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Simulation and Modelling of Hybrid Heuristics Distribution Algorithm for Flow Shop Scheduling Problem to Optimize Makespan in an Indian Manufacturing Industry

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This study presents a heuristic formulation of the flow shop scheduling problem by the hybrid algorithm fitness function. The genetic algorithm is used to model the time-estimates such as makespan and completion time. This paper aims to optimize the sequence-independent and sequence-dependent time-estimates. The production scheduling parameters such as permutation, non-permutation, no-wait, tardiness, and several workstations are identified from a piston manufacturing industry, in Northern India. Different machine operating parameters were collected from the piston manufacturing industry to work on reducing the makespan. The MATLAB programming in heuristics algorithm distribution function resulted in a reduction of makespan of the product by five times. The reduced completion time is 23 minutes for the piston ring product and 26 minutes in the cumulative validation of the proposed model. The cumulative optimized standard error of 0.26; (n=3) simulate and synthesize the suggested model with its validation. The system efficiency through completion time optimization ranged from 70–82 percent in piston ring, and 63–89 percent in cumulative validation of the model has been worked out for each machine type. The data generated through system optimization helps the scientific world and entrepreneurs in the advancement of sequence-based transportation.

Keywords: Completion time, Genetic algorithm, Meta-heuristics, Non-permutation, Permutation, Sequence-based

Introduction

Nowadays, hybrid heuristics algorithms development to optimize time-estimates in the flow shop scheduling problem is a high requirement for many sectors.[1–3] In particular, the genetic algorithm (GA) approach is a useful optimization tool to simulate time-estimates and parameters based on the production scheduling group. However, GA does not impose a static or sequential error estimation process, yet it is a continuous and dynamic response. Besides, GA does not have any specific fixed rules or clear proclamations to process in the buffer, *i.e.,* the foremost instruction is related to the hypothetical perception of the factual user or organization.[4–6] Also, the mainstream of the operators of the GA methodology, frequently initiate the order-based process without adequate information about their scheduling capabilities such as unrelated machines, machine eligibility, and stochastic processing time.[7,8] This scenario executes a high ambiguity about the successful execution of the work-in-process, and it does not permit knowing the acceptable period of makespan required to determine the optimization according to the realistic scheduling capabilities.[9–11] Therefore, the meta-heuristics has reduced the encoding time and improved the algorithm and system efficiency.[12] There is a limited modelling formulation and optimization of a GA approach to evaluate the makespan and time-estimates on the realistic capabilities of a workstation. Therefore, a hybrid heuristics distribution GA allows the computation of specific time-estimates in a buffer process with multi-objective optimization.[13] The co-evolutionary genetic algorithms find their role in minimizing the completion time from two-machine flow shop scheduling problems.[14] The heuristics genetic algorithm operators are applied to optimize the total completion time for the handling job at different ready times.[15] The scheduling problems are usually organized on performance measures and shop environments.[16,17] The completion time with a job precedence constraint, and along with transportation times is minimized.[18] This paper proposes a hybrid

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heuristics model for a genetic algorithm distribution approach that uses flow shop scheduling group and time-estimate to optimize the probability of flow process among workstations in a piston manufacturing industry in Northern India for piston ring product.

Proposed Method

Flow Process Formulation

The illustration of the heuristics flow process methodology proposed is required based on specific performance measures to conduct error optimization. The proposed flow process is used to manufacture a piston ring in a piston manufacturing industry (Fig. 1). The modification is based on the preparation of the datasheet, which includes parameters such as cycle time, processing time, release date, and completion time. The most critical factor recognized here is the makespan as it depends on all time-estimates mentioned.

The Proposed Methodology of GA Formulation

- ***Stage 1:*** Select coding for constituting cause parameters, crossover operators, selection operators, and mutation operators.
- ***Stage 2:*** Select population size *'n'* with crossover probability 'p_c' and a mutation Operator 'p_m.' Arrange a stochastic population of the length of strings of size '*l*' and set $T_{max} = zero$.
- ***Stage 3:*** Measure each one and every string in the population.
- ***Stage 4:*** If $T > T_{max}$ or early outcome condition met, then Terminate**.**
- ***Stage 5:*** Execute reproduction along with the population.
- ***Stage 6:*** Execute crossover along with random mates of strings.
- ***Stage 7:*** Execute mutation along every string.
- ***Stage 8***: Measure strings in adifferent population.

