Design of Adaptive Neural Network Algorithm for Superior Job-Shop Scheduling

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Abstract

Artificial Neural Networks are moderately crude electronic models based on the neural structure of the brain. The brain modeling permits less technical approach to create machine solutions. This novel approach used to calculating as well provides a more graceful degradation during system overload than its more traditional counterparts. Artificial Neural Networks can realize higher end computation rates by way of employing anenormous number of smooth processing elements with a large number of connectivity between elements. In this paper an effort is made to provide a Constraint Satisfaction Adaptive Neural Network (CSANN) to solve the global job-shop scheduling problem and it expressions how to manage a difficult constraint satisfaction job-shop scheduling problem onto a simple neural net, somewhere the amount of neural processors equals the amount of operations, and the number of interconnections propagates linearly with the total number of operations. The proposed technique is used to easily construct the neural networks and can alter its weights of network connection based on the sequence and sourceconstrictions of the job-shop scheduling problem during its processing. SLAM Simulation language used to simulate the proposed neural network and produce good solutions for job-shop scheduling problem.

Keywords: Job-Shop Scheduling, Artificial Neural Networks,Constraint Satisfaction Adaptive Neural Network, SLAM Simulation language, Learning Capability, Priority rules.

I. INTRODUCTION

Job shop scheduling (or job-shop problem) is an optimization problem in computer science and operations research in which optimal jobs are allocated to resources at particular times. The most basic version is as follows:

The given n jobs written asJ_1, J_2, ..., J_n of varying sizes, which want to be scheduled on m identical machines, while trying to minimize the makespan. The makespan is the total length of the schedule (that is, when all the jobs have finished processing). Nowadays, the problem is presented as an online problem (dynamic scheduling), that is, each job is presented, and the online algorithm needs to make a decision about that job before the next job is presented.

Production scheduling is the process ofallocating resource over particular time to execute a collection of tasks [1] of all types of Production scheduling problems; the job-shop scheduling problem is one of the most complicated and typical process. The mainobjective is to assigned m machines to perform n jobs in order to optimize certain criterion [8]. Job shop scheduling is a traditional OperationsResearch problem with several applications, but very few applicable solution approaches are available. Owing to the huge number of restrictions, the problem is known to be too hard, in comparison with other combinatorial problems, so that smooth (not necessarily optimal) possible solution (satisfying constraints) is suitable for most applications. Conventionally, there are three types of methodssuitable for the job-shop scheduling problems: Priority rules, combinatorial optimization and constraints analysis [3]. Newlyintellectual knowledge–based scheduling systems have been presented [6], [7]. Foo and Takefuji [4] first used a neural network to solve job-shop scheduling problems.

Some heuristics are also proposed by Shengxiang Yang (9) to be shared with the neural network to promise its conjunction, accelerate its resolving process, and improve the quality of solutions. A comprehensive version of the smallest make span job shop is planned by Michael Masin, Tal Raviv (10) They established algorithm uses the solution of the linear relaxation of a time-indexed Mixed-Integer formulation of the problem. A parallel machine scheduling problem to diminish the total subjective completion time, where product relatives are involved is proposed by Shen et al (11).

But the above article models are not adaptive networks, so that the neural units joining weights and biases must be approved in advance before application of the networks to a specific problem. In this paper, newly designed Constraint Satisfaction Adaptive Neural Network (CSANN) techniques used for the comprehensive job-shop scheduling problem, accommodating free sequence operation pairs or free operations of each job. The proposed CSANN has the ability to simply map the limitations of a scheduling problem into its architecture and eliminate the violation of the planned constraints during its processing and such is based on 'constraint satisfaction'. Moreover CSANN has ability to adaptively regulate its connection weights and bias of neural units according to the actual constraint violations present during processing.

II. JOB-SHOP SCHEDULING

Job-shop means a work position in which a figure of general purpose work stations exists and is used to implement a variety of jobs. Conventionally, the job-shop scheduling problem can be listed as follows [4]: given n jobs to be handled on m machines is a given order under certain restrictive assumptions. The aim of job-shop scheduling is to optimally organize the processing demand and the start times of operations to optimize based on some criteria. In common, there are two kinds of controls for the job-shop scheduling problem. The first kind of constraint states that the precedence between the operations of a job should be guaranteed is called sequence constraint. The second constraint is that not more than one job can be performed on a machine at the same time, this is called resource constraint. In general job-shop scheduling problem, there may be assign dissimilar number of operations for each job; there may be anissue date or due date limitation for each job; and there may exist the situation that every machine can progression more than one operation of a job.

