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Decision-making Approaches and Heuristics Algorithms for Multi-objective Flow Shop Scheduling

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Abstract: The decision-making approaches and heuristics algorithms have a significant role in production scheduling for promising concern in multi-objective flow shop scheduling problem. This paper addresses approaches to decision-making problems and their role in the production shop. The taxonomy of heuristics algorithms and analysis of publications is presented. The decision-making approaches are depending upon exact and approximation methods. This paper refers to the mathematical algorithms for scheduling group and promotes to draw significant interest from both conceptual and practical perspective. The scheduling problem structure is defined by constraints and optimality objectives. Some problems of scheduling are identified that have not been validated using heuristics algorithms. Many recommendations are also suggested to industry after extracting the ideas from the literature review. The scope of the paper is to explain the criteria of problem identification, their inputs, and algorithms used. The future research surveys, trends, and challenges in this field are investigated and recommended.

Keywords* — *Flow shop, Heuristics, Makespan, Multi-objective, and Production scheduling

I. INTRODUCTION

Scheduling is the allocation of the resources for the various activities by organizing and controlling and optimizing over a period of time. The set of parts are to be processed on machines in a specified time and order given to each part. The criterions are such as makespan, machine idle cost, lateness, inventory cost, *etc.* to be fulfilled. The objectives are an increase in production efficiency, optimization of resources and minimizing production cost.

A. Types of Scheduling

(i) Single Machine Scheduling:

- There are ‘n’ independent parts to be processed and each has an only single operation.
- Scheduled on basis of in-process times, parts with less in-process time are scheduled ahead.

(ii) Job Shop Scheduling:

- Each part has’ different operations and it is not compulsory to process part on each machine available.
- Flow is not unidirectional and there are no initial and final machines defined in a system.
- Dummy operations assumed.
- Represent as (I,j,k).

(iii) Flow Shop Scheduling:

- Each part has the same number of operations executed in the same order, following the same sequence.
- Processing times at each machine can be different.
- The flow is unidirectional.
- The job consists of *m* operations and *jth* operation will be carried out on the *jth* machine.

II. RESEARCH MODELS: LITERATURE REVIEW

The brief introduction and analysis of each algorithm are explained in this section. This table shows a summary of methods in solving MFSP (Table 1). It is observed that the GA and B&B method of algorithms are applied most successfully in exact methods and GA meta-heuristic algorithms are observed as the most popular algorithm of approximation methods.

Table 1: Summary of Inputs to Heuristics Algorithms with Findings

Author(s) and Year	Algorithm	Input	Finding
[21]	Lingo, a Heuristic using GA	Process time, weighing factor and unit cost of processing	(i) A hybrid mathematical model for a processor assignment. (ii) Determined the initial sequence of jobs and assignment of the processors to the stages.
[13]	Hybrid GA and MATLAB	Population and Completion Time	(i) FSP with SDST condition. (ii) Optimization using three genetic operators.

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[18]	Teaching-learning-based optimization (TLBO) algorithm	The population of learners, teaching factor	(i) presents teaching-probabilistic learning mechanism to solve the no-wait flow shop scheduling with minimization of makespan criterion. (ii) Three neighborhood structures that include Referenced-insert-search, Insert-search, Swap-search based on speed-up methods, are designed to improve the local search.
[6]	Competitive Memetic algorithm	Number of machines, jobs, due dates	(i) presented a competitive memetic algorithm for solving the multi-objective distributed permutation flow-shop scheduling problem with the makespan and total tardiness criteria.
[8]	Variable Neighborhood Search Algorithm (VNS)	Small-sized Instances	(i) Dynamic VNS (DVNS), are presented to find high-quality solutions for large-sized instances
[12]	Monkey Search Algorithm (MSA)	Work-in-process and process time	(i) a sub-population based hybrid monkey search algorithm is presented to solve the flow shop scheduling problems to minimize the makespan and total flow time. SPT and LPT dispatching rules and NEH constructive heuristics are incorporated to improve the solution quality
[3]	Direct combinatorial algorithms	synchronous flow shops with non-fixed processing times and pliable jobs	(i) It has compared a mixed integer program and a two-stage approach where a local search is performed using the set of all job permutations as search space and for each permutation actual processing times are calculated in the second step
[7]	Hybrid Lagrangian metaheuristic via. volume algorithm	A Lagrangian metaheuristic methodology for the cross-dock FSP with parallel-docks	The cross-docking flow shop scheduling problem is investigated and analyzed a time-indexed formulation

III. INTRODUCTION OF HEURISTICS

The term heuristic is used for algorithms which find solutions among all possible ones, but they do not guarantee that the best will be found, therefore they may be considered as approximately and not accurate algorithms (Fig. 1). These algorithms, usually find a solution close to the best one and they find it fast and easily. Sometimes these algorithms can be accurate, that is they actually find the best solution, but the algorithm is still called heuristic until this best solution is proven to be the best.