AlterT = $T + 1$ and go to Step 3.

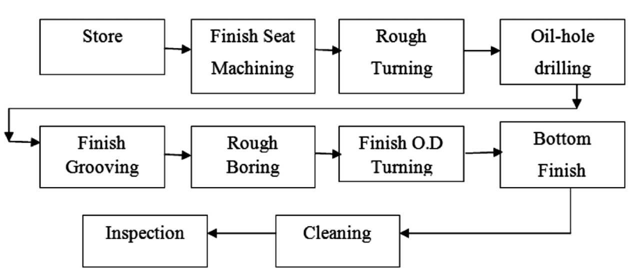

Fig. 1 — Flow shop process a piston manufacturing unit (proposed).

Proposed Genetic Algorithm

(i) Minimization of makespan[19]

$$C_{min} = \sum_{i=1}^{N} C_{Ti} \quad \ldots (1)$$

Machine constraint[19]

$$\sum_{j=1}^{n} x_{t0j} = m_t \quad \ldots (2)$$

(ii) Binary encoding[20]

Each chromosome in a string is assumed from bits: 0 to 1.

Process Observations Conduct

The conduct of the first observation would facilitate the industry to determine (a) Whether it is the right place of conduction of research, (b) Whether all the data needed is available, (c) How much the conditions are right for our work.

Database Sheet Preparation

The preparation of the database sheet depends upon scheduling parameters such as:

(a) Cycle time (b) Processing time (c) Due date (d) Several workers (e) Work in process (f) Task Time.

Field Data Collection

The data is identified from the piston ring manufacturing industry, which is located in Northern India. They are the producers of ring carrier pistons, passenger car pistons, and 4-stroke bi-wheeler pistons. The field data refers to (a) Processing time (b) Due dates (c) Cycle time (d) Idle time and (e) Break down.

Different machine operating parameters were collected from the piston manufacturing industry for working on reducing the makespan. Day wise efficiency percent was calculated based upon the rework time, quantity, scrap time, quality time loss, and valuable operation time. Day wise availability percent was worked out by tool process adjustments, statistical process control (SPC), and time losses such as breakdown, no-material, and no manpower. The availability is a relation of day-wise and shifts-wise operating time which is directly proportional to downtime losses. Day wise system performance percent depends on cycle time, number of tardy jobs, speed losses, and net operating time. It is also measured shift wise and day wise. Overall equipment effectiveness (OEE) depends upon shift wise availability, total processing time, net operating time, and valuable operational time. Overall assets efficiency (OAE) depends upon planned downtime,

Table 1 — Evaluation and reproduction phases on random samples of $11x_1 + 11x_2 \leq 90$ in the iteration

Substring 2	Substring 1	x_2	x_1	$f(x)$	$F(x)$	A	B	Rank
11001111	11100111	18.210	20.320	423.830	0.002	0.090	0.902	1
100011001	111	24.720	0.615	278.685	0.004	0.114	1.137	3
111011001	100000101	41.610	22.960	710.270	0.001	0.054	0.540	
11111	100011111	2.720	25.240	307.560	0.003	0.124	1.244	5
100110101	111011100	27.180	41.870	759.550	0.001	0.050	0.505	
10101101	11101001	15.210	20.450	392.260	0.003	0.098	0.978	
111100100	111111001	42.580	44.430	957.110	0.001	0.040	0.401	
10000101	101010	11.700	3.690	169.290	0.006	0.225	2.253	2
10110101	1000101111	15.920	49.180	716.100	0.001	0.054	0.535	
1000100	11110011	5.980	21.380	300.960	0.003	0.127	1.271	4
				Sum=	0.026			
				Avg=	0.003			

total operation time, valuable operation time, and makespan and quality time loss. Total equipment effectiveness performance (TEEP) will depend upon run time, makespan, net operating time, and shift wise and day wise OEE.

Data Analysis and Documentation

The database sheet and field data are used for drafting the current state and future state map by value stream mapping technique. The whole process is analyzed, and the weak areas are identified, and individual actions are planned from mapping. Specific documentation is compiled for each process for better results.

Statistical Analysis

Statistical analysis of the data was performed using Origin 2019b software. The boxplot graph was plotted to display the distribution of data based on a five-number summary ("minimum", first quartile (Q1), median, third quartile (Q3), and "maximum").

