Optimization of maximum expected cost for stochastic While five factors influence processing times

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Abstract

This paper deals with minimization of maximum expected cost for scheduling problem with stochastic processing time .The longest delay time and Earliest finished time are the goal of a mathematical strategy. Many factors influence the deterministic processing times of tasks in any manufacturing challenge, including machinery, manpower, maintenance time, climate, and current supplies . Many different types of oscillating machines are available in most companies to perform machine operations on small-scale jobs. Shapers, broaching machines, and planners are frequently used for cutting a small field of research in low volume. These tools are used to create very small areas of cutting, perpendicular, curved, and plain surfaces. The goal function is to assign ten different jobs in a shaper machine set up to reduce the overall estimated cost, and to find the best suited sequential order to complete the task in minimum time. Furthermore, the importance of the stochastic approach is determined by comparing the findings to those obtained using the deterministic method. Finally, a number of heuristic techniques are proposed to generate close solutions, which are demonstrated to be very precise and cost-effective by trials using the Excel solver.

Keywords: *Flow shop scheduling; uncertainty; Evolutionary solver, genetic algorithm; stochastic processing times.*

I. Introduction

Whenever timings are uncertain, the resulting problem is known as a stochastic scheduling problem. It is still feasible to arrange jobs by increasing predicted processing durations rather than lowering them. More expansively, stochastic equivalents of deterministic models that attempt to reduce the total cost or the maximum cost try to minimize the estimated total cost or the estimate cost. Uncertainties are present in a large number of real-world problems. The scope and scale of products are growing in parallel with the progress of science and technology. The optimum scheduling problem in production workstations has become a central issue in improving production efficiency.

More expansively, stochastic equivalents of deterministic models that attempt to reduce the overall cost or ultimate cost try to minimize the predicted total cost or expected highest amount. Production scheduling is defined by several constraints and belongs to the class of optimization techniques, which are typically difficult to solve. A stochastic task is fundamentally more difficult than a deterministic problem. The study of stochastic flow shop issues has not progressed very far and continues to be difficult. The stochastic flow shop's analytical conclusions have effectively been confined to the predicted execution of all tasks. Due to tardiness and earliness, this work discusses the minimization of the greatest cost function.

In the stochastic flow shop, estimating the predicted make span entails performing a computer simulation of the program with a high iterations for each feasible schedule, so that differences across sequences can be accurately determined. In reality, in addition to determining schedules, the search technique itself. Uncertainty frequently emerges in a realistic manufacturing process due to the difficulties of having accurate information about facilities and jobs ahead of time. In producing maximum required system level of customer satisfaction in unpredictable situations. Due to its higher likelihood of discovering a globally optimal solution, the Evolutionary algorithm is more reliable than GRG Nonlinear.

The Shaper Machine is a type of rotating machine tool that is used to make straight, perpendicular, or angled flat surfaces using straight-line rotating single-point cutting tools identical that are used in lathe operation.

Shaper Machine Tools is used to

a. create straight and flat surfaces.

b. Make rough surfaces smooth.

c. Create internal splines

d. Create gear teeth.

e. To create dovetail slides

f. Create keyways in pulleys or gears.

