Application of Fuzzy Inference Systems and Genetic Algorithms in Integrated Process Planning and Scheduling

Zalinda Othman, Khairanum Subari and **Norhashimah Morad**

Division of Quality Control and Instrumentation
School of Industrial Technology
University Sains Malaysia
11800 Minden
Penang
Email: ispsamin@hotmail.com , khairanu@usm.my and nhashima@usm.my

Abstract.

This paper proposes a fuzzy inference system in choosing alternative machines for integrated process planning and scheduling of a job shop manufacturing system. Instead of choosing alternative machines randomly, machines are being selected based on the machines reliability. The MTTF values are input in a fuzzy inference mechanism, which outputs the machine reliability. The machine is then being penalized based on the fuzzy output. The most reliable machine will have the higher priority to be chosen. In order to overcome the problem of un-utilization machines, sometimes faced by unreliable machine, the genetic algorithms have been used to balance the load for all the machines.

An example of simulation problem of a 4 jobs 3 machines environment is presented. Simulation study shows that the system can be used as an alternative way of choosing machines in integrated process planning and scheduling.

Keyword: genetic algorithms, integrated process planning and scheduling, fuzzy inference system, load balancing and machine reliability.

1. Introduction

Process planning and scheduling play important roles in manufacturing systems. Their roles are to ensure the availability of manufacturing resources (such as material, machines and labour) needed to accomplish production tasks result from a demand forecast. These two functions are highly related; in process planning, each machining operation is assigned to a certain machine tool and in scheduling the assignment of machine tool over time to different machine is performed. Traditionally, these two functions are accomplished in two different stages. Production scheduling will get its input from the complete process planning. This results in conflicting objectives and the inability to communicate the dynamic changes in the shop floor (Nasr & Elsayed, 1990). By integrating these functions, more flexible and effective schedules can be produced. One way of integrating these functions is by allowing alternative machine routings for operations during the scheduling stage.

In this paper, instead of choosing alternative machines randomly, the fuzzy inference system is being introduced for the purposes of choosing appropriate machines. Machines will be chosen based on the machine's reliability characteristics. This will ensure the capability of the machine in fulfilling the production demand. In addition, based on the capability information, the load for each machine is balanced by using the genetic algorithm (GA). In the following section, an introduction to process planning, scheduling, GA and fuzzy inference system is presented. Section 3 describes the need for an integrated approach, while section 4 presents the proposed approach. Section 5 will discuss the simulation results for a 4 jobs 3 machines problem. Finally, section 6 will draw some conclusions.

2. A brief introduction to process planning, scheduling, genetic algorithms and fuzzy inference system

2.1. Process Planning

Process planning links the design activity and production stage. It translates design specifications into manufacturing operation details. In another words, process planning is a task of precisely specifying how to manufacture a particular product with the objectives of producing product according to specifications and producing product at minimum cost (Palmer, 1996). It emphasizes the technological aspects of manufacture routings and resource assignments.

There are two approaches to process planning; manual-based method and computer-aided process planning (CAPP). Manual-based method requires knowledgeable and experienced process planners to do the job. It is time consuming and the plans developed over a period of time may not be consistent. Computer-aided process planning has been developed to overcome these problems. A few benefits can be achieved by using computers in process planning, such as; accurate and consistent process plans can be produced, reduce the cost and lead time of process planning, increased productivity of planners, reduce the needs of skill planners, and can be integrate with other applications.

2.2. Scheduling

A good scheduling strategy may help companies to respond to market demands quickly and to run plants efficiently. This helps them to be more competitive in today's market.

Scheduling is the task of allocating available production resources (labor, material and equipment) to jobs over time. The scheduling objectives are to satisfy production constraints and minimize production costs.

A general scheduling problems can be stated as (MacCarthy & Liu (1993)):

n jobs $\{J_1, J_2 ... J_n\}$, job means a single part (or batch) or item, have to be processed through m machines $\{M_1, M_2, ..., M_m\}$. The processing of a job J_j on a machine M_i is called operation, O_{ij}. For each operation, there is an associated processing time t_{ij}. In addition there may be a ready time (or release date) r_j associated with each job and / or a due date by which time J_j should be completed. Technological constraints demand that each job should be processed through machines in particular orders. These constraints depend on the types of shop floors (flow shop, job shop or open shop). The general problem is to find a sequence, in which the jobs pass between the machines, which is compatible with the technological constraints and meet certain production objectives.

In general job shop scheduling, every job may have a different routing through machines. A problem of n jobs and m machines has an infinite number of feasible solutions since idle times between operations can vary. These number of feasible solutions increase exponentially along each parameters (such as number of machines and number of jobs). Due to the complex combinatorial problem, the theory and techniques of scheduling have received a lot of attention from OR practitioners, management scientists, production and operations research workers and mathematician. A number of books have been published on the subject, e.g. French (1982), Rinnoy Kan (1976) and Baker (1974). Articles that survey the techniques and development of scheduling include Blackstone et. al. (1982), Rodammer & White (1988), Brandimarte (1992), MacCarthy & Liu (1993), Blazewicz et.al. (1996) and Gargeya & Deane (1996).