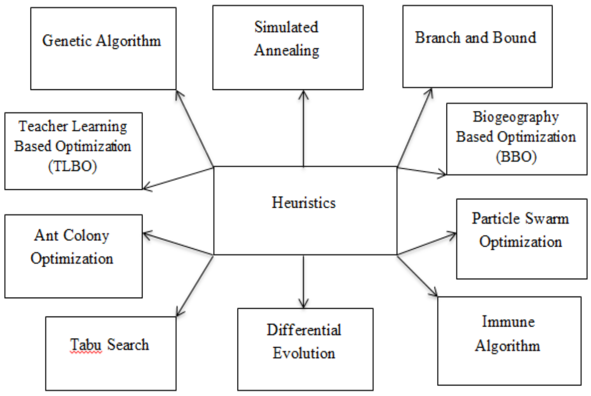

Fig. 1: Depiction of Heuristics to Solve Scheduling Problems

A. Notations α/β/γ for Scheduling Constraints [27]

The constraints (Table 2) can be related to the solution of scheduling problems whether they are implicit or explicit. The first phase α refers to the flow-shop indicators and number of workstations. The field β comprises of a set of variables of the problem. The second phase β addresses a number of job specifications such as preemption. Finally, field γ stands for optimization considerations.

B. Approaches for Decision Making to Solve MFSP

With the rapid change in technology, flipping of increasing customer base, limited time to manufacture with the volatile modifications according to the contemporary products, has made it diligent for researchers to settle multiple objectives in the industries (Fig. 2).

Table 2: Scheduling Notations of Data and Variables

Notation of Data	Description
n	Number of jobs
m	Number of machines
J_i	Job number i, i= 1, 2,….n
$O_{i,j}$	Operation j of job J_i
n_i	Number of operations of job J_i
M_j	Machine number j, j=1, 2, …m
Notation of Variables	Description
$t_{i,j}$	Start time of operation $O_{i,j}$
T_i	Tardiness of job J_i
E_i	Earliness of job J_i
L_i	The lateness of job J_i
C_i	Completion time of job J_i
$C_{i,j}$	Completion time of operation $O_{i,j}$

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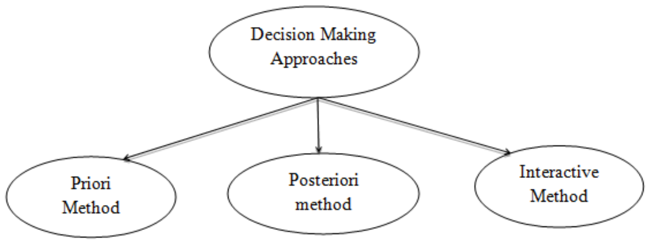

Fig. 2: Depiction of types of Decision Making Approaches for MFSP

(i) Priori method noun for "from the earlier" paddles with the decision maker's knowledge for concluding the initial phase of assumptions and consider something pre-existing related to the problem, which can garner a solution. The objective(s) are pre-defined before the resolution process and research [28].

a. Lexicographic Optimization: The considered multiple objectives to be optimized are based on the lexicographic order, which is based on the optimization of lower priority objectives until they do not interfere in the optimization of high priority objectives.

b. Epsilon Constraint Method: one of the functions is optimized by treating and integrating, the other objectives as constraints in the former function. A new solution can be produced in every run by varying the constrained parameters.

c. Goal Programming: Generally used for conflicting objectives, each of the objectives seeks to achieve a targeted value and any unwanted deviations are extracted in the final function.

Linear and Non-Linear Fitness Combination Methods: Each objective is assigned with fitness value according to their importance for the main problem and is sorted, according to their fitness values.

(ii) Posteriori Methods noun for "from the latter" depends upon the experience of the analyst or supported by factual aspects related to that problem from the past researches. These methods map out all the possible solutions before the analyst to pick out the most desirable for the situation.

(iii) Interactive Methods: These methods search the solution space seeking the preference of the user. In the initial phase, the relations between objectives are not clear, and the user gains more depth of the problem with every result of the computational run.

