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Machine number, priority rule, and due date determination in flexible manufacturing systems using artificial neural networks

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Abstract

When there is a production system with excess capacity, i.e. more capacity than the demand for the foreseeable future, upper management might consider utilizing only a portion of the available capacity by decreasing the number of workers or halting production on some of the machines/production lines, etc. while preserving the flexibility of the production system to satisfy demand spikes. To achieve this flexibility, upper management might be willing to attain some pre-determined/desired performance values in a production system having identical parallel machines in each work center. In this study, we propose a framework that utilizes parallel neural networks to make decisions on the availability of resources, due date assignments for incoming orders, and dispatching rules for scheduling. This framework is applied to a flexible manufacturing system with work centers having parallel identical machines. The artificial neural networks were able to satisfactorily capture the underlying relationship between the design and control parameters of a manufacturing system and the resulting performance targets.

Keywords: Artificial neural networks; Priority rules; Due date assignment; Flexible manufacturing system; Inverse scheduling

1. Introduction

In the global competitive market, several factors might affect the management of demand and capacity. For example, seasonality in demand, a new competitor in the global market, or an economic or political crisis might force underutilization of the available capacity. In any of these cases, upper management might not have the luxury of running production at capacity for a long period of time. One alternative might be to reduce short-run operational capacity by shutting certain production lines/work stations/machines while preserving the flexibility to satisfy demand spikes. This could lead to opportunities for larger orders if the incoming orders are satisfied while achieving some critical and conflicting objectives such as faster delivery speed, greater reliability, higher customer satisfaction, and minimum cost. To achieve these objectives, management might need a decision-support tool that will provide the optimal resource structure and scheduling policy. For a given resource structure and scheduling policy, computing the performance of a production system is straightforward. However, to employ 'what-if' analysis requires simulation. If the goal is to maintain certain performance measures at predetermined levels to accommodate the unexpected demand, then a what-if approach, which might require extensive simulation, may not be feasible at the operational

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level. Therefore, an intelligent decision system is necessary to support management's operational decisions in the short run.

Our goal is to utilize neural networks and simulation as tools for scheduling jobs on the shop floor of a flexible manufacturing system setting in order to achieve the desired system goals set by upper management; specifically we will determine the number of machines in each work center (WC) (design decision), the priority rule used on the shop floor and the due date (scheduling decision) for incoming orders.

2. Literature review

A flexible manufacturing system (FMS) is a computer-controlled production system with a set of connected CNC machines in which routing, loading, and scheduling operations are controlled by a central computer. Fry and Smith (1989) consider the most significant objectives for an FMS as meeting the due dates; maximizing the system and machine utilization rates; minimizing the level of work in process inventory; maximizing the production rate; minimizing the setup, preparation, and team change times; minimizing the mean flow time; maximizing the capability of performing jobs at parallel work stations; and operating according to the pre-determined capacity. In an FMS system, design decisions include selection of hardware, machine types, part types, the material handling system, tools, apparatuses and pallets, and staffing. Control process decisions address short-to medium-range operational issues such as general planning, system setup, and scheduling. Mellichamp and Wahab (1987) identify testing on a small-scale physical model of the system, using analytical methods and simulation as approaches for performance analysis of design alternatives. Chan and Rathmill (1985) propose a three-step approach that includes planning, design, and system setup in an FMS. Stecke (1985) shows that the system performance in an FMS literally depends on selected job loading and control strategies. Edghill and Cewsswell (1986) conclude that generalized control mechanisms will result in performance levels inferior to mixed scheduling policies.

Flexibility in an FMS makes it difficult to use analytical methods to find the optimal solution to planning, scheduling, and control problems (Mahmoodi, Mosier, & Morgan, 1999). When analytical methods are used, the original system is usually over simplified. Even in this case, the resulting problem requires extensive computational power because most of the scheduling problems in a manufacturing system are NP-hard problems (Chryssolouris, Lee, Pierce, & Domroese, 1990). Therefore, methods like simulation, artificial neural networks (ANNs), simulated annealing, and metaheuristics are typically utilized to address such complexities. For example, Sridharan and Babu (1998) use simulation to investigate the effect of scheduling rules on the FMS performance. Sabuncuoglu and Karabuk (1998) recommend artificial intelligence algorithms for solving scheduling problems in an FMS environment. Fonseca and Navaresse (2002) conclude that ANNs can be used as a valid alternative to a simulation approach. Some of the other approaches used in FMS design and control are genetic algorithms for FMS scheduling (Jawahar, Aravindan, & Ponnambalam, 1998), a mathematical modeling approach to optimally solve job shop problems (Gomes, Barbosa-Póvoa, & Novais, 2005), artificial neural networks (Vuyosevic, 1994), a hybrid dynamic programming approach based on a genetic algorithm in FMS scheduling (Yang, 2001), an inductive learning and neural network method for multi-purpose FMS scheduling (Kim, Min, & Yih, 1998), a multi-objective simulated annealing approach (Loukil, Teghem, & Tuyttens, 2005), and a multi-objective scheduling framework for hierarchical FMS control (Tung, Li, & Rakesh, 1999). Unless simplistic assumptions are made to model and solve these complex problems, the number of control variables in designing and controlling any automated manufacturing system is usually very large. Hence, solving design and control problems simultaneously in an FMS setting might require a vast amount of data and/or an extensive amount of computational effort.

An alternative might be utilizing a combination of the above-mentioned methods to determine a good solution efficiently. One way to speed up this process is to utilize ANNs and simulation together. Neural networks have several applications including scheduling and production system design on FMS problems (Chryssolouris et al., 1990; Feng, Li, Cen, & Huang, 2003). Vuyosevic (1994) proposes an FMS design framework integrating simulation and a rule-based initial processor that compares simulation results with target values. Given a set of targeted performance measures, Chryssolouris et al. (1990) determine the number of machines in each WC in an FMS. Cakar, Yildirim, and Barut (2005) extend this work to also select the priority rule used in scheduling. Philipoom, Rees, and Wiegmann (1994) propose a method to determine the due date for incoming orders using ANNs along with alternative due date selection rules. We synthesize the approaches of Chryssolouris et al. (1990); Philipoom et al. (1994), and Cakar, Cil,