Performance Evaluation of FMS under Uncertain and Dynamic Situations

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ABSTRACT

Present era demands an efficient modeling of any manufacturing system that can enable it to cope with the unforeseen situations on the shop floor. One of the complex issues of these manufacturing systems that affect the performance of the manufacturing system is the scheduling of the part types. In this paper, authors have made an attempt to overcome the impact of uncertainties such as machine breakdowns, deadlocks, etc. by inserting the slack that can absorb these disruptions without affecting the other scheduled activities. The impact of the flexibilities in this scenario is also investigated. Authors have formulated the objective functions in such a manner that a better tradeoff between the uncertainties and flexibilities can be established. Consideration of AGVs in this scenario helps in loading or unloading of the part types in a better manner. In recent past, a comprehensive literature survey revealed the supremacy of the random search algorithms in evaluating the performance of these types of dynamic manufacturing systems. The authors have used a metaheuristic known as Quick Convergence Simulated Annealing (QCSA) algorithm and employed it to resolve the dynamic manufacturing scenario. The metaheuristic encompasses a Cauchy distribution function as a probability function that helps in escaping the local minima in a better manner. Various machine breakdown scenarios are generated. A "heuristic gap" is measured and it indicates the effectiveness of the performance of the proposed methodology with the varying problem complexities. Statistical validation is also carried out that helps in authenticating the effectiveness of the proposed approach. The efficacy of the proposed approach is also compared with the deterministic priority rules.

Key Words: Uncertainties, Slack, Flexibility, Breakdown, QCSA

I. INTRODUCTION

The effective implementation of FMS is vital for the success of manufacturing systems. Depending on the state of the shop floor and information on existing orders, an extrapolative schedule is generated initially on the shop floor that is modified subject to unexpected events such as machine breakdown, tool breakage etc for retaining viability in the system. There are some scenarios in scheduling of parts in FMS where adequate slack is provided in the system to negate the undesirable impact of interruptions and need not requires any rescheduling. The slack time is defined as the difference between the cycle time and the elapsed/processing time. However, there are a number of situations where the slack in the system affects the performance of the system and require corrective measures. In this regard, the authors have developed extrapolative schedules, which efficiently take care of the disruptions on the shop floor and retain the high performance value of the system. These schedules are aimed to assign the resources to the different jobs effectively for optimizing the performance measures of FMS. The slack time ratio (Veilleux and Petro, 1996) is sometimes used to assign priorities to the jobs in queue which is defined as follows:

$$Slack\ Time\ Ratio = \frac{Due\ date - today's\ date - processing\ time}{Remaining\ Time}$$

The uncertainties in manufacturing environments have been broadly classified in the three categories such as, complete unknowns, suspicious about the future, and known uncertainties. Due to their nature, the first two types of the uncertainties are practically impossible to be taken care in the shop floor. The third type which is known uncertainties, include informations such as, machine breakdown times and deadlocks that can be resolved in the manufacturing system. Based on the above-mentioned informations, schedules are generated. To overcome the breakdown of the machines, the extrapolative schedule aim to maximize the difference between the repair time and slack time of the operation.

With a view to implement FMS in real time efficiently, the main performance measure of the system that accompanies random machine breakdowns is considered to be average flow time and average delay time. The main aim of the authors is to obtain the sustainable performance measure in dynamic situations that conforms to the consistency with the production plans in the shop floor. Data related to the distributions of the time between breakdowns along with repair time of machines is available to the authors and based on these informations, a schedule is generated. An effort has been made in this paper to optimize the performance of FMS, where flexibilities pertaining to part routing and machine, AGVs and uncertainties in the system are considered in an integrated manner.

Owing to the complex nature of the problem, that contains various uncertainties, existing methodologies such as deterministic routing techniques etc. found it a tedious task to resolve in the real time. Existing mathematical modeling tools have made it more difficult to comprehend. In this paper, authors have attempted to model the problem in a straightforward manner. Application of AI based techniques (Fox and smith, 1984 and Ow *et al.,* 1990) has proved to be very useful in resolving complex production planning problems. Enticed by the efficacies of random search algorithms, authors have used a Quick Converging Fast Simulated Annealing Algorithm (QCSA) (Mishra *et al.*, 2005) to resolve the problem on hand. Applied algorithm that combines the elements of directed and stochastic search is found to maintain the balance between the exploitation and exploration of the search space. The algorithm inherits the effectiveness associated with simple Genetic Algorithm (GA) and Simulated Annealing (SA) and does away from some of their demerits such as premature convergence, extreme reliance on crossover and too slow mutation rate. The algorithm employs a Cauchy distribution function instead of Boltzmann probability function in the selection step that helps in escaping the local minima in an effective manner. The alluring aspect of the algorithm is its ability to converge to a near optimal solution quickly, despite the difficulties such as high dimensionality, discontinuity and multi-modality.

The QCSA based solution methodology is employed to obtain optimal or near optimal performance measure for the system i.e. minimum makespan, average flow time and delay time for the schedules in an FMS. Authors have formulated the different types of problem by considering the uncertainties and flexibilities. The proposed methodology is authenticated by applying heuristic gap that evaluates the efficiency of the procedure and subsequently ANOVA is employed to reveal the robustness of the same. Heuristic gap is the deviation in lower bound from an upper bound for a problem. Intensive computational experiments have been performed for different scenarios of the problem in FMS environment.

The next section deals with the literature review related to the scheduling in FMS that takes care of flexibilities and uncertainties present in the system as well as their impact over the system performance. A complete modeling of the problem that takes into account the uncertainties is detailed in section 3. QCSA algorithm and their application over the underlying problem is discussed in section 4. Computational experiments and discussions are presented in the section 5. The paper is concluded in section 6.

2. Literature Review

In the present competitive and highly dynamic situations, efficient scheduling systems are required that would be able to generate responsive schedules. Several of the literatures regarding the scheduling of FMS are concerned with the schedule generation.

Various approaches in the literature exist that analyze the scheduling problems in a dynamic and stochastic situation and propose the reactive policies for shop floor control. In this regard, Hitomi *et al.* (1989) discussed the design and schedule problem of flexible manufacturing cell with automatic setup equipment. An Optimal queuing network model with general service time and limited local buffers have been studied by Yao and Buzzacott (1985), they also evaluated the performance of the FMS. Choi *et al.* (1988) evaluated the traditional work scheduling rules in FMS with a physical simulator. Hall and Sriskandrajah (1996) presented a survey of scheduling problems with blocking and no-wait. Modeling approaches related to control of a dynamic load condition in a Flexible Manufacturing Cell have been presented by Seidmann (1987), and Tenenbaum and Seidmann (1989). Further, Yih and Thesen (1991) brought into a concept of modeling by utilizing the traits of Semi-Markov decision model for dynamic situations in flexible manufacturing cell and subsequently determined the feasible set of part type sequences in the system.

For highly dynamic situations, the real time decisions are taken as per completely reactive approaches. One of the techniques used in this respect is the priority dispatching rules, where the available highest priority job is selected for processing subject to the constraints related to processing times on machines and have been discussed in detail by Bhaskaran and Pinedo (1991). This predictive-reactive scheduling is aimed to generate a predictive schedule that optimizes some measures of system performance based on the job completion times without taking into account the possible disturbances on the shop floor. The deficiency of the aforementioned approach is how to respond to the disturbances so that the feasibility of the system is maintained. In this regard, Wu *et al.* (1993) proposed a multi-criteria rescheduling approach. The selection of appropriate scheduling rules for FMS by simulation method has been discussed in detailed by Lashkari *et al.* (1991). Knowledge based scheduling approaches also play a major role in selecting a suitable rescheduling policy that has been discussed by some researchers. Denzler *et al.* (1987) carried out experimental investigation of FMS scheduling rules to find out the suitable rules that can result in the efficient production.

To cope up the varying processing times and breakdown of machines in a dynamic job shop environment, Muhlemann *et al.* (1982) examined the scheduling frequency that influences the degree of responsiveness of the manufacturing system. In static scheduling environment, a rescheduling policy has been studied by Yamamoto and Nof (1985) that also considers random machine breakdowns in the system. This policy is mainly motivated to generate a random schedule in presence of unforeseen events. In this regard, various algorithms (Been *et al.* (1991), Wu *et al.* (1993)) have been applied to achieve the better performance measures of the system. Church and Uzsoy (1992) studied the problem of rescheduling in a single machine environment with dynamic job arrivals and proposed that rescheduling takes place at fixed time intervals unless an urgent job triggers an early rescheduling. Mehta and Uzsoy (1998) developed an algorithm that minimizes the maximum lateness and the difference between job completion times in the system. Leon, Wu, and Storer (1994), worked in the area of finding a good initial schedule that maintains its planned performance under stochastic disturbances. Zhou *et al.* (2005) studied the dynamic optimal policies for the processing of jobs on a single machine subjected to random breakdowns. Zhou *et al.* (2003) also studied the stochastic scheduling for minimizing the expected weighted flow time using preemptive repeat machine breakdowns model. M. Savsar (2005) carried out the performance analysis of an FMS operating under different failure rates and maintenance policies. The various procedures that combine simulation and analytical models were used to analyze the effect of maintenance policies on the performance of an FMS in his work. These studies reveal that the schedules that are robust to stochastic disturbances can be generated without too much sacrifice from the performance of the schedule.

Flexibilities pertaining to different machines and jobs play a crucial role in evaluating the performance measures of the system. The available literature clearly indicates towards the future research scope in this field. However, limited research on the flexibility indicates that it has remained ambiguous to a great extent (Sethi and Sethi 1990, Gupta and Buzacott (1989). In particular, there is a lack of precise analytical models that are capable of generating clear relationships between the degree of flexibility in a system and the systems level of performance as rightly pointed by the Slack (1987), Ettlie (1988), and Benjaafar (1992). The work carried out by Jaikumar (1986), Ratna and Tchijov (1990), and Benjaafar (1992) concluded that the vagueness of flexibility has also resulted in complexity in designing it into new systems and sustaining it over the systems life times. The work carried out by Cai *et al.* (2003) focuses on the value of processing flexibility in multipurpose machines. Falkner and Benhajla (1990), Swamidass and Waller (1990), and Suresh and Meredith (1985) demonstrated that lack of adequate methodologies for assessing the value of flexibility that has made it difficult to financially justify the investment, and acquisition of, flexible technologies.

