SCHEDULING OF STEEL MELT SHOP BY USING TEACHING LEARNING BASED OPTIMIZATION

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Abstract: *Scheduling of Steel Melt Shop is a Non-deterministic Polynomial optimization problem, which is one of the most substantial areas of research survey in Integrated Steel Industry. In SMSSP there are n No. of jobs and m No. of machines where each job is processed on every machine in predefined operation sequence. Many traditional and Non - traditional methods such as First cum First Serve, Shortest Job First, Earliest Deadline First, Mixed Integer Linear Programming Model, Integrated Production Process, Ant Colony Optimization, Non Linear Optimization, Linear Programming Model, Lagrangian Relaxation Methods had been applied for some years in the past to find an accurate optimal operation scheduling with minimum Operation Time. The major contribution of this work has been the implementation of an effective scheduling method based on Teaching Learning process for solving SMSSP. TLBO is a recently developed optimization technique based on random population for solving any type of scheduling problem. It consists of two phases namely, Teacher Phase and Learner Phase. Teacher phase signify learning something from a teacher and Learner phase tells about learning by self study. TLBO performance can be attained by solving Scheduling of Steel Melt Shop by minimizing Operation time, Reduction of Tardiness and maximization of number of charges at each stage of SMS at population size of 20,39,1132 charges. The present work is a realistic case study and has proved by the results thus obtained show that TLBO is an active evolutionary algorithm to prosper a best operations scheduling.*

Keywords: *TLBO, Steel Melt Shop Scheduling Problem (SMSSP), PBX and VNS.*

1. INTRODUCTION

1.1 Scheduling

Scheduling is broadly defined as the process of assigning a set of tasks to resources over a period of time. Persuasive Scheduling plays an vital role in present competitive manufacturing world. Performance criteria such as Machine utilization, manufacturing lead times, Inventory costs, Meeting due dates, Customer satisfaction, and Quality of products are all constraints on the effectiveness of the how jobs are scheduled in the system. Hence, it becomes to a greater extent to develop an effective scheduling approaches that help in achieving the desired objectives. In any Production the system will go through for number of Jobs, is a chance of selecting alternative resource sets and sequences for the jobs provided. Thus, the scheduling of jobs aims for flexibility in generating a variety of sequences. Therefore the present work is concentrated on the Scheduling of Steel Melt Shop problem. Tang, et al., [1], have done extensive research on Production planning and scheduling of SMS in the integrated Steel industry, but the SMS scheduling problem as defined in our study and consideration of problem can be modeled as a three-stage modeled hybrid flow shop problem. Gupta [2], has done work on the two-stage hybrid flow shop scheduling problem by heuristic method, but the present study is based on 3 stage of SMS. Bellabdaoui and Teghem [3], have done work on the models developed for scheduling Steelmaking-Continuous Casting and solved for optimum by standard software with in small production system, TLBO has been used in the present work with up to 1132 charges. Pinedo [4], have not partcularly focused on Human-Computer Interaction for schedule guidance, even though this is an valuable topic also in present case. Practical scheduling of SMS problem with 3 Converters, 2 LFs and 3 Continuous Casting Machines can be solved. Tang, et al., and Harjunkoski and Grossmann [5], describe LP models that determine the start, end dates and the casting speeds of all charges, bold that all allocations and sequences are in steady. Tang, et al., [6], specify systematically the SM-CC scheduling with various continuous casters as a mixed-integer programming model and developed a solution method based on Lagrangean relaxation method. Huegler and Vasko [7], developed a heuristic method that estimate an SM-CC schedule for pre determined casting times and start dates of the charges on the continuous caster. Bellabdaoui, et al., [8] develop a creation heuristic that first schedules the Continuous Casting and refining stage and then the Converters. Steel melt process scheduling using Lagrangian relaxation in an integrated Steel Industry is the issue which tells about the scheduling of Casting process, in the name of cost they reduced tardiness in the name of cost of casting process by scheduling of casting process, so they have did it for whole process of SMS, the study tells about the inter link between each stage, for each stage the improvement is needed, in every stage there are so many tardy jobs, my study tells about Reduction of Tardiness, and improvement of No of Charges. Roy, et al., [9], done work on to develop Knowledge model for schedule propagations, rescheduling and the development for managing schedule disturbances. MacKay and Wiers [10], have done work on Human dispatchers utilize extensive knowledge of experience, which often done modification carefully into the scheduling process, Chandra Sekhar, et al., [11], have done work on Three Stage Scheduling of Steel Making using Earliest Deadline First Algorithm, which gives information to develop scheduling of Steel Melt Shop in Optimized sequence. Lixin Tang, Jiyin Liu, et al., [12], have done work on Scheduling of Steelmaking-Continuous Casting Production with a mathematical programming model, thus tells the model structure for SMS, the present study is based for overall SMS to reduce Tardiness and to Maximize No. of Charges. Therefore, the work concludes that there is less number of OR algorithms have been developed to optimize the SM-CC process. In the following a new algorithm for solving the SM-CC problem is developed that plays a very effective role in order to generate schedules. Rao, et al., [13], introduced a newly developed Teaching Learning Based Optimization (TLBO) Algorithm based on the Natural phenomena of Teaching and Learning process like in a classroom. TLBO is a inspired algorithm based on the effect of influence of a teacher on the output of learners in a class. Rao and Vivek Patel [14], had done work on New TLBO algorithm for solving Constrained and Unconstrained Optimization problems which is used to understand more about the algorithm. Rao, et al., [15], used New TLBO algorithm on large scale Non-Linear Optimization problems for solving the optimal solutions. The optimality of the method is runed on so many benchmark problems with different assumptions and the outputs are compared with other optimization methods. Venkata Rao and Vivek Patel [16], done worked on an Improved TLBO algorithm for solving Unconstrained Optimization problems, which inspires for our problem to reach accurate Optimality. Hence, the literature survey concludes that the TLBO algorithm can be effectively used for JSSP.

