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ANALYSIS AND MODELING OF FLEXIBLE MANUFACTURING SYSTEM

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Analysis and Modeling of Flexible Manufacturing System

by

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CERTIFICATE

This is to certify that M. Tech thesis entitled, "Analysis and Modelling of Flexible Manufacturing System" submitted by Naveen Kumar Suniya in partial fulfillments for the requirements of the award of Master of Technology degree in Mechanical Engineering at National Institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance. He has fulfilled all the prescribed requirements and the thesis, which is based on candidate's own work, has not been submitted elsewhere.

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Dedicated to my loving parents

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Analysis and Modeling of Flexible Manufacturing System

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Abstract

Analysis and modeling of flexible manufacturing system (FMS) consists of scheduling of the system and optimization of FMS objectives. Flexible manufacturing system (FMS) scheduling problems become extremely complex when it comes to accommodate frequent variations in the part designs of incoming jobs. This research focuses on scheduling of variety of incoming jobs into the system efficiently and maximizing system utilization and throughput of system where machines are equipped with different tools and tool magazines but multiple machines can be assigned to single operation. Jobs have been scheduled according to shortest processing time (SPT) rule. Shortest processing time (SPT) scheduling rule is simple, fast, and generally a superior rule in terms of minimizing completion time through the system, minimizing the average number of jobs in the system, usually lower in-process inventories (less shop congestion) and downstream idle time (higher resource utilization). Simulation is better than experiment with the real world system because the system as yet does not exist and experimentation with the system is expensive, too time consuming, too dangerous. In this research, Taguchi philosophy and genetic algorithm have been used for optimization. Genetic algorithm (GA) approach is one of the most efficient algorithms that aim at converging and giving optimal solution in a shorter time. Therefore, in this work, a suitable fitness function is designed to generate optimum values of factors affecting FMS objectives (maximization of system utilization and maximization of throughput of system by Genetic Algorithm (GA) approach.

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Chapter 1: Introduction

In today's competitive global market, manufacturers have to modify their operations to ensure a better and faster response to needs of customers. The primary goal of any manufacturing industry is to achieve a high level of productivity and flexibility which can only be done in a computer integrated manufacturing environment. A flexible manufacturing system (FMS) is an integrated computer-controlled configuration in which there is some amount of flexibility that allows the system to react in the case of changes, whether predicted or unpredicted. FMS consists of three main systems. The work machines which are often automated CNC machines are connected by a material handling system(MHS) to optimize parts flow and the central control computer which controls material movements and machine flow. An FMS is modeled as a collection of workstations and automated guided vehicles (AGV). It is designed to increase system utilization and throughput of system and for reducing average work in process inventories and many factors affects both system utilization and throughput of system in this research system utilization and throughput of system has been optimized considering factors, which is discussed in next sections.

1.1. Flexible manufacturing system

A system that consists of numerous programmable machine tools connected by an automated material handling system and can produce an enormous variety of items. A FMS is large, complex, and expensive manufacturing in which Computers run all the machines that complete the process so that many industries cannot afford traditional FMS hence the trend is towards smaller versions call flexible manufacturing cells. Today two or more CNC machines are considered a Flexible Manufacturing Cell (FMC), and two or more cells are considered a Flexible Manufacturing System (FMS)

"*Flexible manufacturing system is a computer controlled manufacturing system, in which numerically controlled machines are interconnected by a material handling system and a master computer controls both NC machines and material handling system."[1]*

The primary goal of any manufacturing industry is to achieve a high level of throughput, flexibility and system utilization. System utilization computed as a percentage of the available hours (Number of the machines available for production multiplied by the number of working hours), it can be increased by changing in plant layout, by reducing

transfer time between two stations and throughput, defined as the number of parts produced by the last machine of a manufacturing system over a given period of time. If the no of parts increases throughput also increases and also system utilization increases. Flexible manufacturing system consist following components

Work station: work station consist computer numerical controlled machines that perform various operations on group of parts. FMS also includes other work station like inspection stations, assembly works and sheet metal presses.

Automated Material Handling and Storage system: Work parts and subassembly parts between the processing stations are transferred by various automated material handling systems. Many automated material handling devices are used in flexible manufacturing system like automated guided vehicle, conveyors, etc. there are two types of material handling system

Primary handling system - establishes the basic layout of the FMS and is responsible for moving work parts between stations in the system.

Secondary handling system - consists of transfer devices, automatic pallet changers, and similar mechanisms located at the workstations in the FMS.

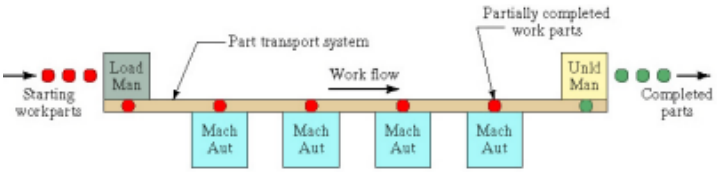
Computer Control System: It is used to control the activities of the processing stations and the material handling system in the FMS.

1.2. Flexible manufacturing system layouts

Flexible manufacturing system has different layouts according to arrangement of machine and flow of parts. According to part flow and arrangement of machine, layout of flexible manufacturing system are discussed below

1.2.1. In-line FMS layout

The machines and handling system are arranged in a straight line. In Figure 1(a) parts progress from one workstation to the next in a well-defined sequence with work always moves in one direction and with no back-flow. Similar operation to a transfer line except the system holds a greater variety of parts. Routing flexibility can be increased by installing a linear transfer system with bi-directional flow, as shown in Figure 1(b). Here a secondary handling system is provided at each workstation to separate most of the parts from the primary line. Material handling equipment used: in-line transfer system; conveyor system; or rail-guided vehicle system.



(a)

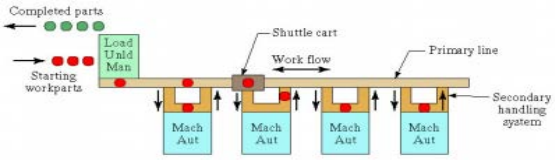


Figure 1 in line FMS layout

1.2.2. Loop FMS layout

Workstations are organized in a loop that is served by a looped parts handling system. In Figure 2, parts usually flow in one direction around the loop with the capability to stop and be transferred to any station.

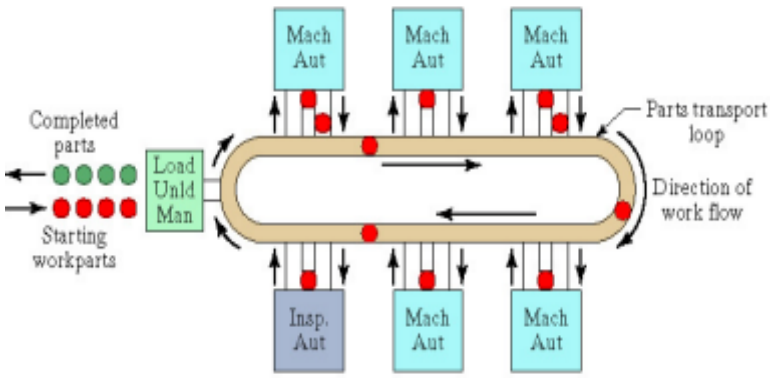


Figure 2: Loop FMS layout

Each station has secondary handling equipment so that part can be brought-to and transferred from the station work head to the material handling loop. Load/unload stations are usually located at one end of the loop.

1.2.3. Rectangular FMS layout

This arrangement allows for the return of pallets to the starting position in a straight line arrangement.

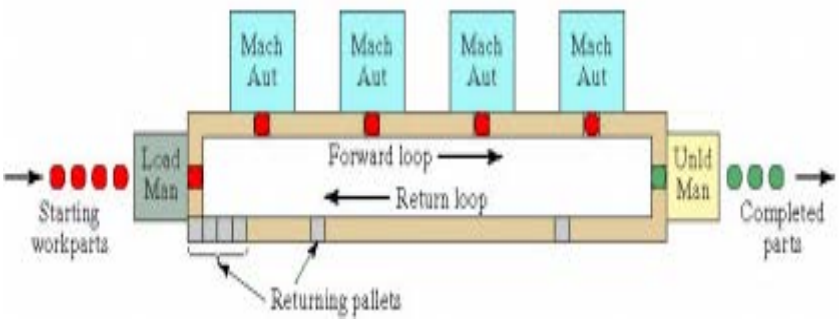


Figure 3: Rectangular FMS layout

1.2.4. Ladder FMS layout

This consists of a loop with rungs upon which workstations are located. The rungs increase the number of possible ways of getting from one machine to the next, and obviate the need for a secondary material handling system. It reduces average travel distance and minimizes congestion in the handling system, thereby reducing transport time between stations. See Figure 4.