III. CONSTRAINT SATISFACTION ADAPTIVE NEURAL NETWORK (CSANN)

Main criteria of job-shop are problem scheduling, applicability of a constraint satisfaction adaptive neural network is considered. The following methods explain the training steps of the competitive neural network.

Step 1: Set the number of output nodes. Initialize the learning rate and the maximum number of iterations. Initialize the weight vectors randomly.

Step 2: Present on input vector.

Step 3: Find the output node, whose weighing vector is the closest to the input Vector geometrically.

Step 4: Update the weighing vector of the output mode by the Kohoner'slearning rule [2].

Step 5: Present the next input vector and go to step 3.

Step 6: If the iteration number equals the maximum number of interactions, then Stop, else increase the iteration numbers by one and go to step 2.

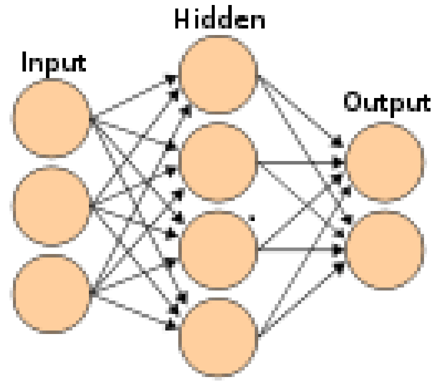

Fig. 1 Adaptive Neural Network Performance Model

Figure 1 shows the implementationorder of the scheduling problem. The Job-shop operator gives the scheduler input data containing of the preferred relative objectives of assessment criteria. The neural network creates a matching class in which the relative objectives of the combined input vectors are related to those of the input data specified by the operator allowing to the scheduling problem.

IV. EXPERIMENTAL DESIGN

A. *Experimental Problem*

For example of job-shop model shown in Figure 2 it is a 2/3 job-shop that means2 jobs three machines and three operations for each job, (the same problem as in the Foo and Takefuji [4] in order to make a comparison) this problem used as an example to show the illustration of the general job-shop problem. Each job i contains of $k_i$processes. Each operation has three identifiers, i, j, and k, where i represents the job number to which the operation has belongs; j, the sequence number of the operation; and k, the number of the machine required to perform the operation. The distance of every operation block in Figure 2 is proportional to the processing timeessential to perform the operation, and the numbers below the block are used to designate the completion time. A reasonable schedule is agreed by the starting times of all actions so that the operations of each job will be achieved in the required order and there will be no conflicts on each machine. Figure 3 proves the solution from (the optimal schedule for the problem in Figure 2). The operation tablets are relocated into rows by machine numbers. The main objective is to provide a schedule to finish a set of jobs in the shortest time subject to constraints. If the problem size is too bulky, it is difficult to find a feasible solution, so that cannotfind an optimal solution. For instance, in some cases, there are 20 jobs on a machine. At that moment there might be 20! Discrete sequences, where 20! = 2432902008176640000. It takes nearly 9 months to discover the best solution for this problem using exhaustive search on a 1000 MIPS computer.

Figure 2: A 2/3 Job-Shop Problem

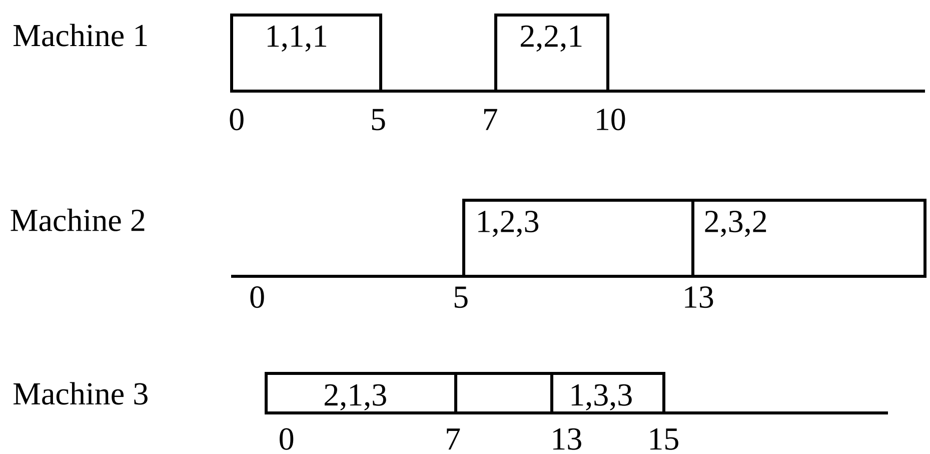

Figure 3: A 2/3 Job-Shop Solution (Optimal Schedule)

B. Software Solution

The simulation software tool is developed by C based SLAM II simulation language used to modelling of job-shop scheduling problem. The neural network is established using the neural network tool box in the mat lab software [2].

