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Job shop flow time prediction using neural networks

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Abstract

In this paper we investigate the use of Artificial Neural Networks (ANN) for flow time prediction and, consequently, to estimate due dates (DD) in a hypothetical dynamic job-shop. The effectiveness of the proposed ANN based DD assignment model is evaluated comparing it performance with the performance of two dynamic DD assignment rules proposed in the literature: Dynamic Total Work Content, and Dynamic Processing Plus Waiting. Results show that ANN based DD assignment models are more effective than, not only available static DD assignment rules, as concluded by other researchers, but also than the more effective Dynamic DD assignment rules.

Keywords: Dynamic job shop, Dynamic due date assignment rules, Simulation, Artificial Neural Networks, Dispatching rules.

1. Introduction

With increasing globalization, competitiveness and current emphasis on costumers-oriented markets, companies are facing more challenges than ever. In order to gain competitive advantages in the intense market competition, companies must be able to provide customers with better quality, reduced lead time and reliable due dates [1]. The importance of meeting promised due dates (DD) is highlighted in [2] where the authors claim that it not only

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increases the customer service but also improves the resources utilization by making it more efficient. Thus, DD assignment as been pointed out as a key task in shop floor control [3].

The dynamic job shop system has been widely used in DD assignment problem research since it provides a more accurate representation of the operating conditions of a real-world environment [4]. In this kind of environment, the DD assignment problem consists in making an estimation of a job flow time, when it arrives to the shop, and setting a completion date based on that estimation [5], for example by adding an external lead time buffer to the estimated flow time. However, flow time prediction is a challenging task since every arriving job has its own processing needs, in different machines and it will experience different congestion levels which will, consequently, alter the flow of the jobs through the shop [6]. Moreover, as stated in [7], if the shop dispatching rule is not First in First Out, the arrival of a new job can change the processing sequence and thus the expected completion date of a job already in the system.

The general flow time estimation, for a given job i, arriving to a shop, can be represented by equation (1).

$$f_i = r_i + p_i + k_i \tag{1}$$

where f_i, r_i, p_i and k_i are the flow time estimation, the arrival time, the total processing time and the allowance factor for job i, respectively. The arrival time and the processing time of a job are known upon it arrival to the shop, thus the only variable that needs to be estimated is the allowance factor k. The flow allowance is a variable used to control the tightness of the DD which reflect the waiting time that a job will experience in the shop. Choosing the appropriate allowance factor is a trade-off between the tightness of the DD and the job earliness/tardiness. If the allowance factor provides a looser DD, it may be possible to complete all the jobs on time. However, this will lead to a higher number of jobs completed before the DD (earliness). On the other hand, tighter flow allowance will lead to a higher amount of jobs completed after the DD (tardiness). The literature provides a wide variety of methods to estimate job flow times. The main difference among them is the number and type of factors considered to estimate the allowance factor k.

Earlier studies on the DD assignment problem focused in the use of simple rules for flow time estimation. Five examples of this kind of rules: Constant (CON), Number of Operations (NOP), Slack (SLK), Total Work Content (TWK) and Processing Time Plus Waiting (PPW) are presented in Table 1.

Table 1. Examples of DD assignment rules.

DD Assignment rule	DD prediction
CON	$d_i = r_i + k$
NOP	$d_i = r_i + km_i$
SLK	$d_i = r_i + p_i + q$
TWK	$d_i = r_i + kp_i$
DPPW	$d_i = r_i + kp_i + q$

where d_i is the DD of job i, m_i is it number of operations and pi it total processing time. In this class of assignment rules, the constants k and q, the allowance factor and the slack allowance respectively, are determined by linear regression based on historical data.

In this class of rules, the same degree of flow time allowance is given to all the jobs and, for this reason, they are known as static rules. The accuracy of these rules depends on the determination of the most appropriate flow allowance for all the jobs [8]. The main issue stated for this class of rules is that by given the same allowance factor to all the jobs, the shop load is not being taken into account for DD prediction. Yet, the shop load influences the time that a job will experience in the system. If the shop load is heavy a higher flow allowance should be assigned and, in the other hand, if the shop load is moderate, a lower flow allowance should be considered [9].

To overcome the limitation of the static rules for DD assignment, two dynamic DD setting rules were proposed by Cheng and Jiang [9]. In these rules: (1) Dynamic Total Work Content (DTWK), based on the TWK static rule