IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

SCHEDULING OF JOBS ON MACHINES USING NON TRADITIONAL OPTIMIZATION METHODS

[1]Arun Teja Nuthikattu, [2]Musalaiah K

[1]Department of Mechanical Engineering, Eswar College of Engineering, Narasaraopet-522601, Andhra Pradesh-India

[2]Associate Professor, Department of Mechanical Engineering, Eswar College of Engineering, Narasaraopet-522601, Andhra Pradesh-India

Abstract: Scheduling plays an important role in achieving timely and cost effective production, which is becoming increasingly important in today's highly competitive manufacturing environments. Scheduling is a decision making process that is concerned with the allocation of limited resources to competing tasks (operations of jobs) over a time period with the goal of optimizing one or more objectives. This project exploits the interactions between the job scheduling on machines with an objective of minimization of make span and to study the overall feasibility of generation of optional schedules. A heuristic scheduling algorithm is developed which takes into account machine constraints and determines the starting and completion times of operations for each job by using priority rules such as Most Work Remaining (MWKR), shortest processing time (SPT) and random rules. In this work job shop scheduling problem is done for a particular type of FMS environment by means of one of the following Non Traditional Methods viz., Tabu Search Method, Simulated Annealing, Differential Evolution Method & Variable Neighbourhood Search.

Among the above, project objective issues (determining elapsed time and job idle time) is to be resolved by choosing the Tabu Search method. Tabu search is a metaheuristic algorithm which can be used for solving combinational optimization problems.

KEYWORDS - Make Span, Waiting time, Processing time, Route matrix, Generations

1. INTRODUCTION

Now a days, the manufacturing industries are experiencing many impulsive market conditions like reduced product life cycles, technological progress, extreme pressure from competitors, and increasing customer's believes on high quality products at a lower cost, high dynamic market conditions and more customer's ambitions. The product price is not a measuring tool for manufacturing performance; instead other cutthroat parameters such as flexibility, quality, and delivery are also equally important. For this reason, the manufacturers wish a type of production methods over which alterations can be seen with minimum possible time and cost to produce medium to small batches of products. So, manufacturing flexibility is the most sought after property of the modern production systems and such type of flexibility can be attained through the adaptation and implementation of FMS (Flexible manufacturing systems).[1]

The job-shop is an important scheduling theory, as it is measured to be a good demonstration of the general domain and has gained a reputation being is more difficult to evolve the combinational optimistic problems. Problems arising in the fields like scheduling assignment, vehicle routing are mostly Non polynomial (NP) hard problem. These problems need efficient results. If checking with an NP-hard problem, one may have three ways to go: one chooses to apply an enumerative method that yields an optimum solution, or apply an approximation algorithm that runs in polynomial time. Research in scheduling theory has evolved over the past four decades and has been the subject of much significant literature with techniques ranging from unrefined dispatching rules to highly effective parallel branch and bound algorithms and bottleneck based heuristics. Not surprisingly, approaches have been formulated from a diverse spectrum of researchers ranging from management scientists to production workers. However with the advent of new technologies, such as neural networks and evolutionary computation, researchers from fields such as biology, genetics and neurophysiology have also become regular contributors to scheduling theory emphasising the multidisciplinary nature of this field.

The present day manufacturing environments are highly effective and are concentrated with the continuous changing in customer's requirements. Flexible manufacturing systems (FMS) consider as a powerful one due to its wide flexibility, which is essential to stay competitive in this highly dynamic environment. FMS is an effective system is having elements like machine, automated guided vehicles, storage and retrieval system.

2. JOB SCHEDULING IN FMS ENVIRONMENT:

In recent years, there has been a growing interest in the implementation of flexible manufacturing systems (FMS) that are manufacturing systems consisting of a group of numerically controlled (NC) machines connected by an automated material handling system under computer control and set-up to process a wide variety of different parts with low to medium demand volume. FMS can also be viewed as an automated job shop. However, because of its integrated nature, a scheduling task for an FMS requires additional consideration of tools, fixtures, automated guided vehicles (AGVs), pallets, etc. Since machines and material handling systems are also more versatile, there is a large number of alternative operations and material handling routes to be considered in the scheduling decision. The job scheduling in FMS environment consist of job shop as well as batch scheduling mechanism where the jobs have to be transported between the machines based on priority dispatch rule. The FMS consists of a set of different machines performing different tasks and a conveyor performing the material handling and transportation tasks between the machines. Scheduling is difficult for a variety of reasons [2]:

1. Desirability: difficulty in determining when a good schedule has been achieved, given that different people, agencies, etc, have different goals and priorities;
2. Stochasticity: unpredictability in the domain that makes predictive scheduling Problematical;
3. Tractability: computational complexity of the domain, that is, the "size" of the Scheduling problem;
4. Decidability: it may be provably impossible to find an algorithm that produces an Optimal schedule, depending on the definition of optimality choosen.