Results and Discussion

Analysis and Synthesis for Makespan Optimization by GA

The recognition of the analytical probability of the j^{th} string was performed for the population group.[21] The process is the selection of the most constructive chromosomes when roulette-wheel selections are applied.

$$P_j = F_j / (\textstyle\sum_{j=1}^{n} F_j) \quad \ldots (3)$$

F_j = 'j' depicts the fitness of the string as $f(x)$
P_i = Selected probability of string 'j',
n = Count of entities in the population.

The best-fitted operation in a maximization problem is selected to keep optimal points unchanged.[21]

Table 2 — Proposed evaluation and reproduction phases on random samples

Mathematical Eqs	x_1	x_2
$11x_1 + 11x_2 \leq 90$	20.32	18.21
$11x_1 + 12x_2 \leq 60$	8.46	7.8
$12x_1 + 15x_2 \leq 90$	20.32	18.21
$19x_1 + 21x_2 \leq 100$	4.11	13
$11x_1 + 13x_2 \leq 60$	8.46	7.8
$15x_1 + 14x_2 \leq 120$	8.33	13.032
$19x_1 + 24x_2 \leq 90$	3.43	6.95
$15x_1 + 17x_2 \leq 120$	4.57	9.266

$$X_i = X_i^{(LB)} + X_i^{(UB)} + X_i^{(LB)} \quad \ldots (4)$$

$$F(x) = \frac{1}{1+f(x)} \quad \ldots (5)$$

The iteration sample of mathematical Eq. $11x_1+11x_2 \leq 90$ exploring the genetic operators is determined (Table 1).

The solutions are x_1 = 20.32 and x_2 = 18.21, and is obtained by mathematical computations with 18 iterations. The estimated value of variables are determined, and selected based on the best-fitness function, $F(x)$ = 0.00235 (Eq. 5). Similarly, the proposed evaluation of empirical equations of reproduction phases on random samples has been determined (Table 2).

Simulation Analysis by Genetic Algorithm using MATLAB

GA addresses the genetic algorithm in the command line to minimize the objective function MATLAB modelling for solving the constraint equations. The chromosomes are determined by the encoding of the initial stages and after applying the binary integers (Eq. $11x_1+11x_2 \leq 90$). Thus, up to 20 integers are constituted by applying 10-bits. The

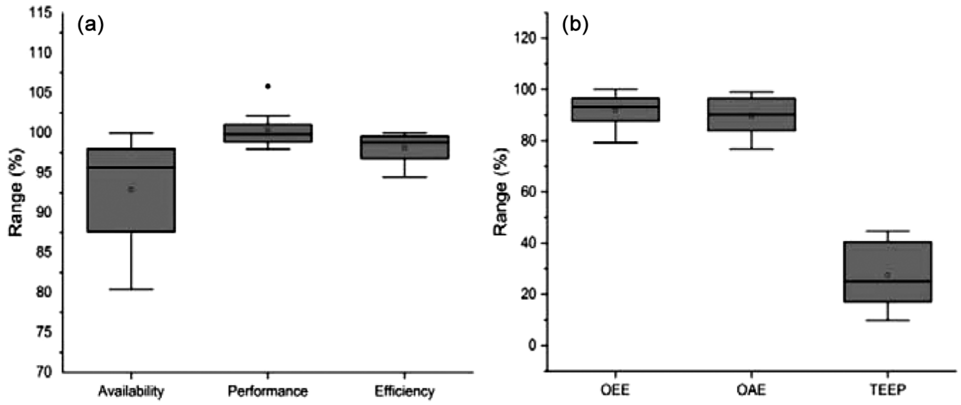

Fig. 2 — Machine operating parameters from the piston manufacturing industry (a) Day wise Performance parameters; (b) Different machine efficiencies

population size assumption is 20 and the preliminary population at random. The proposed chromosomes can be either genotypes or stereotypes. The fitness value for a particular is computed herewith. The genetic algorithm implantation in coding can be represented as follows:

[*x, fval, exitflag*] = *ga(@lincontest6, 2, A, b, [], [], lb)* … (6)

While studying the light vehicle diesel line-3 (LVD-3), the maximum resource availability percent of the line remained between 87–95%. The performance and efficiency were almost near to 100% (Fig. 2a).Similar results have been reported in other research works done in this field.[14] The OEE (Overall equipment effectiveness) per day and overall assets efficiency (OAE) was higher than 80 percent for LVD-3. TEEP (Total equipment effectiveness performance) remained lower than 50 percent as it did not include the net operating time and makespan (Fig. 2b).