Various studies have reported that the effectiveness of the certain manufacturing systems depend on how efficiently the AGVs are routed in the system that takes into account various uncertainties too. In this context, Egbelu and Tanchoco (1984) first attempted the simulation-based studies for testing the scheduling rules for an AGV based material handling system. In their proposed work, various AGV scheduling rules were developed and through the simulation model their performances were measured. Later on, various cart selection and tool allocation rules were tested by Smith *et al.* (1985). Tanchoco *et al.* (1987) presented approach to determine the optimal flow path for AGVs, which minimized total travel of loaded vehicles. Tang *et al.* (1993) identified six decision rules for FMS scheduling involving operations among parts, machine, and AGVs. Sabuncuoglu and Hommertzheim (1992a, 1992b; 1993, 1995, 1999) studied machine and AGV scheduling rules against various performance measures for a random type FMS. Their result signified the importance of AGV scheduling in FMSs. The estimation of part waiting time and fleet sizing in AGV systems was studied by Koo *et al.* (2005) using the queuing model. However, authors have noticed a remarkable research gap in the previous approaches, i.e. related with the application of AI based approaches in evaluating the performance of such type of manufacturing systems. Even, a comprehensive mathematical analysis of such type of manufacturing systems where different types of uncertainties and flexibilities are considered is missing. These research issues became the motivating factor to authors who considered such type of complex manufacturing system and applied a random based search technique "Quick Convergence Simulated Annealing (QCSA)" in resolving the same.

3. MODEL FORMULATION

The authors have formulated a mathematical model to represent FMS and its layout (shown in Figure 1). The notation of this model has been presented in the Appendix I. The proposed model consists of machines that are capable of performing wide variety of operations. These machines can execute at most one operation at a time. The proposed model also incorporates the different flexibility measures that help in absorbing the uncertainties prevailing in the FMS. These uncertainties often restrict the development of a robust schedule for FMSs and subsequent performance of the system gets hampered. Thus, flexibility measures such as routing and machining flexibilities have been incorporated at the operational level. The AGVs are also taken into account in the modeling to deliver part types among the machines. The flexibilities have also been incorporated in the loading and unloading of part types from the central storage and machines running under the possibility of random breakdowns. A comprehensive study of the related literature revealed that still the issues pertaining to mapping of various uncertainties in a FMS environment are yet to be efficiently accomplished. In this context, authors have made an attempt to model FMS where AGV routing, flexibilities pertaining to machine and part routing exist along with the uncertainties such as breakdown, deadlocks. The uncertainties are to be handled properly, so that the loss incurred could be minimized.

<<Insert Figure 1 about here>>

Let a FMS consists of set of N part types that are to be processed on a set of M machines. It is assumed that part types arrive dynamically to the machines with arrival rate φ_j. This arrival rate is previously based on the departure processes of earlier machines along with the operating characteristics of the part delivery system. Each part type requires an operation on the corresponding machine with an average processing time $1/\lambda_j$. The part inter-arrival and processing times are exponentially distributed with respect to the means $1/\varphi_j$ and $1/\lambda_j$. Symbol α_a^2 and β_b^2 refer, respectively to the coefficients of variance. Higher values of α_a^2 correspond to the higher variability in part type arrivals and can be used to indicate higher part type demand variability and predictability. The values of β_b^2 explain the variability in part processing times that is in the model to represent the variability in the processing capabilities of the machine, or the processing requirements of the part types. Variability in processing speeds, tool handing, setups, and machine breakdowns are referred to as machine related variability. The part related variability (ϑ) is due to part variety in the product mix or too frequent changes in design and manufacturing specifications of the part types and is expressed in equation (1). The variability is expressed as an increasing function that follows the Poisson distribution P(X),

$$\vartheta = \frac{(1+\beta_b^2)(\alpha_a^2+\mu^2\beta_b^2)}{2(1+\mu^2\beta_b^2)} * P(\mathrm{X}) \qquad \dots (1),$$

where, the ratio of processing time to part inter-arrival time is expressed as

$$\mu = \frac{\varphi}{\lambda} \qquad \dots (2),$$

The coefficient of variance β_b is mathematically expressed as,

$$\beta_b^2 = \lambda^2 \sum_{j=1}^{J} \frac{\varphi_j}{\varphi} \left(\frac{1}{\lambda_j} - \frac{1}{\lambda} \right)^2 \qquad \dots (3)$$

The overall average arrival rate is expressed as,

$$\varphi = \sum_{j=1}^{J} \varphi_j \qquad \dots (4)$$

and average processing time is expressed as,

$$\frac{1}{\lambda} = \sum_{j=1}^{J} \frac{\varphi_j}{\varphi} \frac{1}{\lambda_j} \qquad \dots (5)$$

The Poisson distribution function is defined in equation (6),

$$P\{X = h\} = \begin{cases} e^{-\hbar \frac{\hbar^u}{u!}} & h \geq 0 \\ 0 & h < 0 \end{cases} \qquad \dots (6)$$

where parameter $\hbar$ of the Poisson distribution represents the average rate of occurrence of the event of interest.

Proposition 3.1: The probability function is selected in such a manner that makes the variability an increasing function.

Proof: Since Benjaafar *et al.* (1995) has already demonstrated that ϑ is an increasing function. So, inherent task is to prove P (X) as an increasing function. we assume that,

Let $f(h) = e^{-\hbar \frac{\hbar^u}{u!}}$ $\qquad \dots (7)$

$$f'(h) = -u\hbar^{u-1} e^{-\hbar \frac{\hbar^u}{u!}} \qquad \dots (8)$$

Since $f^{'}(h)$ is less than zero and $f^{''}(h)$is greater than zero this implies that the function is monotonically increasing that means the variability is an increasing function. The plot of variability versus P(X) is shown in figure (2).

<<Include Figure 2 about here>>

The performance measures are increasing function of demand and processing variability. The effect of flexibility on the performance can be easily shown to increase in magnitude as variability in either processing or demand increases. That is, the performance improvement due to flexibility rises in significance as variability increases. The flexibility plays a major role in determination of the performance measures of the system, thus flexibility is expressed as an increasing function following the Gaussian probability distribution,

$$\Re = \left(\frac{m\lambda - \varphi}{\pi m} + \frac{R_z}{m} \right) * G(x) \qquad \ldots (9)$$

where G is Gaussian probability distribution function, defined in equation (10)

$$G(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\bar{x})^2}{2\sigma^2}} \qquad \ldots (10)$$

where, σ is the variance.

Proposition 3.2: The Gaussian probability is to be chosen in such a manner that the flexibility remain as an increasing function.

Proof: As already proved by Benjaafar *et al.* (1995) that $\frac{m\lambda - \varphi}{\pi m}$ is an increasing function, so to prove that $\frac{m\lambda - \varphi}{\pi m}$ * *G(x)* is an increasing function, differentiating the equation (10) gives,

$$G'(x) = -\frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(x-\bar{x})^2}{2\sigma^2}} \qquad \ldots (11)$$

Since *G' (x)* is less than zero and *G'' (x)* is greater than zero, this implies that function is monotonically increasing i.e. flexibility is an increasing function. The plot of flexibility versus Gaussian probability distribution function is shown in Figure (3).

<<Include Figure 3 about here>>

The proposed model also incorporates the AGVs for the loading and unloading of the part types on the machines. The mechanism of load and unload is based on the priority assignment to the part types and machines. This priority determination primarily depends on the various part characteristics e.g. processing time, machine loading flexibility (average number of machines per operation) etc. Part types are processed on the machines according to the priority based on the mean time between failures of machines, distances from the position of part etc. In the present work, authors have mainly considered the machine prioritization.

The priorities for the machines are evaluated as follows;

$$P_m = \frac{f_j}{f} \quad \ldots (12)$$

The above equation indicates that higher priority is assigned to the machine having larger mean time between failures.

$$P_m = \frac{D_j}{D} \quad \ldots (13)$$

Equation (13) indicates that higher priority is given to the machine having smaller distance from the position of part. The priority of the machines based on the meantime between failures and distance between parts are presented in Table (1) and Table (2) respectively. After the priority assignment the next task is the transportation of these part types in-between the job shop with the aid of AGVs. The part types may exist at the following positions:

a. Part may be partly processed and is on a machine.

b. Part may be waiting to be processed and is in the central storage.

c. Part may be processed and waiting for unloading from the machine

If the AGV reaches the machine before the previous operation on the part is completed, it has to wait until the previous operation is finished, and otherwise it can load the part, transport it to the selected machine and unload the part on the machine. The AGV, which can load the selected part on the selected machine in the least possible time, is considered. The AGV has the flexibility to load any part on any machine. In the proposed work, the authors have used AGVs for delivering the part types based on the priority determination among the machines. To overcome the uncertainties existing in the FMS scenario the AGV routing, loading and unloading has been made flexible so that the total delay time can be minimized and part types can be delivered in least possible time at desired locations.