g. Die, punch, straight and curved slot machining

h. Operation of Vertical cutting

i. Operation of inclined cutting

j. Operation of angular cutting

II. LITERATURE REVIEW

Minimization of maximum Expected cost for stochastic Processing time while processing times are affected by five factors Juliana Castaneda et.al[1] studied at the permutation flow shop problem using both stochastic and fuzzy processing times in this study. The main purpose is to identify a solution (task permutation) that reduces the projected time to completion. However, because of the uncertainty, additional features of the solution are also considered. For individual instances, a MILP system was presented, [2]while for medium and big cases, a genetic algorithm (GA) is devised as a solution approach. In comparison to the mathematical model for tiny instances, the GA consistently found the best answer in 100% of the cases. By analyzing its properties, a multi objective artificial bee colony method using a stochastic simulation approach was proposed[3]. On a set of cases, simulation tests are run, and various state optimal control algorithms are selected as peer techniques. For flow shops with sequential setup, he introduced [4] a two-stage, multi-objective unpredictable programmed. The first step generates ideal schedules in order to reduce overall completion time. Under a time-of-use power pricing structure, the second stage evaluates global energy options to minimize energy consumption. Stochastic and fuzzy processing times were used [3] to identify the best sequence of jobs also find optimum completion time Evolutionary algorithm used by [5],[7],[18] dynamic constrained multi objective optimization problems. Without job block criteria were studied by [6],[8] to find optimum value Monte Carlo simulation used [9] to solve Optimization of Multi-Objective Migrating Birds algorithm . Mathematical programming model was built, as well as a fireworks algorithm with several unique tactics. When compared to three state-of-the-art inter optimization techniques, the experimental findings show that the model and suggested [10] algorithm may obtain good result. Job shop with stochastic flow shop were studied by[11]. To improve exploration and exploitation ability, evolutionary methods, local search methods, and information exchange tactics between two populations were used[12] , Monte-Carlo tree search, unique neighborhood moves, mimetic algorithms, and hyper-heuristic methods were among the techniques [13]employed. The approach was also designed to boost the rate with which repetitions are completed and to take advantage of multicore computers' computational capacity. Empirical Projects with consistent processing times and stochastic due dates were expected [14] to arrive in the chamber at random. Each job's due date was expected to follow a normal distribution with a specified mean and variance. [15],[16]proposed a decomposition-based technique for making a flexible flow shop (FFS) scheduling problem with stochastic processing times have the shortest make span possible. An FFS is decomposed into many machine clusters, each of which may be solved more readily by different technologies. Kenneth R. Baker [17] described three heuristic techniques for the stochastic, two-machine flow shop problem and identified on computational experiments comparing their effectiveness. Q. F. Zhang et.aldiscovered that all three techniques are capable of quickly generating solutions that are close to the most well sequences[18] used simulated annealing-based algorithms with logarithmic cool down schedules to manage flow shops. The goal is to reduce the overall run time, which is referred to as the makespan. He established a theoretical limit for the number of steps required to attain a best result with a high degree of certainty. Alcaide D et al proposed [19] a heuristic strategy for solving stochastic open-shop scheduling issues with the possibility of unpredictable machine failures. A generic dynamic technique is established in the approach, which models every unpredictable problem vulnerable to random failures as a succession of unpredictable problems without failures Genetic algorithms have been studied [20],[22] extensively and utilized in scheduling domains as an useful contextual, but only rarely for stochastic cases. To tackle the stochastic workflow scheduling problem and avoid early convergence of the GA, a hypothesis-test approach, an useful methodology in statistics, is used and implemented into a GA in this study. A hypothesis test and statistical analysis underpin the results obtained. Talwar's[21] rule for scheduling processes with independently and exponentially distributed processing times is definitely the most important. To estimate the predicted makespan, [23] suggested a recursive technique based on a Markov chain, as well as a simulation models model to evaluate the predicted make span. The recursive approach extends a solution presented in the literature for the two-machine flow shop problem to the m-machine flow shop with limitless buffers. Static flow shop problem were discussed by Michel Gourgand [24] He also developed an expansion of Graham, Lawler, Lenstra, and Rinnooy Kan's notation to allow for uncertain factors.The data size also has an effect on the usefulness of the scheduling techniques studied by G. Don Taylor et al.[25] and it revealed some interesting interaction effects between the number of iterations and the other research concerns. Allahverdi A et.al [26] has proposed the flow shop scheduling problem with stochastic machine breakdowns, but its scale is confined to the two machines. S. Suresh et.al [27] hypothesized that in a stochastic flow shop with m machines, a sequence minimising the predicted makespan would schedule one of the stochastic tasks first and the other last, with n-2 deterministic jobs with one production time and two stochastic jobs each with mean 1. Forst F.G looked[28] at an n-job, two-machine flowshop sequencing problem with exponential distributions for task processing times. For finding a job sequence that minimises a total predicted linear cost function, three adequate conditions are derived. For a number of exceptional circumstances, better outcomes are found. J. R. King et.al [29] studied three Heuristics and found best one by comparison method for flow-shop scheduling Johnson's and Talwar's scheduling principles for minimising introduced by [30]the makespan in a two-machine stochastic flow shop'

III. THEOREM FOR EXPECTED COST FUNCTION

Job i may be allocated to the last slot in the sequence when the goal is to reduce the greatest projected cost. If[17]

$$E(b_i(T)) \leq E(b_j(T)) \forall j \neq i$$

where T represents the total time required to perform all tasks. Expected value of cost function is defined by

