Knowledge Acquisition using Neural Network and Simulator

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Abstract

There are so many researches about the search method for the most compatible dispatching rule to a manufacturing system state. Most of researches select the dispatching rule using simulation results.

This paper touches upon two research topics: the clustering method for manufacturing system states using simulation, and the search method for the most compatible dispatching rule to a manufacturing system state. The manufacturing system state variables are given to ART II neural network as input. The ART II neural network is trained to cluster the system state. After being trained, the ART II neural network classifies any system state as one state of some clustered states. The simulation results using clustered system state information and those of various dispatching rules are compared and the most compatible dispatching rule to the system state is defined. Finally there are made two knowledge bases.

The simulation experiments are given to compare the proposed methods with other scheduling methods. The result shows the superiority of the proposed knowledge base.

Keywords: Knowledge Acquisition; Knowledge Base; ART II; Simulation

Introduction

One of the catch phrases of new emerging manufacturing world is ever increasing pressures from domestic and foreign customers. Customers demand shorter lead times and higher product variety without making concessions on product price and quality. To remain competitive, a manufacturing system needs to react adequately to perturbations on its environment and uncertainties in manufacturing processes.

This paper is concerned with neural network (ART II) to define the system states and select the best dispatching rule for each system state. The neural network uses the simulation results as training examples.

Related Researches

The control strategy of manufacturing system has much influence on the efficiency of a manufacturing system. Specifically an effective scheduling is the only means to make the expensive equipment to be operated effectively and there have been so many researches about scheduling.

Many researchers have studied the dispatching rules using simulation experiment because the rules may be applied for real-time scheduling.

Panwalkar [PANW77] summarized 113 dispatching rules. Sabuncuoglu [SABU98] and Liu [LIU92] studied the effect of AGV (Automated Guided Vehicle) dispatching rules on FMS performance. Wu [WU87, WU88, WU89] developed the concept of the multi-pass simulation and dynamic scheduling method. Ishii [ISHI91], Cho [CHO93b] modified the multi-pass simulation based scheduling method using changes on system states and variations of pass time.

Knowledge Acquisition is the process of learning knowledge from one or more sources and passing it on in a suitable form to someone else or to some system.
Automated methods might be more competent than humans for acquiring or fine-tuning certain kinds of knowledge and might significantly reduce the high cost in human resources involved in constructing expert systems.

Many of the existing automated knowledge acquisition methods use a bottom-up approach. This is because they learn from a set of examples and produce general principles. There are two learning algorithms.

- Input space partitioning algorithm
  - A method for generating the next partition: this typically involves selecting an attribute for subdividing
  - A stopping criterion for halting further subdivisions of a partition
  - A rule for assigning the partition to an output
- Output space projection algorithm
  - A method of relation a given output to points in the input space
  - A criterion for selecting the points that map to that output
  - A criterion for identifying the boundary of the regions of interest in the input space.

Learning algorithm should use data as training example (If conditions, Then results). Regression (Supervised Learning) uses the training examples that are consisted of condition and result pair. But Clustering does not use results. Clustering only uses the condition data, clusters some states.
One of clustering methods, Adaptive resonance theory (ART) was developed by Carpenter and Grossberg [CARP87]. One form, ART1, is designed for clustering binary vectors; another, ART2 accepts continuous-valued vectors. These nets cluster inputs by using unsupervised learning. Input patterns may be presented in any order.
Each time a pattern is presented, an appropriate cluster unit is chosen and that cluster's weights are adjusted to let the cluster unit learn the pattern. As is often the case in clustering nets, the weights on a cluster unit may be considered to be an exemplar for the patterns placed on that cluster.

Overview

This paper has the overview as [Fig 1]. ART KB (Knowledge Base) is made by SSP (System State Platter). And the ART KB is used at SystemState Finder.