1.2 Introduction to Steel Melt Shop

Visakhapatnam Steel Plant (VSP), Rashtriya Ispat Nigam Limited (RINL) is the first shore based integrated steel plant with present capacity of 3.5 million Ton (MT) liquid steel production per annum. Now VSP is expanding its liquid steel capacity to 6.3 MT per annum. In the expansion phase, a New Steel Melt Shop (SMS-2) with 2.8 MT liquid capacities is being installed. In SMS, there are 3 levels 3 Linz Donawitz (LD) converter, 2 Ladle Furnace (LF), 3 Continuous Casting (CCD).

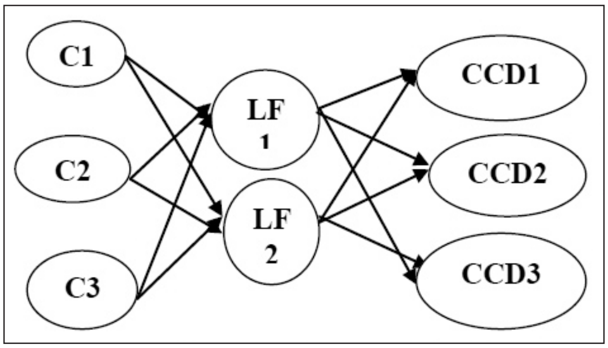

Fig 1. Network Diagram of SMS

The C1, C2, C3 are three converters in sms, LF1 and LF2 are two refining stages in SMS and CCD1, CCD2, CCD3 are three continuous castings with 6 stands per CCD. These are three stage machines running 24 hours in steel shop. Basically the iron metal comes from blast furnace to SMS. Here the three stage machines converters iron metal to hot steel metal and gives products like billets and rounds by going through three processes that explained below.