$E(b_k(T)$ where

$b_k(t) = \delta(t - D_k)(\alpha_k + \beta_k(t - D_k)$ ………….(i)

Since $\alpha_k \geq 0, \beta_k \geq 0,$

Also $\delta(x) = \begin{cases} 1 & x > 0 \\ 0 & oterwise \end{cases}$ ………..(ii)

and $b_k(t) = \begin{cases} 1 & c_k > D_k \\ 0 & c_k \leq D_k \end{cases}$ ....(iii)

Since Expectation of the maximum cost function is considered as probability of completion time of each job is strictly greater than its corresponding due date

IV. STOCHASTIC FLOW SHOP SCHEDULING

The challenge that arises when processing times are random is known as a stochastic scheduling problem. The makespan often shows a positive Jensen gap in the stochastic flow shop model with even two devices, making the issue more difficult than in the deterministic model

V. PROPOSED ALGORITHM

In any production problem deterministic processing times of jobs are affected by so many factors like machines , Man power, Maintenance time, Climate, Current supply. Ten different jobs are being assign to a shaper machine which takes different processing times and different Due date for completing each jobs . The algorithm is being used to execute this scenario.

A. ASSUMPTION

For Stochastic Flow shop scheduling

(i) Initially there are n only one jobs available for processing at the same time

(ii) A machine can only process one single job.

Job setup times are not affected by project completion time and are factored into processing times.

(iii) Job descriptions are predetermined and predictable.

(iv) When there is a backlog of work, machines are never left idle.

(v) Once a process is started, it continues uninterrupted Once a process is started, it continues uninterrupted

B. Problem Description

In any production problem deterministic processing times of jobs are affected by so many factors like machines , Man power, Maintenance time, Climate, Current supply.

Notation

D_k - Due date of job

$E(P_k)$-Expected processing time

α_k – parameter of Earliness cost function

β_k – Parameter of Tardiness cost function

$b_k(t)$ = cost function

T- Every row's summation of n components

Abbreviation

GO-given order

SPT- Shortest Processing Time

RD-Random Order

EDD-Earliest Due Date

GA-Genetic Algorithm

PA-Proposed algorithm.

C. Procedure

- The Given processing times are uniformly distributed
- For all scenarios find Expected Processing time for each jobs
- Apply theorem for Earliness and Tardiness cost parameters
- From Iteration –I choose the lowest value and considered it as the last job for required job sequence .
- Continue the iteration until all jobs are selected

Table-I Jobs With Deterministic Processing Time

job	1	2	3	4	5	6	7	8	9	10
E(pj)	5	4	5	6	8	9	7	6	10	12
dj	10	30	25	40	55	60	30	80	85	68

Table-II Earliness and tardiness cost function

Jobs	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
α	3	2	4	6	1	7	5	8	3	2
β	0.2	0.6	0.5	0.1	0.4	0.2	0.8	0.1	0.2	0.4

Table-III Jobs with stochastic processing time

scenario	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10	Cj
1	6.715	5.839	3.621	5.198	8.748	9.608	8.726	7.315	9.628	12.946	78.344
2	3.656	4.770	5.473	7.377	7.160	9.683	5.903	5.368	10.481	10.061	69.932
3	4.449	2.121	6.319	6.263	6.174	8.992	7.735	6.513	9.179	11.664	69.410
4	3.146	5.659	4.788	5.312	8.099	9.433	8.588	4.151	9.633	13.046	71.854
5	6.046	4.210	3.734	7.096	6.275	8.078	5.679	5.066	11.678	13.212	71.073
6	3.721	3.260	5.721	4.798	7.347	9.014	5.374	7.670	10.187	13.116	70.208
7	3.528	5.421	3.639	5.010	8.977	7.277	5.624	5.290	10.128	10.189	65.083

