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Study of SOM-based intelligent multi-controller for real-time scheduling

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ABSTRACT

Earlier studies have indicated that the use of multiple scheduling rules (MSRs) for various zones in a system can significantly enhance the production performance over the performance obtained with the use of a single scheduling rule (SSR) over a given scheduling interval for all machines in the system through a multi-pass simulation approach for a real time scheduling (RTS) problem. However, if a classical machine learning approach is used, an RTS knowledge base (KB) can be developed using the appropriate MSR strategy (this method is called an intelligent multi-controller in this study) as obtained from training examples. A classical machine learning approach main disadvantage is that the classes (scheduling decision variables) to which training examples are assigned must be pre-defined. Hence, developing an RTS KB by the classical machine learning approach to generate training examples becomes an intolerably time consuming task because the MSRs for the next scheduling period must be pre-determined. To address this issue, this study proposes an intelligent multi-controller that consists of three main mechanisms: (1) a simulation-based training example generation mechanism, (2) a data preprocessing mechanism, and (3) a self-organizing map (SOM)-based MSR selection mechanism. The results reveal that over a long period of time this approach provides better system performance based on various performance criteria than the system performance of the machine learning-based RTS based on the SSR approach for two different types of manufacturing systems (FMS and FAB). Hence, the proposed intelligent multi-controller approach is efficient enough to be incorporated into the operation of an RTS system.

1. Introduction

In order to remain competitive in the market, modern manufacturing enterprises must provide a wide range of low-cost high-quality products within a short period of time; therefore, many enterprises are now resorting to e-manufacturing and flexible manufacturing system (FMS) technologies to achieve this objective [1–3]. Many researchers [4–6] believe that the development of an efficient real-time scheduling (RTS) mechanism is the key to satisfying various performance criteria of the shop floor control system (SFCS).

RTS employs different scheduling rules in a dynamic and multi-pass manner, which selects the best scheduling strategy among feasible alternatives at each decision point over a series of scheduling periods to meet the performance criteria of the shop floor [4]. On the basis of earlier studies, RTS uses two main approaches: the multi-pass simulation approach [7,8] and the machine learning approach (called intelligent controller in this paper) [9–11].

Multi-pass simulation is used to evaluate candidate scheduling rules and select the best strategy based on simulated information such as the current system status and the management goals for each short scheduling period. The multi-pass simulation approach is inappropriate for shop floor control because it requires extensive computational effort to select the best scheduling rule for each short scheduling period.

In the machine learning approach for intelligent controller, a set of training examples generated by system simulations are used to determine the best scheduling rule for each possible system state; although the machine learning approach of collecting training examples and learning processes to acquire the knowledge base (KB) of RTS tends to be time consuming and relatively slow. Such a KB has the advantage of yielding fast and acceptable solutions that enable the system to make decisions in real-time, and it can conform to the operational characteristics in a dynamic manufacturing environment [6,10]. Earlier studies [9,10] have defined three major machine learning approaches for constructing an RTS system KB: artificial neural networks (ANNs) [12], decision tree (DT) learning [13], and support vector machines (SVMs) [14].

Based on earlier studies, two strategies determine the scheduling rules in an RTS system: single scheduling rule (SSR) and multiple scheduling rules (MSRs) for a manufacturing cell. The SSR usually

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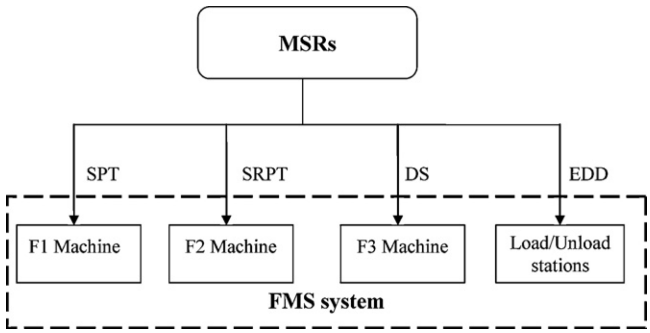

Fig. 1. The role of MSRs in this study.

assigns an individual heuristic scheduling rule for all machines in a system during a given scheduling interval (i.e., scheduling period), whereas the MSRs assign different scheduling rules (i.e., scheduling decision variables) for all machines in a system. This method will henceforth be referred to as the intelligent multi-controller. Fig. 1 depicts the role of the intelligent multi-controller in the FMS case study in this research. For F1, F2, F3, and load/unload stations the MSRs method here selects the SPT, SRPT, DS, and EDD dispatching rules, respectively, as the scheduling decision variables for job selection in the next scheduling period. Ishii and Talavage [8] proposed a search algorithm that employs MSRs in bottleneck machines using predictions based on the multi-pass simulation. Their results show that the MSR strategy can improve the performance of a flexible manufacturing system (FMS) by up to 15.9% in comparison with the best result obtained using the SSR strategy. However, their approach was not well suited to an RTS system that uses the machine learning approach.