Flow chart for job scheduling in FMS environment:

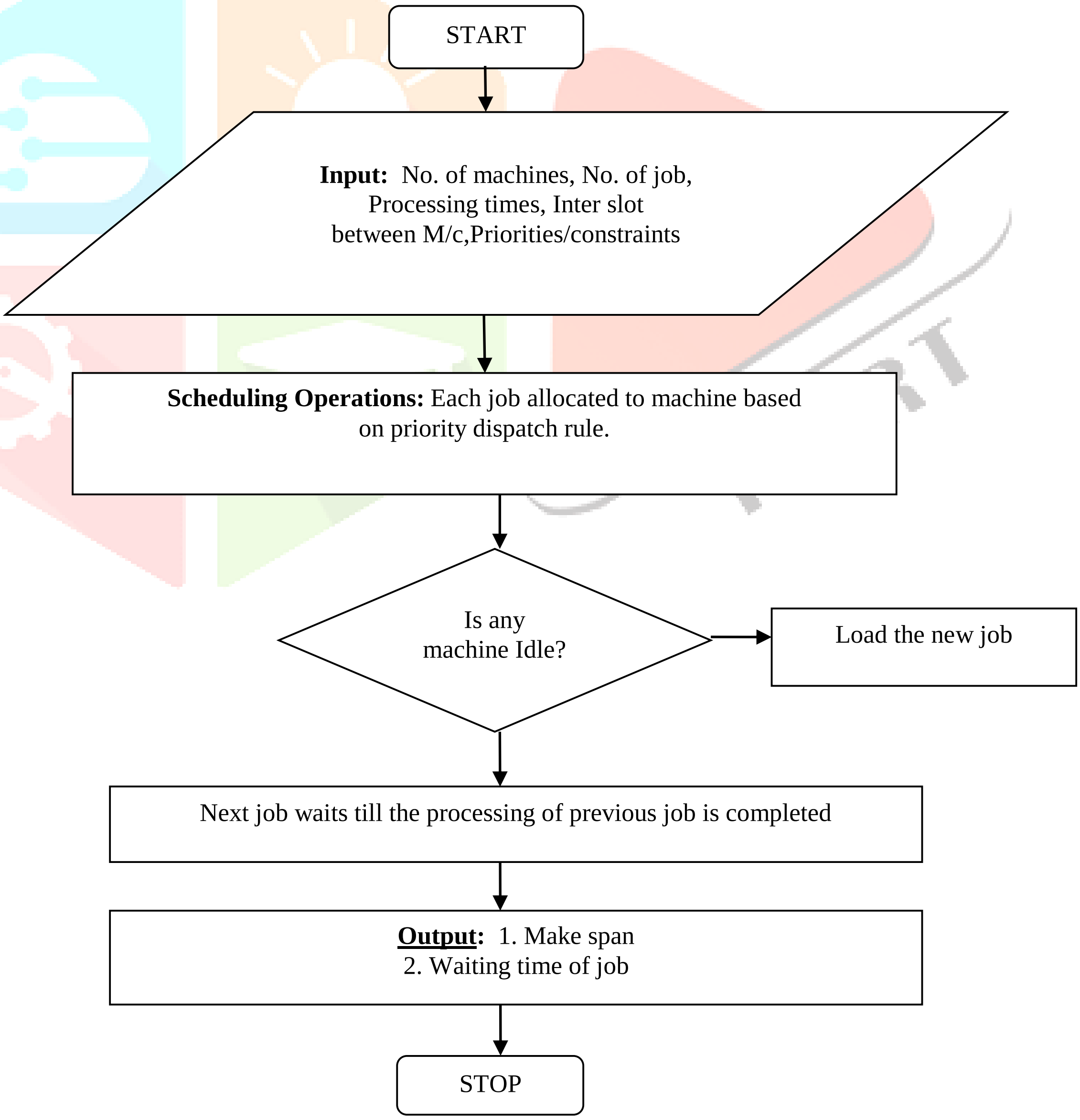

Figure-1 : Schematic flow chart for job scheduling in FMS environment

3. NON-CONVENTIONAL TECHNIQUES:

Non conventional techniques are also called as approximation methods. These methods are very fast but they do not guarantee for optimal solutions. The following are the different types of non-conventional techniques.

a) Dynamic Methods(Precedence pass on rules, multiple dispatch rules),
b) Insertion Algorithms (Bottleneck based heuristics, Shifting Bottleneck Procedure(SBP)),
c) Evolutionary Programs(Differential evolution algorithm, Genetic Algorithm, Particle Swarm Optimization),
d) Local Search Techniques(Ants Colony Optimization, Simulated Annealing, adaptive Search, Tabu Search, problem Space Methods like Problem & Heuristic Space and GRASP),
e) Iterative Methods((Artificial Intelligence Techniques, Expert Systems, Artificial Neural Network),
f) Heuristics Procedure,