2.3. Integrated process planning and scheduling

Palmer (1996) defined conventional scheduling as a task that uses input from rigid process plans. These plans specify a unique choice of machines for each operation, and a unique sequence of operations. Whereas, integrated process planning and scheduling (or integrated scheduling) uses more flexible process plans as input. The flexible plans allow a choice of operation sequences and / or machines.

Zhang and Mallur (1994) stated that integration would result in simultaneous consideration of objectives resulting in reduced cost. Also, there is a possibility to have balanced loading on the machines and some degree of flexibility is added to the scheduling function. This flexibility will allow scheduling to respond to changing conditions on the shop floor such as overloading and underloading situations, bottlenecks and the unavailability of some machines due to breakdown or unscheduled maintenance.

There are an increase number of works that have been done on this subject. Various applications to the integrated problem have been introduced.

Sundaram & Fu (1988) were among the earlier researchers who shown that there exists a need for integrating the process planning and scheduling functions in manufacturing for productivity improvements. They used heuristic procedures as the integrated approach. Some other approaches are integer programming (Nasr & Elsayed, 1990), rule-based approach (Khoshnevis and Chen’s, 1990), simulated annealing approach, tabu search (Brandimarte & Calderini, 1992) and genetic algorithms approach (Morad (1997), Husbands & Mill (1991) and Jain & Elmaraghy, (1997)).

2.4. Genetic algorithms

Genetic algorithms searching mechanism starts with a set of solutions called a population. One solution in the population is called a chromosome. The search is guided by a survival of the fittest principle. The search proceeds for a number of generations, for each generation the fitter solutions (based on the fitness function) will be selected to form a new population. During the cycle, there are three main operators namely reproduction, crossover and mutation. Reproduction process is the combination of evaluation and selection process. It copies an individual from one generation to the next. Crossover is the process that takes two or more parents and swapping information between them in order to produce one or more children. Mutation is the process that randomly modifies a part of chromosome's information. The cycle will repeat for a number of generations until certain termination criteria are met. It could terminate after a fixed number of generations, after a chromosome with a certain high fitness value is located or after a certain simulation time.

2.5. Fuzzy inference system

Vagueness can frequently be associated with many day-to-day activities mainly when human evaluation, observation and decision are present. The lack of precise knowledge events' and statements' semantic meanings is often present in systems controlled by human operators, such as production system.

In machine reliability, mean time to failure (MTTF) is a measure of expected time where the machine will fail. In a case of an exponential distribution, the MTTF value is the reciprocal of the failure rate. In a conventional analysis, failure rate is modeled by a probability theory. A large amount of data is needed to estimate the rate. Uncertainty occurs since failures seldom happen; thus it is difficult to collect enough data for a statistical "probability of failure" basis. Furthermore, it is costly and the relevance of the data to any particular system, as well as its validity, is often questionable. In addition, the probability of failure for certain item usually does not exist in the early design stage. It has to be estimated based on engineering judgments or experience from similar item. Uncertainty will increase when these failure probabilities are being extrapolated through statistical methods to calculate a system level reliability.

In order to overcome the uncertainty and imprecision, fuzzy logic theory helps to restore the integrity of reliability. Fuzzy logic consists of the theory of fuzzy sets and possibility theory. It was introduced by Zadeh (1965) as a means of representing and manipulating data that was not precise but rather fuzzy. Fuzzy sets are functions that map a value, which might be a member of a set, to a number between zero and one, indicating its actual degree of membership. A degree of zero means that the value is not in the set and a degree of one means that the value is completely representative of the set. Whereas a fuzzy set gives the degree of membership of each element in the set, possibility theory works with the possibility that a variable may have a particular value.

Fuzzy inference system (FIS) is a method, based on the fuzzy theory, which maps the input values to the output values. The mapping mechanism is based on some set of rules, a list of if-then statements. Figure 1 shows the general case of fuzzy inference system. There are five steps in a fuzzy inference system. These steps are fuzzification of the input variables, application of the fuzzy operator (AND or OR), if any, in the antecedent, implication from the antecedent to the consequent, aggregation of the consequent across the rules and defuzzification.

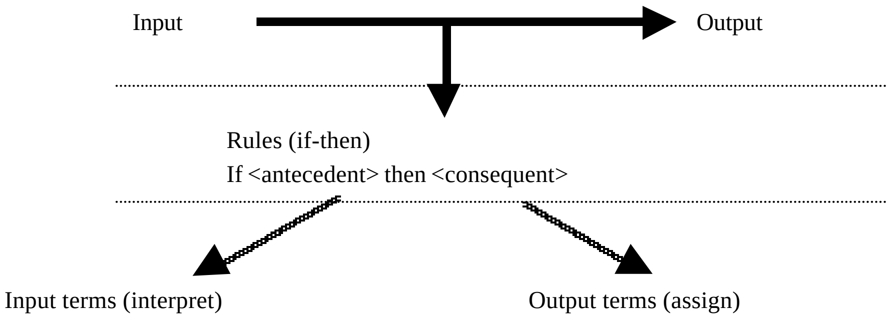

Figure 1. Fuzzy inference system – A general case.