A steel Melt shop production introduces a scheduling of jobs on given machines is very difficult. Allocation of jobs to machines based on time intervals is called a schedule and the aim is to find a optimal schedule sequence that minimizes the operation time required to complete all jobs. The objective is to find optimal operation scheduling with minimum operation time, reduction of Tardiness and increase number of charges.

2. SCHEDULING OF STEEL MELT SHOP

The Scheduling of Steel Melt Shop (SSMS) is a complex problem and it consists of a set of n No. of jobs and m No. of machines where each job has to be processed on every machine with a different operation sequence. The time difference between the start and end of operation sequence of a job is known as Operation Time.

2.1 Objective of the Present Work

Based on lot of research work in the Literature, still there is a chance to develop Scheduling of Steel Melt Shop.

To overcome such limitations, a solemn attempt is made in the present work to study the scheduling problem in a Steel Manufacturing Industry with the realistic objective as given below.

1. Reduction of Tardiness by Minimizing Processing time, delay time.
2. Maximize number of Charges at Steel Melt Shop for continuous process.

The following general assumptions usually made in HFS scheduling are also reasonable for this problem.

(a) All charges follow the same process path: Converter, Ladle Furnace and Continuous Casting. At each stage, a charge can be processed on any one of the Machines at that stage, and the parallel Machines at that stage are identical.

(b) A Machine can process at most one job at a time.

(c) A job can be processed at most on one Machine at any time.

(d) Job processing is non-pre-emptive.

To model the problem, the constraints with the time parameters, for example processing, set-up, removal, ladle treatment and transportation times, are of integer time units. The Steel-making, refining and Continuous Casting stages are referred to as stages 1, 2 and 3, respectively. The model is

2.2 Mathematical Model of Objective

$$\text{Min } Z = \sum_{i=1}^{n} ((St_c\text{-}Ft_c)_I+(Lct_c)_I-(dt_c+Rt_c+Lwt_c))+t_{1i}$$

$$+\sum_{i=1}^{n} ((St\text{-}Ft_{lf})_I + (Lct_{lf})_I-(dt_{lf}+Rt_{lf}+Lwt_{lf}))+t_{2i}$$

$$+\sum_{i=1}^{n} ((St_{ccd}\text{-}Ft_{ccd})_i+(Lct_{ccd})_i\text{-}(dt_{ccd}+Bt_{ccd}))$$

Subject to constraints

$$(St_c)_i \geq (Ft_c)_{i-1} + (Lct_c)_{i-1}$$

$$(St_c\text{-}Ft_c)_i \leq 16$$

$$(St_c)_i \geq (Ft_c)_{i-1} + (Lwt_c)_{i-1}$$

$$(St_c\text{-} Ft_c+Rt_c)\geq(dt_c)$$

$$(Rt_c+dt_c)_i \leq (St_c+t_c)_i$$

$$(St_{lf})_i \geq (Ft_{lf})_{i-1} + (Lct_{lf})_{i-1}$$

$$(St_{lf}\text{-}Ft_{lf})_i \leq 18\text{-}(Rt_{lf})_i$$

$$(St_{lf})_i \geq (Ft_{lf})_{i-1} + (Lwt_{lf})_{i-1}$$

$$(St_{lf}\text{-} Ft_{lf}+Rt_{lf})\geq(dt_{lf})$$

$$(Rt_{lf}+dt_{lf})_i \leq (St_{lf}+t_{lf})_i$$

$$(St_{lf}\text{-}Ft_{lf})_i\geq(St_{lf}\text{-}Ft_{lf})_{i+1}$$

$$(St_{ccd})_i \geq (Ft_{ccd})_{i-1} + (Lct_{ccd})_{i-1}$$

$$(St_{ccd}\text{-}Ft_{ccd})_i \leq 60$$

$$(St_{ccd})_i \geq (Ft_{ccd})_{i-1} + (Lwt_{ccd})_{i-1}$$

$$(St_{ccd}\text{-}Ft_{ccd})_i \geq (dt_{ccd}+Bt_{ccd})_i$$

Assumptions

$$\Omega= \sum P+\sum T$$

$$\sum P_{=}((St_c\text{-}Ft_c)+(St_{lf}\text{-}Ft_{lf})+(St_{ccd}\text{-}Ft_{ccd}))$$