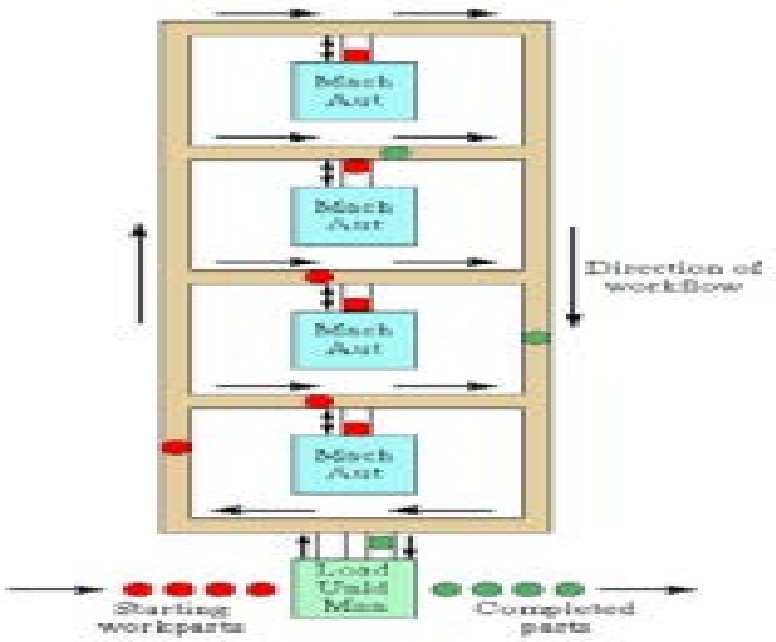


Figure 4: Ladder FMS layout

1.2.5. Open field FMS layout

It consists of multiple loops and ladders, and may include sidings also. This layout is generally used to process a large family of parts, although the number of different machine types may be limited, and parts are usually routed to different workstations depending on which one becomes available first. See Figure 5.

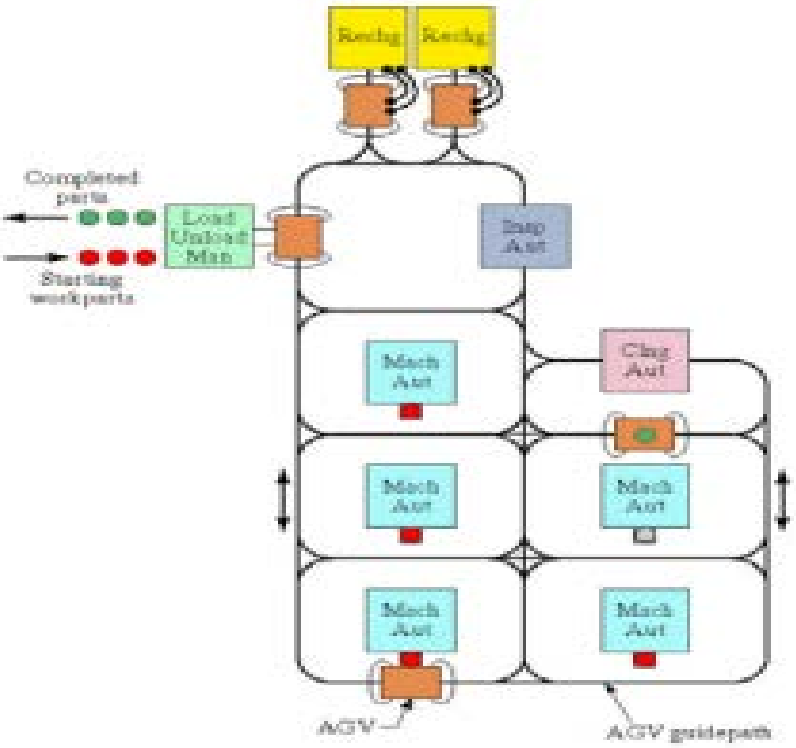


Figure 5: Open Field FMS layout

1.2.6. Robot centered FMS layout

This layout uses one or more robots as the material handling system. See figure 6

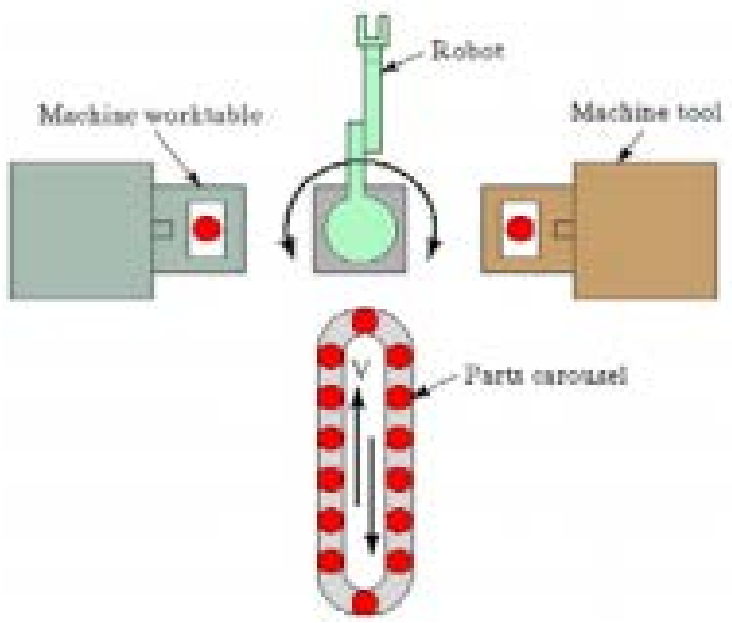


Figure 6: Robot centered FMS layout

1.3. Sequencing of jobs

The machines are arranged in a typical layout in a given FMS environment. The set of jobs are processed, those have different operations. According to their processing time, due dates these jobs scheduled to minimize make span.There are following rules selected from many existing priority scheduling rules to obtain optimum sequence.

First-Come, First-Serve (FCFS) - the job which arrives first, enters service first (local rule). It is simple, fast, “fair” to the customer. And disadvantage of this rule is, it is least effective as measured by traditional performance measures as a long job makes others wait resulting in idle downstream resources and it ignores job due date and work remaining (downstream information).

Shortest Processing Time (SPT) - the job which has the smallest operation time enters service first (local rule). Advantages of this sequencing rule is simple, fast, generally a superior rule in terms of minimizing completion time through the system, minimizing the average number of jobs in the system, usually lower in-process inventories (less shop congestion) and downstream idle time (higher resource utilization), and usually lower average job tardiness and disadvantages is, it ignores downstream, due date information, and long jobs wait (high job wait-time variance).

Earliest Due Date (EDD) - the job which has the nearest due date, enters service first (local rule) and it is simple, fast, generally performs well with regards to due date, but if not, it is because the rule does not consider the job process time. It has high priority of past due job and it ignores work content remaining.

Critical Ratio (CR) Rule - sequences jobs by the time remaining until due date divided by the total remaining processing time (global rule). The job with the smallest ratio of due date to processing time enters service first. The ratio is formed as (Due Date-Present Time)/Remaining Shop Time where remaining shop time refers to: queue, set-up, run, wait, and move times at current and downstream work centers. it recognizes job due date and work remaining (incorporates downstream information)but in this sequencing, past due jobs have high priority, does not consider the number of remaining operations

Slack Per Operation - is a global rule, where job priority determined as (Slack of remaining operations) it recognizes job due date and work remaining (incorporates downstream information)

Least Changeover Cost (Next Best rule) - sequences jobs by set-up cost or time (local rule).it is simple, fast, generally performs well with regards to set-up costs. it does not consider the job process time, due date and work remaining.

1.4. Simulation modeling

"Simulation is the process of designing a model of real system and conducting experiments with this model for the purpose either of understanding the behaviors of the system or of evaluating various strategies (within the limits imposed by criterion or set of criteria) for the operation of the system". Definition has given by R.E. Shannon.

We simulate rather than experiment with the real world system because the system as yet does not exist and experimentation with the system is expensive, too time consuming, too dangerous. Experimentation with the system is appropriate is inappropriate. A system is defined as a group of objects that are joined together some regular interaction or interdependence toward the accomplishment of some purpose. A system that does not vary with time is static whereas another one varies with time is dynamic system. A system consist following components

- Entity: An entity is an object of interest in the system.
- Attribute: AN attribute is a property of an entity. A given entity can process many attributes.
- Activity: An activity represents a time period of specified length
- State of a system: it is defined to be that collection of variables necessary to describe the system at any time, relative to the objectives of the study
- Event: An event is defined as an instantaneous occurrence that may change the state of the system
- Progress of the system: The progress of the system is studied by following the changes in the state of the system.

Simulation is a powerful problem solving technique. It can be used to experiment with systems which are not yet in existence, or with existing systems without actually altering the real system; and therefore offers valuable reductions in terms

of time, cost, and risk involved in modeling systems, designing experiments and playing scenario analysis games.

Although simulation analysis is limited in some aspects, its popularity as a decision making aid is increasing in direct relation to the capability and accessibility of today's high speed digital computers. Computer simulations are assuming the role of traditional experiments in many areas of business and scientific investigations as coding and running simulation models of large, complex real life systems (both in the manufacturing and service sectors) is becoming more and more profitable with the improving technology.