3. The proposed approach

Figure 2 shows the proposed approach, which consisting mainly of GA and FIS (available in Mathlab Fuzzy Logic Toolbox).

In GA, a search begins with an initial population. The population consists of a number of chromosomes. Each chromosome is represented by the sequence of job orders, the sequence of operations and the set of machines to be used to accomplish the operation (Morad, 1997). The representation does not directly represent a schedule; a transition from chromosome representation to a legal production schedule has to be performed by a schedule builder. In this work the schedule builder is based on Giffler and Thompson Algorithm (Baker, 1974). This algorithm generates feasible active schedules. Some studies have shown that the optimal schedules can be found from the set of active schedules (Chang & Sullivan, 1990). Therefore, the chances to get optimal schedules are higher from the set of active schedules.

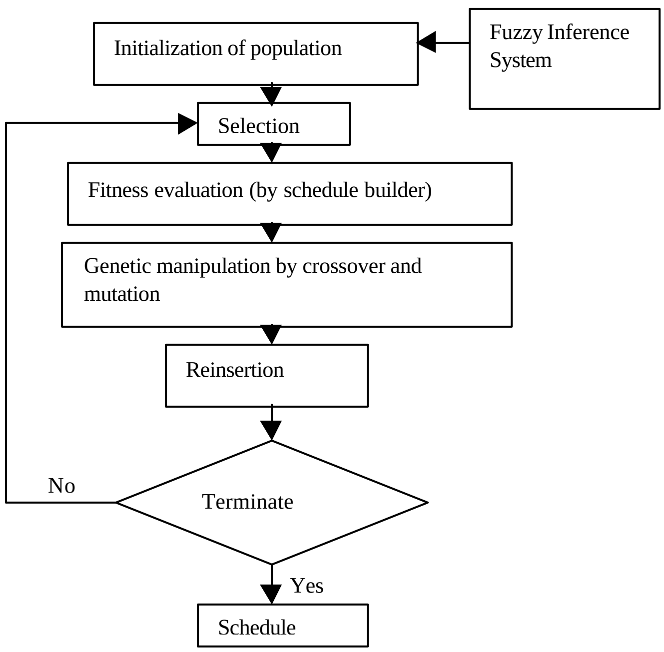

Figure 2. The schematic diagram of the proposed approach

Two crossover operators used in the formulation are order-based operator and plan-resource operator.

Order-based crossover changes the order of jobs; the order of jobs in the selected position in one parent is imposed on the corresponding tasks in the other parent. The order-based mutation interchanges the positions of the jobs at random.

Plan-resource crossover, as developed by Morad (1997), changes the operation sequences as well as the machines to perform operation. The sequence of the job remains the same. Meanwhile, in the mutation, the operation sequences as well as the machines are re-chosen at random.

The initial population is generated at random and stochastic universal sampling is used to reproduce new generation.

Three objective values are used to measure the effectiveness of the schedule. Those objectives are:

Minimise total completion time of all jobs or the makespan

Minimise total number of rejects – the total number of rejects can be calculated by adding all the number of scrap produced:

$$F1 = \sum_{l=1}^{n} Y_l^s = \sum_{l=1}^{n} Y_l^o \left(\sum_{j=l}^{op} k_j^s \right) \qquad (1)$$

Minimise total processing cost – the total processing cost can be calculated by summing all the processing costs for all the operations;

$$F2 = \sum_{l=1}^{n} N_l^i \sum_{j=1}^{op} \left[k_{lj}^i X_{lj}^i - k_{lj}^s X_{lj}^s + k_{lj}^i f\left(Y_{lj}^i\right) \right] \qquad (2)$$

For equation (1) and (2): Y_l^s is the scrap unit, Y_i^o is the output unit, k_j^i is the input technological coefficient per unit output, k_j^s is the scrap technological coefficient per unit, X_j^i, X_j^s are the unit average cost of input and scrap respectively, $f(Y_j^i)$ is the processing cost per unit, n is the total number of jobs, l is the job number, op is the total number of operations and N^i is the number of input units. The equations (1) and (2) are detailed in Singh (1996).

FIS supports the genetic algorithm loop by providing the machines capability information in terms of the reliability index. Figure 3 shows the FIS approach that composed of (1) fuzzification of MTTF values; (2) implication from the antecedent to consequent; (3) aggregation of the consequences across the rules; and (4) relative reliability index.

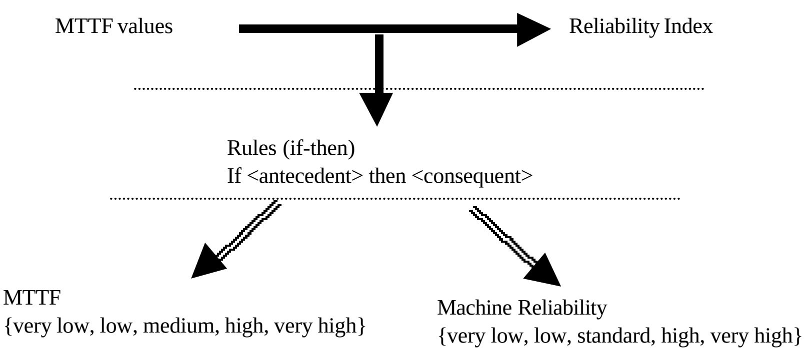

Figure 3. Fuzzy inference system – the proposed method

Each machine will be assigned an imaginary MTTF value randomly. The values will be in a range between 0 to 50 units. These values are represented by the triangular membership function as shown in Figure 4.