$$\sum T=(dt_c+Rt_c+ dt_{lf}+Rt_{lf}+ dt_{ccd}+Bt_{ccd})$$

$$\sum P \geq \sum T$$

$$\sum\Omega =\Omega_1+\Omega_2+\Omega_3+\ldots\ldots\ldots\ldots\ldots+\Omega_n$$

3. MODEL DEVELOPMENT

At every stage the development of optimality is shown as follows:

3.1 Mathematical Model for Converter

Min $\sum_{i=0}^{n} TJ$ (Tj = Max(0,Cj-dj))

Sub to

Cj ≥ Pj +Lttj

Sjk ≥ 0

Sjk ≥ Lttj

Rj ≤ Pj

Cj=Pj +Lttj +Rj

dj =[(Lttj-1)+ Rj+(20-Pj)]

3.2 Mathematical Model for Ladle Furnace

Min $\sum_{i=0}^{n} TJ$ (To = Max(0,Cj-dj))

Sub to

Cj ≥ Pj +LWtj

Sjk ≥ 0

Sjk ≥ LWtj

Cj=Pj + LWtj

dj =[(LWtj-10)+(45-Pj)]

3.3 Mathematical model for Continuous Casting

Min $\sum_{i=0}^{n} TJ$ (Tj =Max(0,Cj-dj))

Sub to

Cj ≥ Pj + Lwtj

Sjk ≥ 0

Sjk ≥ Lwtj

Cj=Pj+LWtj

dj=[(20-Lwtj)+(50-Pj)]

Where n = Number of jobs; m = Number of machines; i = job index; j = machine index,

Pij = Processing time of Job i on machine j;

Sij = Start time of job i on machine j, f_{ij}=end or finish time, Ri = Reheat time of job i,

Cij = completion time of Job i on machine j,

Cj = Total completion time of all jobs on machine j,

Lttj=ladle treatment time

Lwtj= ladle waiting time, T_j=Tardiness.

4. Teaching learning based optimization (TLBO)

TLBO algorithm is the effective Algorithm developed by R V Rao [8,9] based on a natural inspiration from both Teaching and Learning processes, where a teacher plays a crucial role on the results of students in a class. The TLBO algorithm consists of two phases 1) Teacher Phase 2) Learner Phase

4.1 Teacher Phase: In this phase, a teacher tries to improve the student's knowledge to his/her level. But practically it is impossible for a student to compete with the teacher's knowledge. The solution is improved using the difference mean which is given by:

Difference Mean = ri x (MNew - TF x Mi) (7)

The Old solution will be modified using the difference mean according to the following equation, SNew, i = SOld, i +Difference Mean (8)

If SNew, i is better than the SOld, i then accept SNew, i otherwise keep it as it is.

4.2 Learner Phase: In teacher phase the student improves his/her knowledge up to a certain level by self studying. In this phase student modification is given below. For iteration i (i=1:K); randomly select two learners Si and Sj where i ≠ j

SNew, i = SOld, i + ri (Si-Sj) if f(Si) < f(Sj) (9)

SNew, i = SOld, i + ri (Sj-Si) if f(Si) ≥ f(Sj) (10)

If SNew, i gives better solution than SOld, i then accept it otherwise keep as it is.

5. Implementation: The adopted algorithm is illustrated and the stepwise procedure for the implementation of TLBO for Steel Melt shop scheduling problem [1] is given as follows:

5.1 Initialization phase

5.11 Initial Parameters: Initially the parameters like Number of jobs (n), number of machines (m), processing times of jobs on each machine (P), machine sequence (z) and population size (N) to be given.

