Available online at www.sciencedirect.com
ScienceDirect
Procedia CIRP 17 (2014) 499 – 504
www.elsevier.com/locate/procedia

Variety Management in Manufacturing. Proceedings of the 47th CIRP Conference on Manufacturing Systems

Knowledge-based estimation of manufacturing lead time for complex engineered-to-order products

Mourtzis D.[a]*, Doukas M.[a], Fragou K.[a], Efthymiou K.[a], Matzorou V.[a]

[a] Laboratory for Manufacturing Systems and Automation, University of Patras, 26500, Greece
* Corresponding author. Tel.: +30 2610 997262; fax: +30 2610 997744. *E-mail address:* mourtzis@lms.mech.upatras.gr

Abstract

Product complexity leads to increased unpredictability of indices related to manufacturing performance estimation. This phenomenon is intensified in companies that produce engineered-to-order products, such as the knowledge and labour intensive mould-making industry. During the initial capturing of product specifications formalisation difficulties arise. Moreover, the estimation of delivery times for new moulding project is solely based on the engineers' experience. A methodology, which has been developed into a software tool is proposed that exposes graphical interfaces for customers to submit new orders and establish a formalised communication with the engineering team. The collected data are stored in a knowledge repository and are processed by a case-based reasoning mechanism for the lead time estimation. A real-life pilot installation has been initiated to a mould making SME. Preliminary results depict a significant reduction in the number of iterations between customers and engineering department compared to the traditional approach followed by the company, and improved accuracy of lead time estimation.

Selection and peer-review under responsibility of the International Scientific Committee of "The 47th CIRP Conference on Manufacturing Systems" in the person of the Conference Chair Professor Hoda ElMaraghy"

Keywords: Manufacturing; Lead Time Estimation; Case-Based Reasoning, Knowledge Management

1. Introduction

In modern manufacturing the reuse of past knowledge constitutes a key factor for improving manufacturing performance, during design, planning and operational phases [1, 2]. A particular type of manufacturing industry, the production of engineered-to-order products, essentially relies to the experience of human operators. However, valuable knowledge generated and associated to products and processes in a daily basis, remains tacit and its reusability is confined to a specific machine operator [3]. Usually in this kind of industry, an initial estimation of manufacturing lead time can be provided by the machinist through examination of the characteristics of a new product. The accuracy of the estimation however, is empirical and significant deviations may arise. Nevertheless, a solid estimation about the delivery date is expected by the customer. In case of delivery tardiness, the customer may experience capital loses, considering that moulds are the most productive tool in the disposal of a mass producer. In today's immensely competitive environment, the profitability of companies is based on its quick adaptation to market needs and establishment of communication channels with the customers. Integrating the customers in the design phase of new products and making them a part of the supply chain can improve the performance of a company [4, 5].

Towards that end, this paper proposes a method for the estimation of manufacturing lead time based on past knowledge of engineered-to-order projects. The method exploits Case Based Reasoning (CBR) [6] and similarity measurement techniques for the generation of an accurate estimation for the expected manufacturing lead time for a new engineered-to-order product. The remainder of the paper is as follows. Section 2 includes a literature survey on lead time estimation. Section 3 analyses the proposed methodology and

Selection and peer-review under responsibility of the International Scientific Committee of "The 47th CIRP Conference on Manufacturing Systems" in the person of the Conference Chair Professor Hoda ElMaraghy"
doi:10.1016/j.procir.2014.01.087

section 4 demonstrates a real-life case study in a mould-making machine shop.

2. State of the art on manufacturing lead time estimation

Lead time or throughput time [7] is the amount of time between the placement of an order and the receipt of the ordered product / service by the customer. The main components of manufacturing lead time are: queue, processing and transportation times and are a critical measure of manufacturing performance. Lead times are affected by many factors including capacity; loading, batching and scheduling, and themselves affect many aspects of costs, and control.

From a customer perspective, lead time can be translated into delivery time. The correlation between customer's satisfaction and delivery time is investigated in [9] depicting the utmost importance of accuracy when estimating this performance index.

Various methods have been proposed for the estimation of lead time (Fig. 1). Indicatively, the methods used include simulation [1], queuing theory [2], logistic operating curves [10], statistics [11], stochastic analysis [8], artificial intelligent methods [12] and hybrid methods [13] (combination of two or more of the previous methods).