4. TABU SEARCH (TS) ALGORITHM INTRODUCTION:

```
algorithm Tabu search
 begin
        T:= [ ];
        s:=initial solution;
        s*:=s
        repeat
           find the best admissible s' ϵ N(s);
        if f(s') > f(s*) then s*:=s' s:=s';
           update tabu list T;
        until stopping criterion:
  end;
```

Figure-2: A basic tabu search algorithm Where T is a tabu list and N(s) is the set of neighbourhood solutions.

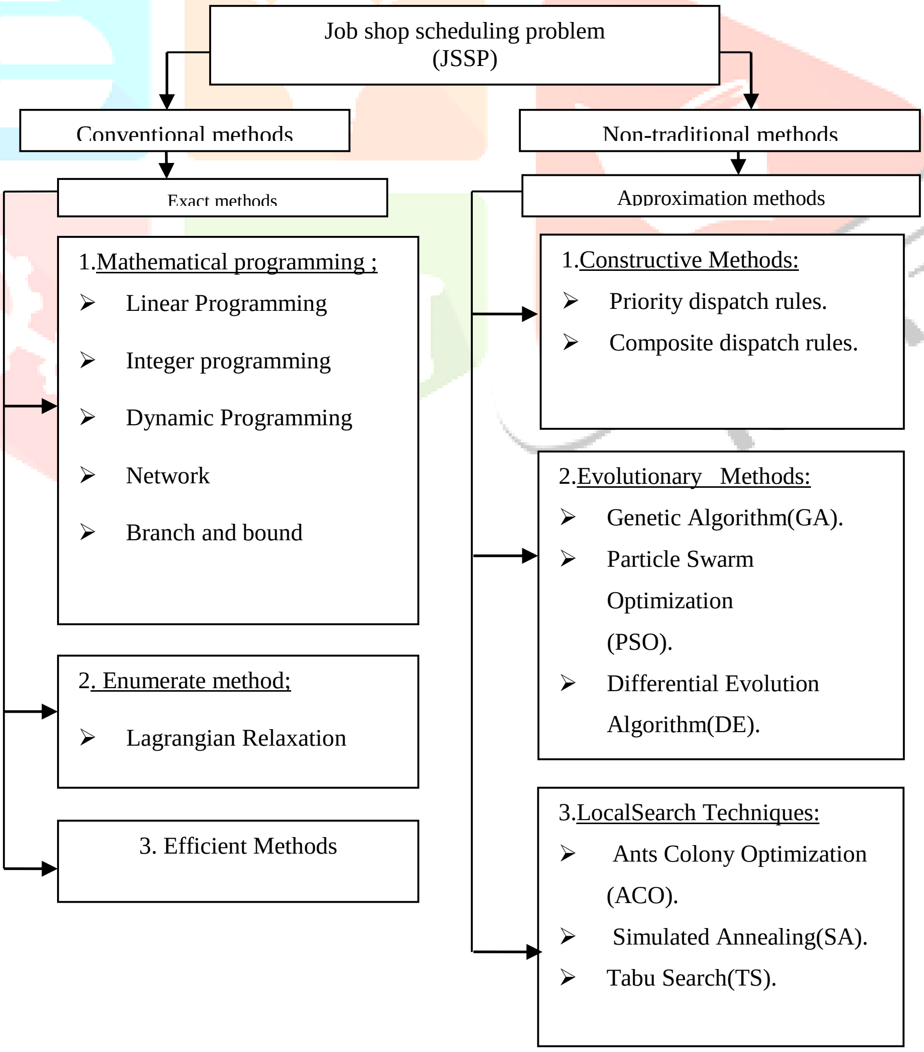

Figure-3: Classification of different algorithms for JSSP

5. OPTIMIZATION OF JOB SHOP SCHEDULING PROBLEM:

In optimisation of a create the aim objective could be simply to decrease the cost of invention or to make best use of the good organization of creation. An optimization algorithm is a procedure which is executed iteratively by comparing various solutions till an optimum or a satisfactory solution is found. With the advent of computers, an optimization has become a part of computer aided design activities. There are many distinct types of optimization algorithms widely used today. But the authors are currently interested to focus and implement the tabu search and differential evolution algorithms.