<<Insert Table 1 about here>>

<<Insert Table 2 about here >>

The dynamic scheduling of FMSs consists of the assignment and sequencing of a set of part types among the machines in order to maintain an optimized schedule when an unexpected change of production occurs. The FMS scheduling problem consists of processing of a number of part types on a number of machines. The objective is to optimize the some measures of performance based on the completion times of the part types. Extensive research has been carried out in this area, the review of which can be found in the work carried out by Ovacik and Uzsoy (1997). The complexity prevailing in the FMSs enforced the development of a robust schedule that can absorb the uncertainties existing in the FMS environment. The proposed work deals with the generation of an extrapolative schedule that incorporates machine breakdowns, the impact of flexibility at the system operational level, and AGV scheduling under uncertain environment. Authors have made an attempt to combine these objectives in their proposed model which is mathematically represented in the following manner. The undertaken objective functions are as follows:

[a] Min $Z_{jk} = \sum_{jk \in O_l} \max\{E[RD_{jk}] - S_{jk,J}(P^S), 0\} + Y_n$ …(14)

[b] Min $E(\psi_m) = \chi + \frac{\vartheta}{\Re}$ …(15)

[c] Min $\aleph^{n}_{j,k} = TJ_{j,k} + \min\{G_{n1}\}; \forall_j, \forall_k, \forall_n$ …(16)

j= 1, 2, 3 …J; k=1, 2, 3…K

These objectives are subject to the following constraints:

$$\sum_{j=1}^{J} \sum_{k=1}^{K} W_{jkm} \leq \chi_m \qquad \dots (17)$$

$$\Re \leq 5 \qquad \dots (18)$$

$$\vartheta \neq 0 \qquad \dots (19)$$

$$E_{jk} > C_{jk} \qquad \dots (20)$$

$$\beta_b > m - 1 \qquad \dots (21)$$

$$\sum_{j=1}^{J} \sum_{k=1}^{K} P_{jk}(m_{jk}) \leq x_m \qquad \dots (22)$$

The first objective function shown in equation (14) emphasizes on minimizing the difference between the expected repair duration and the slack time inserted with random machine breakdowns. It is assumed that a set of N part types are to be processed on a set of M machines. The processing time P_{jk} are deterministic and known a priori. Let M_f be the set of machines, which are subjected to random breakdowns. The time between the breakdowns and repairs are known for the set of machines (M_f) subjected to breakdown. An extrapolative schedule is generated at the beginning of the planning horizon. Extrapolative schedule (P^S) determines the sequence of operations on machines and the amount of idle time to be inserted. To improve predictability, sequences of operations on the machines are first determined, and then idle time is inserted. The purpose of this additional idle time is to minimize the expected part completion time deviations. However, it is difficult to model directly due to the multifaceted effects of multiple, interacting breakdowns, and complex rescheduling policies. To overcome this surrogate measures are used, which are not only simple enough to be calculated easily, but also provide good measure of schedule predictability for an extrapolative schedule. Once it is selected, the amount of idle time required to be inserted before operation *k* can be determined, to optimize the selected surrogate measure for P^S.

Extrapolative scheduling enhances the predictability by inserting the additional idle time into P^S; the disturbances are absorbed by the additional inserted slack time. Let O_j be the set of operations on the machines in M_f which can affect part j i.e. the set of operations, where there exists a path from node *jk* to node J^* in the directed graph corresponding to P^S. Let S_{jk} (P^S) be the slack time of operation $k \in O_j$ with respect to part j. Let η_m be the mean rate at which breakdowns occur, and Y_m the mean repair duration on machine *m*. The expected repair duration $E[RD_{jk}]$ for operation *k* of part type *j* processed on machine *m* is given by

$$E[RD_{jk}] = \frac{P_{jk} Y_m}{\eta_m} \qquad \ldots (23)$$

Where P_{jk} is the processing time of operation *k* with respect to part type *j*
The slack of operation *k* with respect to part type *j*, if a path from *k* to J^* in the directed graph exists is given by

$$S_{jk}(P^s) = C_1(P^s) - \{V(0, jk) + V(jk, J^*)\} \qquad \ldots (24)$$

If for operation $k \in O_j$ where E $[RD_{jk}] > S_{jk}$ (P), the part type *j* will be delayed by $Z_{jk,J} = E[RD_{jk}] - S_{jk,J}(P^S)$ where $Z_{jk,J}$ is the delay in processing of part type *j* due to breakdowns during the processing of operation *k*. The first objective function defined above in equation (14) includes the parameter Y_n that is defined below in equation (25) as,

$$Y_n = G_n + TF_n ; \forall_n \qquad \ldots (25)$$

Breakdown information is used at an aggregate level, as the shapes of the distributions are not considered. The limiting factor here is that, the slack S_{jk} may not be available if operation is delayed by breakdowns during the processing of the preceding operations. The factor Y_n governs for the minimum time by which partly processed part j will be ready for loading on the nth AGV. This factor takes account the AGV routing under such dynamic conditions.

The second objective incorporates the relationship between flexibility, performance and variability and emphasizes on the determination of the flow time. In order to reduce the flow time, one can either increase the capacity, decrease variability or increase flexibility. When demand or processing variability cannot be eliminated and capacity is costly to upgrade, system flexibility becomes critical. As seen in equation (15) flexibility is of value only in the presence of some degree of variability. Thus authors have tried to minimize the flow time which incorporates all the abovementioned relationships presented in equation (15).

Finally the authors have considered an objective function that proves to incorporate AGV scheduling and is presented in equation (16). In this the authors have minimized the time of loading and unloading in order to avoid any delay associated with the product delivery. The heuristic adopted for the scheduling of AGV (Mukhopadhyay *et al.*, 1991) has been described later in the flow chart of the proposed algorithm. According to the heuristic, the AGV selection begins with associating time counters with different part types, machines, and AGVs. After prioritization of the part types, and machines, the time upto which the AGV is engaged in calculated. At last the time after which the AGV will reach the central storage is compared with the time by which the partially processed part will be ready for loading on the AGV, and the part satisfying the condition mentioned in the heuristic is selected for loading on the AGV. At first the AGV is selected randomly and later the AGV which is free is selected. If the machine breakdown occurs the machine having the priority adjacent to the previous one is selected for loading and unloading.
The constraints are defined in the equation (17) - (22). The constraint defined in equation (17) governs for the avoidance of the deadlocks. It also defines the capacity pertaining to each machine group. Equation (18) defines that flexibility should be less than 5, as increasing flexibility beyond that gives minor improvement. Equation (19) describes that variability can never be zero, as if the condition fails, flow time becomes equal to processing time and remains constant despite the consequences of the level of flexibility. Constraint (20) describes that the next operation can never start until the previous operation is finished. Constraint (21) need to be at least greater than $m-1$ for the dedicated scenario to become more desirable. Equation (22) indicates that machining time for any operation can't exceed the capacity of any machine.

4. QUICK CONVERGING SIMULATED ANNEALING (QCSA) ALGORITHM

The complexities existing in the real world environment need to be tackled by the modern optimization techniques. The scheduling problem existing in the FMS is dynamic in nature and is prone to uncertainties such as machine breakdown, deadlocks, tool breakages etc. These problems are very difficult to be solved by the conventional optimization methods. The conventional techniques such as integer linear programming (ILP), branch and bound, and other mathematical programming methods are not only time consuming as well as they do not guarantee the optimal solution. Latest development in the area of optimization methods have led to the advancement of local search heuristics such as Genetic algorithm (GA), Simulated annealing (SA) and Tabu search etc.

As the complexities are increasing in the existing scenario, the conventional optimization methods are unable to cope with those uncertainties in effective manner. They are prone to get entrapped in local optima and results in the degraded performance of the system. The probability to be entrapped in the local optima and requirement of the large search space and computational time to converge to the desired solution necessitated the development of new methodologies. A random search technique known as simulated annealing (SA) was independently proposed by Kirkpatrick *et al.* (1983) and Cerny (1985). Even if the simulated annealing is found to be more superior than GA, computational expensiveness restricts its application in some special cases (Creutz, 1983). Hence in order to map the complex problem existing in such uncertain environment motivated the authors to adopt a robust algorithm that can be proficient in exploring the search space in more efficient manner leading to the optimal solution.

The present paper deals with a latest intelligent exploration technique known as Quick Converging Simulated Annealing (QCSA), which merges the significant features of GA and SA, with some corrections incorporated in order to enhance the escaping tendency of the local optima. This new technique converges to the optimal solution requiring less computational time.

4.1 ALGORITHM

The quick converging simulated annealing (QCSA) algorithm amalgamates the elements of directed and stochastic search in order to maintain the astonishing balance between exploration and exploitation of the search space. It starts with randomly generated set of population. The crossover and mutation operations are then introduced to explore the extensive solution space. Afterwards new solutions are generated by the introduction of simulated annealing which carries out the evolution process. After the finite number of iterations the convergence occurs at the optimal or near optimal solution of the problem. The flow chart of the algorithm over the undertaken problem has been shown in Figure 4.

<<Insert about Figure 4 here>>

The steps of the QCSA algorithm are described as follows:

Step 1 : Assign number of generation n = 1. Assign the values of population size (P), maximum number of generation (G) and T (1).

Step 2 : Randomly generate a set of population size chromosomes as initial parent population.

Step 3 : Compute the fitness (X1) for each parent.

Step 4 : By using crossover and mutation produce children from each parent.

Step 5 : Compute fitness function of each child of every family. Select the best one in every family according to having highest fitness value (X2).

Step 6 : Compute ΔX = X2 – X1.

Step 7 : Get the parent for next generation out of each family, adopting following transition rules:

If (ΔX>0 or F (T (n), ΔX)>γ)

best child is accepted as parent for new generation.

else

the earlier one remains as new parent.

Step 8 : Reduce the temperature as per following cooling schedule:

$$T(n) = \frac{3.2 * T(1)}{1 + \log(T^n(1))}$$

Step 9 : Perform n = n+1.

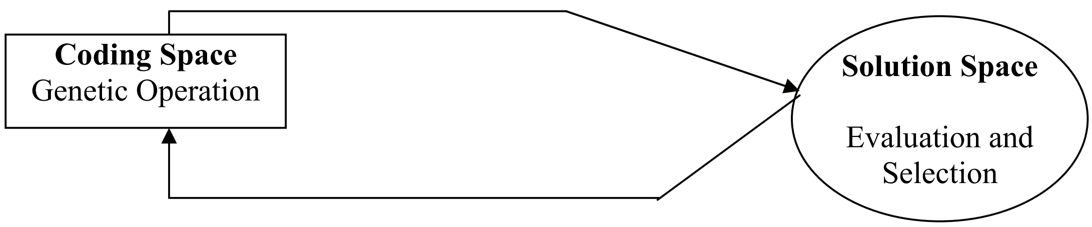
Step 10 : Select the best one of the final population according to having highest fitness value. This gives the optimal or sub-optimal solution.

STOP.