8	3.755	4.741	3.172	6.992	8.611	8.220	8.149	5.714	9.688	12.620	71.663
9	3.693	4.146	3.928	7.458	8.956	7.364	8.911	5.862	9.500	10.363	70.181
10	5.337	3.500	3.940	6.016	9.723	10.499	5.130	7.342	10.672	10.085	72.243
11	4.073	5.749	6.016	6.920	9.381	9.925	8.417	4.578	11.082	13.907	80.048
12	6.729	5.032	4.602	7.140	8.431	7.568	6.350	7.512	10.826	13.952	78.142
13	6.574	2.215	6.968	5.672	7.498	9.639	8.299	5.770	8.400	11.858	72.894
14	4.381	4.199	5.815	6.533	8.786	8.135	7.816	6.841	8.063	12.289	72.859
15	6.572	3.752	4.486	6.491	6.039	7.391	5.348	7.002	9.512	13.731	70.325
16	4.246	4.258	5.704	5.254	7.177	8.774	5.962	5.665	9.076	11.645	67.761
17	3.232	4.210	3.760	4.262	6.330	7.034	6.092	6.450	8.975	13.850	64.196
18	6.007	5.043	6.247	5.725	7.399	7.453	8.988	5.144	8.529	13.385	73.920
19	5.218	3.182	5.458	6.755	7.909	7.311	8.838	5.797	9.048	12.360	71.876
20	6.782	4.747	3.892	6.766	7.324	10.241	6.488	7.993	9.146	12.607	75.986
21	5.091	4.412	6.136	5.355	7.966	10.396	7.507	7.864	8.312	12.612	75.652
22	5.381	5.405	3.526	7.940	6.205	7.742	7.840	6.087	9.169	11.571	70.865
23	4.191	5.254	6.718	4.480	6.515	10.331	6.784	4.264	11.308	12.149	71.993
24	6.745	2.842	5.863	5.927	7.937	8.503	5.774	6.151	9.426	12.933	72.101
25	6.063	3.832	3.856	6.530	8.308	8.711	8.377	4.382	11.484	12.383	73.926
26	5.364	2.135	4.814	5.449	8.208	8.278	6.736	4.571	8.033	10.553	64.140
27	3.120	5.793	3.460	5.824	6.710	9.906	8.491	5.671	8.339	10.704	68.018
28	6.613	5.957	5.983	5.351	6.876	7.322	8.729	4.421	9.187	11.613	72.051
29	4.627	5.547	3.962	6.678	6.527	8.316	5.514	6.888	8.453	10.750	67.264
30	6.766	4.031	4.576	7.372	7.638	7.198	6.642	6.737	9.904	11.897	72.761
31	4.820	2.299	3.500	4.053	8.570	10.205	6.857	5.223	11.774	10.339	67.642
32	4.207	3.890	5.169	5.357	9.606	8.476	7.261	6.305	9.598	10.680	70.550
Average	5.026	4.295	4.839	6.042	7.732	8.657	7.154	5.988	9.638	12.033	
Dj	10	30	25	40	55	60	30	80	85	68	

Table-IV Iteration table for Cost function

scenario	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
1	16.669	31.007	30.672	9.834	10.338	10.669	43.675	0.000	0.000	6.138
2	14.986	25.959	26.466	8.993	6.973	8.986	36.946	0.000	0.000	2.773
3	14.882	25.646	26.205	8.941	6.764	8.882	36.528	0.000	0.000	2.564
4	15.371	27.113	27.427	9.185	7.742	9.371	38.483	0.000	0.000	3.542
5	15.215	26.644	27.037	9.107	7.429	9.215	37.859	0.000	0.000	3.229
6	15.042	26.125	26.604	9.021	7.083	9.042	37.166	0.000	0.000	2.883
7	14.017	23.050	24.041	8.508	5.033	8.017	33.066	0.000	0.000	0.000
8	15.333	26.998	27.331	9.166	7.665	9.333	38.330	0.000	0.000	3.465
9	15.036	26.108	26.590	9.018	7.072	9.036	37.145	0.000	0.000	2.872
10	15.449	27.346	27.621	9.224	7.897	9.449	38.794	0.000	0.000	3.697
11	17.010	32.029	31.524	10.005	11.019	11.010	45.038	8.005	0.000	6.819
12	16.628	30.885	30.571	9.814	10.257	10.628	43.513	0.000	0.000	6.057
13	15.579	27.736	27.947	9.289	8.158	9.579	39.315	0.000	0.000	3.958
14	15.572	27.715	27.930	9.286	8.144	9.572	39.287	0.000	0.000	3.944
15	15.065	26.195	26.662	9.032	7.130	9.065	37.260	0.000	0.000	2.930
16	14.552	24.657	25.380	8.776	6.104	8.552	35.209	0.000	0.000	0.000
17	13.839	22.518	23.598	8.420	4.679	7.839	32.357	0.000	0.000	0.000
18	15.784	28.352	28.460	9.392	8.568	9.784	40.136	0.000	0.000	4.368
19	15.375	27.126	27.438	9.188	7.750	9.375	38.501	0.000	0.000	3.550
20	16.197	29.592	29.493	9.599	9.394	10.197	41.789	0.000	0.000	5.194
21	16.130	29.391	29.326	9.565	9.261	10.130	41.522	0.000	0.000	5.061
22	15.173	26.519	26.933	9.087	7.346	9.173	37.692	0.000	0.000	3.146
23	15.399	27.196	27.496	9.199	7.797	9.399	38.594	0.000	0.000	3.597
24	15.420	27.261	27.550	9.210	7.840	9.420	38.681	0.000	0.000	3.640
25	15.785	28.356	28.463	9.393	8.570	9.785	40.141	0.000	0.000	4.370
26	13.828	22.484	23.570	8.414	4.656	7.828	32.312	0.000	0.000	0.000
27	14.604	24.811	25.509	8.802	6.207	8.604	35.414	0.000	0.000	2.007

