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

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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.

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

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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).

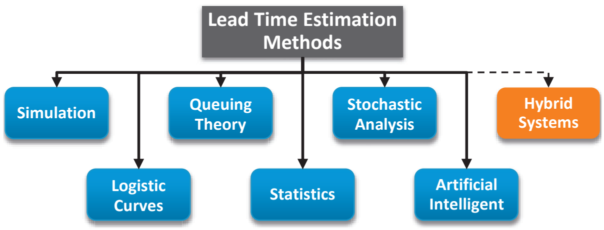

Fig. 1: Lead Time Estimation Methods

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].

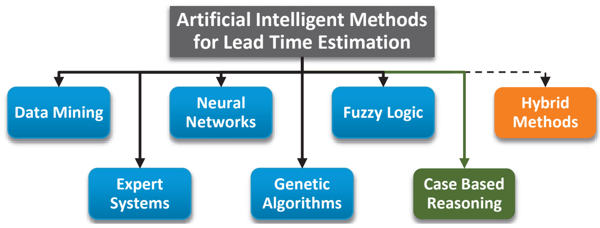

Fig. 2: Artificial Intelligent Techniques for Lead Time Estimation

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

Reasoning engine and similarity measures is utilised for the estimation of lead time. The methodology is currently applied in a real production environment. A case study using data from a mould-making SME is presented for the verification of the performance of the methodology.

3. Lead time estimation methodology

3.1. Description of the Case Based Reasoning mechanism

CBR systems have been developed for enhancing traditional rule-based approaches [21]. Their greatest advantage is that they can be applied to one-of-a-kind problem instances after appropriate adaptations, without needing assistance from expert rationales and experience [16]. Thus, previous knowledge is effectively reused for the acquisition of valuable knowledge for e.g. estimation of performance indices for a newly introduced case. An issue in case retrieval is the vast amount of embedded knowledge in past cases. CBR excels in managing case memories by incorporating a case memory organisation model. CBR is based on a dynamic memory related to past earlier cases and situation patterns to learn and solve new problems [22].

Case retrieval is the most important step of CBR because the quality of the estimation is tightly related to the degree of similarity between the cases [23]. For the problem under investigation, once a new order enters the system, the CBR mechanism is triggered (Fig. 3). It, then retrieves from the case base, all previous cases and performs a similarity check. If one of the retrieved problems is identical to the new case, the solution is directly revealed and the relevant indices can be reused after appropriate adaptation (e.g. considering current copper prices). Otherwise, an adaptation stage is required utilising stored knowledge. Case adaptation is the process of transforming the most similar cases retrieved from the case base into a solution appropriate for the current problem. A significant issue in adaptation is limiting the number of produced rules. In case an acceptable solution is found, it will be reported and the retaining stage will commence.

It should be noted here that previous cases are always available in unstructured form. All contemporary manufacturing companies store one way or another the completed projects. In the type of investigated manufacturing environment, namely a machining shop-floor, each project is documented using Excel sheets that include the features of the mould. In addition, each machine operator is obliged to hand-write a report at the end of every working day in order to justify the tasks that have been carried during the day (machining processes and time that was required regarding specific orders). Therefore, through a processing of these raw information, past cases are able to be formulated.

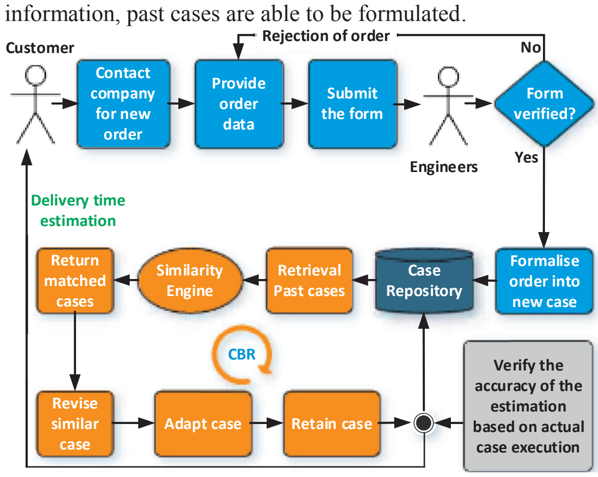

Fig. 3: Workflow of lead time estimation including steps of the CBR method

3.2. Similarity Measurement Engine

Case retrieval and adaptation are supported by a similarity measurement engine. The similarity measures improve the retrieval accuracy [23] and are based on the concept of distance between the attributes of past and new cases (Fig. 5). The larger the distance between two cases the smaller the degree of similarity. For numerical data, in comparison to other types of data, among the various distance functions, the Euclidean, Manhattan and Minkowski distances are found. The Euclidean distance, which is used in the present work, is given by the Pythagorean formula; it is the ordinary distance between two points that one would measure with a ruler.