IV. METHODS/ALGORITHMS TO COMPUTE RESULTS FOR MFSP

As the formulation of the theoretical set of information required to solve the selected multi-objective problem, the next step is to describe the information empirically and summary of scheduling problems (Table 3).

A. Heuristics

Heuristics refers to as an approach to problem-solving, or discovery that employs a practical method not guaranteed to be optimal, but sufficient to obtain results. Heuristics are described as the strategies, influenced by experiences with resembling problems, using readily approachable, though loosely applicable information to control solving in machines, man and abstract issues.

B. Genetic Algorithms

Genetic Algorithm (GA) inspired and originated from the natural selection, an approach to produce off-springs from the parent population called chromosomes, which consists of a gene, by using a crossover, inversion, mutation and selection operators (Fig. 3).

C. Simulated Annealing

Simulated Annealing (SA) published is a probabilistic approach and is a by-product of the Monte Carlo method to determine states in the thermodynamic system [29].

D. Ant Colony Optimization

Table 3: Summary of Scheduling Problems

Problem	Algorithm	Reference
$n/m = F_2/C_{max}$, F	GA	[14]
$F_2\|\|C_{max}$, F	GA	[1]
$C_{max}\geq C_j/F_2$	GA	[23]
$F_2\|\|C_{max}$, F	GA	[24]
min f (y), MAE	GA	[4]
$F2\|\|C_{max}$, F	B&B	[25]
$F2\|\|C_{ma}x$, F	B&B	[20]
$N_3=N_{3.}n_4$	GA	[2]
f_2, $C_{max}(f_1,f_2)$	GA	[11]
$f_2\|\|C_{max}$, F	GA	[15]
f_2,$C_{max}(C_m$-$D_i)$	Heuristics	[16]
$Fm\|\|Z_{cost}, F$	HGA-TS	[19]
$F2\|\|C_{max}, F$	HMSA	[12]
$Fm\|r_j,perm\|\sum F(C_j)$	ILS/IGS	[17]
$Fm\|blocking\|\ C_{max}$	DIWO	[9]

Ant Colony Optimization (ACO) is a probabilistic method (Fig. 4) to solve combinatorial problems by determining the paths through graphs [2].

E. Tabu Search (TS)

Tabu Search (TS) is a local search method [32] used for optimization. It approaches the neighborhood solution, which means similar solutions except with minor details to generate a new improved solution (Fig. 5).

F. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a meta-heuristic approach [30], to optimize the problem by taking candidate solution as an input and moving them around the search space by its velocity and position and is influenced by their own and entire swarms (population) best-known position, and guided toward best positions (Fig. 6).

G. Differential Evolution

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Differential Evolution (DE) is a meta-heuristic, and an optimization method, which improves the solution with respect to the desired quality, required. The characteristic feature is the non-requirement of the gradient of the problem, i.e. a problem does not need to be differentiable.

H. Immune Algorithm

Artificial Immune System (AIS) is a technique intended to function and mechanize as an immune system do, to solve the computational problems from engineering, mathematics and information technology [33].

I. Teacher Learning Based Optimization (TLBO)

TLBO is an optimization method is based on the teacher and student learning process [31]. It is a naturally inspired population method, where the class of learners will represent the population. The best learner in the process is selected as a teacher, as only a teacher is considered with the best knowledge and then increments the knowledge level of the students known as learners, so as to obtain the good marks.

J. Biogeography Based Optimization (BBO)

Biogeography optimization is induced from nature's geographic distributions and proportioning of the biological organisms [8]. It is a bio-motivated and population-based optimization approach where the virtuousness of the habitat is measured by using (HSI). Suitability index variable (SIV) is used for characterizing the attributes of the natural habitat and expressed as one dimension in a solution.

K. Water Wave Optimization (WWO)

The water wave optimization is inspired by the shallow water wave theory. In the WWO algorithm, the solution space is equivalent to the seabed area while the depth of seabed depth figures out the fitness of a point in the space [35].

L. Cuckoo Optimization Algorithm (COA)

The Cuckoo optimization algorithm is an evolutionary algorithm inspired by the lifestyle of cuckoo's birds that uses a special technique for egg laying and breeding. The cuckoos simply replace their own eggs with the host bird eggs [36].