28	15.410	27.231	27.526	9.205	7.821	9.410	38.641	0.000	0.000	3.621
29	14.453	24.358	25.132	8.726	5.905	8.453	34.811	0.000	0.000	0.000
30	15.552	27.657	27.881	9.276	8.105	9.552	39.209	0.000	0.000	3.905
31	14.528	24.585	25.321	8.764	6.057	8.528	35.113	0.000	0.000	0.000
32	15.110	26.330	26.775	9.055	7.220	9.110	37.440	0.000	0.000	3.020
Expected	15.281	26.843	27.203	9.141	7.562	9.281	38.124	0.250	**0.000**	3.136

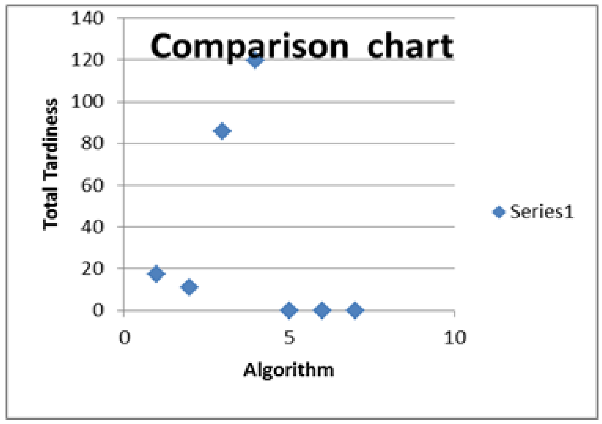
As mentioned in the Iteration Table above in Table IV seven Iteration will carried out. Because there is just one job left, the final stage is simple. At each level, the approach is the same , the collection of jobs under review varies. The best sequence is 1-3-2-7-4-5-6-10-8-9.,. The option is made at each stage based on the lowest predicted expenditure in the last row, which is highlighted in bold.

Table- V- comparison table

. Method	Total Tardiness
Go	17.15
SPT	10.91
RD1	85.69
RD2	119.87
EDD	0
GA	0
PA	0

This chart depicts the comparison value of various algorithm given in the table -V

Fig-1 Comparison of Total Tardiness



D. Hypothesis Test

Null hypothesis: There is no significance difference between Deterministic and stochastic Processing time

Alternative hypothesis:There is a difference between Deterministic and stochastic Processing time

Table- VI Deterministic Vs Stochastic

F-Test Two-Sample for Variances		
	Deterministic	stochastic
Mean	7.2	7.14045287
Variance	6.4	5.914104635
Observations	10	10

