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A Systematic Literature Review Of Machine Learning Approaches For The Prediction Of Delivery Dates

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Abstract

Manufacturing companies tend to use standardized delivery times. The actual delivery times requested by the customers and the current capacity utilization of the production are often not taken into account. Therefore, such a simplification likely results in a reduction of the efficiency of the production. For example, it can lead to an obligation to use rush orders, an unrealistic calculation of inventories or an unnecessary exclusion of a Make-to-Order production. In the worst case, this results not only in an economically inadequate production, but also in a low achievement of logistic objectives and therefore in customer complaints. To avoid this, the delivery dates proposed to the customer must be realistic. Given the large number of customer orders, a wide range of products, varying order quantities and times, as well as various delivery times requested by customers, it is not economical to determine individual delivery dates manually. The ongoing digitalization and technological innovations offer new opportunities to support this task. In the literature, various approaches using machine learning methods for specific production planning and control tasks exist. As these methods are in general applicable for different tasks involving predictions, they can also assist during the determination of delivery dates. Therefore, this paper provides a comprehensive review of the state of the art regarding the use of machine learning approaches for the prediction of delivery dates. To identify research gaps the analyzed publications were differentiated according to several criteria, such as the overall objective and the applied methods. The majority of scientific publications addresses delivery dates only as a subordinate aspect while focusing on production planning and control tasks. Therefore, the interrelationships with several production planning and control tasks were considered during the analysis.

Keywords

Delivery Date; Production Planning And Control; Prediction; Machine Learning; Literature Review

1. Introduction

The level of customer expectations regarding the logistic performance has strongly increased in the last decades. Nowadays, customers expect not only individual products with a high quality for low prices, but also short and especially reliable delivery times [1]. This results in major challenges for manufacturing companies. From an economical point of view, operating a finished goods store might not be beneficial due to the large number of products and product variants. Therefore, companies tend to use standard delivery times within an Assemble-to-Order or a Make-to-Order production [2]. This leads to a strong fluctuation of the capacity utilization and requires a high amount of effort for continuously adjusting the capacity. In addition, the requirements of customers can vary greatly. While in some cases the delivery should just be as fast as possible, others demand a specific time window for the delivery or even a just-in-time delivery.

Customers tend to buy more and in some cases are willing to pay a significantly higher price in case of short and reliable delivery times [3]. Therefore, in practice concepts such as rush orders or delivery time classes with corresponding price differences exist. In the literature, the focus lies on the design of the products and production processes. Even though many approaches such as product platforms exist [4], authors also highlight the importance of the negotiation process in supply chains [5]. As the price and the delivery date are stated to be the two most critical factors in various industries [6], the assignment of delivery dates has been addressed by some authors [7]. However, the majority of these approaches is based on numerous assumptions and has been published several decades ago. Therefore, they do not reflect the high dynamics of today's markets. To compete successfully, manufacturing companies need to predict their delivery dates continuously, quickly, and realistically. In this context customer heterogeneity provides a challenge but also offers opportunities [8]. Customers expect a fast estimation of the delivery date, especially if the delivery time and the price per unit can be negotiated [9] or if they need to be present in person to receive the delivery [10]. Looking at the large amount of customer orders and products combined with varying order quantities and times, predicting delivery dates manually is impossible from an economic point of view. The need of assistance can also be seen in the development of numerous decision support systems [11].

Machine learning (ML) methods provide the possibility to process the necessary high amount of data and are generally suitable for applications involving predictions [12]. As data availability, consistency and integrity increase, the use of these methods to solve production planning and control (PPC) tasks is becoming increasingly popular [13] [14]. The aim is commonly to optimize a system with predefined delivery dates. This includes tasks like the order acceptance [15], order release [16], or sequencing [17]. All these tasks relate at least indirectly to the prediction of delivery dates. The throughput time is not only a main part of the delivery time, it also interacts with upstream decisions such as the selection of the order processing strategy [18]. Although many researchers have already addressed this topic and the use of ML in PPC in general, the need for research in this area remains. A recent study shows that about 75% of the possible research domains for ML in PPC have been examined only to a minor extent or not at all [19].

In this paper, a systematic literature review of ML approaches for the prediction of delivery dates is presented. The subsequent section outlines the applied procedure. This includes the research questions, the selection criteria, the quality assessment and the data analysis of the systematic literature review. The selected publications were differentiated and examined according to several criteria. The results of the analysis are presented and discussed in section three. Lastly, in section four a summary is given and research gaps are highlighted.

2. Method and data

The study aims for a comprehensive overview of the state of the art regarding the prediction of delivery dates and the identification of research gaps. A systematic literature research was conducted following the guidelines of Kitchenham [20]. In the following, the individual steps are outlined.

2.1 Research questions

The following research questions (RQ) were raised:

- RQ1: What research topics are being addressed?
- RQ2: Which use cases are being addressed?
- RQ3: Which methods have been used?
- RQ4: Do ML models outperform non-ML models?
- RQ5: Which trends are recognizable?
- RQ6: What are the limitations of current research?