5.12 Initial Population: Generate a population of size N at random. In TLBO, population size

Table 1: Operation Scheduling Representation for 3×3 JSSP

OS	Job 1	Job 2	Job 3
OP 1	1	4	6
OP 2	2	5	7
OP3	3	4	8

means the number of students in a class. Each student represents an operations scheduling. Next find makespan values for each student in population. Generally an operation scheduling can be represented as follows.

5.2 Teacher phase: Now calculate the mean of the make span values (M) and select the solution that is nearer to the mean (MD). The best solution among the students will be a teacher to that iteration (M New). Now the difference solution (DD) is evaluated by using Position Based Crossover mechanism [9] (PBX). An example of PBX is shown in Table 2,3,4.

Table 2 : Representation of Operations Scheduling 3

OS 3	Job 1	Job 2	Job 3
OP 1	M1	M5	M7
OP 2	M2	M4	M8
OP3	M3	M5	M6

Table 3 : Representation of Operations Scheduling for New Mean Solution

OS	Job 1	Job 2	Job 3
OP 1	M1	M4	M6
OP 2	M2	M5	M7
OP3	M3	M4	M8

Table 4 : Representation of Operations Scheduling for Difference Solution(DD)

OS	Job 1	Job 2	Job 3
OP 1	M1	M4	M6
OP 2	M2	M5	M8
OP3	M3	M4	M7

Now the difference solution is considered as a New mean solution (SNew) and every solution in population as an Old mean solution (SOld), for once, the solutions in the population are updated.

5.3 Learner phase: Now the solutions obtained in teacher phase are improved in learner phase by using the self studying concept which is applied using Variable Neighborhood search method [10] (VNS). In VNS method, two processes to be considered are Exchanging process and Inserting process. Let i and j be two random integers between 1 and n*m. Exchanging process means exchanging the operations i and j in scheduling S (i≠j). The example of exchanging process is shown in fig. 4.

Old Solution =

OS	Job 1	Job 2	Job 3
OP 1	M1	M5	M6
OP 2	M2	M4	M7
OP3	M3	M5	M8

New Solution =

OS	Job 1	Job 2	Job 3
OP 1	M1	M4	M6
OP 2	M2	M5	M7
OP3	M3	M5	M8

Processing Time value of New Solution is 448.8
Update all solutions in the population using VNS method.

5.4 Termination Criteria: The algorithm stops when the termination criterion is satisfied else algorithm restarts from step 2 with the final solution in previous iteration as initial solution to next iteration. Thus the termination criterion is number of iterations i.e. till the Teacher phase and Learner phase are completed in a generation. The same may be reputed for all the generations. Thus, the output of Reduction of tardiness is 276 minutes.

6 RESULTS AND DISCUSSIONS

Case 1: Delay Time at each Converter compared to Processing Time at each Converter, which gives the information how much time is elapsed by delays for 10 charges.

Case 2: Delay Time at each Ladle Furnace compared to Processing Time at each Ladle Furnace, which gives the information how much time is elapsed by delays for 10 charges.

Case 3: In Case 3 at Continuous Casting, the data considered for 10 Charges, from Particular Sequence of Continuous Casting the Start and End