The intelligent multi-controller builds a KB through the machine learning approach. Its main disadvantage is that the classes (scheduling decision variables) to which the training examples are assigned must be pre-defined. For example, for a given set of system attributes, the best scheduling rule is determined using the set of candidate scheduling rules identified via simulations of each scheduling decision variable. The resulting MSRs are considered as a class. However, as the rules must be determined for each period [15,16], this process becomes intolerably time consuming. Furthermore, the local approach does not satisfy the global objective function (i.e., the overall production performance of the shop floor). In other words, although the best decision rule for each scheduling decision variable can be determined, a combination of all the decision rules may not simultaneously satisfy the global objective function. However, very little research has been focused on harmonizing RTS using the intelligent multi-controller to meet the global performance criteria. In addition, the Ishii and Talavage [8] experiment did not consider both the input control and the dispatching rule problem simultaneously, which is an important issue in the semiconductor wafer fabrication (FAB) environment [17,18]. To achieve a competitive advantage in FAB operations, a dynamic nature combined with uncertainties leads to the emergence of the need for dynamic selection of scheduling rules. Therefore, this issue is worthy of research to identify a combination of input controls and dispatching rule policies that consistently offer good performance under various situations.

This study attempts to develop an intelligent multi-controller by a learning-based approach by assigning different scheduling rules for all machines in a dynamic manufacturing environment, such as FMS during a given scheduling interval. Moreover, the proposed intelligent multi-controller can also be applied to consider both the input control and the dispatching rule, such as those in a FAB manufacturing environment.

Clustering is a data mining technique [19] that involves grouping of data into classes or clusters such that the patterns in the data within each cluster are highly similar, but patterns in different data clusters are considerably dissimilar. Based on this concept, the clusters of input vectors of the training examples, which are defined by the system attributes and current MSRs, are categorized into different classes to develop an intelligent multi-controller KB for the RTS system. The corresponding output vectors of training examples (i.e., decision MSRs in the next scheduling period can assign the same class thereafter). Kohonen's self-organizing map (SOM) neural network [20] is the most widely used technique and is an excellent testing tool for data mining [21]. According to various system statuses and current MSRs, SOM clustering can generate a number of MSR classes based on various performance criteria. Hence, SOM clustering and MSR selection algorithms are a promising prospect for constructing an intelligent multi-controller KB for RTS.

This study seeks to develop an intelligent multi-controller that uses the SOM-based real-time MSRs selection mechanism to support an RTS system. We believe that using the proposed approach, we can provide better system performance than that obtained using machine learning-based RTS, based on the classical machine learning approach, which is based on various types of manufacturing systems (i.e., FMS and FAB) and performance criteria (throughput or cycle time). This is the main aim of this study.

This paper is divided into six sections: in Section 2, the relevant theoretical background of SOM algorithms has been introduced. Section 3 formulates the RTS system problem using the intelligent multi-controller approach and states the research objectives. Section 4 describes the methodology of the proposed intelligent multi-controller. Section 5 presents the FMS and FAB case study experiment results and analyzes the proposed intelligent multi-controller approach as well as the classical machine learning approach. Finally, in Section 6, the paper concludes with a summary and suggests some topics for future research.

2. Theoretical background

The most widely applied clustering ANN is SOM, which is an excellent tool in the exploratory phase of data mining because of its prominent visualization properties. Unlike other ANN approaches, the SOM network performs unsupervised learning, i.e., during the learning processes the processing units in the network adjust their weights primarily on the basis of lateral feedback connections. A more common approach to ANNs requires supervised learning of the network, i.e., the network is fed with a set of training samples and the generated output is compared with the known correct output. Deviations from the correct output result in adjustment of the weights attached to the processing units. Such networks are said to be trained when they work satisfactorily for the test cases. The SOM network, on the other hand, does not require the knowledge of the corresponding outputs. The nodes in the network converge to form clusters that represent groups of entities with similar properties. The number and composition of the clusters can be visually determined from the output distribution generated by the learning process.

There are three basic steps involved in the application of the SOM algorithm after initialization: sampling, similarity matching, and updating. These three steps are repeated until the formation of the feature map completed. The SOM algorithm is summarized as follows:

1. *Initialization*: Choose random values for the initial weight vectors $\mathbf{w}_j(0)$. The only restriction here is that $\mathbf{w}_j(0)$ must be different for $j = 1, 2, \ldots, J$, where J is the number of neurons in the lattice. It may be desirable to keep the magnitude of the weights small.