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Flow shop scheduling of Drying and Distribution Unit of an automobile braking system

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***Abstract* - Any group of machines served by a unidirectional, non-cyclic conveyor would be considered as a flow shop. This paper focuses scheduling of product families of Drying and Distribution Unit (DDU) through Shortest Processing Time (SPT) rules and Teaching Learning Based Optimization (TLBO) algorithms. The algorithm has been strengthened with visual C++. The study carried out in an automobile brake manufacturing company. Eight products were developed depends on the configuration of the product. Each product configuration contains for completion of the product; it requires nine work stations. Seven different layouts were considered based on the travel times. The data such as processing time, and travel time were taken to come up with the best solution**

Keywords - Product configuration, SPT, Scheduling, TLBO, Travel time etc.

INTRODUCTION

In a flow shop, machinery is set up in series and job begin processing on an initial machine, proceed through several intermediary machines, and completed on the final machine. Each machine will take up the jobs in a sequence to perform the operation required. The order of jobs for all the machines is same.

Flow shop scheduling problems occurs in a workshop or group shop where the flow control should allow for suitable job sequencing and processing on a set of machines. It is essential to maintain a constant flow of processing activities with the least amount of idle and waiting time possible. Flow shop scheduling is a form of job shop scheduling in which all operations on all jobs must be executed in the very same order. Flow shop scheduling may apply as well to production facilities as to computing designs. Deepak et.al. (2013) attempted to study general n x m Under a no-idle requirement, the processing time of jobs is connected with probabilities in a flow shop scheduling problem. The objective of to develop a heuristic algorithm to n x m flow shop scheduling. so that no machine remains idle during working for any given sequence of jobs. The proposed algorithm is simple, and easy to understand and provides an important tool in many practical situations for minimizing the expected hiring the machines' budget for a fixed sequence of job processing.

The TLBO algorithm is a Rao et al. (2011) and Rao and Savsani (2012) teaching-learning process-inspired algorithm based on the effect of a teacher's influence on a student's output in a class. The algorithm explains two primary ways of learning: I learning from a teacher (known as the teacher phase) and (ii) learning from other learners (known as the learner phase) (known as learner phase).

METHODOLOGY

House of Quality and Analytic Network Process (H o Q -ANP) approach was adopted to determine the critical features. For the drying and distribution unit of an automobile's brake system, the following elements are considered the most critical.

TABLE 1: Technical features of DDU

Sl.No	Technical features of the DDU
1	Air Drying unit (AD)
2	Un-loader Valve (UV)
3	Safety Valve (SV)
4	Quadruple System Protection valve (QSPV)
5	Central Tyre Inflator (CTI)
6	Purge Tank (PT)

A group of 50 stake holders has been surveyed as per their preferences according to each feature. Based on the information gathered the customer preferences in linguistic terms is converted to numerical terms using Five level Likert scale. Further the numerical terms are analyzed by Cluster center to identify the perfect scenario four cluster, three cluster and two cluster scenario. Sum, average and variance of three scenarios of 4-clusters, 3 clusters and 2 clusters are shown in following tables
variance of three scenarios of 4-clusters, 3 clusters and 2 clusters are shown in following tables.

TABLE 2: Sum, average and variance of 4-clusters scenario

Cluster No	Sum	Average	Variance
1	13.158	0.263	0.0212
2	12.240	0.245	0.0034
3	12.163	0.243	0.0068
4	12.437	0.249	0.0030

TABLE 3: Sum, average and variance of 3-clusters scenario

Cluster No	Sum	Average	Variance
1	16.475	0.330	0.002
2	16.219	0.324	0.010
3	17.306	0.346	0.018

TABLE 4: Sum, average and variance of 2-clusters scenario

Cluster No	Sum	Average	Variance
1	25.614	0.512	0.0179
2	24.386	0.488	0.0179

Lowest variance of 0.0030 is obtained with 4 cluster scenario indicates the best cluster scenario. The six features considered in this study has different alternatives shown in the following table.

TABLE 5: Alternatives of each technical feature

Technical Feature	**Alternatives**
1.Air Dryer(AD)	(i)Membrane Dryer (AD1) (ii) Desiccant Dryer (AD2) (iii) Deliquescent dryer(AD3)
2. Unloader Valve (UV)	(i)Low Pressure (<100psi) (UV1) (ii)Medium Pressure (100-105 psi) (UV2) (iii) High Pressure (125-130 psi) (UV3)
3. Safety Valve (SV)	(i)Individual safety valve (SV1) (ii) Integrated safety valve.(SV2)
4. Quadruple System Protection Valve (QSPV)	(i) Series arrangement (QSPV1) (ii) Parallel arrangement(QSPV2) (iii) Bypass arrangement(QSPV3)
5. Central Tire Inflator (CTI)	(i) Electronically controlled (CTI1) (ii) Pneumatic controlled (CTI2) (iii) Electromagnetic Pump Driven(CTI3)
6. Purge Tank (PT)	(i) Low Volume -2.5 L(PT1) (ii) Medium Volume -4 L (PT2) (iii) High Volume-7.5 L (PT3)

Based on the three attribute indicators Strength, Operational safety and cost effectiveness standardized fuzzy decision matrix is studied. Further Fuzzy preference relations of product features are identified by trapezoidal fuzzy number decision matrix. The Fuzzy preference relations that are utilized to build product configurations for each cluster are shown in the results below.

