M12	7102	M1-M7-M12-M13
8	8202	M4-M8	8202	M4-M8	8101	M12-M13	8203	M5-M7
9	9202	M2-M12-M14	9105	M8-M8-M9-M13	9202	M2-M12-M14	9202	M2-M12-M14
10	10101	M6-M8	10101	M6-M8	10201	M9-M12-M14	10104	M10-M9
11	11201	M7-M10	11203	M9-M10	11202	M7-M14	11204	M9-M14
12	12101	M6-M8-M9	12101	M6-M8-M9	12202	M6-M12-M14	12201	M6-M12-M9
13	13203	M10-M8	13101	M9-M13	13103	M12-M13	13101	M9-M13
14	14103	M8-M8	14104	M8-M13	14204	M12-M14	14202	M9-M14
15	15203	M3-M8-M14	15203	M3-M8-M14	15205	M14-M8-M14	15202	M1-M10-M14
16	16102	M6-M13	16102	M6-M13	16203	M12-M5	16104	M9-M13
17	17104	M1-M4-M13	17105	M4-M5-M7	17106	M4-M5-M13	17101	M1-M5-M7
18	18202	M1-M9	18202	M1-M9	18103	M13-M12	18204	M13-M9
19	19101	M4	19101	M4	19203	M12-M5	19102	M7
20	20102	M4-M9-M7	20104	M7-M9-M7	20206	M4-M12-M13	20104	M7-M9-M7
21	21103	M7-M11	21103	M7-M11	21202	M2-M12	21104	M7-M14
22	22102	M6-M13	22101	M6-M9	22203	M13-M5	22201	M9-M5
23	23202	M1-M6-M13	23201	M1-M6-M11	23104	M13-M5-M13	23104	M13-M5-M13
24	24203	M10-M13	24203	M10-M13	24104	M13-M12	24104	M13-M12

Table 7.3 Cont'd

Part Type	Case 9		Case 10		Case 11		Case 12	
	Process Route	Machine Sequence	Process Route	Machine Sequence	Process Route	Machine Sequence	Process Route	Machine Sequence
1	1201	M1-M7	1201	M1-M7	1201	M1-M7	1201	M1-M7
2	2104	M5-M7	2104	M5-M7	2102	M4-M7	2101	M4-M6
3	3206	M10-M13	3204	M3-M13	3204	M3-M13	3206	M10-M13
4	4104	M2-M5-M13	4102	M2-M3-M13	4102	M2-M3-M13	4102	M2-M3-M13
5	5203	M12-M9-M14	5201	M6-M9-M14	5201	M6-M9-M14	5201	M6-M9-M14
6	6101	M1-M13	6101	M1-M13	6101	M1-M13	6101	M1-M13
7	7102	M1-M7-M12-M13	7101	M1-M7-M10-M13	7102	M1-M7-M12-M13	7101	M1-M7-M10-M13
8	8204	M5-M8	8203	M5-M7	8201	M4-M7	8201	M4-M7
9	9105	M8-M8-M9-M13	9105	M8-M8-M9-M13	9101	M6-M8-M9-M13	9105	M8-M8-M9-M13
10	10104	M10-M9	10101	M6-M8	10101	M6-M8	10102	M6-M9
11	11203	M9-M10	11201	M7-M10	11202	M7-M14	11201	M7-M10
12	12101	M6-M8-M9	12101	M6-M8-M9	12101	M6-M8-M9	12101	M6-M8-M9
13	13203	M10-M8	13202	M6-M13	13201	M6-M8	13201	M6-M8
14	14104	M8-M13	14103	M8-M8	14101	M6-M8	14102	M6-M13
15	15103	M10-M8-M9	15101	M6-M8-M9	15102	M6-M98-M13	15101	M6-M8-M9
16	16203	M12-M5	16102	M6-M13	16102	M6-M13	16102	M6-M13
17	17101	M1-M5-M7	17201	M1-M10-M13	17107	M4-M8-M7	17107	M4-M8-M7
18	18202	M1-M9	18202	M1-M9	18204	M13-M9	18204	M13-M9
19	19102	M7	19102	M7	19101	M4	19102	M7
20	20104	M7-M9-M7	20104	M7-M9-M7	20104	M7-M9-M7	20104	M7-M9-M7
21	21104	M7-M14	21104	M7-M14	21204	M6-M12	21203	M6-M10
22	22202	M9-M14	22102	M6-M13	22101	M6-M9	22101	M6-M9
23	23204	M1-M9-M13	23202	M1-M6-M13	23202	M1-M6-M13	23202	M1-M6-M13
24	24104	M13-M12	24203	M10-M13	24104	M13-M12	24203	M10-M3