4.2 SOLUTION METHODOLOGY:

4.2.1 Encoding:

The solution encoding of the problem into a chromosome is essential for the genetic algorithm to maintain the effectiveness of the algorithm. There are various encoding schemes proposed by researchers (binary coding by Holland (1975), adjacent coding by Grefenstette *et al.*(1985), matrix-based encoding scheme by Sawaka *et al.*(1996), etc.) such as real number encoding for constrained optimization problems and integer coding for combinatorial optimization problems. Choosing an appropriate representation of candidate solutions to the problem at hand is the foundation for applying Genetic Algorithm (GA) to solve real world problems, which conditions all the subsequent steps of GAs. One of the basic features of GAs is that they work on coding space and solution space alternatively. Genetic operators work on coding space (chromosomes), while evaluation and selection works on solution space which is also known as genotype and phenotype space respectively. The solution space is the desirable area where the selection operators direct the genetic search to look for the optimal or sub-optimal solution in the possible feasible area. The coding space is the area where the genetic operators are defined in order to initiate the search process in the solution space. The mapping from the genotype and phenotype space considerably affects the performance of the genetic search. The problems usually associated with the mapping are that some individuals correspond to infeasible solutions to a given problem. It gives rise to two basic concepts of Infeasibility and Illegality. Infeasibility refers to the phenomenon that a solution decoded from chromosome lies outside the feasible region of a given problem whereas, illegality refers to the phenomenon that a chromosome does not represent a solution to a given problem. The coding and solution space is shown as follows:



4.2.2 INITIALIZATION:

The QCSA algorithm operates on a set of randomly generated population strings known as chromosomes. Chromosomes consist of a set of genes. The total number of chromosomes in the population is known as population size. The pseudo codes for this are given as,

{

begin

for i ← 1 to pop_size do

produce a random chromosome S_i ; $S_i \leftarrow$ random [i, num]

if (S_i is not feasible) then

i $\leftarrow$ i-1;

end

end

end

}

4.2.3 **EVALUATION:**

The evaluation of the fitness function is significant in deciding the appropriate population during each generation. The following steps are performed for evaluation:

Step 1: Convert the chromosomes genotype to its phenotype.

Step 2: Evaluate the objective function $f(x^k)$.

Step 3: Convert the value of objective function into fitness. For maximization problem, the fitness is simply equal to the value of objective function eval(S_k) = $f(x^k)$, k=1,2,......, pop_size.

The evaluation of this algorithm is in accordance to the multi-objective minimization problem which has been modeled in section. This evaluates the values for the problem and tries to minimize it in the larger search space by modifying the attributes of the genetic operators of the algorithm. The evaluation function of QCSA ensures that the values obtained are not trapped in local minima.

4.2.4 **CROSSOVER**

Crossover is the main genetic operator. It operates on two chromosomes at a time and generates offspring by combining features of both chromosomes. A simple way to accomplish crossover is to choose a random cut-point and generate child by combining the segment of one parent to the left of the cut-point with the segment of the other parent to the right of the cut-point. The performance of the GAs depends to a great extent on the performance of the crossover operator used. The crossover probability (p_c) is defined as the ratio of the number of the offspring produced in each generation to the population size (pop_size). This ratio controls the expected number (p_c * pop_size) of chromosomes to undergo the crossover operation. A higher crossover rate allows exploration of more solution spaces and reduces the chances of resolving for a false optimum; too high rate results in the consumption of a lot of computation time in exploring unpromising regions of the solution space. The single cut-point crossover method is explained below:

{

begin

$k \longleftarrow 0$

while ($k <= $ pop_size) do

$r_k \longleftarrow$ random number from [0,1];

if ($r_k < 0.25$) then

select S_k as one parent for crossover

end

$k \longleftarrow k+1$;

end

$h \longleftarrow 0$;

while ($h<0.25$) do

randomly take two parents;

$r_c \longleftarrow$ random number from $[1, \sum_{N=1}^{N} P_N]$;

while ($r_c \neq \sum_{N=1}^{N} P_N$) do

swap the genes;

$r_c \longleftarrow r_c + 1$;

end

$h \longleftarrow h+1$;

end

end

}

Example: Let us assume as described in the proposed problem that there are five machines. In the example shown below each digit represents the operation and their corresponding machine employed for performing the operation. Considering two parent chromosomes consisting of 16 genes each and the crossover point is selected randomly after 8TH gene. It can be represented as,

↓

Parent1 2 1 5 4 3 2 5 2 3 1 5 1 4 3 2 5

Parent 2 1 2 1 2 4 3 1 4 3 2 5 1 5 3 4 2

After performing the crossover operation by swapping the right parts of the genes, following the cut point with the other parent, the resulting child or offspring is obtained as,

Child 1 2 1 5 4 3 2 5 4 3 2 5 1 5 3 4 2

Child 2 1 2 1 2 4 3 1 2 3 1 5 1 4 3 2 5

4.2.5 MUTATION

Mutation is a background operator which produces spontaneous random changes in various chromosomes. It can be performed by altering one or more genes. The mutation rate (p_m) is defined as the percentage of the total number of genes in the population. It controls the rate at which new genes are introduced into the population. If p_m is too low many useful genes would never tried out, but if it is too high, there will be much random perturbation, the child generated will start loosing their resemblance to the parents, and the algorithm will loose the ability to learn from the history of search. The procedure for the random change mutation method is explained below:

{

begin

i ⟵ 0

while (i <= pop_size * $\sum_{N=1}^{N} P_N$ * p_m) do

select a chromosome randomly from [1, $\sum_{N=1}^{N} P_N$ *pop_size];

pick up two genes randomly;

exchange their positions;

i $\leftarrow$ i+1;

end

end

}

Example: To explain the mutation operation the same example is considered as used to explain the crossover operation. Assuming that there are five machines. Each digit in the chromosome represents the operation and the corresponding machine on which it is performed. Considering that 3^{RD} and 12^{TH} gene are selected randomly for performing mutation. It can be shown as,

↓ ↓

Parent 2 1 2 5 3 2 4 3 1 4 5 4 1 2 3 5

Both the positions of the chromosome are swapped and the resulting child is represented as

Child 2 1 4 5 3 2 4 3 1 4 5 2 1 2 3 5

The child generated after mutation consists of 4 at position 3 and 3 at position 4.

4.2.6 SELECTION

After performing the crossover and mutation, the best child produced in each family is selected on the basis of some selection criteria for the next generation's population. This selection criterion is inspired by the simulated annealing approach, which uses transition probability function to accept downhill moves escaping the entrapment at local minima.

These criterions are:

Fitness criterion: The next generation's population is selected on the basis of the fitness value. If the offspring generated has fitness better than the parent, it will go to the next generation. This can be calculated as:

$\Delta X = X2 - X1$ where, X2 = fitness function of the best child in each family

X1 = fitness function of the parent of that family

If the difference of the functions ΔX comes out to be greater than zero, the best child is accepted as parent for new generation.

Probabilistic Criterion:

In some cases if the child has fitness value less than that of the parent of that family, there is given some probability for its acceptance, to escape the chances of entrapment in the local optimum. The Cauchy's distribution function is used here to define the probability, as:

$$F(T(n), \Delta X) = \frac{T(n)}{T^2(n) + (\Delta X)^2},$$

Where *T (n)* = temperature during n^{th} generation.

When F (T (n), ΔX) > γ, where γ is any random number in the interval [0, 1], then the substandard one moves to the next generation.

4.2.7 COOLING SCHEDULE:

Cooling schedule is of prime significance as it determines the value of transition probability function used during the selection criterion. In the present work the cooling schedule is defined as:

$$T(n) = \frac{3.2 * T(1)}{1 + \log(T^n(1))}$$

Where *T (1)* = temperature for the 1^{ST} generation.

The search is started with a high temperature that results in a high probability of moving away from the best solution found till then. But the temperature declines as the search proceeds and at the end it is expected to move away from a worse neighboring solution.

4.2.8 TERMINATION CRITERION:

The process is re-iterated for a finite number of times from the beginning. To terminate the search procedure the following termination criterion is incorporated:

```
{
Begin
n ⟵ n+1;
if (n > max_no_gen) then
terminate the search;
```

the final population with the best fitness is the optimal or sub-optimal solution;
end
end. }

5. Results and Discussion

The present section details the various results pertaining to underlying issue. The paper deals with a FMS model that is capable of performing a wide variety of operations. The model incorporates the flexibility measures to cope up with the underlying uncertainties. The authors have attempted to study the impact of those flexibility measures under such dynamic conditions in the FMS environment. The data sets for the mean repair duration, mean time between breakdowns, and processing time of the part types (Chan *et al*., 2004) for the machines are presented in Table (3), Table (4), and Table (5) respectively. Part inter-arrival times and distance between part types are shown in Table (6) and (7). After the intensive experimentations over the genetic parameters, the crossover probability is found to be 0.5 and mutation probability to be 0.01. The initial temperature was considered to be 500 and final temperature was found to 10 by the applied algorithm.

<<Insert Table 3 about here>>

<<Insert Table 4 about here>>

<<Insert Table 5 about here>>

<<Insert Table 6 about here>>

<<Insert Table 7 about here>>

The model consists of a set of five machines (M_f) working under such dynamic environment. Total eight different part types are to be processed on those machines. To study the impact of the uncertainties such as machine failure, the authors have constructed a breakdown scenario, which is represented in Table (8). The breakdown scenario consists of different parameters such as number of machines subjected to failures, time between the breakdowns, and the expected repair durations (E [RD_{jk}]). The number of machines prone to breakdowns is given by ωM_f, where ω is the fraction of machines subject to breakdowns. The authors have considered the values of ω to be 0.2 and 0.6. Thus, the total number of machines prone to failure ranges from 1 to 3 machines. The time between the breakdowns varies for different machines and it is exponentially distributed with mean $\ell E\ [P_{jk}]$, where $E\ [P_{jk}]$ is the expected processing time for operation k. The value of ℓ is considered to be 5 and 10. The repair durations also differ for each machine and are distributed with mean € $E\ [RD_m]$ where, value of € is considered to be 0.1 and 0.3. Thus, as per the Table (8) the total eight different breakdown scenarios have been generated. To show the impact of flexibility on the flow time, the data sets are prepared with the incorporation of flexibility under the similar scenario. System performance is obtained for various levels of variability and it is achieved by gradually increasing the variance in the part inter-arrival times and processing times. The effect of flexibility shows a diminishing rate of return curve for all levels of variability, it also shows that effect of flexibility is particularly significant when either demand or processing variability is high. With increasing flexibility after certain level the flow time remains almost unaffected (figure 6). This diminishing effect of the flexibility has also been studied by Bobrowski *et al.* (1988) and Chen *et al.* (1991). In the highly flexible and dynamic environment considered in the present work, the authors have tried to find appropriate schedule for AGV routing. The time taken by the AGV to load the part and deliver to the central storage has been evaluated under the existing breakdown scenario.