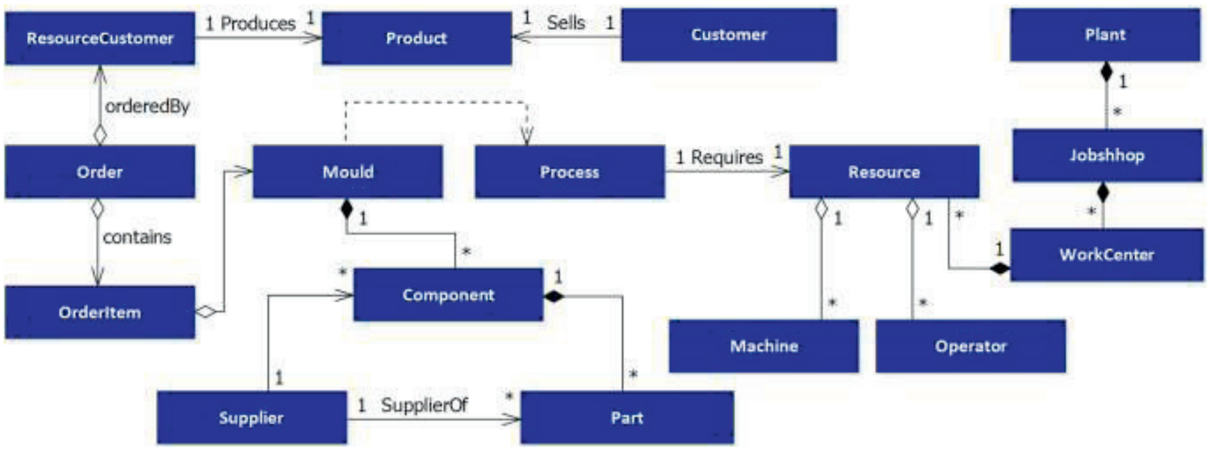

Fig. 4. Ontological data model. Snapshot of the basic datatypes related to a mould

3.3. Workflow of the framework

Following on the submission of a new order from the customer, the estimation of the lead time must be carried out (Fig. 3). CBR retrieves the past cases from the case repository. The similarity engine compares the new order attributes with the attributes of the past cases and yields as an output the most similar case. Afterwards, the new order is revised based on the past one and then stored in the knowledge repository as a past case (Fig. 5). In order to obtain the delivery time approximation for the order, the relationship between its attributes and time is crucial. Production rate is an aggregate of design, manufacturing processes, human labour, machines and tools selection. Thus, it is necessary to incorporate in the calculations information about the number and the kind of product's components, about suppliers, logistics, and materials, about the type of processes, about the type and the number of machines and tasks, and about the tools. The formulas for the calculation of the similarity measure are include in section 4 below.

A formal representation of the concepts is depicted in the ontological schema of Fig. 4. The ontology is a representation of a set of concepts and their domain as well as the complex relationship between these concepts and knowledge that optimise the searching of the useful knowledge by getting relevant concepts and reusing previous knowledge from complex data base, as well [24].

4. Industrial Case Study from the Mould-making Industry

The industrial sector of mould-making is among the most crucial enablers for the realisation of mass production and customisation. Mould variety is essential to achieve the desired variety in component level. Engineer-to-order products (ETOs) such as moulds are one-of-a-kind extremely complex products. A mould needs to be designed and constructed in such a way that it can produce an injection plastic component with a single stroke of the press and eject it without any imperfections. Thus, the geometry of every mould component and all the specialised built-in mechanisms i.e. cooling system, are attributes that increase the construction difficulty exponentially, making the manufacturing process unexpectedly time consuming and exceedingly precision dependent.

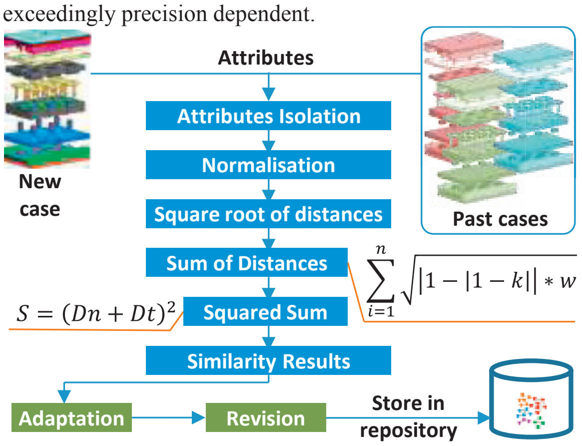

Fig 5. The similarity measurement engine

The mould of the case study is depicted in Fig. 6. At least 15 main parts are identified that require approximately 6 processes each. Moreover, manual fitting is required in many steps of the process. Fitting is one of the core processes as it defines the overall performance of the mould. Fitting is exclusively performed by a very experienced human operator. The enormous complexity of the mould is evident.