Generally, the real life systems we analyze are composed of closely interconnected sub-systems. There are various -seemingly independent- sources of information and multiple points of decision making. What is more, randomness is a very important, non-negligible factor in life: real systems are usually hierarchical, distributed, and contain a large number of relatively independent, but still implicitly coordinated decision makers operating under great uncertainty. The complexity of real world problems are such that in a lot of cases, the simplifying assumptions made by the corresponding analytic model might not be realistic, or the appropriately formulated model cannot be solved analytically.

When the uncertainty encountered in a system is sufficiently small, existing analytical methods can be suitably modified to cope with them: In fact, many of the algorithms dealing with stochastic systems are closely related to their counterparts in deterministic systems. However, when uncertainty is large, modifying existing algorithms is not enough: new paradigms have to be considered to take care of the random environment, and simulation modeling is a very promising alternative to capture the real stochastic behavior of the system under study.

1.5. Genetic algorithm

Genetic Algorithms (GA) are direct, parallel, stochastic method for global search and optimization, which imitates the evolution of the living beings, described by Charles Darwin. GA is part of the group of Evolutionary Algorithms (EA). The evolutionary algorithms use the three main principles of the natural evolution: reproduction, natural selection and diversity of the species, maintained by the differences of each generation with the previous.

Genetic Algorithms works with a set of individuals, representing possible solutions of the task. The selection principle is applied by using a criterion, giving an evaluation for the individual with respect to the desired solution. The best-suited individuals create the next generation. It optimizes with both continuous and discrete variables efficiently. It doesn't require any derivative information. It searches from a wide sampling of the cost surface simultaneously. It handles a large no. of variables at a time. It optimizes variables with extremely complex cost surfaces. It provides a list of optimum variables, not just a single solution. Genetic algorithm has following steps

1. Generate initial population – in most of the algorithms the first generation is randomly generated, by selecting the genes of the chromosomes among the allowed alphabet for the gene. Because of the easier computational procedure it is accepted that all populations have the same number (N) of individuals.
2. Calculation of the values of the function that we want to minimize of maximizes.
3. Check for termination of the algorithm – as in the most optimization algorithms, it is possible to stop the genetic optimization by:
    - Value of the function: the value of the function of the best individual is within defined range around a set value. It is not recommended to use this criterion alone, because of the stochastic element in the search the procedure, the optimization might not finish within sensible time
    - Maximal number of iterations: this is the most widely used stopping criteria. It guarantees that the algorithms will give some results within some time, whenever it has reached the extreme or not
    - Stall generation: if within initially set number of iterations (generations) there is no improvement of the value of the fitness function of the best individual the algorithms stops.
4. Selection – between all individuals in the current population are chose those, who will continue and by means of crossover and mutation will produce offspring population. At this stage elitism could be used – the best n individuals are directly transferred to the next generation. The elitism guarantees, that the value of the optimization function cannot get worst (once the extreme is reached it would be kept).
5. Crossover – the individuals chosen by selection recombine with each other and new individuals will be created. The aim is to get offspring individuals that inherit the best possible combination of the characteristics (genes) of their parents.

6. Mutation – by means of random change of some of the genes, it is guaranteed that even if none of the individuals contain the necessary gene value for the Figure 2.7 – General scheme of the evolutionary algorithms 8 extreme, it is still possible to reach the extreme.
7. New generation – the elite individuals chosen from the selection are combined with those who passed the crossover and mutation, and form the next generation. It works smoothly with both numerical and experimental data. it is well suited for parallel computing.

1.6. Objectives of research

The primary goal of any manufacturing industry is to achieve a high level of productivity and flexibility which can only be done in a computer integrated manufacturing environment. The objective of this research is to maximize machine utilization, maximizing throughput of system and optimize factors those affects system utilization and throughput of system by using taguchi philosophy and genetic algorithm

Chapter 2: Literature Review

2.1. Scheduling of flexible manufacturing system

Han et al. [8] presents the setup and scheduling problem in a special type of flexible manufacturing system, where all the machines are of the same type, and tools are 'borrowed' between machines and from the tool crib as needed. In their model, there were limited tools. The objective of their model is to assign tools and jobs to machines so that the 'borrowing' of tools is minimized while maintaining a 'reasonable' workload balance. This is a nonlinear integer programming problem, and is computationally expensive. To solve the problem efficiently, the authors propose to decompose the problem. The two sub-problems each have the same objective as shown above. But the constraints are divided. The first problem finds an optimum tool allocation, given the job allocation. The second problem finds an optimal job allocation, given the tool allocation. Phrased in this way, both problems become linear. The first problem is a capacitated transportation problem, and the second is a generalized assignment problem. It is suggested to solve the two problems iteratively. The flexible manufacturing system investigated by Han et al., is special. All machine tools are assumed identical. hence, the jobs remain at one machine, and the tools are moved to the machines as needed. Kimemia and Gershwin [9] report on an optimization problem that optimizes the routing of the parts in a flexible manufacturing system with the objective of maximizing the flow while keeping the average in-process inventory below a fixed level. Operation has different processing time for different machines in cell. Network of queues approach is used. The technique showed good results in simulation. Chen and Chung [10] evaluate loading formulations and routing policies in a simulated environment. Their main finding was that flexible manufacturing system is not superior to job shop if the routing flexibility is not utilized. Avonts and Van Wassenhove [11] present a unique procedure to select the part mix and the routing of parts in a FMS. A LP model is used to select the part mix using cost differential from producing the part outside the FMS. The selected loading is then checked by a queuing model for utilization in an iterative fashion.

Hutchison et al. [12] provide a mathematical formulation of the random FMS scheduling problem, where random jobs arrive at the FMS. Their formulation is a static one in which N jobs are to be scheduled on M machines. The objective is to minimize the make span. They present a mixed integer 0-1 programming formulation. They solve this problem by a branch and bound scheme. A single formulation solves the allocation of the operations to the machines and the timed sequence of the operations. However, their study assumes

that material handling devices, pallets, buffers, and tool magazines do not constrain the system. Further, at most one alternative is allowed for any operation. An alternative approach to this problem is to divide it into two sub problems. The first problem is the allocation of the jobs to the machines in the routings. The second problem is the time bound sequencing of the jobs, the standard job shop problem. Hutchison et al. [12] report on a comparison of the performance of the above two methodologies and another methodology which was based on dispatching rule (SPT). A novel feature of their simulation experiment is their use of a measure of flexibility, probability of an alternate machine option for any operation. They concluded that the programming formulations produced substantial improvement in make span over the dispatching rules. However, as compared to the decomposed problem, the unified formulation did not produce significant improvement in make span to justify the additional computational effort required.

In the above approach, the tool magazines do not constrain the system. Hence the first sub problem of the decomposition can allocate all the jobs to their machines. However, when the tool magazine is considered restraining, it may not 8 be possible to allocate all the jobs for one tooling setup. Then this sub problem resolves to a selection problem. Out of the pool of waiting jobs, jobs are selected to be processed in the next planning period (part type selection problem). The selected parts are then sequenced. The process is repeated period by period. In this approach, it is assumed that at the beginning of each planning period all the tools are reassigned and replaced in the tool magazine. Shanker and Tzen [13] propose a mathematical programming approach to solve this part selection problem for random FMS. Their approach is similar to Stecke, Stecke assumes the part ratio as given and the planning horizon as indefinite whereas Shanker and Tzen consider individual parts and a fixed planning horizon. They have a constraint on the tool magazine capacity which is very similar to Stecke's. They constrain the model to find a unique routing for each part type (in contrast to Stecke). Two objectives are considered: 1) Balancing the workload, and 2) Balancing the workload and minimizing the number of late jobs. The resulting problems are, again, non-linear integer problems. Even after linearization, the problems are computationally too sumptuous, and they further propose two heuristics corresponding to the two objectives. For balancing the workload, they propose essentially a greedy heuristic which attempts to allocate to the most lightly loaded machine the longest operation first. For the second objective, the same heuristic is modified to include the overdue jobs with the highest priority. Their computational experience showed that the analytical formulations would be too formidable to be of practical use. Shanker and Srinivasulu [14] modify the objective to

consider the throughput also. A computationally expensive branch and backtrack algorithm is suggested as well as heuristics.

In the above approaches for random FMS, the scheduling of the FMS is decomposed into two problems, part type selection, and sequencing of jobs. The nine sequencing is done using one of the dispatching rules. Of course, some (e.g. branch and bound) search could be used to solve the sequencing problem too. Hwan and Shogun [15] present the part selection problem for a random FMS with machines of a single general purpose type capable of producing all part types. They include the due date and the quantity of parts needed to be produced in their formulation. By ignoring the tool overlapping Stecke [16], they considerably simplify the tool magazine constraint. Their objective is to maximize the number of part types selected over a planning horizon. They take care of due dates by weighting on the selected part types. By assuming a single machine type, their problem essentially boils down to maximizing the utilization of the tool slots in the tool magazines. They report computational experience on two Lagrangian relaxation techniques they used to solve the problem. Their heuristics and Lagrangian methods obtained solutions close to optimal solutions found by the branch and bound method. The CPU times required by the three methods are successively order of magnitudes higher.