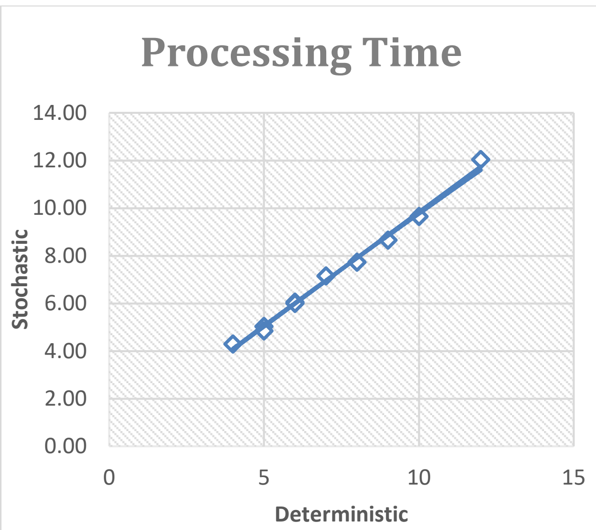
df	9	9
F	1.082158737	-
P(F<=f) one-tail	0.454149583	-
F Critical one-tail	3.178893104	-

Since p-value is greater than the level of significance(0.05), we fail to reject the null hypothesis. refer table –VI.

Null hypothesis is accepted. We conclude that stochastic processing time does not affect the makespan

This chart depicts the processing time of Deterministic and Stochastic.

Fig-2 Stochastic Vs Determionistic Processing time



VI. CONCLUSION

The stochastic one device (shaper machine)scheduling problem was tackled throughout this study, where the effects of learning on processing speed are taken into account simultaneously. Additionally, it is believed that random variables convey the uncertainty related to job production time. A number of heuristic rules are also proposed to compute near-optimal solutions, and testing using the Excel solver have proved these rules to be highly effective and accurate. The method may give an excellent performance for job scheduling issues under unpredictable conditions, according to the findings of simulation studies. Further we extend this work into stochastic Dominance and Safety Schedule

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References

Juliana Castaneda, Xabier A. Martin, Majsa , Javier Panadero Ammouriova, “A Fuzzy Simheuristic for the Permutation Flow Shop Problem under Stochastic and Fuzzy Uncertainty”, Mathematics 2022, 10(10), 1760

Andrés Felipe Guevara-Guevaraa, Valentina Gómez-Fuentesa, Leidy Johana Posos-Rodrígueza, Nicolás Remolina-Gómeza and Eliana María González-Neirab Earliness/tardiness minimization in a no-wait flow shop with sequence-dependent setup times, Journal of Project Management, 7 (2022) 177–190

Yaping Fu, Member, Hongfeng Wang , Junwei Wang , and Xujin Pu, Multi objective Modeling and Optimization for Scheduling a Stochastic Hybrid Flow Shop With Maximizing Processing Quality and Minimizing Total Tardiness IEEE Systems Journal Digital Object Identifier 10.1109/JSYST. 2020. 3014093

Shasha Wang , Scott J. Mason , Harsha Gangammanavar ,Stochastic optimization for flow-shop scheduling with on-site renewable energy generation using a case in the United States 149 (2020) ,106812

Q. D. Chen, J. L. Ding, S. X. Yang, and T. Y. Chai, “A novel evolutionary algorithm for dynamic constrained multiobjective optimization problems, ” IEEE Trans. Evol. Comput., vol. 24, no. 4, pp. 792–806, Aug. 2020.

E,Janaki, A. Mohamed Ismail, Flow Shop Scheduling Model for 5machine without Job Block Criteria Using NEH Technique, 2019 J. Phys.: Conf. Ser. 1377 012020

Yaping Fu, MengChu Zhou, Xiwang Guo, Liang Qi, Scheduling Dual-Objective Stochastic Hybrid Flow Shop With Deteriorating Jobs via Bi-Population Evolutionary Algorithm, EEE Transactions on Systems, Man, and Cybernetics: Systems,2019, 10.1109/TSMC.2019.2907575

E,Janaki, A. Mohamed Ismail, Flow Shop Scheduling Model for Three Machine without Job Block Criteria Using Branch& Bound Technique, Jour of Adv Research in Dynamical & Control Systems, Vol. 10, 05-Special Issue, 2018

Yuyan Han, , Junqing Li, Dunwei Gong , Hongyan Sang Multi-objective migrating birds optimization algorithm for stochastic lot-streaming flow shop scheduling with blocking .2018. 2889373, IEEE