V. EXPERIMENTAL RESULTS

Simulations performed in following problems 2/3, 4/3, 5/3, 6/6, 7/7, 10/10 and 20/20 job-shop has been effectively solved by software.The results of 2/3 job-shop scheduling is done, shown in fig. 3. In figure 4 shows, the result for a 10/10 job-shop scheduling problem, alljobs has 10 operations so that there are a total of 100 operations, and all the restrictions of the problem are caused randomly it would be measured a general large size problem. For the small size problems with known ideal solutions, such as 2/3 job-shop with optimal completion time 22, 4/3 with 33, 5/3 with 117, the simulation outcomes are 21, 32 and 120 respectively. For huge size problems, assuming that the numeral operations is equal to the number of jobs, there are 100 operations for the 10/10 job-shop are 400 operations for the 20/20 job-shop.

For large size problems there are no feasible optimal solutions. By using CSANN results revolved out to be very good solutions if not optimal, based on the contrast with two problems the total completion time of the longest job. Perhaps, in Figure 2 the total conclusion time of the stretched job i.e. Job 2 is 19, and the optimal solution is nearby but greater than that, and is equal to 22. Correspondingly, the results for large problems provide solutions similar to the longest job completion time, which is a good indication of near optimality. As the network complexity (the simulation time) develops linearly with the problem size (the totalnumber of operations), there seem to be no limitations on the size of the job-shop scheduling problem that can be touched by the recommended model.

For 2/3 job-shop problem has been successfully solved with completion time 22, 4/3 with 33, and 5/3 with 115, the simulation consequences are 22, 33 and 119 respectively. For large size problems, assuming that the number of operations is equal to the number of jobs, there are 100 operations for the 10/10 job-shop are 400 operations for the 20/20 job-shop. For problems of this size there are no known optimal solutions. Our results turned out to be very good solutions if not optimal, based on the comparison with the total completion time of the longest job. For example, in Figure 2 the total achievement time of the longest job i.e. Job 2 is 20 and the ideal solution is close to but bigger than that, and is equal to 22. Likewise, our results for large problems provide solutions equivalent to the longest job accomplishment time, which is a good suggestion of near optimality. Since the network complication (and hence the simulation time) propagates linearly with the problem size (the total number of operations), there seem to be no restrictions on the size of the job-shop scheduling problem that can be pick up by the proposed model.

VI. CONCLUSION

Constraint satisfaction adaptive neural network is talented to fulfill the requirements, according to the scheduling criterion used to convey the neural network. The neural network avoids the use of hypothetically low quality proficiency in job shop scheduling. Likewise a system has the probable of adaptive and sensitive scheduling to encounter the highly variable demands on production scheduling. The consequences of this testingtoughly indicate that applying this procedure to obtain a control strategy in an effective material for handling with the difficulty of job-shop scheduling problem. Particularly in a real time control system, it is suitable to use pre-obtained control knowledge as a time convertiblemode to attainrapid response in a dynamically varyingsituation.

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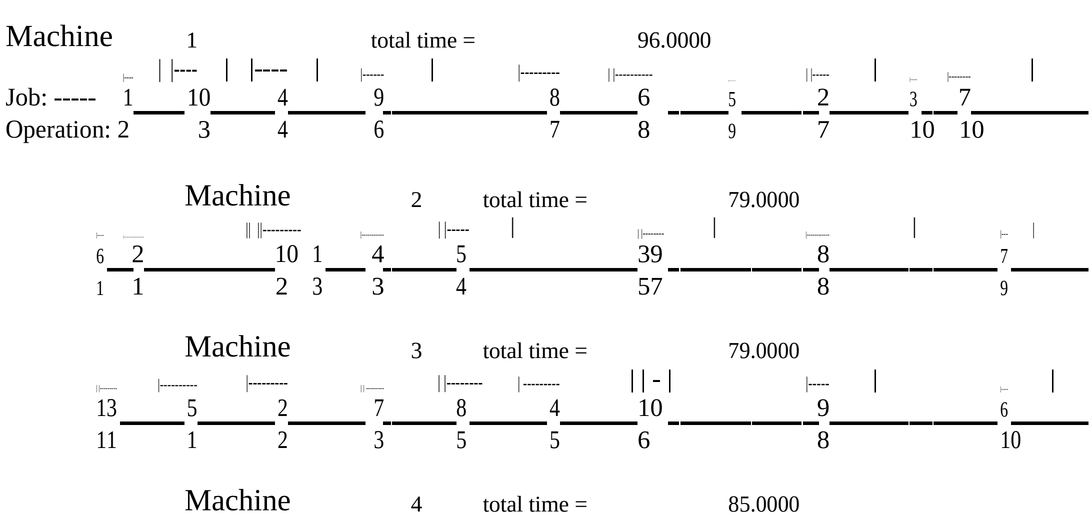