Sarin and Chen [17] approach the loading problem from the viewpoint of machining cost. Computational methodologies to solve the integer programming formulation are proposed. Ram et al. [18] consider this problem as a discrete generalized network and present a branch and bound procedure. Co et al. [19] have suggested a four pass approach to solve the batching, loading and tool configuration problems of random FMS. In this approach, compatible jobs are batched together using integer programming. The solution is then improved upon in three further stages. Jaikumar and Van Wassenhove [20] propose a hierarchical planning and scheduling decomposition of FMS operation problems. In the first level, an aggregate production model is used. This is a linear programming model that chooses parts to be produced in a FMS during the next planning period. The ten remaining parts are assumed to be produced elsewhere at a cost difference. The objective is to maximize the cost difference while allowing for the inventory cost for work in process. The essential constraints are the demand for the parts and the machine capacity. Put simply, the objective of the second level is to minimize tool changeover. The production requirements and the tool and machine allocation are determined in levels one and two. All that remains in the third level is to determine a feasible schedule that will fulfill the above requirements. Detailed requirements such as buffer requirements, and material handling constraints, are taken care of at this level.

Jaikumar and Wassenhove recommend simulation using some dispatching rule to carry out this level. If a feasible schedule cannot be obtained, the planning process is reiterated. They discuss the application of their framework in an existing FMS and point out that the primary problem is at the first level - selection of parts. Once this is decided upon, the other two problems can be solved by simple heuristics.

Mathematical models in the literature are not efficient for reasonably sized problems. Further, they make simplifying assumptions which are not always valid in practice. The assumptions, of course, change with the models: some models assume automatic tool transport, some others will neglect delays caused by automated guided vehicles (AGV), still others will assume that tool magazines, pallets and fixtures do not constrain the models in any way, and so on. The models also take a static view of the shop floor. It is assumed that all the planned activities will be carried out exactly, or the disruptions are infrequent enough that periodic solution of the problems will be practical. Quite often the flexible manufacturing system scheduling problem is seen as part of a larger (hierarchical) planning system, taking care of e.g. the part types to be processed at the same time, the set-up of machines and the scheduling. An example of such an approach is the model presented in Stecke [16], in which the objective of the scheduling is to minimize the maximal lateness of processing the jobs. Another approach is to consider the flexible manufacturing system scheduling as a separate problem, taking the batches and the set-up of the system as given. Examples of such a model include the integer programming model presented in Sarin and Chen [17] and the model presented in Stecke [16]. In both of these papers the objective is to minimize the maximal completion time of the jobs. Finally, one of the often used scheduling approaches is to use dispatching rules. Here a dispatching/priority rule is used to choose the course of action every time the status of the system changes. Montazeri and Van Wassenhove [21] give an extensive simulation study of numerous dispatching rules under several objectives. As a conclusion to this brief overview of literature dealing with flexible manufacturing system scheduling one can say that what is to be understood as the scheduling problem in an flexible manufacturing system is not clearly defined and consequently it is very bard to assess the quality of the different approaches. Hierarchical models for production planning usually discriminate between an aggregate capacity planning decision on the tactical level and a detailed scheduling decision on the operational level. Planning decisions may be taken at the Master Production Scheduling level and usually assume fixed lead times at the operational level VolIman et al.[22]. This lead time is then controlled by some form of input-output or workload control Bensana et al., [6]. In order to keep track of the lead times which will be realized, adequate aggregate models of the

detailed production situation need to be available. In job shops, stochastic queuing network models are used to investigate these issues Shaw [23].

2.2. Taguchi Philosophy

Taguchi technique is step by step approach to identify causal relationship between design factors and performance, which results to increased quality performance into processes and products at development as well as production level. Taguchi's technique used by a many industries to optimize their process design, through identifying independent and dependent variables with the help of identified factors and factor levels. Design of Experiment is an approach that facilitates analytically alters in number of inputs and output variables and examines the impact on response variables. The authors like Taguchi [24,25] and Ross [27] discovered analytical techniques to design highly efficient and cost effective experiments. The foundation of Taguchi's philosophy is the loss function concept. "*The quality of a product is the (minimum) loss imparted by the product to society from the time the product is shipped.*" [26].The main reason behind loss is not only non–conformance of products, rather loss increases further if one of the parameter deviates from specification (objective value/ reading/ degree).Quality should be implanted to products. The author also pointed that quality is best accomplished by increasing accuracy and the cost of quality should be calculated as a function of the divergence from the desired specifications. The robust design concept given by Taguchi can be realized with design of experiments. This design refers to design a process or a product in a way that it has minimal sensitivity to the external nuisance factors .Klien, I.E [28] has emphasized the importance signal-to-noise ratio analyses which was given by Taguchi to develop a design for Rayleigh surface acoustic wave (SAW) gas sensing device operated in a conservative delay-line configuration. Recently Chen [29] calculated signal-to-noise ratio on the basis of ANOVA. In this paper author has used 10 step methodologies as mention by koilakuntla [30] for deploying robust Taguchi design in process optimization of a molding operation by using MINITAB.

2.3. Genetic Algorithm

A genetic algorithm is simply a search algorithm based on the observation that sexual reproduction, and the principle of survival of the fittest, enables biological species to adapt to their environment and compete effectively for its resources. While it is a relatively straight forward algorithm, the algorithm is an effective stochastic search method, proven as a robust problem solving technique [31] that produces better than random results [32].

This observation was first mathematically formulated by John Holland in 1975 in his paper, "Adaptation in Natural and Artificial Systems" [33]. Usually the algorithm breeds a predetermined number of generations; each generation is populated with a predetermined number of fixed length binary strings. These binary strings are then translated (decoded) into a format that represents suitable parameters either for some controller, or as output.

The product resulting from evolution (whether natural or simulated) is not simply discovered by a random search through the problem state space, but by a directed search from random positions in that space. In fact, according to Goldberg, the simulated evolution of a solution through genetic algorithms is, in some cases, more efficient and robust than the random search, enumerative or calculus based techniques. The main reasons given by Goldberg are the probability of a multi-modal problem state space in non-linear problems, and that random or enumerative searches are exhaustive if the dimensions of the state space are too great [34].

An additional advantage of the genetic algorithm is that the problem solving strategy involves using “the strings’ fitness to direct the search; therefore they do not require any problem-specific knowledge of the search space, and they can operate well on search spaces that have gaps, jumps, or noise” [35]. As each individual string within a population directs the search, the genetic algorithm searches, in parallel, numerous points on the problem state space with numerous search directions.

According to Koza, “the fact that the genetic algorithm operates on a population of individuals, rather than a single point in the search space of the problem, is an essential aspect of the algorithm. The advantage conferred by the existence of a population is not merely the obvious benefit of dropping 1,000 [i.e., population size] parachutists, rather than one, on the landscape. The population serves as the reservoir of the probably-valuable genetic material that the crossover operation needs to create new individuals with probably-valuable new combinations of characteristics” [39, 37].

Chapter 3: Methodology

In this research methodology has been adopted as shown in figure 3.1, it starts with scheduling of job by using sequencing rules, and then according to scheduling a simulated small flexible manufacturing has been developed. The process variables those affects FMS objectives were designed by using Taguchi philosophy has been treated as input function for simulation model of FMS to generate the throughput and working hours for each machine per year and then system utilization and throughput has been optimized as discussed below

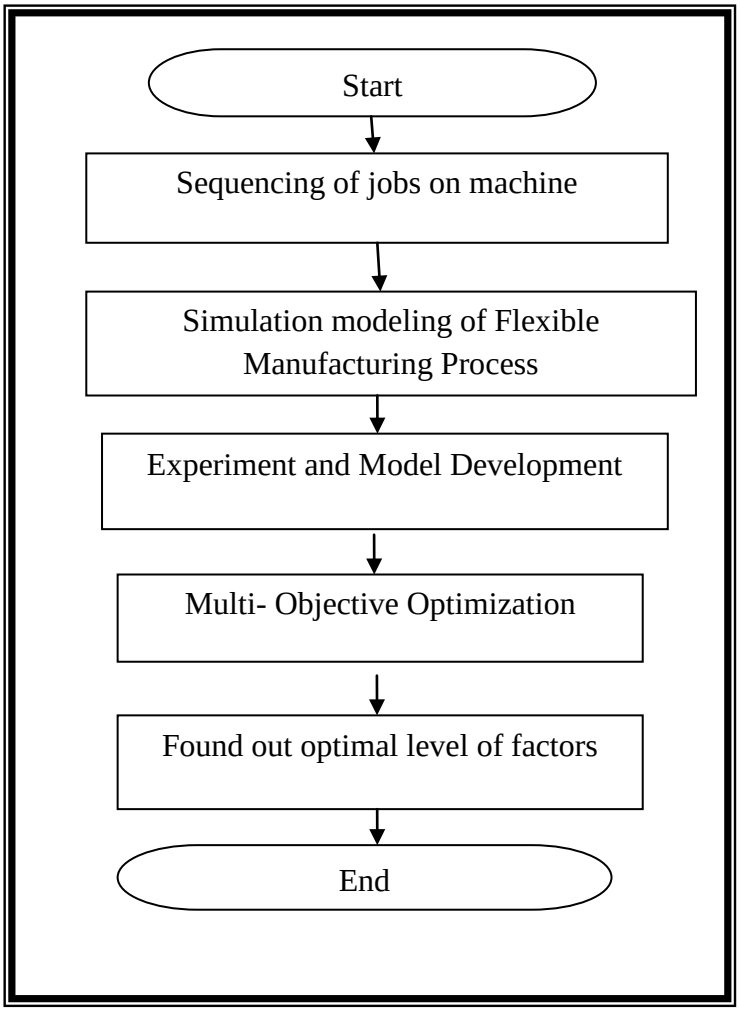


Figure 7: Flowchart of analysis of FMS

3.1 Sequencing of jobs on machines

In this research, four part types and five machines has been used. Processing time for each operation on different part types on different machines are as shown in table 1, in this research shortest processing time sequencing rule has been used for scheduling.