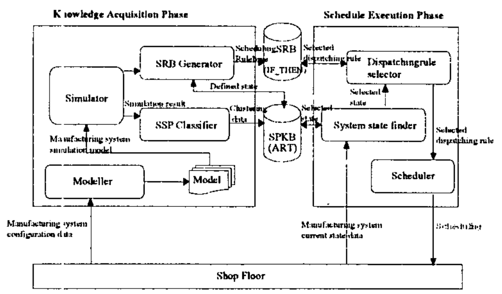

Figure 1 - Overview & ART

ART II

The basic architecture of an adaptive resonance neural net involves three groups of neurons like [Fig 2].

1. Input processing field (called the F1 Layer)
2. The cluster units (the F2 Layer)
3. A mechanism to control the degree of similarity of patterns placed of the same cluster (A Reset Mechanism)

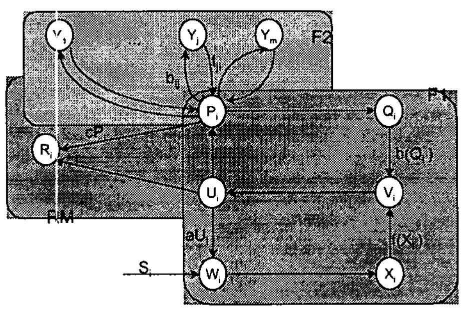

Figure 2 - ART II

The F1 Layer can be considered to consist of two parts: the input portion and the interface portion. Some processing may occur in the input portion (especially in ARTII). The interface portion combines signals from the input portion and the F2 Layer, for use in comparing the similarity of the input signal to the weight vector for the cluster unit that has been selected as a candidate for learning. We shall denote the input portion of the F1 layer as F1(a) and the interface portion as F1(b).
To control the similarity of patterns placed on the same cluster, there are two sets of connections (each with its own weights) between each unit in the interface portion of the input field and each cluster unit. The F1(b) layer is connected to the F2 Layer by bottom up weights: the bottom-weight on the connection from the i^{th} F1 unit to the j^{th} F2 unit is designated b_{ij}. The F2 layer is connected to the F1(b) layer by top-down weights; the top-down weight on the connection from the j^{th} F2 unit to the i^{th} F1 unit is designated t_{ji}.
F2 layer is a competitive layer. The clustered unit with the largest net input becomes the candidates to learn the input pattern. The activation of all other F2 units is set to zero. The interface units now combine information from the input and cluster units. Whether or not this cluster unit is allowed to learn the input pattern depends on how similar its top-down weight vector is to the input vector. This decision is made by the reset unit, based on signal it receives from the input(a) and interface(b) portion of the F1 layer. If the cluster unit is not allowed to learn, it is inhibited and a new cluster unit is selected as the candidate.

Application Example: Scheduling

Dynamic strategies have more potential than static strategies for better schedule because they can react more quickly to changes in system states that are defined by neural net.
As [Fig 1], the knowledge acquisition phase has two steps: Pattern classification step for system states and Scheduling rule base generation step. The knowledge acquisition phase provides two kinds of knowledge: System State Pattern Knowledge Base (SPKB) and Scheduling Rule Base (SRB). SPKB is the knowledge base for the classification of the current system state patterns. SRB is the knowledge base for suggesting the most proper dispatching rule to the classified current system state pattern.
System state variables are fed into each system state pattern classifier made by each ART II network as input data. As a result, a state vector consisting of six symbols presents a system state.
At the schedule execution phase, System State (SS) Finder classifies the current system state pattern corresponding to the system state variables. Dispatching Rule (DR) selector selects a proper dispatching rule to the system state pattern at each decision point. Scheduler makes a schedule with the dispatching rule. The decision point, in this paper, is defined as the time when a machine needs to select a job from the waiting jobs. A real time performance is considered to acquire scheduling rule base.
At the beginning, we have only one state, and various dispatching rules are applied. Once other state is classified and a dispatching rule is applied, the real time performance during the interval from the start time and the finish time of the state is measured.
The performance of each dispatching rule is measured for the state. The results of simulation experiments are used for comparing the proposed method with other scheduling methods (single dispatching rule and multi-pass simulation) as shown in next section.