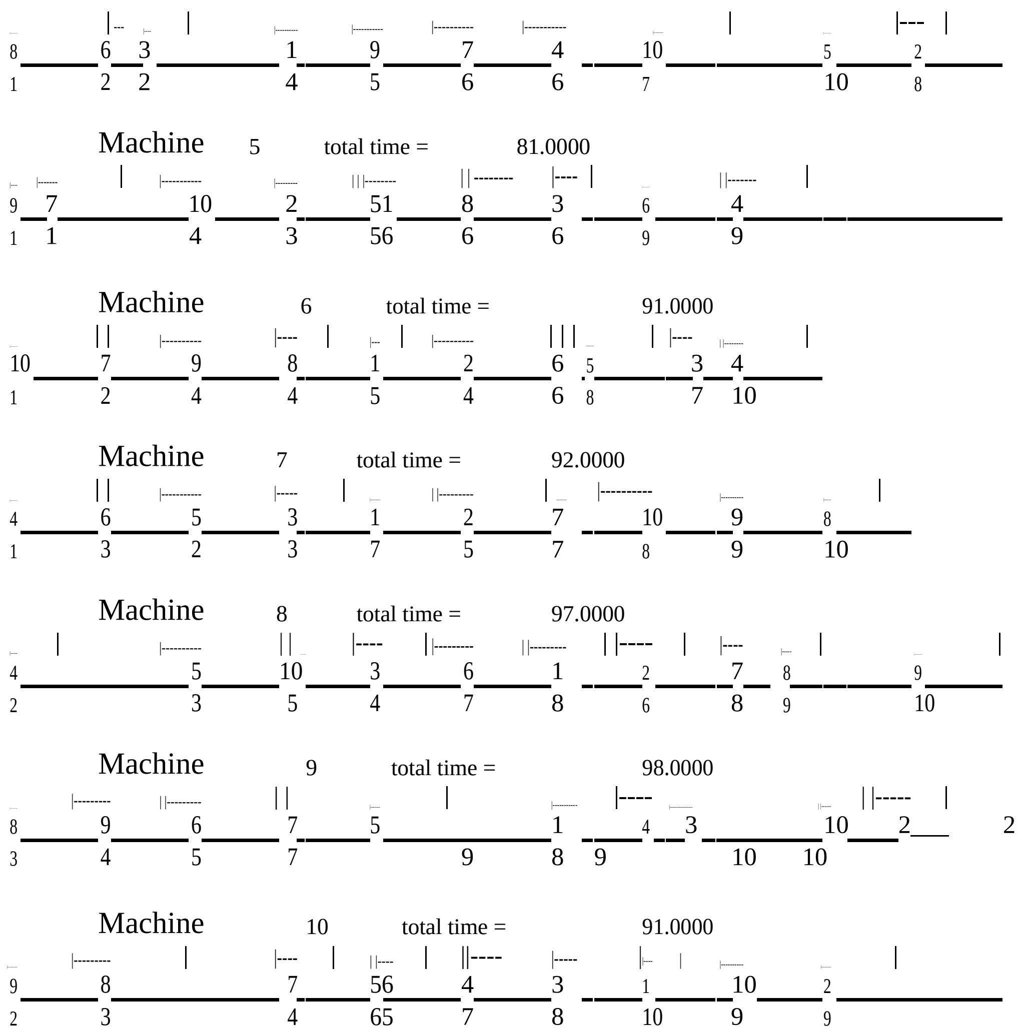

Figure 4: Simulation Result of a 10/10 Job-Shop Problem