Table 1: Processing time of each operation on each machine (min.)

Part/Machine	Operation	M/C 1	M/C 2	M/C 3	M/C 4	M/C 5
P_1 (n_1=3)	O_{11}	2	5	4	1	2
	O_{12}	5	4	5	7	5
	O_{13}	4	5	5	4	5
P_2(n_2=3)	O_{21}	2	5	4	7	8
	O_{22}	5	6	9	8	5
	O_{23}	4	5	4	5	5
P_3(n_3=4)	O_{31}	9	8	6	7	9
	O_{32}	6	1	2	5	4
	O_{33}	2	5	4	2	4
	O_{34}	4	5	2	1	5
P_4(n_4=2)	O_{41}	1	5	2	4	12
	O_{42}	5	1	2	1	2

According to shortest processing time rule, the job with the shortest processing time is processed first and here each operation can processed on each machine with different processing time. Operation on part will be processed on that machine which machine takes less processing time for operation.

Table 2: Sequencing of operation of jobs on machines

M/C_k	Sequence of operation
M/C_1	O_{21}-O_{41}-O_{23}
M/C_2	O_{12}-O_{42}-O_{32}
M/C_3	O_{31}
M/C_4	O_{11}- O_{13}-O_{33}-O_{34}
M/C_4	O_{22}

For example operation O_{11} will be processed on machine 4 because machine 4 takes less processing time than other machine. Similarly for all operations of different jobs can be sequence on machine. Sequencing of operation of jobs on different machine is as shown in figure 8.

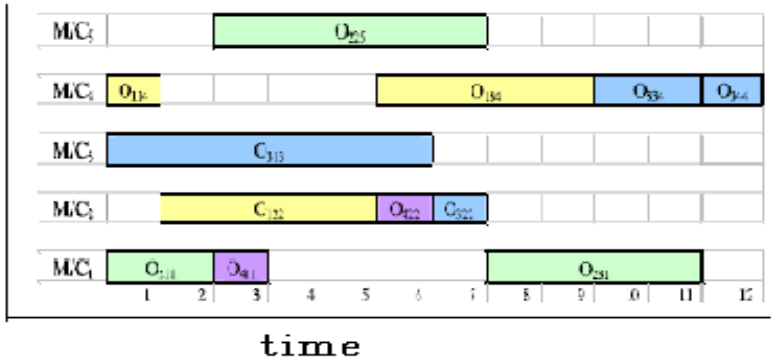


Figure 8: Gantt chart of operation on machines

3.2 Modeling of flexible manufacturing system

In this research, five machines and four different part types has been used. As shown in figure 3.4 there are five machines, and in this model, simulation has been run for 1 year with 3820 hours warm up period which is calculate by using Welch's method. According to this method we obtained moving average of work in process then plot graph and at 3820 hours, this graph almost smooth. So it is the warm up period

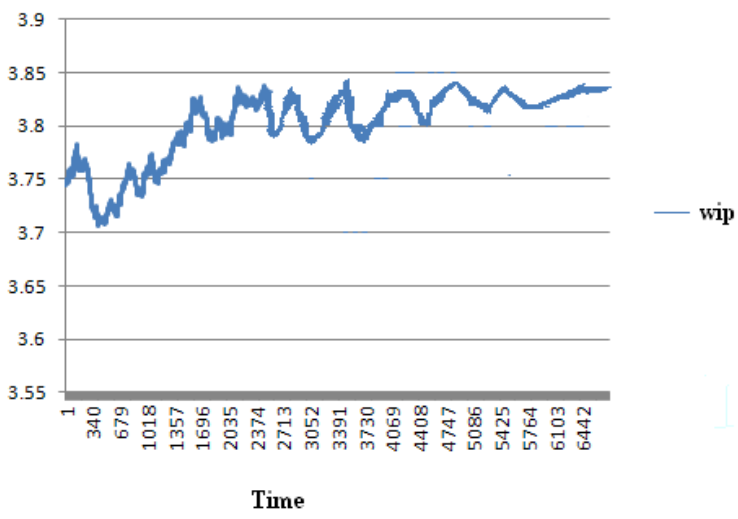


Figure 9: Graph between average work in process and time

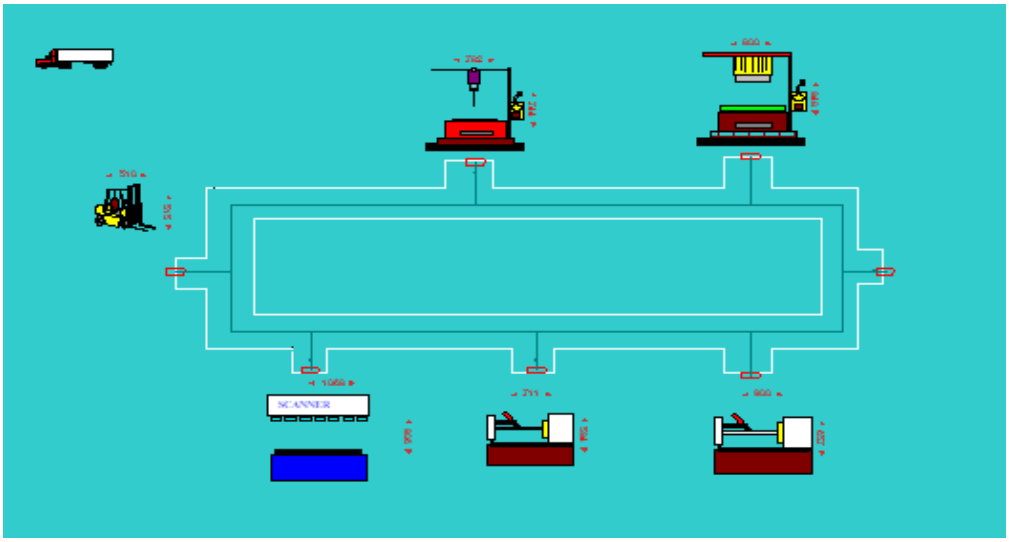


Figure 10: Small manufacturing system

AGVs has been used for transfer parts from one station to other station and in figure 3.5 shows logical data module those has been used in simulation modeling.

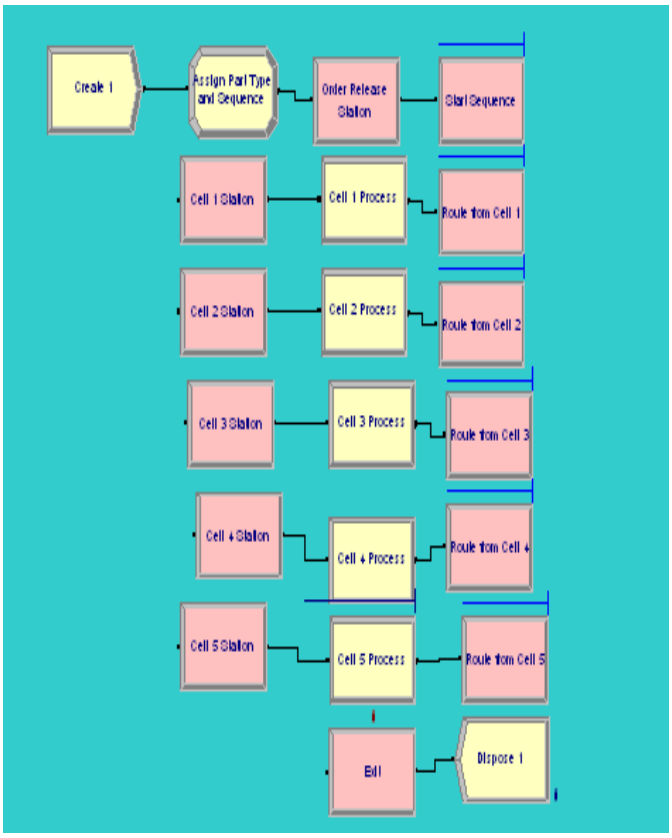


Figure 11: Simulation model of small manufacturing system

To build a FMS model and to carry out simulation runs with Arena, a user performs the following steps:

1. Construction of a basic model. Arena provides the model window flowchart view, which is a flowchart-style environment for building a model. The user selects and drags the flowchart module shapes into the model window and connects them to define process flow of the model.
2. Adding data to the model parameters. The user adds actual data (e.g., processing times, resource demands, others) to the model. This is done by double-clicking on module icons and adding data.
3. Performing a simulation run of the model. The user runs the simulation and examines the results.
4. Analysis of the simulation results provided by the automatic reports of Arena. The user can expand the statistics.
5. Modifying and enhancing the model according to the user needs

In this research we have used 5 work station and 5 machines those produces 4 part types having different operations. The processing time of operation is exponentially distributed as shown in table 1.