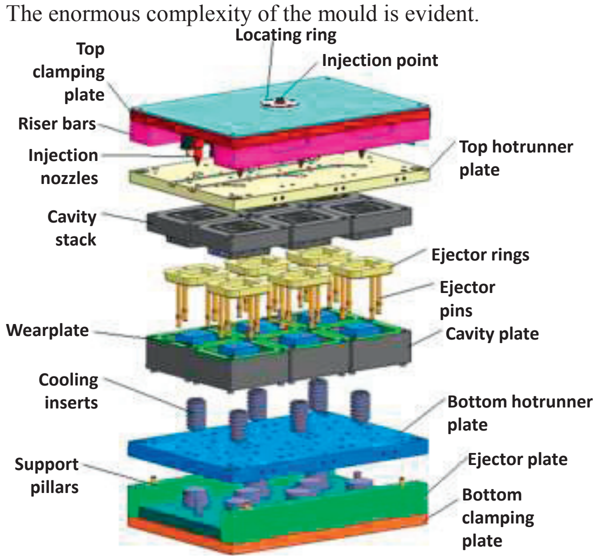

Fig. 6. Major parts and components of the mould of the case study

The overview of the business model of the mould making SME of the case study is depicted in the diagram of Fig. 7. The estimation of required time and its communication to the customer is carried out during the second phase. However, the accuracy of the estimation greatly impacts subsequent stages. This is due to the fact that the company, during phase 2, makes a verbal commitment to the customer and in case of any tardiness, customer satisfaction will be reduced.

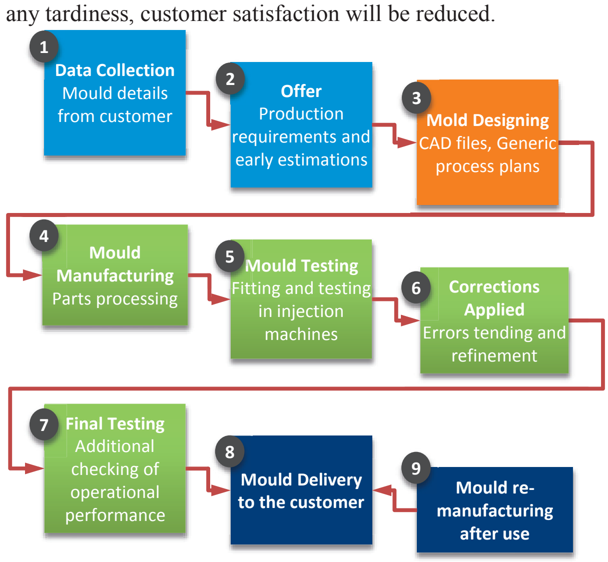

Fig. 7. Business model of the mould-making SME

Table 1 includes the attributes of three moulds, called A, B and C for reasons of simplicity. For each mould, the attributes related to the number of cavities, surface quality, number of components, and processes are provided. Moreover, data related to manufacturing processes are included as collective figures for all the required processes of every mould case.

The three cases included in Table 1 contain similarities between one another. It is therefore, expected that their lead time is fairly similar, ranging from 52 days (case C) to 64 days (case A). After that, for alleviating any conflicting nature and for constituting them independent from the units of measurement, the features are normalised in (0, 1) and are multiplied with the assigned weights. The selected weights represent the relative importance of the features of the case based on their influence on lead time. Therefore, their values have been defined through semi-structured questionnaires and interviews with expert engineers of the case study. Moreover, normalisation is achieved by the fraction T_{pi}/T_{ni} that is being subtracted from 1. The weighted values are defined based on their impact on the lead time. The bigger the weight value for an attribute, the higher its impact on manufacturing lead time. Following on that, the square root of the Euclidean distance for numerical attributes is calculated using equation (1).

$$D_n = \sum_{i=1}^{n} \sqrt{\left| \frac{T_{ni}}{T_{ni}} - \left| 1 - \frac{T_{pi}}{T_{ni}} \right| * w_i \right|} \tag{1}$$

where:

- D_n = numerical distance
- n = number of features
- T_{ni} = the feature for the new case
- T_{pi} = the feature for the past case
- w_i = the weight of attributes