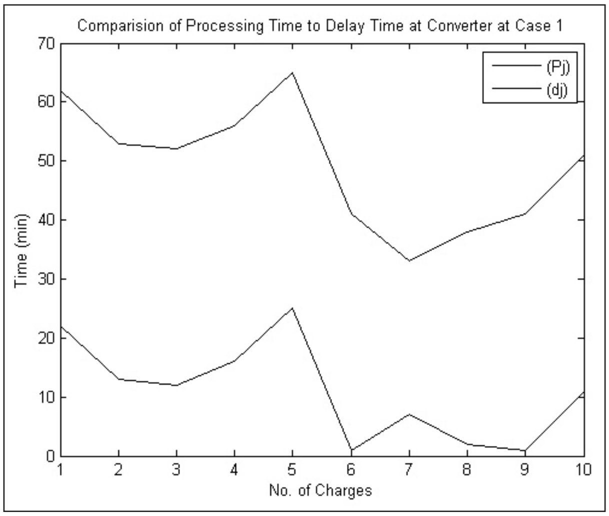

Fig 2. Variation of Processing time and Delay time at Converter for 10 Charges

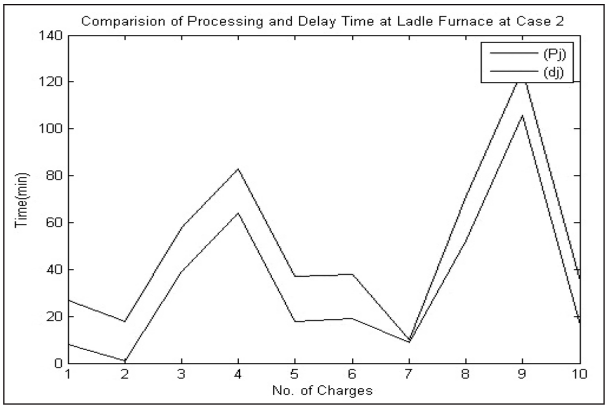

Fig 3. Variation of Processing time and Delay time at Ladle Furnace for 10 Charges

times are noted. The P_j and d_j is compared.

Case 4: The Tardiness Time at each Converter compared to Processing Time at each Converter, which gives the information how much time is

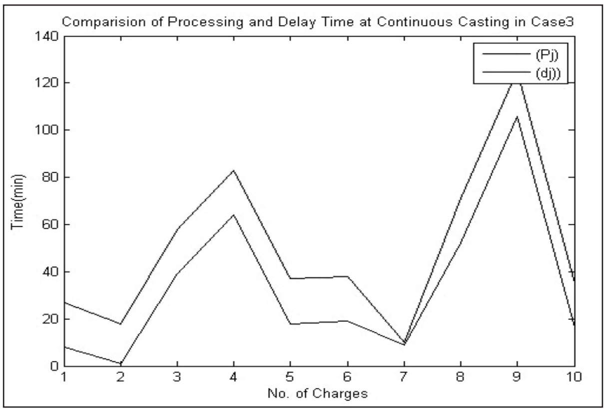

Fig 4. Variation of Processing, Completion, Delay for CCD

elapsed by delays and how much tardiness is developed for 20 charges.

Case 5: The Tardiness Time at each Ladle Furnace, compared to Processing Time which gives the information how much time is elapsed by delays and how much tardiness is developed for 20 charges.

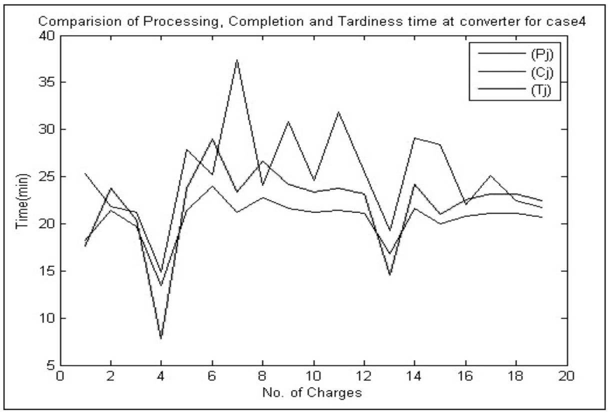

Fig 5. Variation of Processing, Completion, Tardiness time at Converter

Case 6: The Tardiness Time at each Converter compared to Processing Time at each Ladle Furnace, which gives the information how much time is elapsed by delays for 20 charges.