In this research, processing time taken as exponentially distributed. Arrival of demand also taken as exponentially distributed. It means that demand of part will come exponentially distributed here in this research, arrival demand time taken as 10, 15 and 20 minutes that means each demand come in 10, 15, 20 minutes and the parts will process according to given sequence.

3.3 Experiment and model development

Small manufacturing system modeled in this thesis is taken from [2]. Which consists five work stations and five machines and there is four parts produced by these machines. Every work station consist one machine.

Here we have used four factors which affects the objective of FMS: these factors and there levels are as follows:

1. Distance preference ($X_{1)}$: distance preference means what distance between two stations. It can be smallest distance between two stations or largest distance between two stations or the distance in cyclic order as shown in figure. So the level of distance preferences is smallest distance(S), largest distance (L), cyclic distance (C).
2. Arrival (demand) time (min.) (X_2): it's the time of arriving demand of parts. Here for in simulation three levels of demand time were assumed 10 min., 15min. and 20 min.

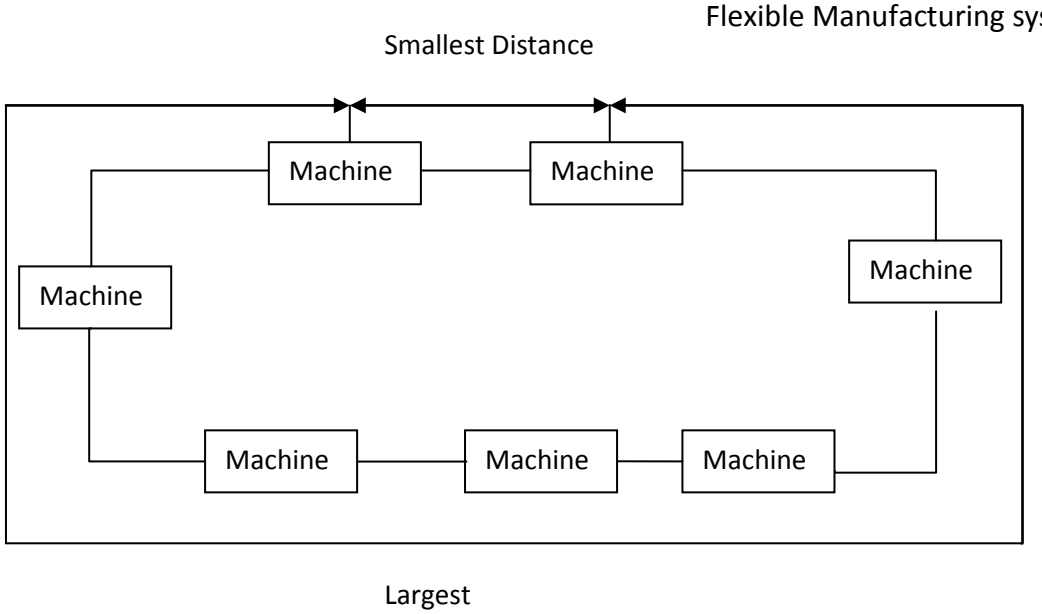


Figure 12: Distance preferences

3. No. of carts(X_3) = No. of carts used in simulation, here in simulation three levels of no. of carts were assumed 2, 3 and 4.
4. Speed of carts (feet/min.) (X_4)=it's the speed of carts or AGVs, which is also affects the FMS objectives. Here in this thesis three level of speeds were assumed 60, 65 and 70.

From above each factor at three level so the degree of freedom of each factor is 2, and three interaction of arrival demand time and other three factors (distance preferences, no. of carts, velocity of carts) so each interaction have 4 degree of freedom . Hence the total degree of freedom factors is 20. The degree of freedom of model should be equal to or greater than the total degree of freedom of factors. So in this research for precise results 'L_{27}'has been selected, and the process variables as designed by using Taguchi philosophy has been treated as input function for simulation model of FMS to generate the throughput and working hours for each machine per year, as shown in table 3 and table 4 respectively, and the system utilization of system should be carried out by following formula

$$\text{System Utilization} = \frac{\sum_{i=1}^{n} \text{Wi}}{n * 365 * 24}$$

Where i = No. of machine

n = Total no. of machine

Here total no. of machine is five. System utilization for each treatment has been calculated by using above formula.

Table 3: Experimental design of L_{27} array for throughput

Distance preference	Demand time	No. of Carts	Velocity of Carts	Throughput
Small	10	2	60	29586
Small	10	3	65	29733
Small	10	4	70	29552
Small	15	2	60	19463
Small	15	3	65	19586
Small	15	4	70	19812
Small	20	2	60	14870
Small	20	3	65	14778
Small	20	4	70	14976
Large	10	2	65	29373
Large	10	3	70	29284
Large	10	4	60	29380
Large	15	2	65	19844
Large	15	3	70	19623
Large	15	4	60	19749
Large	20	2	65	14595
Large	20	3	70	14670
Large	20	4	60	14594
Cyclical	10	2	70	29285
Cyclical	10	3	60	29595
Cyclical	10	4	65	29285
Cyclical	15	2	70	19875
Cyclical	15	3	60	19865
Cyclical	15	4	65	19770
Cyclical	20	2	70	14764
Cyclical	20	3	60	14732
Cyclical	20	4	65	14885

Table 4: Experimental design of L27 array for System utilization

Distance preference	Demand time	No. of Carts	Velocity of Carts	System utilization
Small	10	2	60	0.106313
Small	10	3	65	0.106346
Small	10	4	70	0.105746
Small	15	2	60	0.070139
Small	15	3	65	0.070316
Small	15	4	70	0.070486
Small	20	2	60	0.055483
Small	20	3	65	0.052751
Small	20	4	70	0.053747
Large	10	2	65	0.105842
Large	10	3	70	0.105249
Large	10	4	60	0.105111
Large	15	2	65	0.071236
Large	15	3	70	0.070445
Large	15	4	60	0.071466
Large	20	2	65	0.052381
Large	20	3	70	0.052368
Large	20	4	60	0.052429
Cyclical	10	2	70	0.10518
Cyclical	10	3	60	0.106638
Cyclical	10	4	65	0.105174
Cyclical	15	2	70	0.071295
Cyclical	15	3	60	0.071832
Cyclical	15	4	65	0.070563
Cyclical	20	2	70	0.052861
Cyclical	20	3	60	0.05335
Cyclical	20	4	65	0.054687

3.4 Optimization:

Optimization of system utilization and throughput has been done by genetic algorithm. Regression equation generate by taguchi philosophy for system utilization and throughput were used as fitness function for genetic algorithm and genetic algorithm gives the optimize value of factors for maximizing throughput and system utilization discuss in next chapter.

Apart from the single objective functions considered for this problem, a combined function is also used to perform the multi-objective optimization for the FMS parameters. The function and the variable limits are given using following function. Equal weights are considered for all the responses in this multi-objective optimization problem. Hence W_1 and W_2 are equal to 0.5.

$$Z_{Multi} = w_1 * \frac{Z_{system\ utilization}}{system\ utilizationa_{max}} + w_2 * \frac{Z_{throughput}}{Throughput_{max}}$$

Chapter 4: Results and Discussions

4.1. Scheduling

In this research, Shortest Processing Time (SPT) has been used. In Shortest Processing Time (SPT), the job which has the smallest operation time enters service first (local rule). SPT rule is simple, fast, generally a superior rule in terms of minimizing completion time through the system, minimizing the average number of jobs in the system, usually lower in-process inventories (less shop congestion) and downstream idle time (higher resource utilization), and usually lower average job tardiness. Scheduling of flexible manufacturing system according to SPT rule is as shown in table 5. According to this sequence make span is 12 min.