Validation of the Model

The obtained makespan and processing time are minimized for machine 1 to machine 8 and is controlled minimally. It also contributes to optimum results to obtain the best-fitness function. The standard processing time for every single machine is reliant on one another. The theoretical results and mathematical results are displayed. Hence, the computed value validates the makespan and its processing time by its optimization and simulation.

Validation of Actual Data, Mathematical Data, and Optimized Data

The piston manufacturing industry in Northern India has been identified as medium-and-large scale industry. It has been working for producing piston rings. The multi-optimized function to assess by a genetic algorithm is created (Fig. 3). It expands the number of population size, assuming string length, and identifying the best fitness function. The analytical data shows the exact optimum results for makespan and processing time.

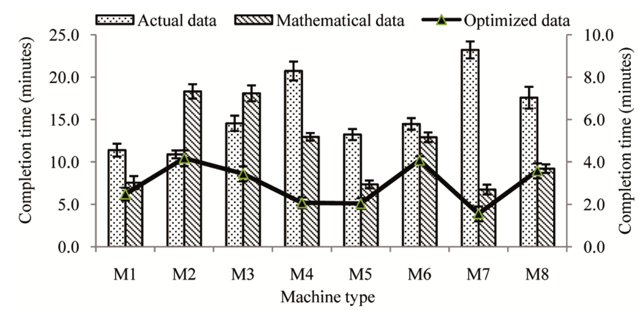

Fig. 3 — Comparison of the actual, mathematical, and optimized the product's completion time (piston ring); The standard deviation is represented by error bars (*n*=3)

The optimized data values are minimized by mapping the tangible data and optimized data. The path function has decreased the actual data values. It shows the optimized values for machine 1–8 type; the actual and mathematical data comparison has reduced the product's completion time (Fig. 3). The proposed algorithm helps to optimize the actual value, and the results are worked accordingly (Figs 2 and 3). The cumulative completion time per process and operation (minutes) has been worked out in Fig. 4.

The total optimized time taken to complete the process came out to be 23 minutes compared to the 126 minutes actual time observed in the industry to complete the process. The two variables are taken after assigning the bits to each variable. The size of each variable is 10 bits, and therefore, the total size required is 20 bits. The observations received from the

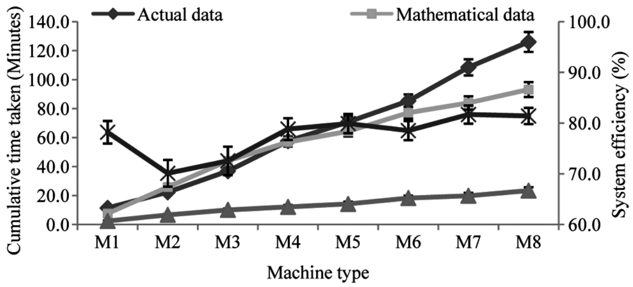

Fig. 4 — Cumulative time is taken in process completion and system efficiency through optimization; The standard deviation is represented by error bars (n=3)

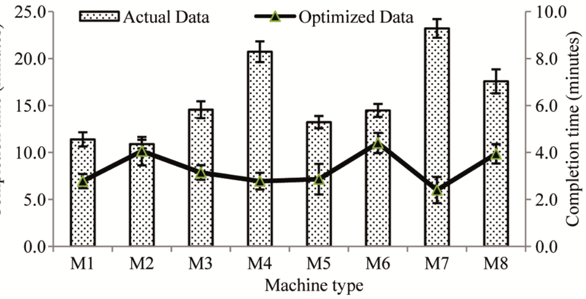

Fig. 5 — Cumulative validation of variation results for the product (piston ring); The standard deviation is represented by error bars (n=3)

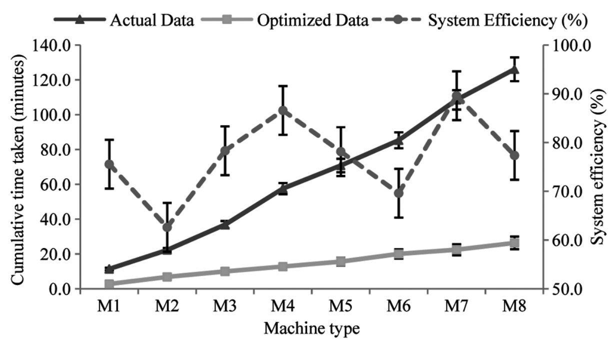

Fig. 6 — Cumulative time is taken in process completion and system efficiency through optimization; The standard deviation is represented by error bars (n=3)

relationship of actual data, the analytical data, and the optimized data using MATLAB are obtained (Fig. 3).

