Multi-objective Optimization of Parallel Machine Scheduling Using Neural Networks

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Abstract - This paper considers the problem of scheduling jobs on Parallel Machines with the combined objective to minimize the make span, total tardiness and total earliness. Neural Network is a technique which can deal with impreciseness and non linearity in problem solving. Neural Network technique was found to be effective and used to select the best optimal schedule which minimizes the make span, total tardiness and total earliness.

Keywords: Parallel Machines, Combinatorial optimization, Neural Network, Optimal Schedule

Notation

SPT – Shortest Processing Time

LPT – Longest Processing Time

EDD – Earliest Due Date

WSPT – Weighted Shortest Processing Time

WLPT – Weighted Longest Processing Time

SA – Simulated Annealing

NN – Neural Network

I. INTRODUCTION

The case of identical jobs within a batch is common in manufacturing systems, where products or jobs have identical processing requirements. Individual products may be subjected to different constraints, while all units of the product require equal processing times on the same machine [6]. Research in identical Parallel Machine Scheduling problems has predominantly been concerned with minimization of make span or total completion time. Many of the researchers applied Genetic algorithms to solve the scheduling problems. Hybrid operation methods capable of providing a better solution in less time was achieved through the combination of Genetic algorithms and other evolutionary algorithms such as Fuzzy logic, Mimetic algorithms etc. The key feature of these evolutionary algorithms is to use available knowledge about the problem and have been found most successful approximation techniques for Non-Polynomial optimization problems.

Parallel machine scheduling is used to schedule jobs on a series of same function machines in order to achieve certain objective functions. The complexity usually grows with the number of machines, making the problem intractable. This problem, like all deterministic scheduling problems belongs to wide class of combinatorial optimization problems, which are known to be NP-hard [5].

This research effort proposes two different approaches to solve the Parallel Machine Scheduling Problem with multi objective optimization. Section 2 of this paper presents the literature reviewed on Neural Networks. Section 3 and 4 presents the mathematical model and discusses the Neural Network approach. Section 5 presents the experimental results. Section 6 gives the conclusion and future directions of research.

II. LITERATURE REVIEW

Considerable research has already been conducted in the field of Parallel Machine scheduling. In the subsequent sub sections a brief survey of the literature on multi objective scheduling, Application of Neural Networks are presented.

2.1 Multi objective scheduling:

In the literature, different approaches have been found considering multi objective scheduling problems in [3] and [4]. The main approaches found are as follows:

- Simultaneous method aims to generate the complete Pareto set or to approximate a set of efficient solutions.
- Weighting objectives method creates a weighted linear combination of the objectives to obtain a single function, which can be solved using any single optimization method.
- Hierarchical optimization method allows the decision maker to rank the objectives in a descending order of importance. Each objective function is then minimized individually subject to a constraint that does not allow the minimum for the new function to exceed a prescribed fraction of a minimum of the previous function.
- Goal Programming method takes the objectives into constraints which express satisfying goals. The aim is to find a solution which provides good values of predefined goals for each objective.
- Measuring the relative goodness of the selected solution by comparing it with another solution in the feasible region.

  K. Raja et al presented that conventional methods are not efficient in handling multi objective functions and GA technique had been applied for generating multiple schedules with multiple objectives. Fuzzy logic is then applied to select the best optimal schedule satisfying the multiple objectives.

  Similarly Fuzzy logic technique had been applied for generating multiple schedules when the available data is insufficient and imprecise. And also simulated annealing technique had been found very useful for the problems with multiple objectives [10].