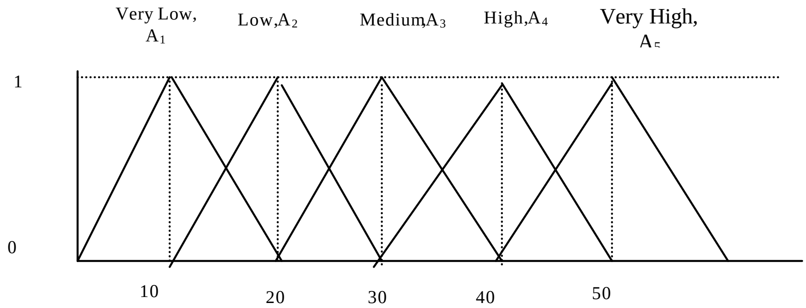

Figure 4. Input membership function

Let X be a nonempty set whose elements are denoted by x. A fuzzy sets A_1, A_2, A_3, A_4 and A_5 are characterized by it membership functions (i.e. triangular function) as below:

$$A_1(x) = \begin{cases} 1 - \dfrac{|10-x|}{10} & \text{if } |10\text{-}x| \le 10 \\ 0 & \text{if otherwise} \end{cases} \tag{3}$$

$$A_2(x) = \begin{cases} 1 - \dfrac{|20-x|}{10} & \text{if } |20\text{-}x| \le 10 \\ 0 & \text{if otherwise} \end{cases} \tag{4}$$

$$A_3(x) = \begin{cases} 1 - \dfrac{|30-x|}{10} & \text{if } |30\text{-}x| \le 10 \\ 0 & \text{if otherwise} \end{cases} \tag{5}$$

$$A_4(x) = \begin{cases} 1 - \dfrac{|40-x|}{10} & \text{if } |40\text{-}x| \le 10 \\ 0 & \text{if otherwise} \end{cases} \tag{6}$$

$$A_5(x) = \begin{cases} 1 - \dfrac{|50-x|}{10} & \text{if } |50\text{-}x| \le 10 \\ 0 & \text{if otherwise} \end{cases} \tag{7}$$

The system will take the input values and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. For example, if MTTF=5, this value will belong to a membership function A_1. From a "very low" membership function, the value MTTF will corresponds to 0.5. In another words, the MTTF value is very low to the degree of 0.5. In this manner, each input is fuzzified over all the qualifying membership functions required by the rules. In this work, only one input variable is being considered. Therefore, the AND or OR operator is not applicable. The next step is the implication method from antecedent to consequent. A consequent is a fuzzy set represented by membership functions, which is shown in Figure 5. The output membership functions chosen are the triangular functions. Both input and output membership functions are simply chosen to show how FIS can be used to provide machine reliability information. In real manufacturing environment, these functions should be able to represent the data used in the problem.

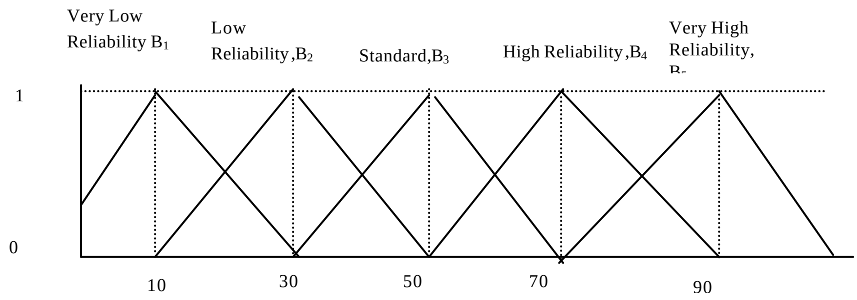

Figure 5. Output membership function

The output membership functions represent fuzzy sets B_1, B_2, B_3, B_4 and B_5 (equations (8) to (12)).

$$B_1(x) = \begin{cases} 1 - \dfrac{|10-x|}{10} & \text{if } |10\text{-}x| \le 20 \\ 0 & \text{if otherwise} \end{cases} \quad (8)$$

$$B_2(x) = \begin{cases} 1 - \dfrac{|30-x|}{10} & \text{if } |30\text{-}x| \le 20 \\ 0 & \text{if otherwise} \end{cases} \quad (9)$$

$$B_3(x) = \begin{cases} 1 - \dfrac{|50-x|}{10} & \text{if } |50\text{-}x| \le 20 \\ 0 & \text{if otherwise} \end{cases} \quad (10)$$

$$B_4(x) = \begin{cases} 1 - \dfrac{|70-x|}{10} & \text{if } |70\text{-}x| \le 20 \\ 0 & \text{if otherwise} \end{cases} \quad (11)$$

$$B_5(x) = \begin{cases} 1 - \dfrac{|90-x|}{10} & \text{if } |90\text{-}x| \le 20 \\ 0 & \text{if otherwise} \end{cases} \quad (12)$$

The input for the implication process is a single number given by antecedent and the output if a fuzzy set. The implication methods, (built-in methods supported by Mathlab Fuzzy Logic Toolbox) are min (minimum), which truncates the output fuzzy set, and prod (product), which scales the output fuzzy set.