The job-shop scheduling problem is one of the most studied problems in combinatorial optimization and has been established to be NP-hard problem. In the past decades, several researchers have dedicated their effort to develop evolutionary algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for job shop scheduling problem. Differential Evolution (DE) algorithm is a more recent evolutionary algorithm which has been widely applied and shown its strength in many application areas. In this work, job shop scheduling problem (ʃJ) is done with the help non-traditional optimization technique such as tabu search and differential evolution algorithm. The work is focused on differential evolution algorithm the performance of proposed method is evaluated on a set of benchmark problems and compared with results of tabu search. The numerical results established that the proposed algorithm is able to provide good solutions especially for the large size problems [4].

6. TABU SEARCH (TS) ALGORITHM:

Tabu search (TS) is one of the most efficient heuristic techniques in the sense that it finds quality solutions in relatively short running time. This chapter will provide a basic description of TS as well as introduce application areas and provide comparisons of TS to other meta-heuristic procedures. TS can be considered as a generalization of an iterative improvement. It is regarded as an adaptive procedure having the ability to use many methods, such as linear programming algorithms and specialized heuristics, which it guides to overcome the limitations of local optimality (Glover, 1989). TS are based on concepts that can be used in both artificial intelligence and optimization fields. Over the years TS was improved by many researchers to become one of the preferred solution approaches. Substitute constraints, cutting plane approaches, and steepest climb are big milestones in the improvement of TS. TS apply restrictions to guide the search to diverse regions. Memory in TS has four dimensions: quality, recency, frequency, and influence [3].

7. METHODOLOGYOF TS:

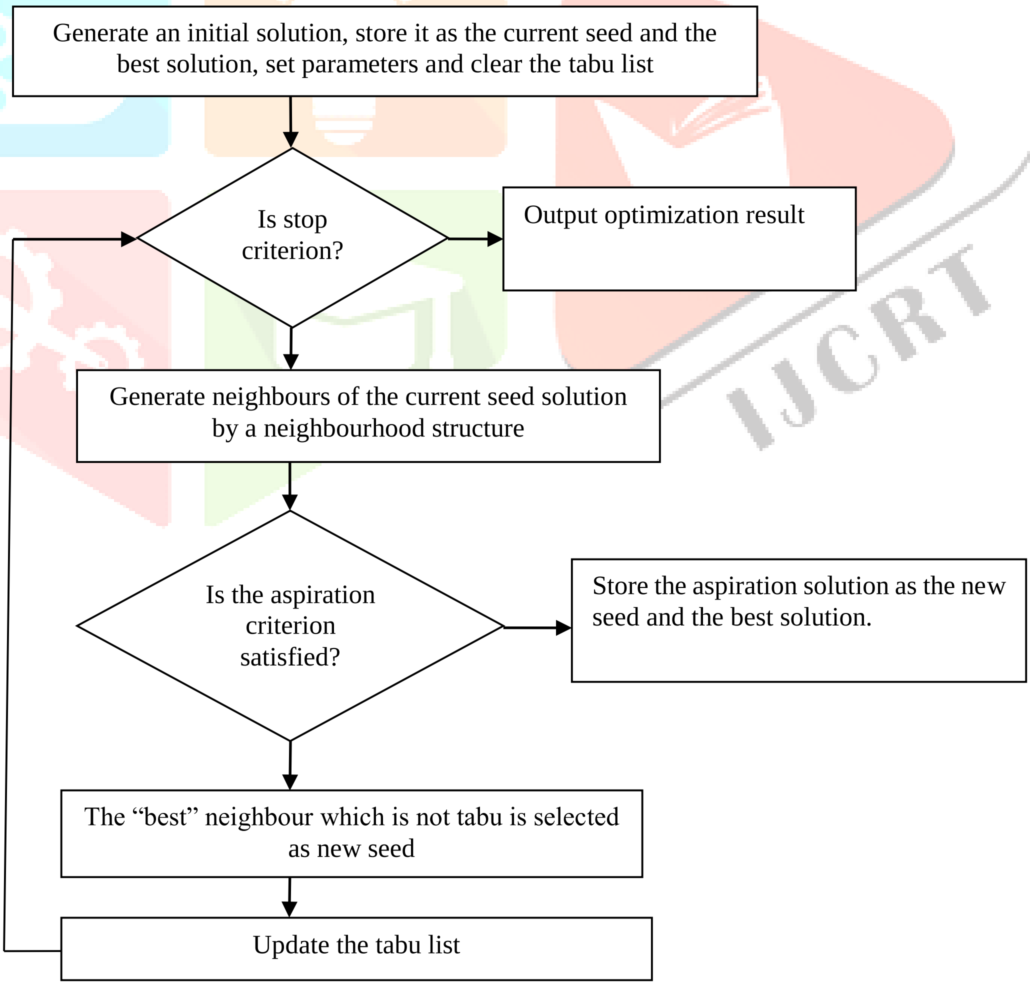

Figure-4: Generic flowchart of tabu search (TS) algorithm.