Table 5: Sequencing of Operation on jobs

M/C_k	Sequence of operation
M/C_1	O_{21}-O_{41}-O_{23}
M/C_2	O_{12}-O_{42}-O_{32}
M/C_3	O_{31}
M/C_4	O_{11}- O_{13}-O_{33}-O_{34}
M/C_4	O_{22}

4.2. Experimental design

In this research L_{27} array has been used as discussed in previous chapter. When the process variable designed by using Taguchi philosophy has been treated as input function for simulation model of FMS to generate the working hours for every machine per year, and also gives the throughput of system. According to objective of FMS throughput and system utilization are larger is better. So using larger is better in L_{27} array in taguchi philosophy following plots and regression equations obtained.

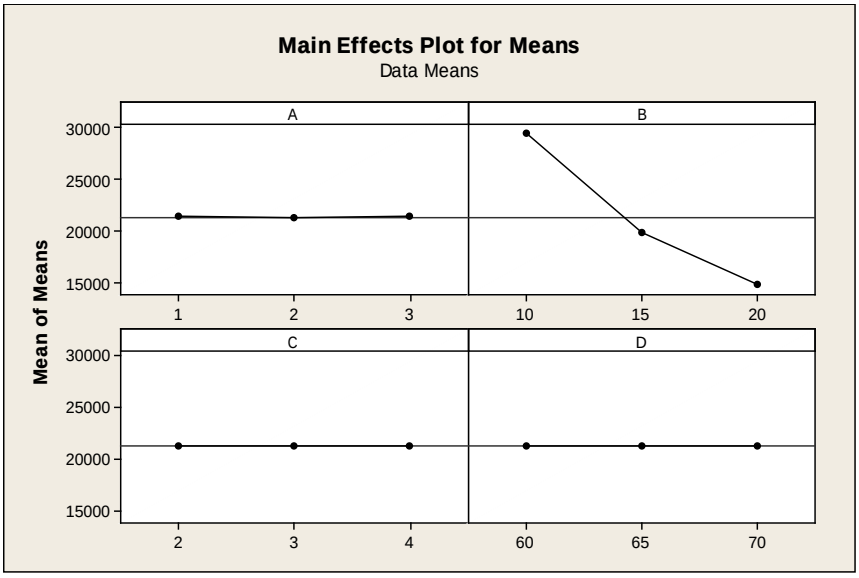


Figure 13: Main effect plot for means of throughput of system

Main effect plot for means of throughput shows that distance preference should be at first level means distance preference should be smallest for this simulated flexible manufacturing system for maximizing throughput of system and throughput of system is maximum at demand time is 10 min. and no. of carts is 4 and velocity of cart is 65 feet/min.

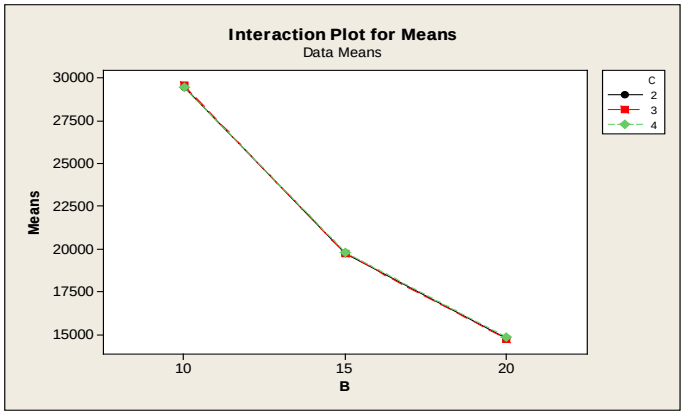


Figure 14: Interaction plots between demand arrival time (B) and no. of carts(C) for throughput

Interaction plots for means between demand arrival demand time (B) and no. of carts (C) gives that as arrival demand time increases throughput of system decreases there is very less effect of no. of carts on throughput according to this research in this problem.

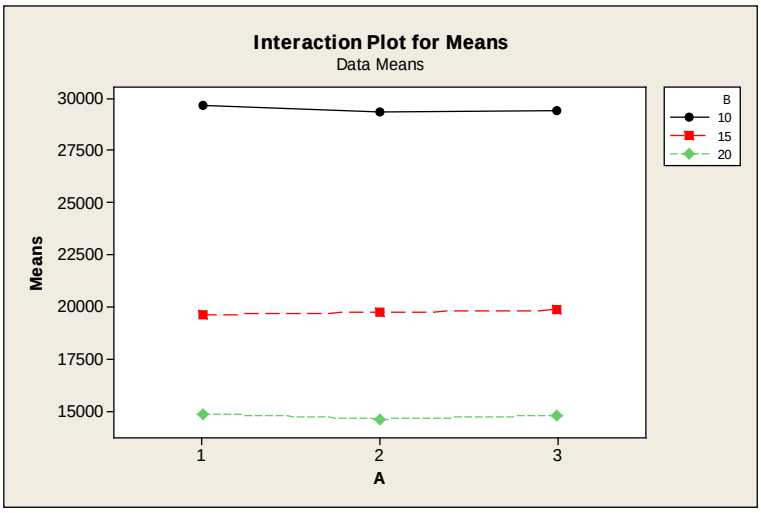


Figure 15: Interaction plots between and distance preference (A) and demand arrival time (B) for throughput

Interaction plots for means between demand arrival demand time (B) and distance preference (A) gives that as arrival demand time increases throughput of system decreases and when arrival demand time is 20 min., throughput maximum at level 1 means when the distance preference is smallest but when arrival demand time is 15 min., throughput maximum at level three means the distance preference is cyclical, and when arrival demand time is 10 min. and distance preference is smallest so throughput of system is maximum. It means as arrival time increases, throughput of system decreases

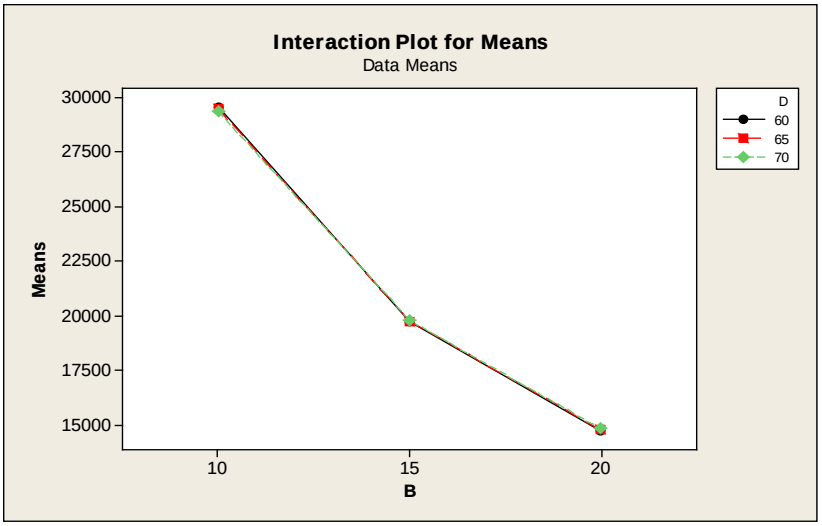


Figure 16: Interaction plots for means between demand arrival time (B) and velocity of carts (D) for system throughput

Interaction plots for means between demand arrival demand time (B) and velocity of carts (D) gives that as arrival demand time increases throughput of system decreases

there is very less effect of velocity of carts on throughput according to this research in this problem.

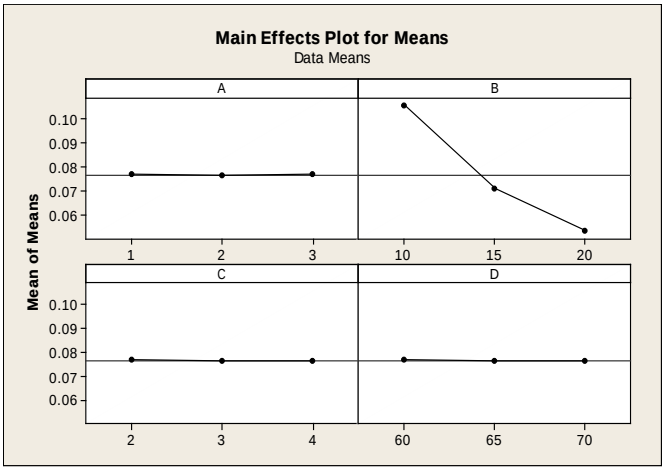


Figure 17: Main effect plot for means of system utilization

Main effect plot of system utilization shows that distance preference should be at first level means distance preference should be smallest for this simulated flexible manufacturing system for maximizing system utilization of system is maximum at demand time is 10 min. and no. of carts is 2 and velocity of cart is 60 feet/min.