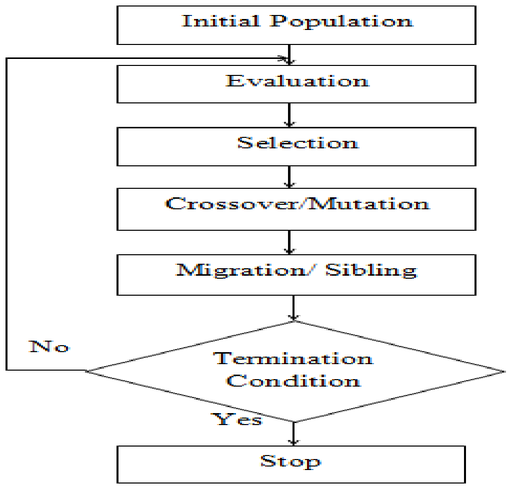

Fig. 3: GA System Architecture

V. SYSTEM ARCHITECTURES OF ALGORITHMS

The flow process charts of algorithms have been taken from literature of operations carried out.

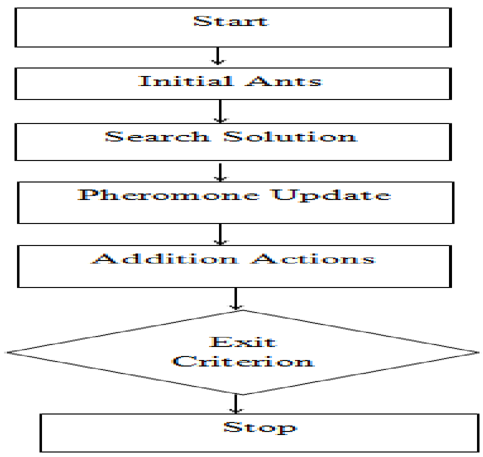

Fig. 4: ACO System Architecture

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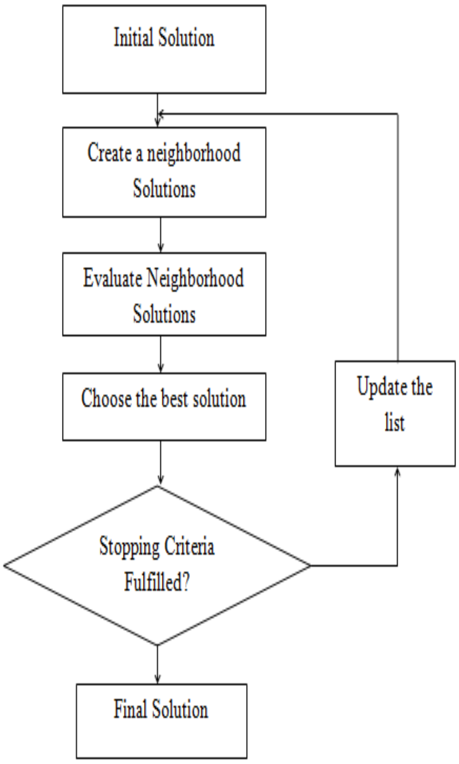

Fig. 5: TS System Architecture

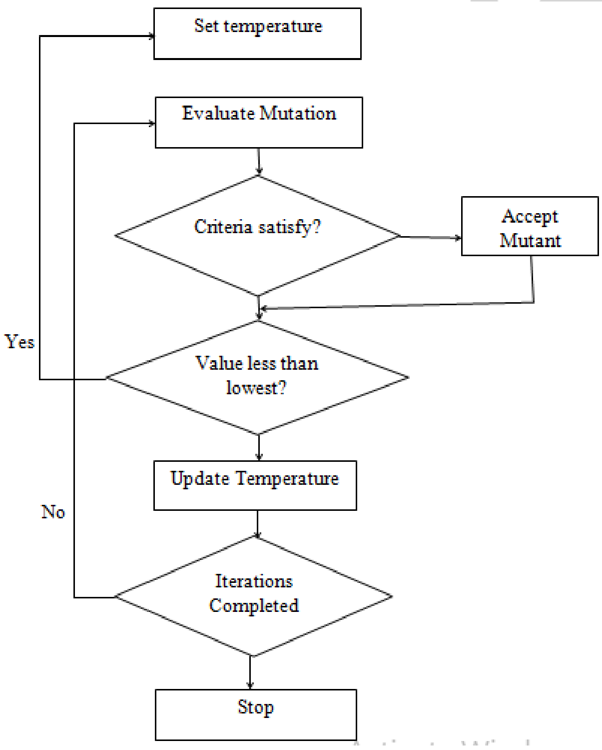

Fig. 6: PSO System Architecture

VI. PARAMETERS OF FLOW SHOP SCHEDULING AND DESCRIPTION

Presently, learning consequences are taken into consideration in the flow shop scheduling problems has pulled implication attention between the investigators in this area [37]. The key factor for flow shop scheduling that may affect the flow of the process and product-related activities (Fig. 7) are some of the parametric quantities that play a major role are described and explained in detail are listed below:

A. Make-Span

The make-span is the time involved to accomplish a bunch of tasks (all n tasks). The make-span is a general documentary in multiple-machine finding out problems [2]. The common theoretical account of make span is regarded as follows: A set of tasks and a set of machines. The tasks have either very similar or dissimilar processing times on the contributed machines. The tasks are too allocation tasks to machines so that the completion time, also called the make-span is minimized. (We might as well as say that we derogate the maximum total processing time on any machine.) The order in which the tasks are processed on a peculiar machine does not behave, and we might take over that they are all together "packed". There may be setup times for different cases of tasks. There may be imputable and release times for more or fewer jobs.

B. Flow Time

The flow time of task i is the time that passes from the initiation of that task on the first machine to the completion of job i. The mean flow time, which is a coarse measure of system performance, is the arithmetical mean of the flow times for all n tasks. The number of flow units comprised of the process is called inventory [37]. Presuming actual determined the process boundary exactly before cutting and exactly after wrapping, this inventory presently existing worked on by any of the three and bagels among the operations. The time it accepts a flow unit to get done the process is called the Flow time (T). If there is more than one route through the procedure, the flow time is combining weight to the length of the longest route.

C. Due Date

Tasks are arranged in enhancing the order of their due dates. The task with the earliest due date is firstly arranged, the one with the following earliest due date is secondly arranged, and so on.

D. Tardiness and Lateness

Tardiness is the positive conflict among the completion time and due date of a job lateness denotes to the difference among the job completion time and its due date and differs from tardiness in that lateness can be positive or negative [22]. If lateness is positive, it is tardiness; when it is earliness. When the completion of the job is in the first place then the due date, the tardiness is zero(0).

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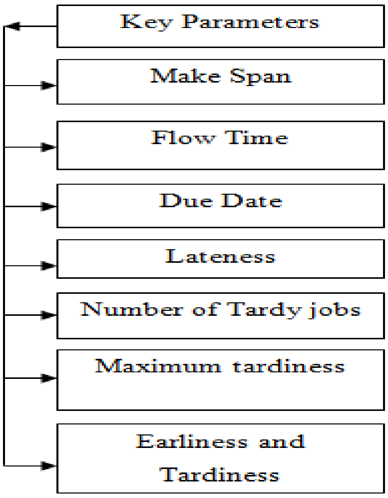

Fig. 7: Main Parameters for FSS Problem in the Manufacturing Industry

VII. CHALLENGES TO OVERCOME IN MFSP

With the advancements in the research related to MFSP, many new methods have paved their way through in outperforming the other existing methods. But, still, there are many problems to be tackled and challenges to be converted into new discoveries.

(i) Challenge in the selection of decision-making approach.

(ii) Grouping and cross-combination of heuristics methods (hybridization).

(iii) Dominance and criterion conditions.

(iv) Framing of the graphical user interface by statistical interference.

(v) Comparison of heuristics methods by validation of the model.

(vi) Challenges to Applicability in the real world manufacturing.

(vii) Duplication of work stations in a production stage.

VIII. CONCLUSIONS AND FUTURE SCOPE OF WORK

The advanced algorithms are known to produce optimal or near-optimal solutions to decision-making approaches. The scheduling problems are always an integral component of every industry. There are many cases of advanced algorithms SA, PSO, ACO, TS, BBO, TLBO, and others to solve the scheduling problems. The locations related to algorithms such as parameters considered, assumptions, types of configurations and social systems of algorithms are helpful in scheduling. The parameters such as processing time, ready time, tardiness, completion time and lateness have been investigated. The general assumptions related to scheduling problems have been distinguished as well. The basic challenges such as the selection of the algorithm, tuning of parameters, dynamic nature of the algorithm and others have been determined. The algorithms, namely, GA, SA, PSO, TS, ACO, DE and IA have applicability in solving small sized problems to large complex ones. GA is mostly used of them all due to high-caliber solutions. PSO and TS are the neighborhood approaches and show rapid convergence which would be helpful for the research community to find future directions.

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