The fuzzy rules are in the format:

if <antecedent, related to the MTTF> then <consequent, the machine reliability>

Rules used in the fuzzy inference system are:

If (MTTF is very low) then (machine reliability is very low)
If (MTTF is low) then (machine reliability is low)
If (MTTF is medium) then (machine reliability if standard)
If (MTTF is high) then (machine reliability is high)
If (MTTF if very high) then (machine reliability is very high)

A decision is based on the testing of all the rules in a fuzzy inference system. A combination of the rules is necessary for decision-making. Aggregation is the process by which the fuzzy sets that represent the outputs of each output are combined into a single fuzzy set. The input of the aggregation process is the list of truncated output functions returned by the implication process for each rule. The output of the aggregation process is one fuzzy set for each output variable.

The last step is to defuzzify the aggregate output fuzzy set. The result from this step is a single number. In this work the result is the reliability index. Figure 6 shows the example of the output of fuzzy inference system. First column shows how the input variable is used in the rules. The input variable is shown at the top, i.e. MTTF = 24.4. The second column shows how the output variable, i.e. machine reliability (mac_reliability), is used in the rules. Each row of plots represents one rule. The five plots (i.e. the triangle plots) in the input column show the membership functions referenced by the antecedent, or the *if* part of each rule. The second column of plots shows the membership functions referenced by the consequent, or the *then* part of each rule. The shaded input plots represent the MTTF value, 24.4 belongs to the membership function A_2 and A_3. The truncated output plots show the implication process. It has been truncated to exactly the same degree as the antecedent. The lower plot of the output column, is the resultant aggregate plot A defuzzified output value is shown by the line passing through the aggregate fuzzy set. In this example, if the MTTF is 24.4, the machine reliability index is 3.9. The index is the defuzzification result of the FIS. It is in the range of 0 to 10.

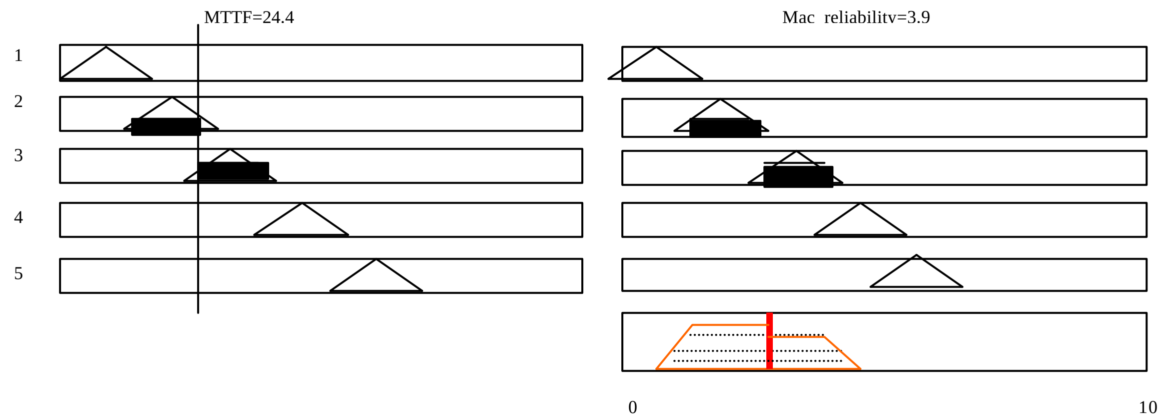

Figure 6. Example of the input-output of the fuzzy inference system

In a case, where numeric input is not available, FIS can be modified to accept linguistic or fuzzy input (such as 'low'). This is one of the advantages of using FIS in integrating machine capability to scheduling.

4. Results and discussion

4.1. Experiment 1

In experiment 1 an imaginary data used by Morad (1997), as shown in Appendix A, is used as an example of job shop that consists of 4 jobs and 3 machines. Each job has three operations to be accomplished and only one sequence of operations (i.e. one process plan). There are alternative machines for each operation with different processing time and setup time. The objective is to find the best sequence of jobs, which minimize total completion time or the makespan. Other performance measurements are total number of reject and total processing cost.

During initial stage of generating population, each machine is assigned imaginary MTTF values randomly. These values will be evaluated by FIS. FIS will determine the machine reliability index, and the machine will be ranked based on this index. Table 1 shows the output range and the ranking value. The output range represents the machine reliability index. The higher the reliability index the more reliable the machine. The most reliable machine is given the highest rank. Machine with the maximum ranking value will be chosen for processing jobs. In this work, if two or more machines have equal ranking value then one machine is chosen randomly.