<<Insert Table 8 about here>>

The computational results based on the above mentioned breakdown scenarios for the first objective function have been shown in Table (9).The average flow time and time taken by the AGV to load the part and deliver to the central storage has been evaluated under the same existing breakdown scenario and are presented in Table (10) and Table (11). The results of the data sets under such breakdown scenarios, after successive number of iterations reflect the superiority of the incorporated algorithm to converge towards the optimality. The results comparison of the average flow time with respect to the flexibility measures has been shown in figure (5) and (6). The plot for the time taken by AGV versus the routing flexibility is shown in figure (7). The comparison of the machine priorities based on mean time between failures and distance between parts are shown in figure (8) and (9).

<<Include Figure 5 about here>>

<<Include Figure 6 about here>>

<<Include Figure 7 about here>>

<<Include Figure 8 about here>>

<<Include Figure 9 about here>>

<<Insert Table 9 about here>>

<<Insert Table 10 about here>>

<<Insert Table 11 about here>>

To evaluate the performance of the algorithm, the data sets and the relevant parameters have been organized into three categories known as small (S), medium (M) and large (L) data set. These parameter values are used for testing the performance of the QCSA algorithm and are presented in Table (12).

<<Insert Table 12 about here>>

The performance of the algorithm has been evaluated by a new parameter known as *Percentage Heuristic Gap (PHG)*. It can be mathematically expressed as (Chan *et al., 2007)*:

$$PHG = \frac{(best\ upper\ bound\ -\ best\ lower\ bound\ )}{best\ lower\ bound} \times 100 \qquad ...\ (26)$$

Here, lower bound is calculated by relaxing some of the constraints in the objective function related to the existing problem, whereas the upper bound is the objective function value of any feasible solution satisfying all the constraints. From the definition of *PHG,* it can be clearly visualized that the near optimal solution of the problem is guaranteed if its value is very small. The *PHG* for small, medium, and large data sets are presented in Table (13)-(15). The variation of *Heuristic Gap* with the number of iterations has been shown in Figure (10).

<<Insert Table 13 about here>>

<<Insert Table 14 about here>>

<<Insert Table 15 about here>>

<<Insert Figure 10 about here>>

Figure (10) clearly depicts that as the number of iterations increases *Heuristic Gap* constantly decreases and its very low value at the later stages assures the near optimal solution. These values also establish the efficacy of the proposed algorithm. The average Percentage Heuristic Gap's for different problem sizes mentioned above are shown in Table (16).

<<Insert Table 16 about here>>

To statistically validate the results obtained by the QCSA algorithm the two ways ANOVA without replication was performed on the problem parameters. The results of the ANOVA test are provided in the Tables (17) and (18). The results of ANOVA test shows that the value of $F_{crit} < F$, which proves the accuracy of the proposed algorithm under such breakdown scenarios. F test is carried out at 99.5% confidence level which is highly significant. Thus, it statistically validates the robustness of the algorithm. The proposed QCSA approach has been also compared with some standard priority rules and results are much better than those obtained from the priority rules

(Figure11). These comparisons show significant improvement in the results on applying the QCSA algorithm and the results converge towards the optimality nearly after (40) iterations. The programming for the considered problem have been coded in C++ and tested on Pentium IV, 1.6MHZ processor, having 128 MB RAM.

<<Insert Figure 11 about here>>

<<Insert Table 17 about here>>

<<Insert Table 18 about here>>

6. Conclusion

This research presents the methodology of scheduling while there are various types of uncertainties involved in the manufacturing system. The performance of FMS has been optimized using the developed methodology that includes the flexibilities pertaining to resources such as machines and AGVs in uncertain environment. An extrapolative schedule has been generated to tackle the existing uncertainties such as machine breakdowns, deadlocks etc. in the FMS environment. The developed solution methodology provides the minimum average delay time and average flow time in an unpredictable environment. This has been indicated by plotting the graph for variation of flexibility with respect to system performance. The potential of QCSA in solving a complex and real time manufacturing system problem is highlighted in this paper. Performance of QCSA has been statistically validated using *PHG* and ANOVA analysis. The comparison with the standard priority rules further states the ability of the tested algorithm to converge towards the optimality.

7. Future Research

Although lot of work have been already done in this area, still the need of further improvisation of the system performance can be well viewed by the increasing trend of the complexities prevailing in the present scenarios. In our view the proposed approach can be extended to cover more practical situations which include the multistage scheduling of parts in uncertain FMS. The ability of the QCSA algorithm to converge towards the optimality in less computational time, and escaping the local optima, lefts its scope of further extension in other complex scenarios. The real time problems are more complex than those considered in this paper. Hence there is need of further study in this area involving more constraints and objective functions.

APPENDIX I

Notation:

C_{jk} = completion time of operation *k* for part type *j*.

Dj = Distance between the part types.

$E\ [RD_{jk}]$ = Expected repair duration for operation *k* processed on machine m.

$E_{j,\,k}$ = Starting time of operation *k* for part *j*.

$E\ (\Psi_m)$ = expected flow time.

f_j = mean time between failures.

G(X) = Gaussian probability distribution function.

G_{n1} = time taken by nth AGV to reach to the selected part.

G_n = time count for the nth AGV indicating time up to which the AGV is engaged

j = number of part types to be machined

k = number of operations to be performed

K_T = Part type counter.

m = number of machines.

P_{jk} = processing time of part type *j* with respect to operation *k*.

P(X) = Poisson's probability distribution function.

P^s = extrapolative schedule.

P_m = priority of the machine.

p_m = mutation rate

S_{jk} = slack of operation *k* with respect to the part type *j*.

$TJ_{j,\,k}$ = time count for part *j* processed by operation *k* indicating time up to which the part will be engaged or scheduled.

TF_n = time taken for the nth AGV to reach the central storage from present position.

TH_m = time up to which the machine m will be engaged

$TAGV_n$ = total time taken by nth AGV to load, transport and load on the selected machine

V (a, b) = length of the longest path from a to b.

W_{jkm} = workload for part *j* processed by operation *k* on machine m

χ_m = processing speed or capacity.

$\aleph^n_{j,k}$ = minimum time by which partly processed part *j* processed by operation k will be ready for loading on nth AGV.

Y_m = mean repair duration on machine *m*.

Y_n = minimum time by which partly processed part *j* will be ready for loading on the nth AGV.

Z_{jk} = delay time of part type j processed by operation k.

α_a = coefficient of variance of the processing time distributions.

β_b = coefficient of variance of the part inter-arrival time distributions.

φ = part arrival rate.

λ_j = part processing time of part *j*.

μ = ratio of processing time to the part inter-arrival time.

η_m = mean rate at which breakdowns occur.

ϑ = an increasing function of variability.

$\Re$ = an increasing function of flexibility.

n : number of generation

T(n) : temperature during the n^{th} generation

X1 : Fitness function of the parent of each family

X2 : Fitness function of the best child in each family

ΔX : difference between the fitness function of the best child and the parent in each family

F (T (n), ΔX) : Cauchy distribution function defined as $\frac{T(n)}{T^2(n)+(\Delta X)^2}$

γ : random number distributed uniformly between 0 and 1

G : maximum number of generation

P : size of population i.e. number of chromosomes in a population

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Table 1: Priority table for machines on the basis of mean time between failures

Machine Number	Priority
1	0.2258
2	0.2903
3	0.1290
4	0.1613
5	0.1935

Table 2: Priority table for machines on the basis of distance from the selected part types

Machines (*m*)	Priority
1	0.066
2	0.133
3	0.200
4	0.266
5	0.333

Table 3: Mean repair durations on machines

Machine Number	Mean repair durations
1	35
2	45
3	20
4	25
5	30

Table 4: Mean Time between failures

Machines (m)	Mean time between failures
1	1940
2	2000
3	1850
4	1720
5	1640

Table 5: Processing Times for different Parts (Chan *et al.*, 2004)

Part Type	Operation I		Operation II		Operation III		Operation IV	
	M/C	Time (min)	M/C	Time (min)	M/C	Time (min)	M/C	Time (min)
1	1 (2)	15 <18>	3	24	5	10	2 (1)	30 <25>
2	2 (3)	20 24	3 (2)	10 <16>	5	35	4	25
3	5	40	1	25	4 (3)	30 <27>	2	15
4	4	30	2	30	5	20	3 (1)	25 <15>
5	1	10	3	20	2 (5)	15 <20>	4	30
6	3 (5)	25 <20>	2	12	1	25	5 (3)	10 <23>
7	4 (1)	35 <38>	5	10	1 (4)	10 <15>	2	15
8	5 (4)	15 <10>	4 (5)	40 <30>	3	25	1	20

(): Alternative machine and <>: Corresponding machining time

Table 6: Part inter-arrival times

Part types	Inter-arrival times (min)
1-2	2
2-3	4
3-4	5
4-5	8
5-6	6
6-7	3
7-8	2

Table 7: Distance Between the part types

Part Types	Distance Between the Part types (meters)
1-2	4
2-3	6
3-4	8
4-5	5
5-6	2
6-7	4
7-8	3

Table 8: Machine Breakdown Scenario

Breakdown Considerations	Values	Total combinations
Number of machines prone to failure M_f	ωM_f where ω = 0.2, 0.6	2
Time between breakdown	Exp(ℓE [P_{jk}]) Where ℓ = 5, 10	2
Repair Durations	€ E [RD_{jk}] where € = 0.1, 0.5	2
Total parameter combinations	(ω, ℓ, €) values S1 – (0.2, 5, 0.1) S2 – (0.6, 5, 0.1) S3 – (0.2, 5, 0.5) S4 – (0.6, 5, 0.5) S5 – (0.2, 10, 0.1) S6 – (0.6, 10, 0.1) S7 – (0.2, 10, 0.5) S8 – (0.6, 10, 0.5)	8