TABLE 6: Fuzzy preference relations of product features when compared to threshold value.

Features	Clusters			
	Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**
AD1	0.2995	0.2995	0.2995	0.2995
AD2	0.3099	0.3099	0.3099	0.3099
AD3	0.3394	0.3394	0.3394	0.3394
UV1	0.0394	0.1792	0.1792	0.3099
UV2	0.1174	0.1483	0.1483	0.2919
UV3	0.0634	0.1707	0.1707	0.3035
SV1	0.1261	0.1261	0.1261	0.1261
SV2	0.2965	0.2965	0.2965	0.2965
QSPV1	0.23	0.23	0.23	0.23
QSPV2	0.296	0.296	0.296	0.296
QSPV3	0.312	0.312	0.312	0.312
CTI1	0.1780	0.2972	0.0394	0.2972
CTI2	0.1778	0.3048	0.0367	0.3048
CTI3	0.2029	0.3014	0.0055	0.3014
PT1	0.1154	0.2881	0.2881	0.2881
PT2	0.1325	0.2695	0.2695	0.2695
PT3	0.1067	0.2931	0.2931	0.2931

The highlighted value denotes the least value in each cluster which is used to form product configuration. From the results shown in the table 6, the product configuration for each cluster is formed and shown in table 7.

TABLE 7: Product Configuration for Each Cluster

Cluster	Product Configuration
Cluster 1	AD1-UV1-SV1-QSPV1-CTI2-PT3
Cluster 2	AD1-UV2-SV1-QSPV1-CTI1-PT2
Cluster 3	AD1-UV2-SV1-QSPV1-CTI3-PT2
Cluster 4	AD1-UV2-SV1-QSPV1-CTI1-PT2

Generic, alternative modular product customization and personalized products are developed to form the family of products of DDU of braking system. These features of alternative product configuration are presented in table 8.

TABLE 8: Alternative product configuration of 8 jobs on 7 layouts

S.No	Product	Product Configuration (PC)	Product Configuration Number
1	Generic Product for cluster 1	AD1-UV1-SV1-QSPV1-CTI2-PT3	PC1
2	Generic Product for cluster 2	AD1-UV2-SV1-QSPV1-CTI1-PT2	PC2
3	Generic product for cluster 3	AD1-UV2-SV1-QSPV1-CTI3-PT2	PC3
4	Generic product for cluster 4	AD1-UV2-SV1-QSPV1-CTI1-PT2	PC4
5	Modular product 1	AD1-SV1-QSPV1-UV3-CTI1-PT1	PC5
6	Modular product 2	AD1-SV1-QSPV1-UV3-CTI2-PT1	PC6

7	Modular product 3	AD1-SV1-QSPV1-UV3-CTI3-PT1	PC7
8	Customized Product	AD3-UV1-SV2-QSPV3-CTI3-PT1	PC8

After identifying the product configuration scheduling can be done through priority rules and metaheuristic algorithms.

The Priority rules are classified into four classes. The first class based on process time namely Shortest Processing Time (SPT) and Longest Processing Time (LPT), rules Earliest Due Date (EDD), Job Slack Time (JST) and Critical Ratio (CR) are a type of set of rules which involve due dates. Class three consists of rules RANDOM, First Come First Serve (FCFS), Last Come First Served (LCFS), Least Flexible Job (LFJ), First Off First on (FOFO) and Least Anticipated Work in Next Queue (LAWINQ) that involves shop and/or job characteristics. Finally, class four is formed by a combination of the last three classes and is known as rules Cost OVER Time (COVERT), Most Operation Remaining Rule(MOPNR), Preferred Customer Order (PCO) and Least Slack (LS).
In this paper scheduling is done through priority rules (FCFS, SPT, LPT) and Teaching Learning Based Optimization (TLBO) algorithms are modified to solve scheduling problems. Each product configuration contains nine work stations for completion of the product are given below.

TABLE:9 Work stations

Station No.	Parts
S1	Plastic valve, silencer
S2	Tyre inflator, screws and washers
S3	Plunger, unloaded valve etc.
S4	Non return valve, sealing ring, filter and valve seat.
S5	Purge tank, lock nut, cartridge retainer and sealing ring.
S6	Governor valve
S7	Quadruple system protection valve, ring guide, top cover etc.
S8	Pressure setting valve, screws spring etc.
S9	Lip seal, stiffener cover etc.

The data such as processing time for 8 Product configurations are shown below.