Output range (machine reliability index)	Ranking value
0 – 2	1
2 – 4	2
4 – 6	3
6 – 8	4
8 – 10	5

Table 1. Output range and the ranking

Table 2 shows the example of the ranking value for each machine. Machine 21 and machine 22 have higher-ranking value compared to machine 23. In the selection process these two machines will be given the same priority to be selected. Machine 23 will have least priority in the selection.

	Machine 21	Machine 22	Machine 23
Ranking value	3	3	2

Table 2.Ranking value

Job	Operation 1	Operation 2	Operation 3
1	M22 (M21 M23)	M22 (M23)	M21 (M23)
2	M21 (M22 M23)	M21 (M23)	M22 (M23)
3	M22 (M21)	M22 (M21 M23)	M22 (M21 M23)
4	M21 (M23)	M22 (M21 M23)	M21 (M23)

Table 3. The list of chosen machines for processing jobs

The chosen machines, compared to the alternatives (list in brackett) are shown in Table 3 and Table 4 displays the best results for makespan, total number of reject and total processing cost. In this experiment, the makespan is being minimized individually by the GA.

	Makespan	Total number of rejects	Total processing cost
Best value	1287	12	678

Table 4. Best solutions obtained

The acceptable value for the total completion time is 1287 unit of time. While the total number of reject is 12 unit and total processing cost is 678 unit of dollar. Figure 7 represents the final schedule in a Gantt chart form.

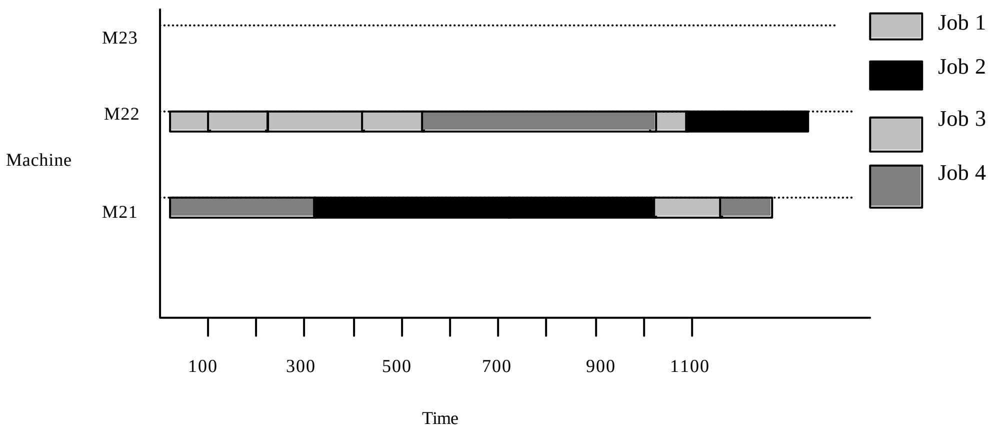

Figure 7. Gantt chart of the schedule

4.2. Experiment 2

In experiment 1, it can be seen that the machine 23 is left empty without doing any processing. In this case the unreliable machine is not be given any job. In real manufacturing environment, this case is unfavorable. Eventhough machine 23 is unreliable, in this case, it should not be left without doing any jobs. At least some operations can be assigned to this machine, in order to avoid any wasting resources.

In order to overcome this problem, another approach is proposed in this work. The GA will be used to balance the load for each machine. The load will be distributed based on the machine capability, which is measured by the reliability index. For the most reliable machine, the load given to the machine will be more compared to the unreliable one. The load on each machine is measured by the machine utilization, i.e. the percent of time the machine is being utilized.

For this purpose, the ranking values from the FIS are being grouped into three levels for penalty purposes. There are:

Unreliable when the machine reliablity index is less or equal to 2

Standard when the machine reliability index is equal to 3

Reliable when the machine reliability index is more than 3

A list of if-then rules has been developed to penalize machine based on its utilization. For unreliable machine, the machine utilization should be less or around 20, for the standard machine the machine utilization should be less or around 40, and the reliable machine the machine utilization should be around total utilization. The utilization is measured in percentage. It can be summarized as:

If machine reliablity <= 2
If machine utilization > 20% or machine utilization =0
Penalty(x) = 10
Elseif machine reliability = 3
If machine utilization > 40% or machine utilization = 0
Penalty(x) = 70
Else
If machine utilization > total utilization or machine utilization = 0
Penalty = 100
End

If these machines exceed the utilization limits, it will be penalized. This criteria will be checked for each chromosome in each generation. The GA will try to minimize the total penalty value until the best chromosome which present the most balanced load is achieved.

Another simulation, using the same data set, has been conducted for the proposed approach. Instead of assigning the MTTF values randomly, in this simulation each machine is being assigned an imaginary value of MTTF. The values are 30, 10 and 50 for machine 21, machine 22 and machine 23 respectively. Based on the FIS, the ranking for the machines are 3, 1 and 5 for machine 21, machine 22 and machine 23 respectively. After 50 generations, the optimized schedule is shown in Figure 8.