Steps involved:

1) Generate an initial solution- store it as the current seed and the best solution.
2) Solution representation and evaluation- the initialized solution is represented systematically and evaluated correctly.
3) Stopping criteria- if the stopping criterion satisfies generate the output optimization result else go to next step.
4) Neighbourhood structure/move mechanism- if the stopping criterion not satisfies then generates neighbours of the current seed solution by a neighbourhood structure.
5) Check tabu status and duration (tenure)- the tabu duration is evaluated by following ways:
    - Empirical evidence shows that effective tabu duration depends on the instance(size, etc)
    - An effective range for tabu tenure can be determined experimentally.
6) Aspiration criteria- if the aspiration solution satisfies then store the generated solution as the new seed and the best solution else the best neighbour which is not tabu is selected as new seed. The choices for aspiration criteria as follows :
    - Better than the best solution found so far.
    - Aspiration by default.
7) Update the tabu list- then finally update the tabu list and check the optimum solution [5].

Table-1: Classification of Meta-heuristics (modified from Glover, 1997)

➢ **Meta-heuristic**	**Classification**
TS	A/N/1-P
SA	M/S-N/1
GA	M/S-N/P
ACO	M/S-N/P
DE	DE/rand/1/bin
PSO	M/S-N/P

From the above meta-heuristic techniques, for the work, authors considered the differential evolution and tabu search algorithm as per their suitability to objective function.

APPLICATIONS OF TABU SEARCH:

TS applications comprise diverse fields like scheduling, computer channel balancing, cluster analysis, space planning, assignment, etc. It also has applications in many different technical problems like the travelling salesman, graph coloring, character recognition, etc. Based on our literature review, TS is used widely on machine scheduling and job-shop scheduling problems. In his study Glover (1990), stated that Widmer & Hertz's (1990) application of TS to flow shop sequencing problems succeeded in obtaining solutions superior to the best previously found by applying a range of methods in about 90% of the cases. TS have shown superior results in other recent applications as well.

8. DIFFERENTIAL EVOLUTION (DE) ALGORITHM:

Differential Evolution (DE) is the Stochastic, population-based optimisation algorithm. It is one of the Evolutionary Algorithms (EAs) for global optimization over continuous search space (Storn and Price, 1995). Its theoretical framework is simple and requires inexpensive computation in term of CPU time (Bin et al., 2008). Due to its advantage of relatively few control variables but performing well in convergence, DE has been widely applied and shown its strengths in many application areas (Godfrey and Donald, 2006; Quan et al., 2007; Qian et al., 2008)[6][11].

As a population-based search method, DE starts with randomly generate initial population of size N of D-dimensional vectors. A solution in DE algorithm is represented by D-dimensional position of a vector. Each variable's value in the dimensional space is represented as the real number. The key idea behind DE is a new mechanism for generating trial vectors. DE generates trial vectors by mutation and crossover operation.