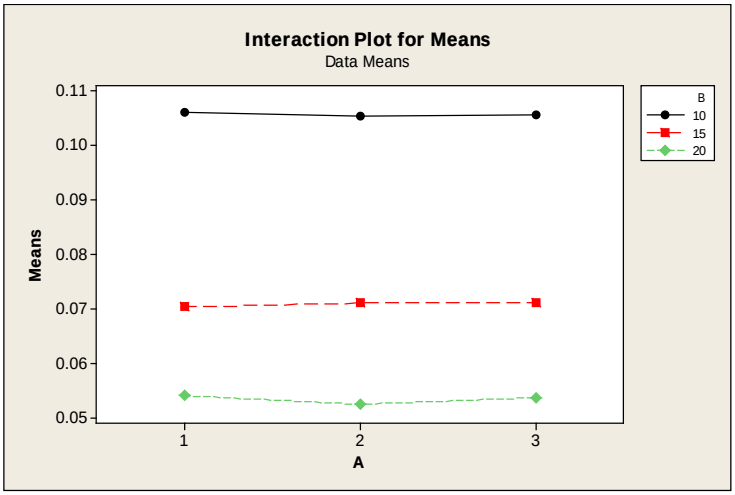


Figure 18: Interaction plots for means between and distance preference (A) and demand arrival time (B) for system utilization

Interaction plots for means between demand arrival demand time (B) and distance preference (A) gives that as arrival demand time increases throughput of system decreases and when arrival demand time is 20 min., throughput maximum at level 1 means when the distance preference is smallest but when arrival demand time is 15 min., throughput maximum at level three means the distance preference is cyclical, and when arrival demand time is 10 min. and distance preference is smallest so throughput

of system is maximum. It means as arrival time increases , throughput of system decreases

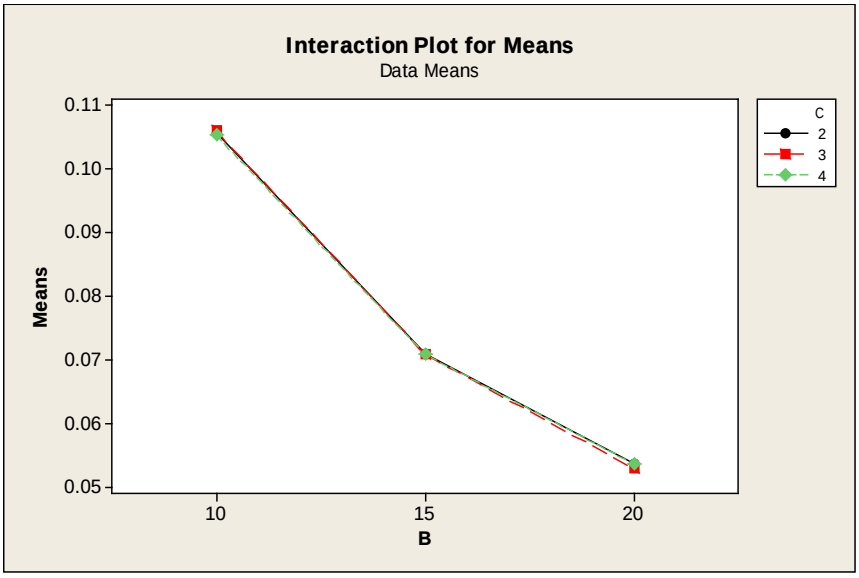


Figure 19: Interaction plots for means between demand arrival time (B) and no. of carts(C) for system utilization

Interaction plots for means between demand arrival demand time (B) and no. of carts (C) gives that as arrival demand time increases throughput of system decreases there is very less effect of no. of carts on system utilization according to this research in this problem.

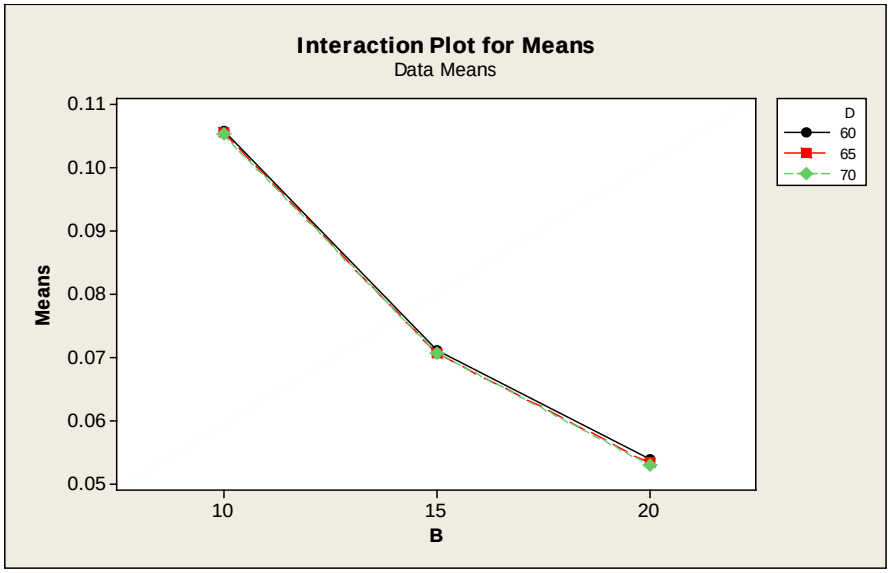


Figure 20: Interaction plots for means between demand arrival time (B) and velocity of carts(D) for system utilization

Interaction plots for means between demand arrival demand time (B) and velocity of carts (D) gives that as arrival demand time increases throughput of system decreases there is very less effect of velocity of carts on throughput according to this research in this problem.

As shown in response table for means gives that demand time is more influencing factor than other factors. Than velocity of carts affects the system utilization and distance preference is very less influencing factor for throughput.

Table 6: Response table for means for throughput

Level	A	B	C	D
1	0.07681	0.10573	0.07675	0.07697
2	0.07628	0.07086	0.07659	0.07659
3	0.07684	0.05334	0.0766	0.07638
Delta	0.00056	0.05239	0.00016	0.0006
Rank	3	1	4	2

As shown in response table for means gives that demand time is more influencing factor than other factors. Than velocity of carts affects the system utilization and distance preference is very less influencing factor for system utilization

Table 7: response table for system utilization

Level	A	B	C	D
1	21373	29453	21295	21315
2	21235	19732	21318	21317
3	21340	14763	21334	21316
Delta	138	14690	39	2
Rank	2	1	3	4

4.3. Optimization

In this research, system throughput of system and system utilization both are optimized by genetic algorithm, using genetic algorithm following results obtained as shown in table 4.4 and table 4.5 respectively for maximum throughput

Throughput = 43321 - 17*distance preferences (X_1) - 1469 *arrival demand + 19* no. of carts (X_3) + 0.1 * velocity of carts (X_4)

Table 8: factor and their level for maximizing throughput through genetic algorithm

Factors	Level	value
Distance preference	Level 1	Smallest distance
Demand arrival time	Level 1	10 minutes
No. of carts	Level 3	4
Velocity of cart	-	62.501

Throughput obtained by value of above factor in simulation is 30013.

System utilization = 0.159 + 0.00001 *distance preferences (X_1) - 0.00524*arrival demand time (X_2) - 0.00007 * no. of carts (X_3) - 0.000060 * velocity of carts (X_4)

Table 9: factor and their level for maximizing throughput through genetic algorithm

Factors	Level	value
Distance preference	Level 1	Smallest distance
Demand arrival time	Level 1	10 minutes
No. of carts	Level 3	4
Velocity of cart	-	69.941

System utilization obtained by value of above factor in simulation is 0.1071%

Apart from the single objective functions considered for this problem, a combined function is also used to perform the multi-objective optimization for the FMS parameters. The function and the variable limits are given using following function. Equal weights are considered for all the responses in this multi-objective optimization problem. Hence W_1 and W_2 are equal to 0.5.

$$Z_{Multi} = w_1 * \frac{Z_{system\ utilization}}{system\ utilizationa_{max}} + w_2 * \frac{Z_{throughput}}{Throughput_{max}}$$

Using above function a following combined function obtained which is optimized by using genetic algorithm and gives results as shown in table 4.6

Z_{Multi} = 0.5 * (1.49155 - 0.0000938 * X(1) distance preferences - 0.049155 * X(2) arrival demand time + 0.0006566 * X(3) No. of carts + 0.0005628*X(4) Velocity of carts)- 0.75*(1.4642 - 0.0005717 * X(1) distance preferences -0.49406 * X(2) arrival demand time +19 * X(3) No. of carts +0.0006390 * X(4) Velocity of carts)

Table 10: factor and their level for maximizing throughput and system utilization through genetic algorithm

Factors	Level	value
Distance preference	Level 1	Smallest distance
Demand arrival time	Level 1	10 minutes
No. of carts	Level 3	4
Velocity of cart	-	62.495
Throughput		30018
System utilization		0.1085%

Chapter 5: Conclusions

In this research, we presented a simulation modeling and optimization of FMS objectives for evaluating the effect of factors such as demand arrival time, no. of carts used in system, velocity of carts, and distance preference between two stations. System utilization and throughput both are affected by these factors. System utilization and throughput is more affected by demand arrival time comparatively other three factors. Distance preference also affects throughput and system utilization. For both system utilization and throughput distance preference should be smallest. And as the demand arrival time increases both system utilization and throughput of system decreases. No of carts and velocity of carts are less affected.

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