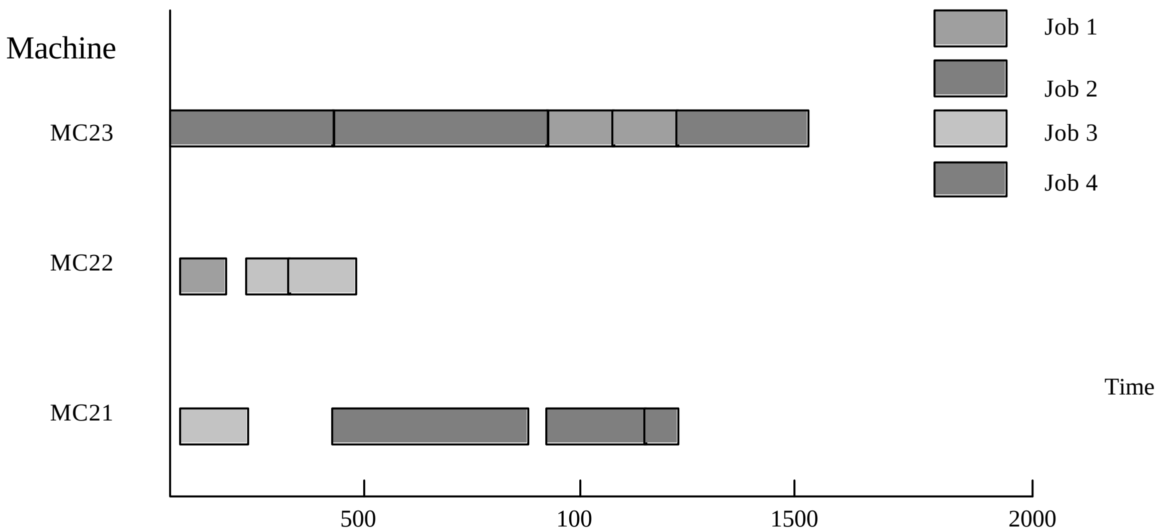

Figure 8. Gantt chart for experiment 2

From the Gantt chart shows in Figure 8, the machine utilization can be calculated as:

Machine 21 utilization = 970/2910 = 33.3 %
Machine 22 utilization = 415/2910 = 14.3 %
Machine 23 utilization = 1525/2910 = 52.4 %

From the calculation, the unreliable machine (i.e. machine 22) have the least load compared to other machines. This machine is being utilized up to 14.2 percent of the time. The standard machine, that is machine 21, having 33.3 percent of its time processing the jobs. Lastly, the most reliable machine, that is machine 23, has the most load compared to other machines. From the calculation, the utilization is 52.4 percent. From the results, it is shows that each machine received loads within a range respective to its capability.

In this experiment, the total penalty value becomes the objective function of the GA. The GA is minimizing the objective individually. The detailed of the schedule is shown in Table 5. It shows the order of the jobs, the machines involved in processing operations, operation sequence, start time of the operation and finish time of the operation.

Job	Machine	Operation	Start time	Finish time
4	3	1	1	406
1	2	1	4	109
3	1	1	2	157
2	3	1	406	911
4	1	2	406	811
1	3	2	911	1116
3	2	2	157	362
2	1	2	911	1216
4	1	3	1216	1321
1	3	3	1116	1321
3	2	3	362	467
2	3	3	1321	1526

Table 5. The detailed information of the schedule

5. Conclusion

Instead of choosing alternative machine randomly, this paper proposed the usage of fuzzy inference system to choose the most reliable machine. This is an alternative way to integrate the production capability during scheduling. In this work an imaginary data is used to simulate the system. This is due to the inability to collect real data. In a real manufacturing environment, MTTF values and the output reliability are determined by experts. There is a case when the machine not being utilized at all if it is unreliable. This is unfavorable in a real manufacturing environment. To overcome this problem, this paper proposes a new approach to balance loads on each machine that used genetic algorithms. From the simulation, this approach shows promising results. However, the choice of the machine for processing jobs in the process plan could affect the distribution of loads on each machine. For example, if machine 21 and machine 22 have the same capability and the choice for machine 22 in the process plan is less than machine 21. Then, in this case, many operations will be done in machine 21. So that, this approach will distribute more loads to machine 21.

This paper shows some promising results in integrating production capability and load balancing during scheduling activity. There are few objectives could be optimized individually or simultaneously. This will give a choice to the scheduler in determining which objective is the most important.

Acknowledgements

The author would like to acknowledge the University Sains Malaysia for sponsoring this study under the Academic Staff Training Scheme and the research grant NO: 305/PTEKIND/622140 provided by University Sains Malaysia that has resulted in this article.

References

A.Rodammer, Frederick, and K. Preston White Jr, "A recent survey of production scheduling," *IEEE Transactions on systems, man and cybernetics 1*8.6 (1988): 841-851.

Bagchi, Sugato, et al., "Managing genetic search in job shop scheduling," *IEEE Expert* 10 (1993): 15-24.

Baker, K.R., *Introduction to Sequencing and Scheduling,* (Wiley, New York, 1974).