Table 9: Average Delay times for various breakdown scenarios

Average Delay Time			
Problem Class	**I (10)**	**I (30)**	**I (40)**
S1 – (0.2, 5, 0.1)	129.68	120.00	119.86
S2 – (0.6, 5, 0.1)	103.36	96.01	95.35
S3 –(0.2, 5, 0.5)	88.25	84.01	82.66
S4 – (0.6, 5, 0.5)	70.56	67.20	66.66
S5 – (0.2, 10, 0.1)	64.84	60.52	59.52
S6 – (0.6, 10, 0.1)	51.84	48.94	48.19
S7 – (0.2, 10, 0.5)	48.63	44.32	44.29
S8 – (0.6, 10, 0.5)	38.88	36.44	36.14

Table 10: Average Flow times for various breakdown scenarios

Average Flow Time			
Problem Class	I (10)	I (30)	I (40)
S1 – (0.2, 5, 0.1)	40.922	39.627	38.988
S2 – (0.6, 5, 0.1)	39.272	38.921	37.132
S3 – (0.2, 5, 0.5)	41.200	38.945	38.265
S4 – (0.6, 5, 0.5)	38.067	37.643	37.158
S5 – (0.2, 10, 0.1)	36.457	35.940	34.663
S6 – (0.6, 10, 0.1)	34.001	33.782	32.808
S7 – (0.2, 10, 0.5)	42.049	38.419	37.614
S8 – (0.6, 10, 0.5)	38.145	36.937	35.739

Table 11: Average delay time for AGV under various breakdown scenarios

Average Delay Time			
Problem Class	I (10)	I (30)	I (40)
S1 – (0.2, 5, 0.1)	24.882	21.499	21.205
S2 – (0.6, 5, 0.1)	21.714	19.64	19.57
S3 – (0.2, 5, 0.5)	23.32	20.855	20.612
S4 – (0.6, 5, 0.5)	19.767	16.395	16.192
S5 – (0.2, 10, 0.1)	22.532	19.212	19.015
S6 – (0.6, 10, 0.1)	18.617	16.362	16.123
S7 – (0.2, 10, 0.5)	17.719	15.668	15.572
S8 – (0.6, 10, 0.5)	13.689	12.480	11.347

Table 12: Parameter values related to the data sets of problem

Classification	Number of Part types	Number of Operations
Small	3	1-2
	4	2-4
Medium	5	4-6
	6	6-8
Large	7	8-10
	8	10-12

Table 13: Computational data for small sized data set

Number of Part Types (j)	Number of Operations (k)	% Heuristic Gap (PHG)
3	1	1.935
3	2	1.595
4	3	1.746
4	4	2.012

Table 14: Computational data for the medium sized data set

Number of Part Types (j)	Number of Operations (k)	% Heuristic Gap (PHG)
5	4	1.271
5	5	2.975
6	6	1.467
6	8	3.015

Table 15: Computational data for the large sized data

Number of Part Types (j)	Number of Operations (k)	% Heuristic Gap (PHG)
7	8	2.051
7	9	2.145
8	11	2.237
8	12	2.225

Table 16: Average Heuristic gap for different problem sizes

Classification	L	H	Average
S	1.765	1.879	1.822
M	2.123	2.241	2.182
L	2.098	2.231	2.1645

Table 17: Intermediate values of the two-way ANOVA test without replication

SUMMARY	*Count*	*Sum*	*Average*	*Variance*
Row 1	2	3.644	1.822	0.006498
Row 2	2	4.364	2.182	0.006962
Row 3	2	4.329	2.1645	0.008845
Column 1	3	5.986	1.995333	0.039946
Column 2	3	6.351	2.117	0.042508

Table 18: Results of ANOVA test.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Rows	0.164808	2	0.082404	1642.608	0.000608	19
Columns	0.022204	1	0.022204	442.608	0.002252	18.51282
Error	0.0001	2	5.02E-05			
Total	0.187113	5				

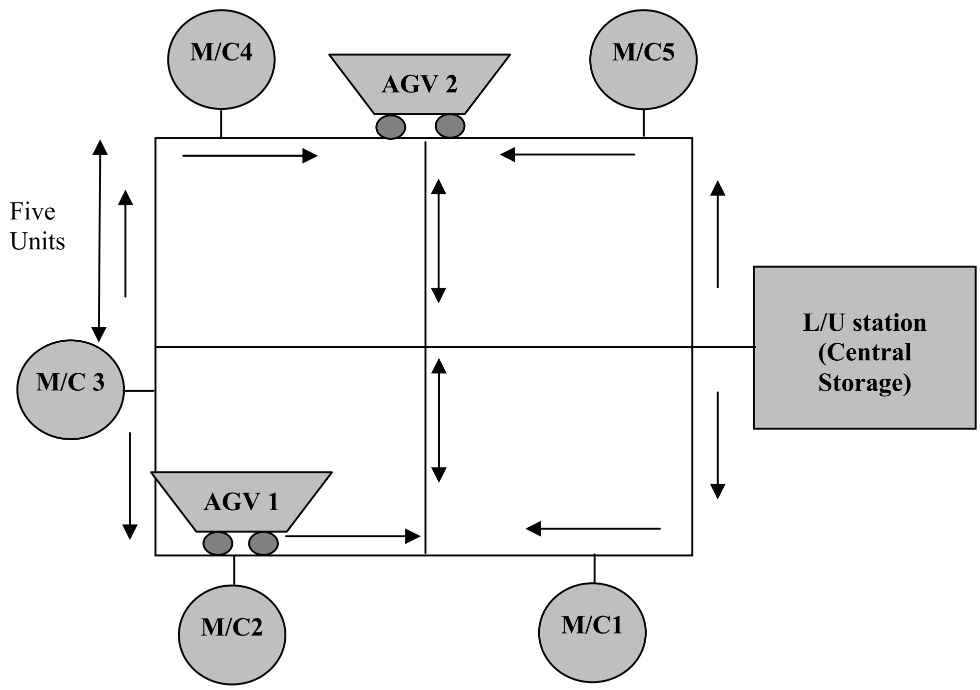


Figure 1: Schematic layout of the FMS model

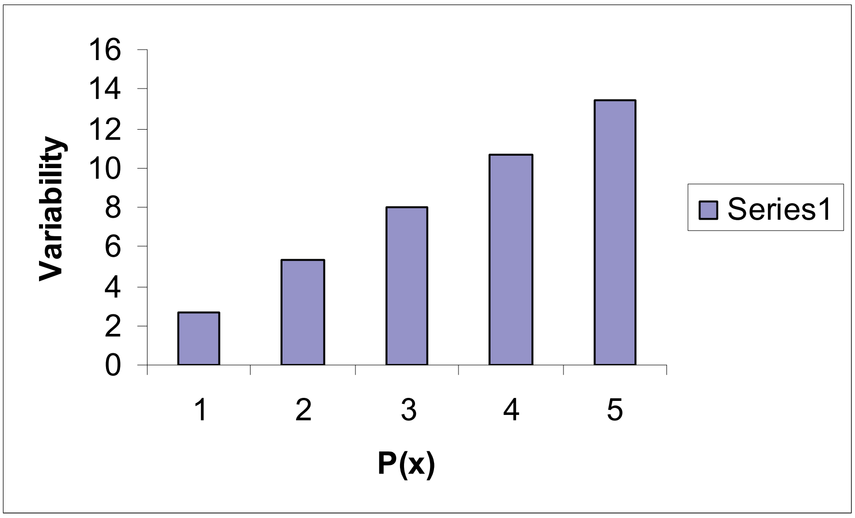


Figure 2: Variability versus Poisson's distribution function

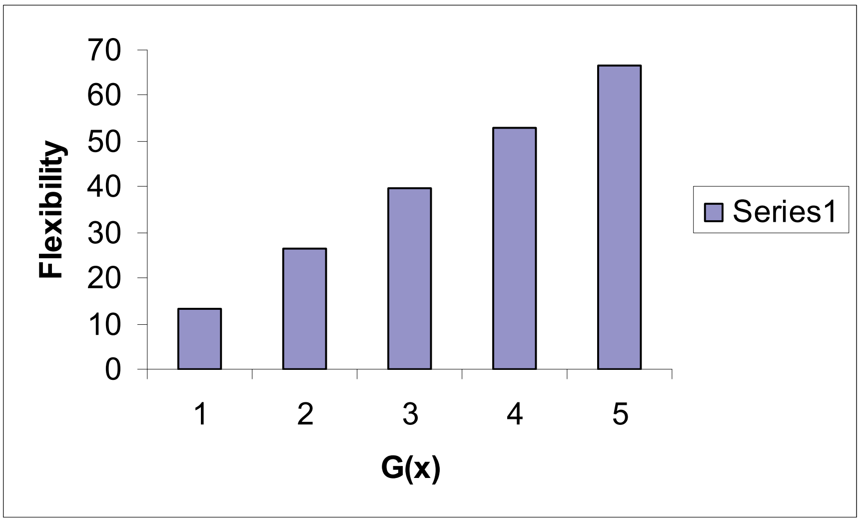
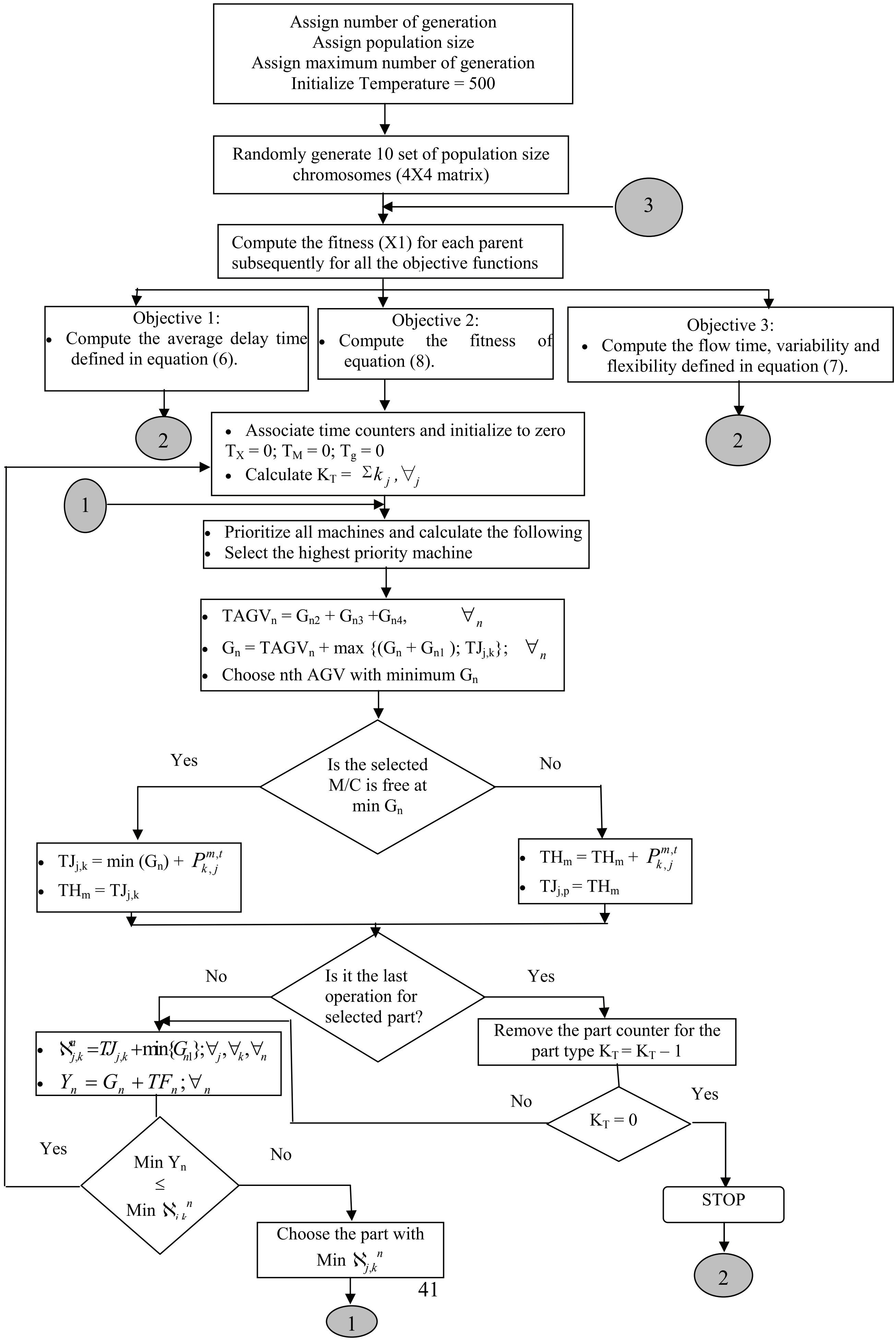