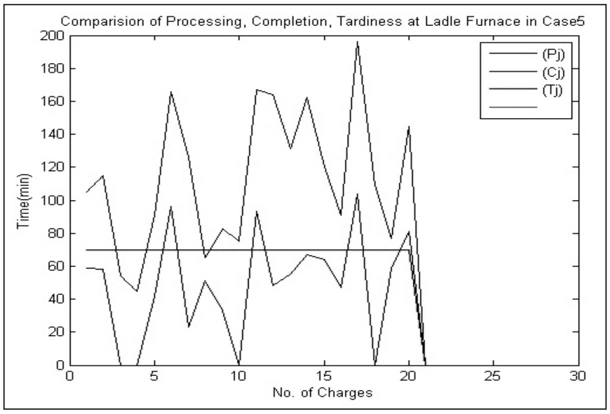

Fig 6. Variation of Processing, Completion, Delay, Tardiness for Ladle Furnace

Case 7: The Bar graph shows the Variation of Completion Time of Steel Melt Shop to Tardiness Time of Steel Melt Shop.

Case 8: Learner phase last solution: The Bar graph Fig – 9. shows the Variation of Completion Time of Steel Melt Shop to Tardiness Time of Steel Melt Shop at Learner Phase

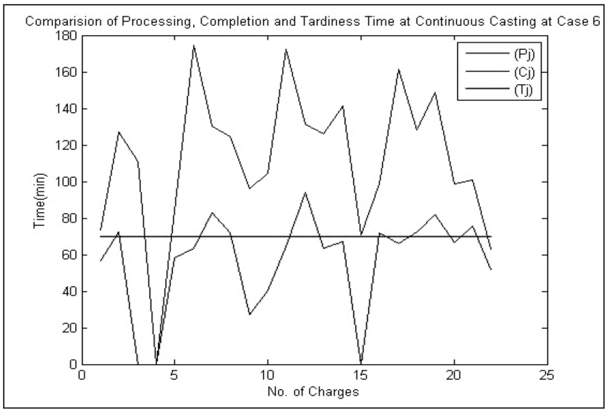

Fig 7. Variation of Processing, Completion, Delay, Tardiness for CCD

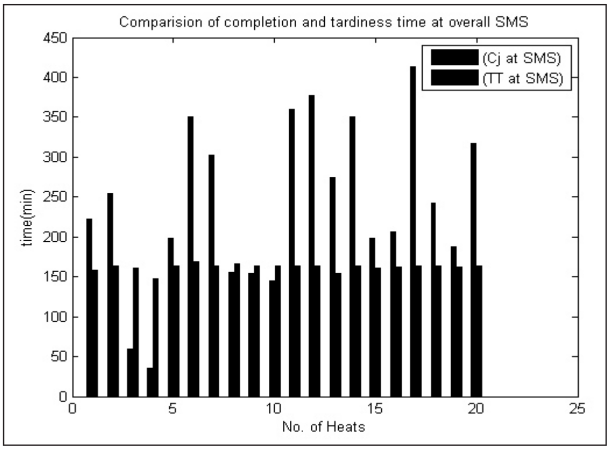

Fig 8. Comparison of Completion Time and Total Tardiness at SMS

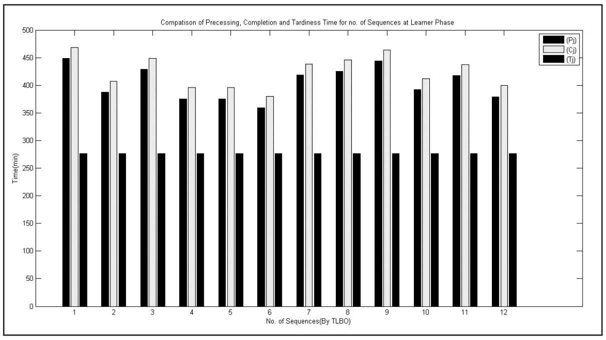

Fig 9. Variation of Processing, Completion and Tardiness for SMS at Learner Phase

Minimization of standard Operation time after TLBO process

Reduction of Tardiness:

Case-9: Results on overall SMS for increase in no of Charges: Thus the No. of Charges increased is shown in the Fig – 10 , which is very effective increase the production of steel melt shop