Experiments

In order to test the performance of the proposed approach, it was put on trial in a computer-simulated FMS (Flexible Manufacturing System) situation.
Above all, ART II classified the chaotic manufacturing system state into [Table 1].

Table 1 - System state example by ART II

		Classified system state	Number of system state
System	Rate	3, 0, 2, 1	4
	Time	2, 5, 1, 7, 8, 0	6
	Jobs	8, 1	2
M/C	Rate	5, 4, 8, 6	4
	Time	2, 6, 3, 8	4
	Jobs	3, 1	2

Long simulation classified the system states as in [Table 1] and made scheduling rule base as follows

- *RULE # 1: IF State < 3, 1>, THEN Apply Longest Processing Time Rule*
- *RULE # 2: IF State < 3, 5>, THEN Apply Earliest Due Date Rule*

• *RULE # 3: IF State < 0, 5>, THEN Apply First In First Out Rule*
• *RULE # 4: IF State < 0, 1>, THEN Apply Earliest Due Date Rule*
• *RULE # 5: IF State < 0, 7>, THEN Apply Largest Total Processing Time Rule*
• *RULE # 6: IF State < 1, 5>, THEN Apply Shortest Processing Time Rule*
• *RULE # 7: IF State < 1, 1>, THEN Apply Shortest Remaining Processing Time*
• *RULE # 8: IF State < 3, 7>, THEN Apply Shortest Total Processing Time*
• *RULE # 9: IF State < 0, 2>, THEN Apply Fewest Operation NO Rule*
• *RULE # 10: IF State < 1, 7>, THEN Apply Shortest Processing Time Rule*
• *RULE # 11: IF State < 0, 8>, THEN Apply Shortest Processing Time Rule*
• *RULE # 12: IF State < 0, 0>, THEN Apply Shortest Total Processing Time*
• *RULE # 13: IF State < 1, 2>, THEN Apply Shortest Total Processing Time*
• *RULE # 14: IF State < 3, 8>, THEN Apply Shortest Processing Time Rule*

Conclusion

This paper proposes a state concept, which was classified autonomously using neural network. The clustering method for system states is proposed. The proposed method may be applied for any existing manufacturing system with minimum installation effort, and can generate efficient schedules if we only have a control computer equipped with a state reporting system. The clustering method for system states and the knowledge acquisition method for scheduling rules are shown to be efficient for the development of autonomous real-time scheduling system.

Table 2 - Simulation Result

Run	Single Pass		This paper		MultiPass	
	SPT	SRPT	method 1	method 2	PJN	Existing
1	97.07	113.05	**84.39**	86.73	93.93	94.38
2	124.36	121.05	120.94	**114.32**	130.32	134.42
3	149.84	144.56	**133.64**	139.79	148.22	148.87
4	99.01	112.46	**96.31**	99.07	98.94	98.94
5	128.3	162.05	116.97	**114.72**	128.3	120.35
6	**103.95**	127.8	106.53	107.99	116.53	113.55
7	73.25	68.68	**61.77**	64.42	70.9	68.05
8	175.96	210.09	155.8	**148.08**	154.11	189.3
9	83.84	81.69	81.53	**76.27**	84.76	78.15
10	156.39	191.07	153.08	157.56	**148.2**	171.26
11	88.54	82.51	**80.69**	81.42	87.15	88.25
12	123.52	**112.07**	114.88	128.08	122.11	129.55
13	118.51	124.04	**103.8**	113.03	120.94	115.29
14	152.83	151.19	**148.35**	153.93	156.05	151.61
15	151.52	181.89	146.11	**142.34**	158.51	160.87
16	122.58	138.42	**110.36**	117.7	121.33	129.67
17	85.92	89.38	**78.29**	86.94	89.11	96.05
18	77.84	88.05	**73.05**	73.66	79.35	84.44
19	98.15	87.37	**86.62**	93.29	98.66	87.38
20	110.93	102.42	**90.54**	95.78	96	120.4

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