2.2. Neural Networks :

Neural network computing is an approach that attempts to mimic certain processing capabilities of the brain. This machine learning technology has the ability to represent knowledge based on massive parallel processing and recognize patterns based on experience. Since the 1980s, the drastic breakthrough of the computing technology has led to an increasing amount of neural network research on a wide variety of functional applications. In recent years, there was an increase interest shown in the utilization of neural networks for various research fields such as robotics, optimization, linear and non-linear programming etc. A great advantage of neural network approach is that most of intense computation takes place during training process. Once the neural network is trained for particular task, operation is relatively fast and unknown samples can be rapidly identified. An artificial neural network is a collection of highly interconnected processing units that has the ability to learn and store patterns as well as to generalize when presented with new patterns. The 'learnt' information is stored in the form of numerical values, called weights that are assigned to the connections between the processing units of the network. Data presented at the input layer of a 'trained' network will result in values from the output layer consistent with the relationship learnt by the network from the training examples. The neural network that is proposed for the e scheduling problem is organized into three layers of processing units. There is an input layer of 10 units, a hidden layer, and an output layer that has a single unit. The number of units in the input and output layers is dictated by the specific representation adopted for the schedule problem. In the proposed representation, the input layer contains the information describing the problem in the form of a vector of continuous values. The 10 input units are designed to contain the following information for each of the n jobs that have to be scheduled:

$$\text{Input 1} = \frac{P_i}{M_p} \qquad (1)$$

$$\text{Input 2} = \frac{d}{100} \qquad (2)$$

$$\text{Input 3} = \frac{SL_i}{M_{si}} \qquad (3)$$

Input 4 = $\frac{\alpha_i}{10.0}$ (4)

Input 5 = $\frac{\beta_i}{10.0}$ (5)

Input 6 = $\frac{\bar{P}}{M_p}$ (6)

Input 7 =1 (7)

Input 8 = $\frac{\bar{SL}}{M_{sl}}$ (8)

Input 9 = $\sqrt{\frac{\sum(P_i - \bar{P})^2}{n \times \bar{P}^2}}$ (9)

Input 10 = $\sqrt{\frac{\sum(Sl_i - \bar{SL})^2}{n \times \bar{SL})^2}}$ (10)

Where

Sl_i Slack for job = d - P_i

M_p Longest processing time among the n jobs = max $[P_i]$

M_{sl} Largest slack for the n jobs

Thus, 10-input vectors represent each job, which holds information particularly to that job and related to the other jobs in the problem. The output unit assumes values that are in the range of 0.1- 0.9, the magnitude being an indication of where the job represented at the input layer should desirably lie in the schedule. High values suggest the lead position and low values indicate less priority and hence position towards the end of the schedule. The number of units in the hidden layer is selected by trial and error during training phase.

III. PROBLEM DESCRIPTION

The problem is to schedule all the jobs such that the make span, total tardiness and total earliness are minimized.

Data of the Problem

Number of identical machines : 3
Number of jobs : 10
Working hours / day : 8

Notations;

Job – J_i
Processing time – P_i
Due date – d_i
Completion time – C_i

The data of the problem is summarized in Table 1

Table 1 Data of the Problem

Job Number	Processing Time Minutes	Due date Days	Batch quantity
0	2	11	218
1	1	07	112
2	7	12	711
3	6	13	655
4	4	03	419
5	3	12	354
6	1	03	174
7	9	07	910
8	2	08	076
9	1	10	249

Earliness of the job J_i, Ei = Max.{ 0, (di - Ci)}

Tardiness of the job Ji , Ti = Max.{ 0, (Ci - di)}

The fitness function considered in this study is the combined objective function (COF) and is given by COF = W_m (maximum make span) +W_c (total earliness) +W_t (total Tardiness)

Weightage given for make span is 0.4 and for tardiness and earliness 0.3 each.

3.1 Neural Network approach:

To illustrate how the neural network is trained. Table 2 shows a 6-job problem that serves as training example for neural network. The 6-jobs are converted first into their vector representations by using the set of equations (1 to 10). The result of this pre-processing stage is presented in Table (3). To train the neural network, each vector with their output is presented individually at the input layer and output layer of the neural network.

Training is considered completed after an average of 500 cycles using a 10-8-1 configuration. A cycle is concluded after the network has been exposed once, in the course of the back propagation algorithm, to each one of the available training patterns. The trained neural network is used to find job schedule for our problem.