9. METHODOLOGYOF DE:

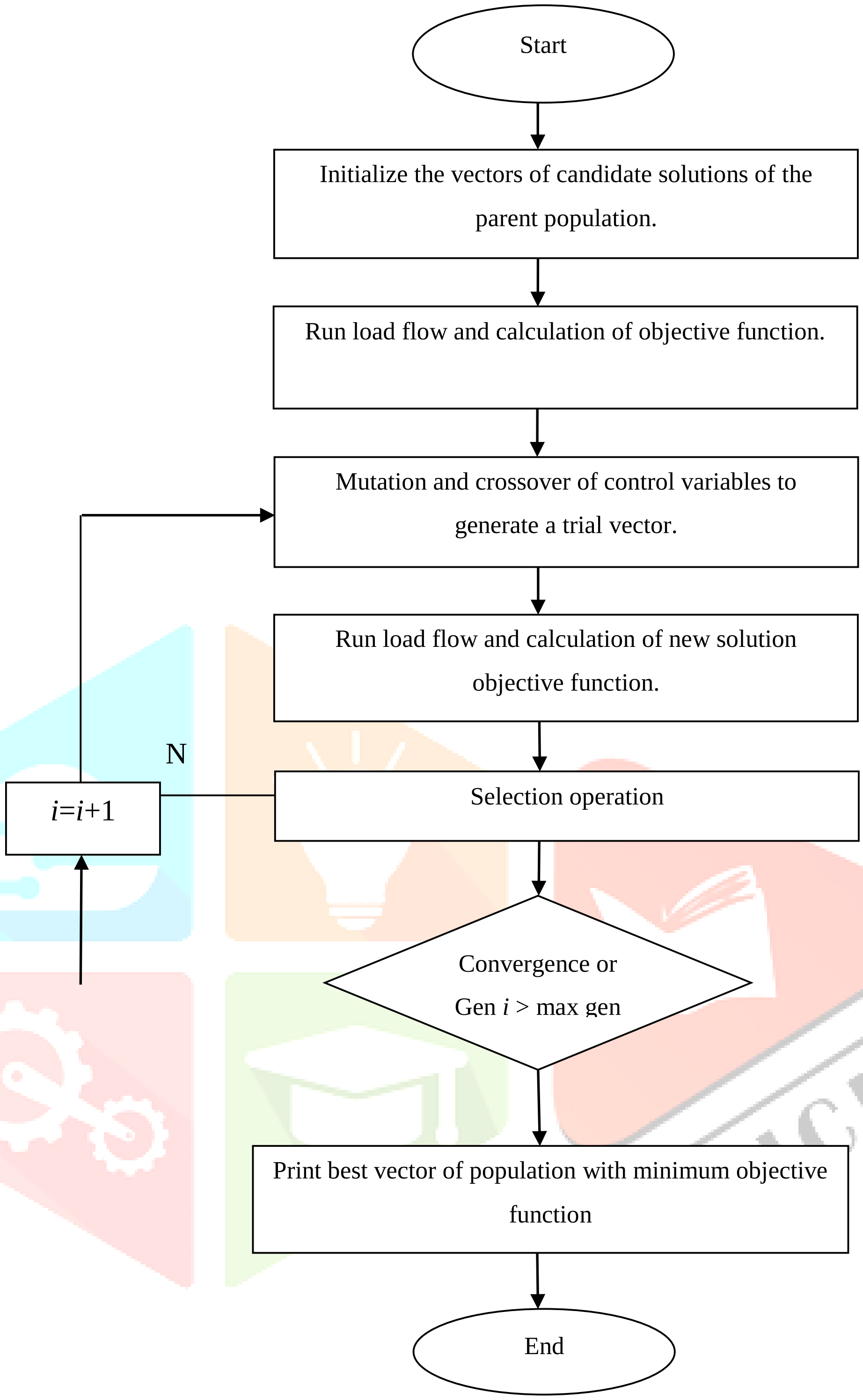

Figure-5: Generic flowchart of differential evolution (DE) algorithm [19].

WORKING PRINCIPLE OF DIFFERENTIAL EVOLUTION:

In DE algorithm, solutions are represented as chromosomes based on floating-point numbers. In the mutation process of this algorithm, the weighted difference between two randomly selected population members is added to a third member to generate a mutated solution followed by a crossover operator to combine the mutated solution with the target solution so as to generate a trial solution. Then a selection operator is applied to compare the fitness function value of both competing solutions, namely, target and trial solutions to determine who can survive for the next generation. The basic DE algorithm consists of four steps, namely, initialization of population, mutation, crossover and selection [7][14][15][16][17].

1. Population initialization: DE starts with initializing the population of size N of D-dimensional vectors. The lower bound bL, and upper bound bU, for the value in each dimension jth (j = 0, 1, …, D-1) must be specified. At initialization step (g = 0), the jth value of the ith vector is randomly generated as follows[8]:

$$x_{j,i,0} = u_j.(b_{j,U}-b_{j,L}) + b_{j,L}$$

Where uj is a uniform random number in the range [0, 1].

2. Mutation: Once initialized, DE mutates and combines current target vectors to produce mutant vectors. For each target vector, $X_{i,g}$, at generation g, the mutant vector, $V_{i,g}$, is generated according to the following equation:

$$V_{i,g} = X_{r1,g} + F(X_{r2,g}-X_{r3,g})$$

It is noted that X_{r1}, X_{r2}, X_{r3} are randomly selected vectors from the population.
They are mutually exclusive and different from the i^{th} target vector, $X_{i,g}$. F is a scale factor which controls the scale of the difference vector between $X_{r2}$and X_{r3} , added to the base vector, X_{r1}.

3. Crossover: DE applies crossover operator on $X_{i,g}$ and $V_{i,g}$ to generate the trial vector $Z_{i,g}$. In the classic DE, the uniform crossover is employed and the trial vector is generated by the following equation [9].

$$Z_{j,i,g} = \begin{cases} v_{j,i,g}, \text{ if } u_j <= C_r \text{ or } j=j_u \\ x_{j,i,g}, \text{ otherwise} \end{cases}$$

where,
u_j : a uniformly random number between [0, 1]
j_u : a random chosen index, $j_u \in \{0, 1,...,D-1\}$
C_r : crossover probability in the range [0, 1]
C_r controls the probability of selecting the value in each dimension for a trial vector from a mutant vector.