Table 1: Attributes and total processing times of the moulds

Attributes	Mold A	Mold B	Mold C
Number of cavities	6	2	4
Type of Hardening	Very good	Very good	Very good
Side of Injection	Moving Side	Moving Side	Moving Side
Mould Size	Medium	Large	Large
Core Cap	No	Yes	Yes
Ejector Rings	6	2	4
Temper Evident	No	No	No
Type Of Data	Idea	Idea	Idea
Surface's Quality	Mirrors	Mirrors	Mirrors
Number of basic components	9	12	11
Process Time (In Hours)			
Roughing	406.5	333.5	212.5
Finishing	87	296.5	221.75
Air & Water Circuit	81	80	89.5
Fitting	124.5	46.5	43.5
Polishing	69.5	33	41.5
Hardening	504	504	504
EDM	34	20	30
Electrodes	51	7.5	11.5
Other Processes	61.5	23.5	10.5
Assembly	72	86.5	72
Design	40	12.25	12.25
Lead Time in hours (days)	1531 (64)	1443.25 (60)	1249 (52)

The text attributes have to be normalised as well. Prior to that, numerical values in [0, 1] are used to replace plain text. This is necessary in order to avoid text processing. The mapping of text attributes to numerical values is included in Table 2. Equation (2) calculates the square root of the Euclidean distance and is used for measuring the distance between the compared alphanumeric attributes.

$$D_t = \sum_{i=1}^{n} \sqrt{\left| \frac{T_{ni}}{T_{ni}} - |1 - k| \right| * w} \tag{2}$$

where:

- D_t = text distance
- k = correspond value for text attributes

Table 2: Correlations of text attributes with numerical values

Attribute	Correlation of Text and Numeric Values	
Type of Hardening	Good	0
	Very Good	1
Side of Injection	Moving Side	0
	Fixed Side	1
Mold Size	Small	0
	Medium	0.5
	Large	1
Core Cap	Yes	1
	No	0
Temper Evident	Yes	1
	No	0
Type of Data	Idea	1
	Item	0.5
	CAD	0
Surface's Quality	Mirrors	1
	Matte	0

The aggregated equation for the similarity measure that combines numerical and text distance is (3):

$$S = (Dn + Dt)^2 \tag{3}$$

For demonstrating the performance of the CBR and similarity mechanism a comparison of the cases included in Table 1 is performed, based on both numerical and text attributes. These attributes affect the processing requirements and therefore the lead time, due to the complexity that they generate. The assumption is made here that case C is a newly entered case, for which we assume that no data are available for processing times. Based on the CBR methodology, the past cases (i.e. A and B) are retrieved and the similarity mechanism calculates the distance of the attributes using equations (1, 2, 3). The results are included in Table 3. The similarity measure between A and C is S_{AC}=6.087550996 and the same value for B and C is S_{BC}=8.381574914. Thus, the stored case B is the most similar past case to the new case C. Afterwards, the adaptation of the case is performed in order to estimate its manufacturing lead time. The lead time of case C mould is multiplied with the similarity measure between B and C and the result is divided by 10. The resulting value for the estimation of the lead time is $LeadTime_C$ = 1,443.25*(8.381575/10) = 1,209.6708 hours. The deviation of the estimated times compared to the actual values (i.e. 1,249) is 3.15%. The deviation between the two values is of high accuracy. A comparison utilising a larger pool of past cases yields results of even higher quality. Nevertheless, the case provided above demonstrated the accuracy of the method even for instances with scarcity of accumulated past knowledge.

Table 3: Similarity Measures

	Distance Measurement	
Compared mould attributes	**A → C**	**B → C**
Number of cavities	0.273861279	0.273861279
Type of Hardening	0.223606798	0.223606798
Side of Injection	0.316227766	0.316227766
Mould Size	0.223606798	0.316227766
Core Cap	0	0.316227766
Ejector Rings	0.223606798	0.223606798
Temper Evident	0.316227766	0.316227766
Type Of Data	0.223606798	0.223606798
Surface's Quality	0.316227766	0.316227766
Number of basic components	0.350324525	0.369274473
Sum	2.467296293	2.895094975
Similarity Measure	6.087550996	8.381574914

5. Discussion and Conclusion

The presented research work tackled the issue of providing a fast and accurate estimation of manufacturing lead time for extremely complex engineered-to-order products. The process is initiated with the collection of customer preferences for a new product and the processing of the order attributes for estimating the required lead time. Both numerical and alphanumerical attributes are taken into account and the similarity between past and new cases is measured using the Euclidean distance.

The results of the application of the methodology into a real-life pilot case with data obtained from the mould making industry verified that the CBR methodology provide solutions of high precision in comparison to the real values. The accuracy of the results constitutes a valuable tool in the hands of the financial and engineering department of the company for improving customer satisfaction. The company has already began to test the developed methodology in everyday practice and the results up to now seem very promising.

Future work will focus on developing the method into a web application and fully incorporating it to the business model of the mould making SME. In addition, quantitative improvement in the performance of the SME will be reported.

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