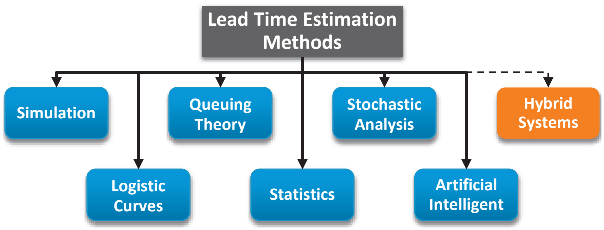

Fig. 1: Lead Time Estimation Methods

Wiendahl et al. proposed the so-called throughput diagrams that can provide a correlation between the lead time with indices such as lot size, manufacturing costs, inventory and utilisation [8, 14]. Nyhuis et al. proposed a simulation model with typical operating curves, to describe the behaviour of logistic performance measures as functions of work-in-process (WIP) levels. In this model, an increase of WIP levels comes with analogous increase in throughput times [10]. Chryssolouris et al. considered discrete event simulation models for shortened lead times and integration of knowledge for increasing the variety of parts and products [1].

For reducing the effort of extensive simulation experiments, the authors in [10] developed approximation equations to calculate the logistic operating curves and proposed a deductive model to represent the output rate and the throughput time of a work system. In addition, a comprehensive overview of queuing theory-based systems and their characteristics (inter arrival, service times, etc.) are provided in [2]. Simulation, queuing theory and logistic curves model the product and / or the production system, to predict lead time performance, however, these methods entail disadvantages [10]. For instance, simulation is difficult to be applied during execution phase and general conclusions are hard to be drawn. Queuing theory and logistic curves require a high effort in definition phase, they are only valid for steady operating states and are limited to resource perspective. Queuing theory has additional limits for the adaptation of models and the parameters may not conform to practical reality.

Nowadays, the most robust methods for lead time estimation are Artificial Intelligent (AI) methods (Fig. 2). A review of AI methods and their exploitation in modelling, prediction, monitoring, simulation, optimisation and control is included in [12]. Ozturk et al. used data mining as an Artificial Intelligent method and attribute tables in order to calculate manufacturing lead time [15]. Moreover, a self-organizing neural network for the design and implementation of cellular manufacturing systems that takes into consideration processing is proposed in [13].

Among AI methods, Case Based Reasoning (CBR), which focuses on solving problems by adapting acceptable solutions and comparing differences and similarities between previous and current products, has been utilised for lead time estimation. A CBR approach applied during product development effectively reduced lead time and improved the problem solving capabilities [16]. A classification model based on CBR and similarity measures for calculation of distances between features depending on their type is proposed in [17]. The study used Euclidean distance for numerical features and other categorical features that are obtained from co-occurrence of feature values. Another classification model based on CBR and the similarity measures is presented in [18], for improving the process of data set classification. The advantages of CBR over the other types of knowledge reuse are discussed in [19].

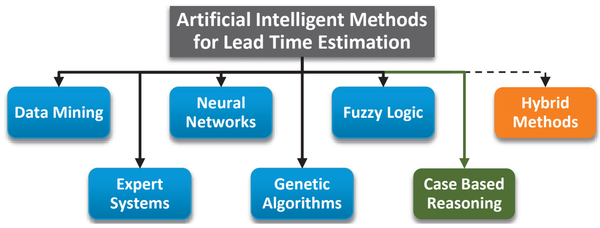

Fig. 2: Artificial Intelligent Techniques for Lead Time Estimation

CBR is distinguished from other methods, not only because it exploits past knowledge for solving new problems in an intuitive way, but also because of the exploitation of similarity measurement. Similarity measures are used to calculate the distances between the features of past and new cases, in order to revise and solve the new case. CBR has been successfully applied in several domains such as design, decision making, planning, diagnosis, medical applications, law, e-learning, knowledge management, image processing or recommender systems, etc. [20].

Building upon the literature on the field, the proposed research work provides an easy to implement methodology for successfully capturing customer requirements and translating them into engineering specifications for the extraction of accurate performance indices estimation. A knowledge reuse mechanism, which consists of a Case-Based