4. Selection operation: The selection operation is performed on each target vector $X_{i,g}$, and its corresponding trial vector $Z_{i,g}$, to determine the survival vector for the next generation. The vector $X_{i,g+1}$, is selected according to the greedy criteria[10].

$$X_{ig+1} = \begin{cases} Z_{i,g}, \text{ if } f(Z_{i,g}) <= f(X_{i,g}) \\ X_{i,g}, \text{ otherwise} \end{cases}$$

It is noted that this selection scheme is applicable for minimization problem. Once each individual in the current population is updated, the population continue to evolve through mutation, crossover, and selection operation until some stopping criteria are met. The DE is commonly denoted as DE/rand/1/bin, where DE stands for DE, rand is the type of base vector selected to be perturbed, 1 is the number of difference vector for permutation, and bin stands for binomial distribution of the number of inherited dimension values of mutant vectors.

9. Inference:

The Convergence graph for problem no.10 plotted with No. of Generations v/s Makespan for optimum solution using proposed methods up to 50 generations. From fig 6.12 it shows that Makespan for DE can find better optimum solutions than that of TS algorithm. [12]

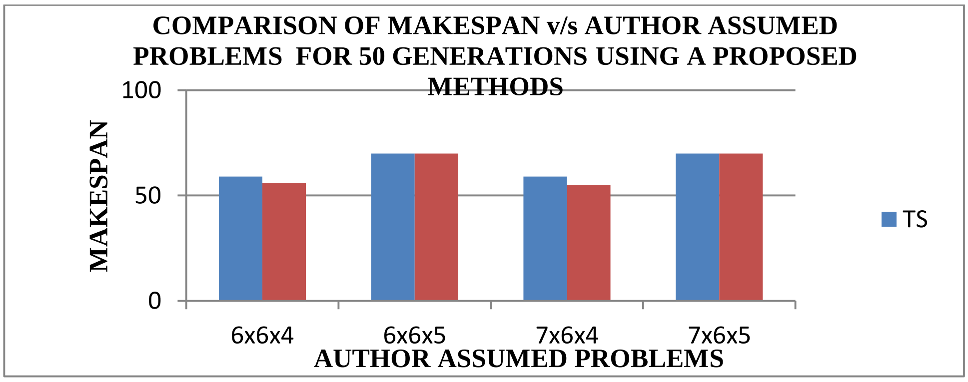

Figure- 6: Comparison of Makespan Performance for 50 generations using proposed methods

Fig 6. Shows that the graph plotted with Makespan v/s benchmark problems for 50 generations using proposed methods.

From fig 6 it shows that Makespan performance for DE can find better optimum solutions than that of TS algorithm [13].

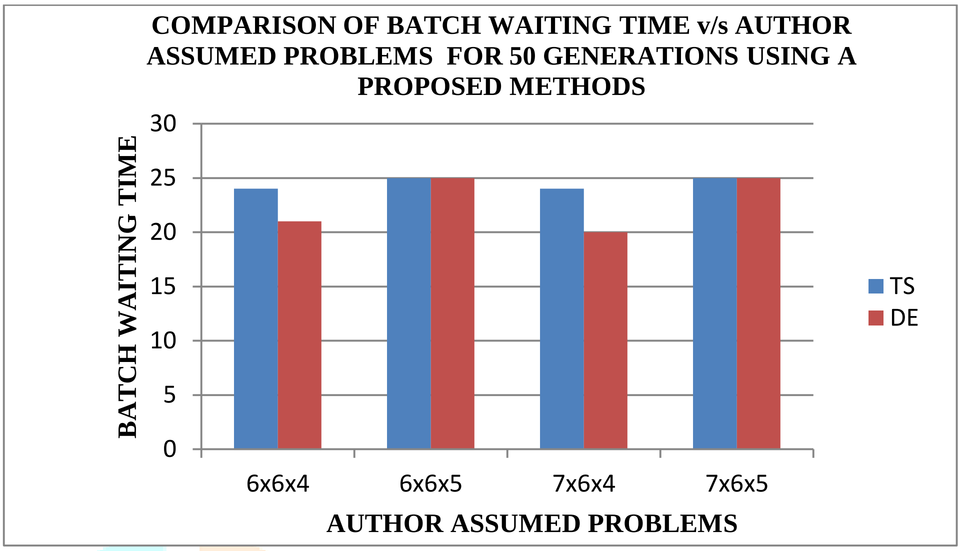

Figure-7: Comparison of Batch waiting time for 50 generations using proposed methods

Fig 7 shows that the graph plotted with Batch waiting time v/s benchmark problems for 50 generations using proposed methods. From fig 7 it shows that Batch waiting time for DE can find better optimum solutions than that of TS algorithm.