Table 2: 6- job problem

Job, J_i	1	2	3	4	5	6
P_i, minutes	3655	4977	1680	6317	214	962
d_i , days	7	9	3	10	12	6

Table 3: Problem representation for the example in Table 2– Input and output:

JOB	1	2	3	4	5	6
Input 1	0.5715	0.7878	0.2659	1	0.03387	0.15228
Input 2	0.1008	0.1296	0.0432	0.144	0.1728	0.0864
Input 3	0.1008	0.467	0.1546	0.4736	1	0.449
Input 4	0.03	0.03	0.03	0.03	0.03	0.03

Input 5	0.03	0.03	0.03	0.03	0.03	0.03
Input 6	0.28185	0.28185	0.28185	0.28185	0.28185	0.28185
Input 7	1	1	1	1	1	1
Input 8	0.29224	0.29224	0.29224	0.29224	0.29224	0.29224
Input 9	1.403	1.403	1.403	1.403	1.403	1.403
Input 10	1.09593	1.09593	1.09593	1.09593	1.09593	1.09593
Output	0.89996	021786	0.9	0.10084	0.10012	0.17529

Table 4 : The output for the example in Table 1

Job	0	1	2	3	4	5	6	7	8	9
Output	0.10012	0.10034	0.10013	0.10012	0.9	0.10012	0.89158	0.88364	0.10012	0.10013

IV. Result and Discussion

Sequences obtained by various methods are summarized below.

Table 3

Method	Sequence	Total Earliness	Total Tardiness	COF
SPT	1-8-6-9-0-5-4-3-2-7	84531	10878	37006
LPT	7-2-3-4-5-0-9-6-8-1	7626	64137	29912
EDD	4-6-1-7-8-9-0-2-5-3	24712	2310	16492
WSPT	1-8-9-0-6-5-3-2-4-7	87087	19323	40307
WLPT	7-4-2-3-5-6-0-9-8-1	54946	4327	26165
SA	4-6-7-1-2-9-0-8-5-3	8583	7714	13278
Fuzzy	6-4-1-8-9-0-5-3-2-7	78078	10878	35070
NN	4-6-7-1-2-9-8-0-5-3	7557	7424	12888

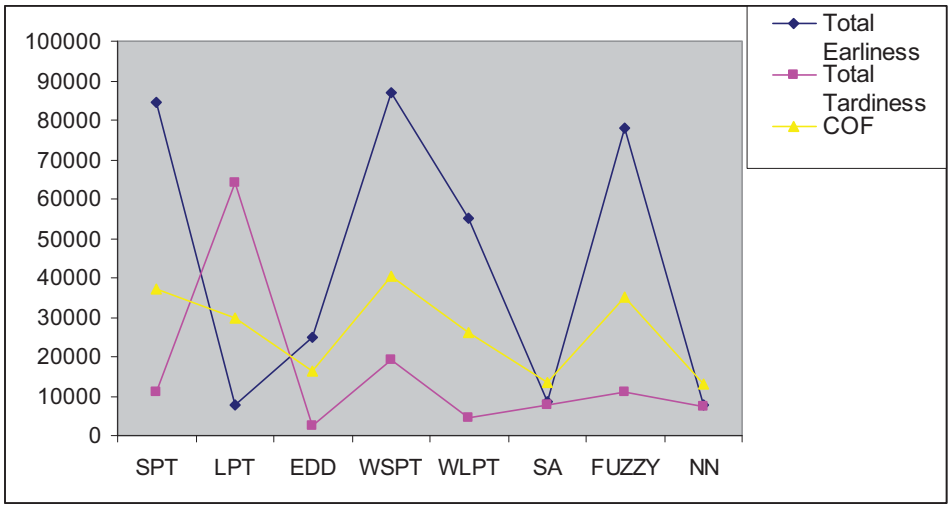

Figure (1) Comparison of Total Earliness, Total Tardiness and COF

It is found from the above Table (3) and Figure (1) that all the parameters such as total earliness, total tardiness and the Combined Objective Function were minimized by applying the Neural Network Technique. It is evident that this method also minimizes the chances of converging at local optimal values, as in the case of Simulated Annealing Technique.

V. CONCLUSION

A Neural Network technique was applied to Parallel Machine Scheduling problem. The schedule obtained is compared with other techniques. The procedure adopted for this technique is simpler when compared to other hybrid or heuristics and can be applied to schedule large number of jobs without training the network again. The same procedure can be extended to optimize other performance measures also.

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