Figure 3: Flexibility versus Gaussian distribution function


Assign number of generation
Assign population size
Assign maximum number of generation
Initialize Temperature = 500
Randomly generate 10 set of population size chromosomes (4X4 matrix)
3
Compute the fitness (X1) for each parent subsequently for all the objective functions
Objective 1:
Compute the average delay time defined in equation (6).
Objective 2:
Compute the fitness of equation (8).
Objective 3:
Compute the flow time, variability and flexibility defined in equation (7).
2
Associate time counters and initialize to zero
$T_X = 0; T_M = 0; T_g = 0$
Calculate $K_T = \Sigma k_j, \forall_j$
1
Prioritize all machines and calculate the following
Select the highest priority machine
$TAGV_n = G_{n2} + G_{n3} + G_{n4}, \quad \forall_n$
$G_n = TAGV_n + \max\{(G_n + G_{n1}); TJ_{j,k}\}; \quad \forall_n$
Choose nth AGV with minimum G_n
Yes
Is the selected M/C is free at min G_n
No
$TJ_{j,k} = \min(G_n) + P_{k,j}^{m,t}$
$TH_m = TJ_{j,k}$
$TH_m = TH_m + P_{k,j}^{m,t}$
$TJ_{j,p} = TH_m$
No
Is it the last operation for selected part?
Yes
$\aleph_{j,k}^n = TJ_{j,k} + \min\{G_{n1}\}; \forall_j, \forall_k, \forall_n$
$Y_n = G_n + TF_n; \forall_n$
Remove the part counter for the part type $K_T = K_T - 1$
No
$K_T = 0$
Yes
Yes
Min Y_n ≤ Min $\aleph_{j,k}^n$
No
STOP
Choose the part with Min $\aleph_{j,k}^n$
1

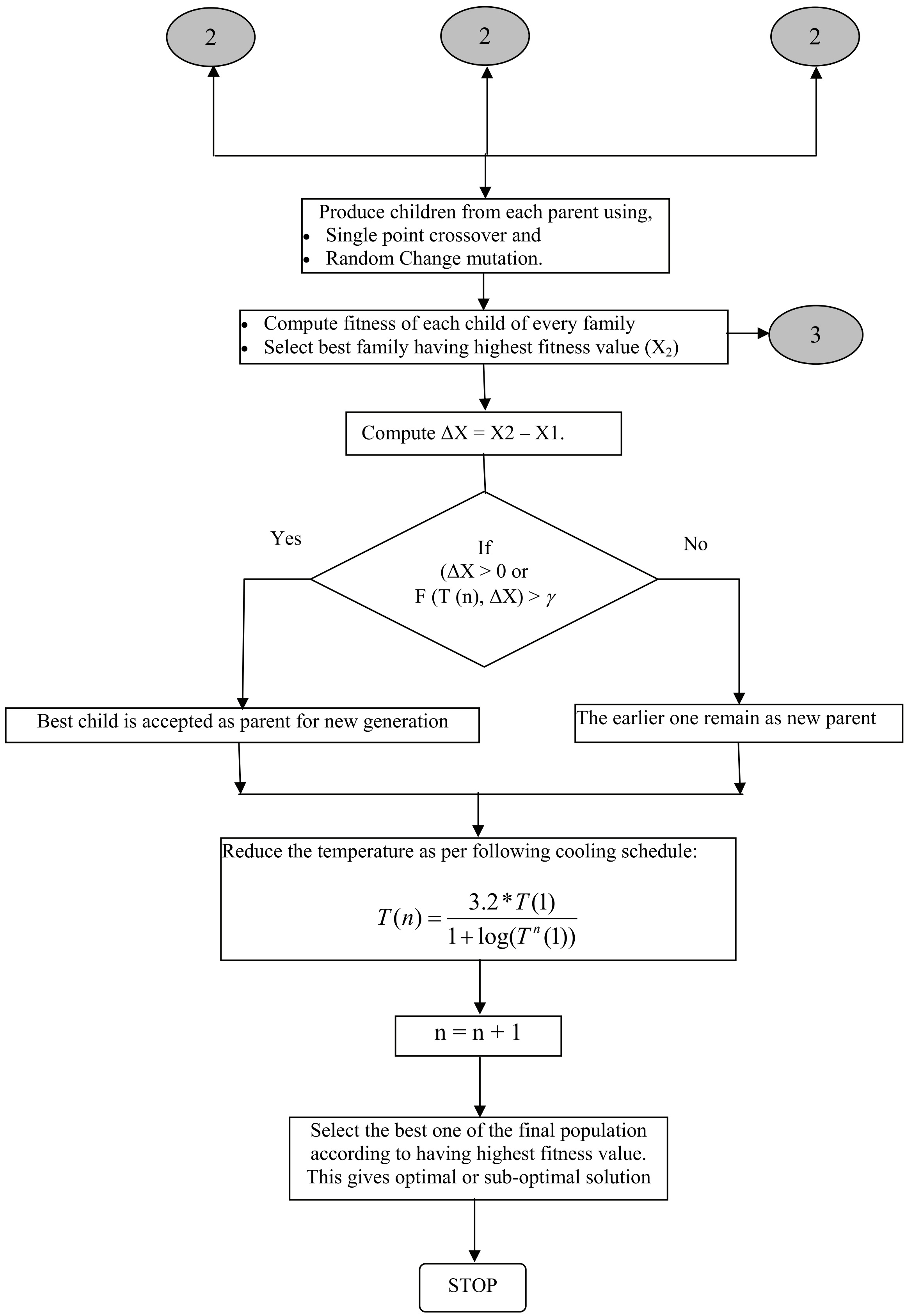


Figure 4: Flow chart of algorithm over the undertaken problem

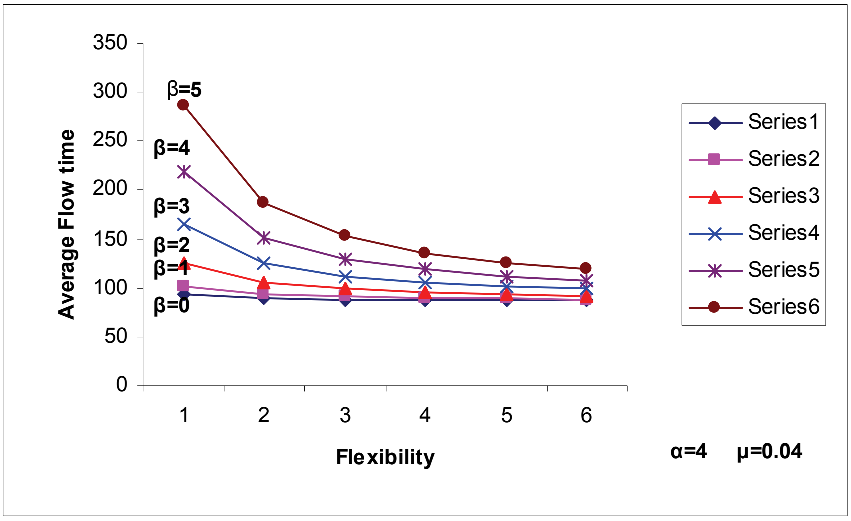


Figure 5: Flow time versus Flexibility (α= 4, μ=.04)