CONCNCLUSION & SCOPE FOR FUTURE WORK:

The following are the conclusions obtained during results and discussions:

1) The special factors that involve the use of differential evolution were presented and the efficiency of calculations has been described. Based on presented results it can be concluded that the proposed approach is quite powerful in dealing with job shop problem than that of TS algotithm.
2) Here author compared the performance of DE with the existing TS algorithm over a suite of 10 constrained numerical optimization problems, and concluded that DE was more effective in obtaining better quality solutions.
3) Industrial scheduling is usually focused in the production planning and design of manufacturing system. Because of its great influence on enhanced productivity, customer needs, decrease in the production cost and global competitive market.
4) From the case studies, it is observed that the convergence speed of the DE is significantly poor than that of TS presented in this work. But the process capability of the DE is better than that of TS.
5) Finally, I am concluding that the iterative algorithm promises improvement in job shop scheduling using non-traditional optimization technique.
6) Future the research will be carried out by relaxing some of the assumptions made in this work and to apply the method to wide range of optimization problems.

REFERENCES:

[1] Fred Glover, “Tabu search” Leeds School of Business, University of Colorado, Campus Box 419, Boulder, CO 80309;

[2] Rafael Martí, “Tabu search” Dpto. De Estadística e Investigación Operativa, Universidad De Valencia, Dr.Moliner 50, 46100 Burjassot (Valencia) Spain.

[3] Local Search Techniques: Focus on Tabu Search, Edited by Wassim Jaziri, and Published by In-Teh branch of I-Tech Education and Publishing KG, Vienna, Austria.

[4] E.Nowicki and C.Smutnicki, “An Advanced Tabu Search Algorithm for the Jobshop Problem” Institute of Engineering Cybernetics, Wroclaw University of Technology, Janiszewskiego 11-17, 50-372 Wroclaw, Poland.

[5] A. Hassam and Z. Sari, “Meta-heuristics for real time routing selection in Flexible Manufacturing Systems (FMS)” Tlemcen Automatic Laboratory, Abou bekr Belkaïd University of Tlemcen, PoBox 230, Tlemcen 13000, Algeria.

[6] Dipak Laha and Uday Kumar Chakraborty, **“**An efficient hybrid heuristic for makespan minimization in permutation flow shop scheduling**”** Int J Adv Manuf Technol (2009) 44:559–569 DOI 10.1007/s00170-008-1845-2.

[7] Yamada thesis, “Metaheuristics for Jobshop and Flowshop Scheduling Problems” Kyoto University Kyoto, japan.

[8] Warisa Wisittipanich and Voratas Kachitvichyanukul, "Differential Evolution Algorithm for Job Shop Scheduling Problem" IEMS Vol. 10, No. 3, pp. 203-208, September 2011, Industrial and Manufacturing Engineering School of Engineering and Technology, Asian Institute of Technology P.O. Box 4, Klong Luang, Pathumthani 12120, Thailand.

[9] Zuzana Cickova and Stanislav Stevo, "Flow Shop Scheduling using Differential Evolution" Management Information Systems Vol. 5 (2010), No. 2, pp. 008-013.

[10] Donald Davendra, "Flow shop scheduling using enhanced differential evolution Algorithm" Faculty of Applied Informatics Tomas Bata University Zlin, Czech Republic.

[11] Godfrey Onwubolu, "Flow shop scheduling using enhanced differential evolution algorithm" School of Engineering and Physics University of the South Pacific Suva, Fiji Islands.

[12] Hymavathi Madivada, "A review on non traditional algorithms for job shop Scheduling" Research Scholar, Department of Mechanical Engineering, National Institute of Technology – Warangal, Warangal– 506004, India.

[13] C.S.P. Rao, "A review on non traditional algorithms for job shop Scheduling" Professor, Department of Mechanical Engineering, National Institute of Technology –Warangal, Warangal – 506004, India.

[14] Vanita G.Tonge & Prof.P.S.Kulkarni, "Permutation flowshop scheduling problem using DE" International Journal of Societal Applications of Computer Science Vol 1 Issue 1 November 2012, computer Technology, RCERT, chandrpur.

[15] K. Qin, V. L. Huang, and P. N. Suganthan, "Differential Evolution Algorithm with Strategy Adaptation for Global Numerical Optimization" IEEE Transactions on Evolutionary Computation, Vol. 13, No. 2, April 2009

[16] Rainer Storn, "Differential Evolution - A simple and efficient adaptive scheme for global optimization over continuous spaces" International Computer Science Institute, 1947 Center Street, Berkeley, CA 94704.

[17] Kenneth Price, "Differential Evolution - A simple and efficient adaptive scheme for global optimization over continuous spaces" International Computer Science Institute, 836 Owl Circle, Vacaville, CA 95687.

[18] J.V.S. Bhaskar, "Optimization of material flow In flexible manufacturing system" International Journal of Engineering Science and Technology, Vol 2(12), 2010, 7703-7709