Table 5: 12- Jobs, 9 Machines Operation Processing Times for Learner Phase

OS	OP	Job 1	Job 2	Job 3	Total Pj
OS1	OP 1	16	18	50	276
	OP 2	17	19	60	
	OP3	18	18	60	
OS2	OP 1	16	19	50	277
	OP 2	17	18	60	
	OP3	18	19	60	
OS3	OP 1	16	18	60	277
	OP 2	17	19	60	
	OP3	18	18	50	
OS4	OP 1	16	18	50	276
	OP 2	17	19	60	
	OP3	18	18	60	
OS5	OP 1	16	18	60	286
	OP 2	17	19	60	
	OP3	18	18	50	
OS6	OP 1	16	18	60	276
	OP 2	17	19	60	
	OP3	18	18	60	
OS7	OP 1	16	18	50	276
	OP 2	17	19	60	
	OP3	18	18	60	
OS8	OP 1	16	18	60	276
	OP 2	17	19	50	
	OP3	18	18	60	
OS9	OP 1	16	19	60	277
	OP 2	17	18	60	
	OP3	18	19	50	
OS10	OP 1	16	19	50	277
	OP 2	17	18	60	
	OP3	18	19	60	
OS11	OP 1	16	19	60	277
	OP 2	17	18	50	
	OP3	18	19	60	
OS12	OP 1	16	18	60	276
	OP 2	17	19	50	
	OP3	18	18	60	

Table 6: 3 Stages Processing, Delay, Completion, Tardiness Solution of Learner Phase

Jobs	Stage 1	Stage 2	Stage 3	Pj	dj	Cj	Tj
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	138	160	149	448	192	468	276
2	112	155	120	387	131	407	276
3	149	130	149	428	172	448	276
4	115	150	110	375	119	395	276
5	115	150	110	375	119	395	276
6	89	160	110	359	103	379	276
7	138	150	130	418	162	438	276
8	115	160	149	425	169	445	276
9	140	155	149	444	188	464	276
10	112	130	150	392	136	412	276
11	149	147	120	417	161	437	276
12	89	160	130	379	123	399	276

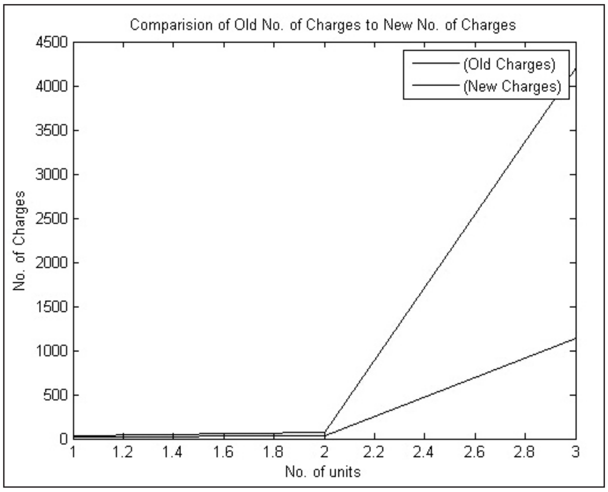

Fig 10. Variation of no of Charges Improved at Overall SMS

6. CONCLUSION

The TLBO algorithm is implemented for Scheduling of Steel Melt Shop of size 12*8. The results indicate that The Teaching Learning Based Optimization Algorithm has effectively solved Steel Melt Shop Scheduling problem to obtain optimal Operation Scheduling with the minimum Tardiness and maximum number of charges at each stage of SMS. The performance for effectiveness of TLBO algorithm is better than other techniques in previous work.

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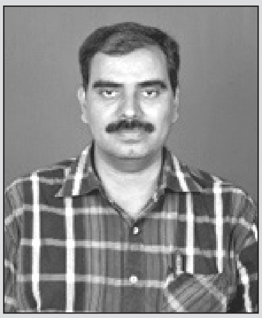

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