The completion time for machine 1 is reduced by 2.5 minutes, machine 2 is reduced by 4.2 minutes, machine 3 is reduced by 3.4 minutes, machine 4 is reduced by 2.1 minutes, machine 5 is reduced by 2 minutes, machine 6 is reduced by 4.1 minutes, machine 7 is reduced by 1.6 minutes and machine 8 is reduced by 3.6 minutes. The data presented in Fig. 4 shows the actual, mathematical, and optimized cumulative time taken for process completion.

The actual cumulative time taken observed for process completion (machine 1–8) was 126 minutes, through mathematical calculations the time taken came out to be 93 minutes whereas the MATLAB optimized calculations reduced the time taken to 23 minutes for process completion (Fig. 4). The system efficiency increased from 70–82 percent for each machine type based on reduced cumulative time (Fig. 4).

The reduction in makespan is obtained on the factors of mutation, crossover, and the fitness function. The fitness function is gained *via* the objective function and applied in genetic operations sequence. The assumption of genetic operators' demand is the non-negative fitness function. The fitness process remains equal to minimization and maximization problems as the requirement of the uniqueness of the optimal point.

Cumulative Validation of the Model

The comparison of the actual data, the analytical data, and the optimized data has minimized the completion time. The actual data, *i.e.* the makespan of all eight machines in a unit, is evaluated. The mutation and crossover functions are generated by proposing a hybrid genetic algorithm based on the fitness function ranking. As a result, the completion time of 8 machines is minimized sequentially with that crossover application.

The completion time for machine 1 is reduced by 2.8 minutes, machine 2 is reduced by 4.1 minutes, machine 3 is reduced by 3.2 minutes, machine 4 is reduced by 2.8 minutes, machine 5 is reduced by 2.9 minutes, machine 6 is reduced by 4.4 minutes, machine 7 is reduced by 2.4 minutes and machine 8 is reduced by 3.9 minutes (Fig. 5).

The data depicted in Fig. 6 shows the actual and optimized cumulative time taken for process completion. The actual cumulative time taken observed for process completion (machine 1–8) was 126 minutes, whereas the programming-oriented optimized calculations reduced the time taken to 26 minutes for process completion. The system efficiency increased from 63–89 percent for each machine type based on reduced cumulative time (Fig. 6). This reduction in time decides the cumulative completion time of 8 machines is reduced by using a genetic algorithm in MATLAB.

Thus, the hybrid heuristics equation is a proficient methodology for modelling of multi-target sequence-dependent setup time flow shop scheduling problem. Hence, the model is validated. The cross-blend of information, such as accurate information, numerical information, and streamlined information programmed in MATLAB to cross-check the validated model again. It shows the real-time information and the scientific information as most extreme because two machines are taken care of by a single individual and the present examination study demonstrates as accepted and henceforth validated. Therefore, better results are achieved by applying the optimization technique in comparison of the analytical data, and hence, this model is proved and validated. The validated model can be executed in the industry to reduce the product's completion time, and therefore, the production can be improved.

Conclusions and Future Interventions

The present work identified the performance measures like makespan and the completion time to the multi-objective fitness function. The actual data, including both the processing time and the makespan in the piston manufacturing industry, are determined, optimized, and simulated by applying a genetic algorithm. The hybrid mathematical modelling genetic algorithm illustrates the better scheduling environment for optimization parameters by the MATLAB tool. The designing and modelling of the parameters can be performed the hybrid genetic algorithm (HGA), hybrid simulated annealing (HAS), and genetic algorithm and simulated annealing (GASA) and can be modelled by meta-heuristics approaches such as teacher-learning based optimization (TLBO), biography-based optimization, hybrid genetic algorithm (HGA), simulated annealing (SA) and particle swarm optimization (PSO) models.

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Declaration of Competing Interest

None

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