Blazewicz, Jacek, Wolfgang Domschke, and Erwin Pesch, "The job shop scheduling problem: conventional and new solution techniques," *Europen Journal of Operational Research* 93 (1996): 1-33.

Brandimarte, Paolo, "Neighbourhood search-based optimization algorithms for production scheduling: a survey," *Computer Integrated Manufacturing* 5.2 (1992): 167-176.

Bruns, Ralf, "Direct chromosome representation and advanced genetic operators for production scheduling," (San Mateo, California: Morgan Kaufmann, 1993), 352-359.

Chang, Yih-Long, and Robert S. Sullivan, "Schedule generation in a dynamic job shop", *International Journal of Production Research* 28.1 (1990): 65--74.

French, Simon, *Sequencing and Scheduling: An Introduction to the mathematics of the job-shop, Ellis Horwood Series in Mathematics and Its Applications,* ed. G.M. Bell (Chichester: Ellis Hollwood Limited, 1982).

Fuzzy Logic Toolbox User's Guide, The Mathworks, Inc. 1998.

Gargeya, V.B., and R.H. Deane, "Scheduling research in multiple resource constrained job shops: a review and critique," *International Journal of Production Research* 34.8 (1996): 2077-2097.

Husbands, P, and F Mill, "Simulated co-evolution as the mechanism for emergent planning and scheduling," (San Mateo, California: Morgan Kaufmann, 1991), 264-269.

J.Palmer, Gareth, "A simulated annealing approach to integrated production scheduling," *Journal of Intelligent Manufacturing* 7 (1996): 163-176.

Jain, A.K., and H.A. Elmaraghy, "Production scheduling/rescheduling," *International Journal of Production Research* 35.1 (1997): 281-309.

John H. Blackstone, Jr, Don T. Philipsj, and Gary L.Hogg, "A state-of-the-art of dispatching rules for manufacturing job shop operations," *International Journal* *of Production Research* 20.1 (1982): 27-45.

Maccarthy, B.L., and Jiyin Liu, "Addressing the gap in scheduling research: a review of optimization and heuristic methods in production scheduling," *International Journal of Production Research* 31.1 (1993): 59-79.

Michalewicz, Z., *Genetic Algorithms + Data Structures = Evolution Programs*, (Springer Verlag, Berlin, 1994).

Morad, Norhashimah, and A.M.S Zalzala, "Optimisation of Cellular Manufact-uring Systems using Genetic Algorithms,", PhD Thesis, University of Sheffield, May 1997.

Morad, Norhashimah, and A.M.S Zalzala, "Genetic algorithms in integrated process planning and scheduling," *Journal of Intelligent Manufacturing* 10 (1999): 169-179.

Nasr, Nabil, and E.A.Elsayed, "Job shop scheduling with alternative machines," *International Journal of Production Research* 28.9 (1990): 1595-1609.

R.Behnezhad, Ali, and Behrokh Koshnevis, "Integration of machine requirements planning and aggregrate production planning," *Production Planning & Control* 7.3 (1996): 292-298.

Rinnooy Kan, A.H.G, *Machine Scheduling Problems:Classification, complexity and computations*, (Martinus Nijhoff, 1976).

Singh, N. *Systems Approach to Computer-Integrated Design and Manufacturing*, New York, John Wiley, 1996.

Sundaram, R. Meenakshi, and Shong-Shun Fu, "Process Planning and scheduling," *Computers and Industrial Engineering* 15.1-4 (1988): 296-301.

Zhang, Hong-Chao, and Srinidhi Mallur, "An intergrated model of process planning and production scheduling," *International Journal of Computer Integrated Manufacturing* 7.6 (1994): 357-364.

Zadeh, L.A., "Fuzzy Sets", *Information and Control*, 8 (1965), 338-353.

Appendix A

Data of Morad
Setup time : 5 units of time for each operation

Part	Operation	Machine	Processing time	Processing cost	% scrap
1	3	M1, M2, M3	15, 10, 20	20, 15, 10	5, 10, 15
	4	M2, M3	15, 20	50, 15	5, 10
	5	M1, M3	15, 20	20, 25	5, 10
2	6	M1,M2,M3	20, 25, 25	50, 15, 15	5, 10, 10
	7	M1, M3	15, 10	15, 50	5, 5
	8	M2, M3	5, 10	90, 5	5, 10
3	1	M1, M2	15, 10	60, 15	15, 10
	2	M1, M2, M3	15, 20, 15	15, 15, 50	10, 10, 5
	3	M1, M2, M3	15, 10, 20	50, 15, 20	5, 10, 15
4	5	M1, M3	15, 20	20, 25	5, 10
	6	M1, M2, M3	20, 25, 25	50, 15, 15	5, 10, 10
	7	M1, M3	5, 10	15, 50	5, 5

Table A.1. Processing details of alternative machines for parts

	Part 1	Part 2	Part 3	Part 4
Output units required (No)	10	20	10	20
Raw cost ($/unit)	10	20	30	40
Scrap cost ($/unit)	2	3	4	5

Table A.2. Output unit required, raw cost and scrap cost of parts