TABLE 10: Assembly time of 8 Product configurations on different stations

Station No.	Assembly time (Sec) for 8 Product Configurations (PC)							
	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**
S1	258	258	258	258	258	258	258	258
S2	194	194	198	190	194	194	194	198
S3	242	225	250	210	242	242	242	242
S4	316	316	316	316	316	316	316	316
S5	291	291	291	295	286	282	289	286
S6	426	426	426	426	426	426	426	426
S7	452	452	452	452	452	452	452	446
S8	420	420	420	420	420	420	420	420
S9	322	322	322	322	322	322	322	322

For implementation of FCFS, SPT, LPT and TLBO Product Configurations and Layouts (PC) 1,2,3 and 4 is considered respectively as an example.

TABLE 18: Work station schedules

Station No.	FCFS		SPT		LPT		TLBO	
	Process Time	**Total Time**	**Process Time**	**Total Time**	**Process Time**	**Total Time**	**Process Time**	**Total Time**
S1	258	258	194	194	452	452	258	258 (S6)

S2	194	482	225	449	426	898	190	468 (S9)
S3	242	739	258	707	420	1318	210	678 (S8)
S4	316	1070	291	1028	322	1660	316	1014 (S5)
S5	291	1376	316	1344	316	1996	295	1309 (S2)
S6	426	1817	322	1696	291	2307	426	1735 (S7)
S7	452	2284	420	2146	258	2585	452	2187 (S3)
S8	420	2719	426	2602	250	2855	420	2627 (S1)
S9	322	3041	452	3054	198	3053	322	2949 (S4)

For the given job set operational completion time (make span) is 3041 secs for FCFS, 3054 secs for SPT, 3053 secs for LPT and 2949 secs for TLBO respectively.

RESULTS AND DISCUSSION

Below are the performance estimates for several algorithms.

TABLE 19: Performance comparison of various algorithms.

Job. No	FCFS	SPT	LPT	TLBO
1.1	3041	3041	3041	3041
2.1	3024	3024	3024	3024
3.1	3053	3053	3053	3053
4.1	3009	3009	3009	3009
5.1	3036	3036	3036	3036
6.1	3032	3032	3032	3032
7.1	3039	3039	3039	3039
8.1	3034	3034	3034	3034
1.2	3071	3071	3071	2981
2.2	3054	3054	3054	2964
3.2	3083	3083	3083	2993
4.2	3039	3039	3039	2949
5.2	3066	3066	3066	2976
6.2	3062	3062	3062	2972
7.2	3069	3069	3069	2979
8.2	3064	3064	3064	2974
1.3	3041	3041	3041	2981
2.3	3024	3024	3024	2964
3.3	3053	3053	3053	2993
4.3	3009	3009	3009	2949
5.3	3036	3036	3036	2976
6.3	3032	3032	3032	2972
7.3	3039	3039	3039	2979
8.3	3034	3034	3034	2974
1.4	3041	3041	3041	2981
2.4	3024	3024	3024	2964
3.4	3053	3053	3053	2993
4.4	3009	3009	3009	2949
5.4	3036	3036	3036	2976
6.4	3032	3032	3032	2972
7.4	3039	3039	3039	2979
8.4	3034	3034	3034	2974
1.5	3071	3071	3071	2996
2.5	3054	3054	3054	2979
3.5	3083	3083	3083	3008
4.5	3039	3039	3039	2964
5.5	3066	3066	3066	2986
6.5	3062	3062	3062	2987

7.5	3069	3069	3069	2994
8.5	3064	3064	3064	2984
1.6	2936	2936	2936	2936
2.6	2919	2919	2919	2919
3.6	2948	2948	2948	2948
4.6	2904	2904	2904	2904
5.6	2931	2931	2931	2931
6.6	2927	2927	2927	2927
7.6	2934	2934	2934	2934
8.6	2929	2929	2929	2929
1.7	2971	2971	2971	2941
2.7	2954	2954	2954	2924
3.7	2983	2983	2983	2953
4.7	2939	2939	2939	2909
5.7	2966	2966	2966	2936
6.7	2962	2962	2962	2932
7.7	2969	2969	2969	2939
8.7	2964	2964	2964	2934

From the table 19 it is observed that make span for 56 cases referred as job numbers with respect to priority rules. With TLBO the make span is same in 16 cases out of 56 instances when compared to the SPT rules. That is 28.57%

Minimum make span is obtained for 40 cases out of 56 cases by TLBO algorithm when compared to the SPT rules. That is 71.43%

No higher make span value is observed when TLBO algorithm compared with to SPT. From results minimum make span is obtained in 71.43 % cases.

Hence TLBO algorithm can be considered for flow shop scheduling. It is as a result of the fact that TLBO is an effective algorithm to solve NP (Nonlinear polynomial) hard problems arising in scheduling.

CONCLUSIONS

The present work is focused on scheduling of product families of DDU through SPT rules and TLBO.

- The objective coordinating work scheduling aimed at optimizing the make span time. Comparison based on make span is made.
- The algorithm has been enhanced with visual C^{++}.
- From this study The validity of the TLBO algorithm has been established to be efficient.
- Since in more than 73% of problems optimum make span is obtained.
- The completion time is also reasonable.

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