Table 7.3 Cont'd

Part Type	Case 13		Case 14		Case 15		Case 16	
	Process Route	Machine Sequence	Process Route	Machine Sequence	Process Route	Machine Sequence	Process Route	Machine Sequence
1	1201	M1-M7	1201	M1-M7	1201	M1-M7	1201	M1-M7
2	2102	M4-M7	2102	M4-M7	2101	M4-M6	2102	M4-M7
3	3204	M3-M13	3204	M3-M13	3204	M3-M13	3204	M3-M13
4	4102	M2-M3-M13	4102	M2-M3-M13	4102	M2-M3-M13	4102	M2-M3-M13
5	5201	M6-M9-M14	5201	M6-M9-M14	5201	M6-M9-M14	5201	M6-M9-M14
6	6101	M1-M13	6101	M1-M13	6101	M1-M13	6101	M1-M13
7	7101	M1-M7-M10-M13	7101	M1-M7-M10-M13	7101	M1-M7-M10-M13	7101	M1-M7-M10-M13
8	8201	M4-M7	8201	M4-M7	8201	M4-M7	8201	M4-M7
9	9101	M6-M8-M9-M13	9101	M6-M8-M9-M13	9101	M6-M8-M9-M13	9101	M6-M8-M9-M13
10	10101	M6-M8	10101	M6-M8	10102	M6-M9	10102	M6-M9
11	11201	M7-M10	11201	M7-M10	11201	M7-M10	11201	M7-M10
12	12101	M6-M8-M9	12101	M6-M8-M9	12101	M6-M8-M9	12101	M6-M8-M9
13	13201	M6-M8	13201	M6-M8	13201	M6-M8	13201	M6-M8
14	14101	M6-M8	14102	M6-M13	14101	M6-M8	14102	M6-M13
15	15101	M6-M8-M9	15101	M6-M8-M9	15101	M6-M8-M9	15101	M6-M8-M9
16	16102	M6-M13	16101	M6-M8	16102	M6-M13	16102	M6-M13
17	17107	M4-M8-M7	17107	M4-M8-M7	17107	M4-M8-M7	17107	M4-M8-M7
18	18204	M13-M9	18204	M13-M9	18204	M13-M9	18204	M13-M9
19	19101	M4	19101	M4	19101	M4	19101	M4
20	20102	M4-M9-M7	20102	M4-M9-M7	20102	M4-M9-M7	20102	M4-M9-M7
21	21203	M6-M10	21203	M6-M10	21203	M6-M10	21203	M6-M10
22	22101	M6-M9	22101	M6-M9	22101	M6-M9	22101	M6-M9
23	23202	M1-M6-M13	23202	M1-M6-M13	23202	M1-M6-M13	23202	M1-M6-M13
24	24203	M10-M3	24203	M10-M3	24203	M10-M3	24203	M10-M3

Table 7.4 Number of units of each machine type

Test Case	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14
1	2	2	2	2	1	2	2	2	2	2	2	1	2	2
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	1	1	1	1	1	1	1	1	1	1	1	1	1	1
6	1	1	1	1	1	1	1	1	1	1	1	1	1	1
7	1	2	1	1	2	1	1	1	1	1	1	2	2	2
8	2	2	1	1	2	1	2	1	2	2	1	2	2	2
9	2	2	1	1	2	1	2	2	2	2	1	2	2	2
10	2	2	2	1	2	2	2	2	2	2	1	1	2	2
11	2	2	2	2	1	2	2	2	2	1	1	2	2	2
12	2	2	2	2	1	2	2	2	2	2	1	1	2	2
13	2	2	2	2	1	2	2	2	2	2	1	1	2	2
14	2	2	2	2	1	2	2	2	2	2	1	1	2	2
15	2	2	2	2	1	2	2	2	2	2	1	1	2	2
16	2	2	2	2	1	2	2	2	2	2	1	1	2	2

CHAPTER 8

DISCUSSIONS AND CONCLUSIONS

8.1 Discussions

This thesis presents a multi-objective, mixed integer, non-linear programming model for the design of cellular manufacturing systems considering the reliability aspects of machines. The CMS design problem involves multiple machine types, multiple machines for each machine type, multiple part types and alternative process routes for each part type. The model attempts to strike a balance between system reliability and total cost. Total cost consists of the variable cost of manufacturing operations (*VCM*), the inter-cell material handling cost (*MHC*), the penalty cost of machine under-utilization (*MNC*) and machine annuity cost (*MAC*). The optimal number of units of each machine type, the alternative process routes for each part, and the effective machine-cell assignments are simultaneously determined to maximize the overall system reliability while minimizing the total cost. Genetic algorithm is applied to solve this optimization problem. The algorithm solves the model efficiently and determines "heuristic optimal" solutions within reasonable amounts of computational times.

Machine reliability is analyzed using a lognormal distribution due to its versatility in dealing with both increasing and decreasing failure rates over time. Machine availability is also considered to estimate the machine's effective capacity which affects the system performance. The model also includes the annuity cost as a performance factor. It accounts for a large proportion of the total cost.

To demonstrate the application of the model and the genetic algorithm, a numerical example is provided, and the results are analyzed over a wide range of possibilities to investigate the appropriate trade-offs between reliability and total cost. For the model chosen, the genetic algorithm was shown to converge to a heuristic solution that was fairly stable in terms of system reliability.

The genetic algorithm coded in MATLAB is easy to implement. It solves the model efficiently and effectively, and within reasonable amounts of computational time. Different from other algorithms which search the solution space one point at a time, GA searches for a candidate solution by considering a set of points all at once, and therefore, it need less iterations to search for the solution.

8.2 Contributions

The contributions of the thesis are summarized as follows:

1. This thesis proposed a multi-objective, mixed integer, non-linear programming model to maximize the system reliability and minimize the total cost simultaneously, while determining the number of units of each machine type and selecting process routes for each part type.

2. Lognormal distribution was applied to analyze machine relibility and availibility for the CMS design.

3. A heuristic method based on genetic algorithm was successfully used to solve the non-linear problem for the model with a lognormal distribution.

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APPENDICE in CD FORMAT

MATLAB FILES

A.1 Matlab programs to solve the numerical model with 14machine types and 24 part types (Programs coded in Matlab are contained in the CD.)

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