Y. P. Fu, J. L. Ding, H. F. Wang, J. W. Wang, “Two-objective stochastic flow-shop scheduling with deteriorating and learning effect in Industry 4.0-based manufacturing system,” Applied Soft Computing, vol. 68, pp. 847-855, 2018

S. Shoval, M. E fatmaneshnik, “A probabilistic approach to the Stochastic Job-Shop Scheduling problem,” Procedia Manufacturing, vol. 21, pp. 533-540, 2018

Yaping Fu, Hongfeng Wang, Guangdong Tian ,Zhiwu Li, • Hesuan Hu. Two-agent stochastic flow shop deteriorating scheduling via a hybrid multi-objective evolutionary algorithm,” Journal of Intelligent Manufacturing, 10845-017-1385-4 ,2017

S. Asta, D. Karapetyan, A .Kheiri, et al, “Combining monte-carlo and hyper-heuristic methods for the multi-mode resource-constrained multi-project scheduling problem,” Information Sciences, vol. 373, pp. 476-498, 2016.

Ali Elyasi & Nasser Salmasi, Stochastic flow-shop scheduling with minimizing the expected number of tardy jobs Int J Adv Manuf Technol (2013) 66:337–346

S.H. Choi , K. Wang , Flexible flow shop scheduling with stochastic processing times:A decomposition-based approach Computers & Industrial Engineering 63 (2012) 362–373

K. Wang, and S. H. Choi, Solving Stochastic Flexible Flow Shop Scheduling Problems with aDecomposition-Based Approach, American Institute of Physics 1247, 374 (2010);

Kenneth R. Baker • Dan Trietsch, “Principles of sequencing and scheduling “A John Wiley & Sons, Inc. Publication , 1943, ISBN 978-0-470-39165-5

Q. F. Zhang and H. Li, “MOEA/D: A multiobjective evolutionary algorithm based on decomposition,” IEEE Trans. Evol. Comput., vol. 11, no. 6, pp. 712–731, Dec. 2007.

Alcaide D., Rodriguez-Gonzalez A., et al. A heuristic approach to minimize expected makespan in open shops subject to stochastic processing times and failures. International Journal of Flexible Manufacturing Systems, 2006, 17(3): 201-226

Wang, L., Zhang, L., & Zheng, D. Z. (2005a). A class of hypothesis-test-based genetic algorithms for flow shop scheduling with stochastic processing time. The International Journal of Advanced Manufacturing Technology, 25(11), 1157–1163.

P. J. Kalczynski and J. Kamburowski ,Generalization of Johnson's and Talwar's Scheduling Rules in Two-Machine Stochastic Flow Shops , The Journal of the Operational Research Society, Vol. 55, No. 12 (Dec., 2004), pp. 1358-1362

O Etiler1, B Toklu, M Atak and J Wilson ,A genetic algorithm for flow shop scheduling Problems Journal of the Operational Research Society (2004) 55, 830–835

K. Steinhofel, A. Albrecht, C.K. Wong; The convergence of stochastic algorithms solving Flow shop scheduling ,Theoretical Computer Science 285 (2002) 101–117

Michel Gourgand, Nathalie Grangeon , Sylvie Norre, A contribution to the stochastic flow shop scheduling problem, European Journal of Operational Research 151 (2003) 415–433

G. Don Taylor, Subramanyam Venkataraman And Malik Sadiq, An evaluation of flow-shop scheduling algorithms for makespan reduction In a stochastic Environment Production Planning & Control,]1 996, Vol. 7, No.2, 129-143

Allahverdi A., Mittenthal. Scheduling on a two-machine flowshop subject to random breakdowns with a makespan objective function. European Journal of Operational Research, 1995,81(2): 376-387

S. Suresh, R. D. Foley, S. Elizabeth Dickey, (1985) On Pinedo's Conjecture for Scheduling in a Stochastic Flow Shop.Operations Research 33(5):1146-1153.

Forst F.G., “Minimizing total expected costs in the two machine stochastic flow shop”, Operations Research Letters, vol. 2, p. 58–61, 1983

J. R. King A. S. Spachis , Heuristics for flow-shop scheduling International Journal of Production Research ,1980 05.VOL.18; ISS.3

Talwar PP (1967). A note on sequencing problems with uncertain job times. J Opns Res Soc Jn 9: 93-97.