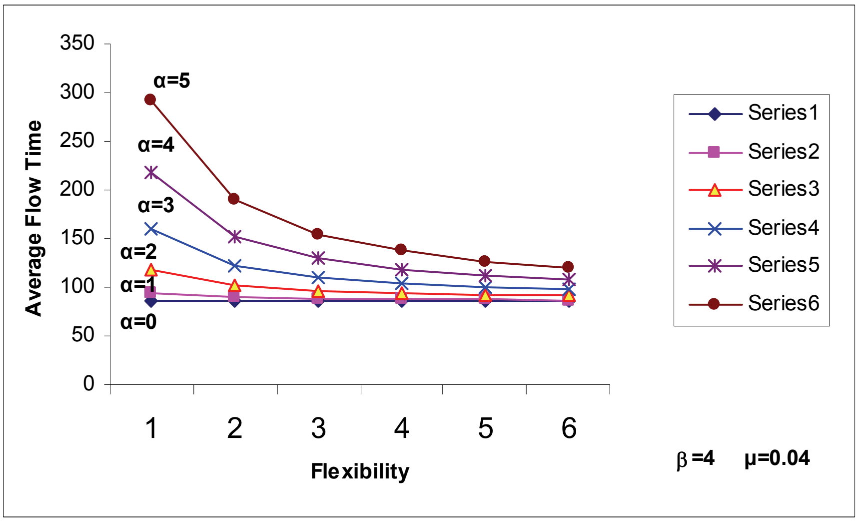


Figure 6: Flow Time versus Flexibility (β=4, μ=.04)

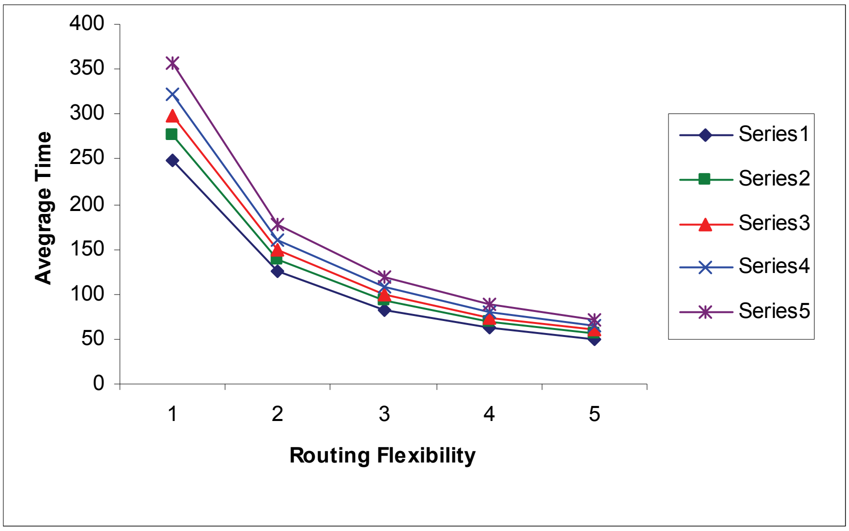


Figure 7: Average time taken by AGV versus routing flexibility

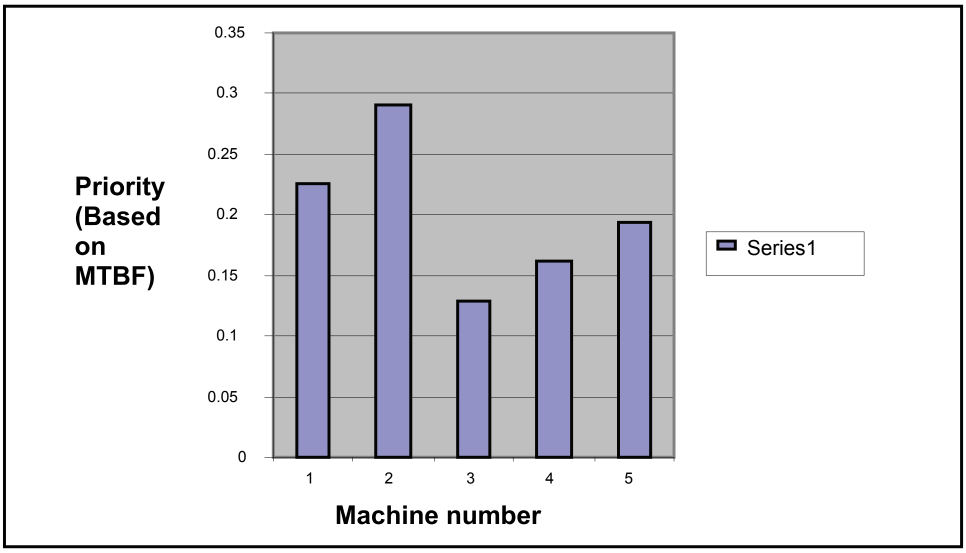


Figure 8: Comparison of priority of M/Cs based on Mean Time between Failures (MTBF)

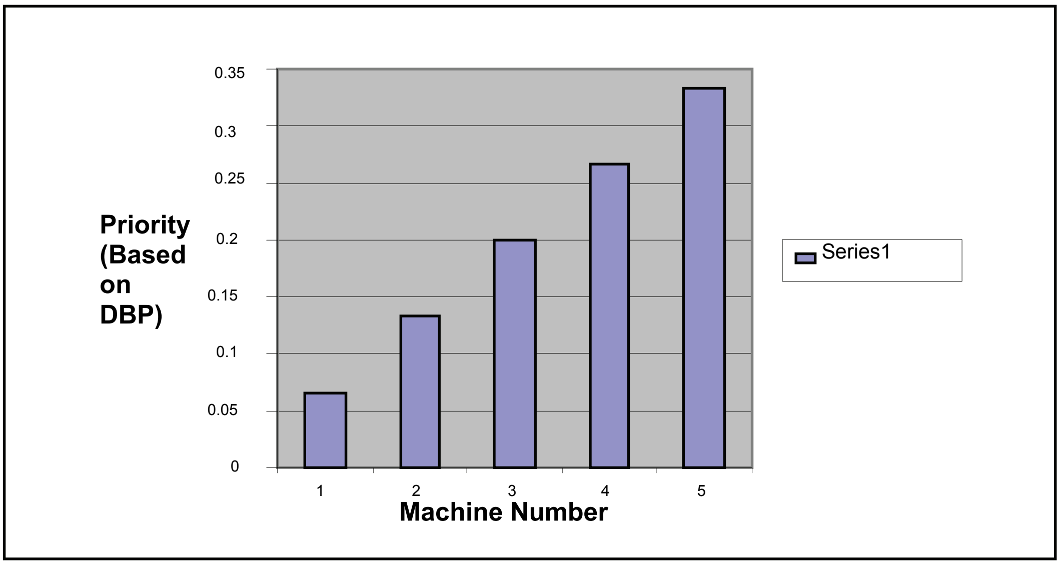


Figure 9: Comparison of priority of M/Cs based on distance between the parts

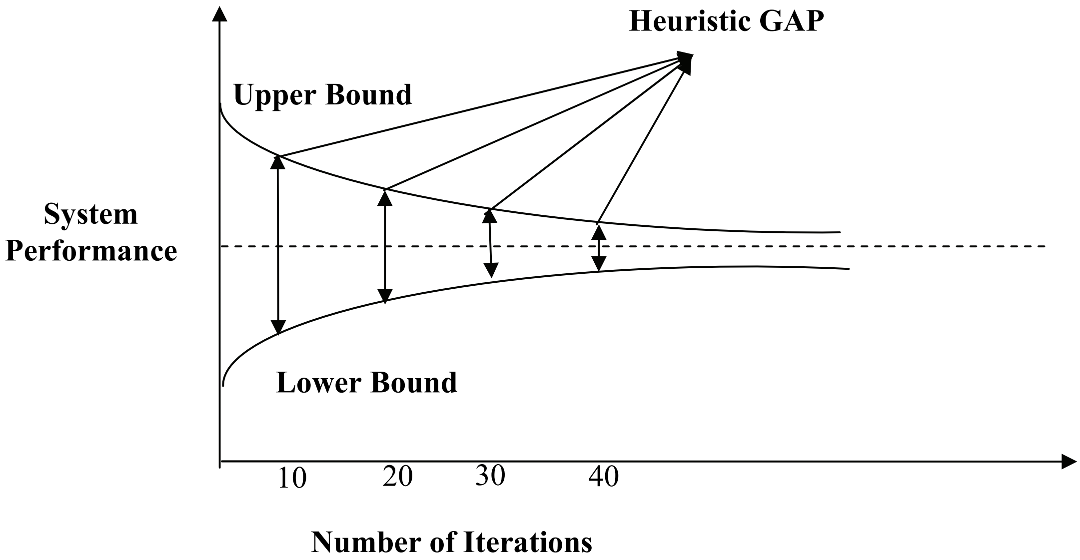


Figure 10: System performance relative to the number of iterations

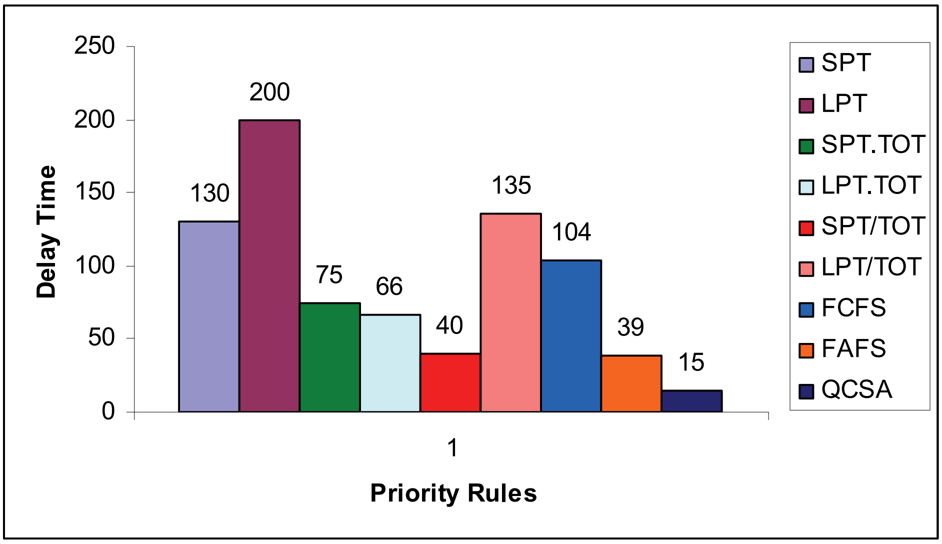


Figure 11: Comparison of QCSA with standard priority rules