RQ1 aims to identify interrelationships between the prediction of delivery dates and PPC tasks as well as upstream decisions and general aspects of production management. RQ2 focuses on how suitable the theoretical research results are for industrial practice and to what extent they have already been implemented. Answering RQ3 and RQ4 provides insights on the methods and helps to identify research gaps. Based on the results gained through RQ1 to RQ4, specific aspects are selected for a detailed analysis. To pinpoint the trends mentioned in RQ5, the timeline is examined with regards to certain innovations and changes, such as the introduction of the term industry 4.0 in 2011. RQ6 is directly related to all other research questions and thus calls for a critical review of the previous results.

2.2 Search process and selection criteria

The search was carried out using the databases Scopus and Web of Science. As these databases are known for their scientific relevance, they are widely used for literature reviews [21]. Regarding the disciplines of economics and engineering, they have numerous overlaps, but are not completely identical [22]. Figure 1 gives an overview of the selection process for the systematic literature review containing the selection criteria as well as the results returned from the databases.

Step	Limitating aspects	Criteria	Results:	
1	Titel, abstract, key words + Publication year	„Delivery date" or synonyms from 2002 to 2021	Scopus: 29,629	Web of Science: 12,813
2	Titel, abstract, key words	„Machine learning" or synonyms	Scopus: 1,705	Web of Science: 601
3	Source	Journals or conference proceedings	Scopus: 1,625	Web of Science: 598
4	Language	Written in English	Scopus: 1,591	Web of Science: 593
5	Research area	Related to production management	Scopus: 810	Web of Science: 360
6	Content alignment	Title, abstract	Scopus: 100	Web of Science: 89
7	Content alignment + Quality assessment	Full paper, No duplicates, full text available, Quality assessment questions	Total: 62	

Figure 1: Selection process during the systematic literature review

The initial step was to search the term "delivery date" and its synonyms in the title, abstracts and keywords of the years 2002 to 2021. As stated above the delivery date and the throughput time are strongly related. Therefore, besides "due date" and "delivery time", the terms "throughput time" and "lead time" were also considered to be synonyms. PPC tasks not directly related to the prediction of delivery dates, such as order acceptance, order release and scheduling, were not considered at this point as their interrelations were taken into account during the examination of the selected papers. A previously conducted study revealed a noticeable growth in scientific publications regarding the use of ML methods in PPC starting in 2007 [23]. To ensure the identification and evaluation of trends and at the same time enable a detailed and efficient analysis of the current state of the research on the prediction of delivery dates the final time horizon was set to be 20 years. As the term PPC as well as its current understanding were established around 40 years ago, e.g. by the PPC model of Hackstein in 1984 [24], analyzing a longer period does not seem to be suitable. This is strengthened by authors suggesting the use of intelligent systems for planning production processes, such as Mill and Spraggett in 1984 [25] or Yang et al. in 1992 [26].

In the basic literature at this time the determination of due dates was focused on internal due dates as part of production scheduling [7] [27]. The delivery date was classified as an external factor as it is decided by the customer or by the sales department.

The next step was to link the terms referring to prediction using ML methods. The Boolean AND as well as the Boolean OR were used to incorporate synonyms and alternative spellings. This resulted in the terms “machine learning”, “deep learning”, “neural network”, “artificial intelligence”, “data analytics” and “data mining”. Although these terms have different meanings, they are often used synonymously in practice [28]. To obtain high-quality publications and at the same time avoid the repetition of content the sources should be limited. It is common to select only articles from scholarly journals [29] and conference proceedings [30] as the majority of these have been peer-reviewed prior to publication [31]. To provide the basis for a detailed evaluation of the full papers the results were limited to papers written in English. Afterwards, all topics not related to production management were excluded as they may use the same terms in a different context. This was followed by the evaluation of the titles and abstracts regarding the content alignment. The databases were compared and duplicates as well as papers with no full text available were removed. Lastly, the full papers were evaluated regarding the content alignment and the quality assessment. Papers with a quality score of less than 5 were excluded from the study.

2.3 Quality assessment and data analysis

To ensure a high quality the relevance, credibility and rigorousness of the selected studies need to be checked [32]. The following ten quality assessment questions (QAQ) were applied [32] [33]:

- QAQ1: Does the study report empirical research or is it a report based on the opinion of an expert?
- QAQ2: Are the aims and the motivation of the research clearly defined?
- QAQ3: Is the estimation context adequately described?
- QAQ4: Are the methods well defined and deliberate?
- QAQ5: Is the research design appropriate and justifiable?
- QAQ6: Does the study contain a sufficient project data set?
- QAQ7: Is the proposed method compared to other methods?
- QAQ8: Are the findings of the study clearly stated and supported by reporting results?
- QAQ9: Are the limitations of the study analyzed explicitly?
- QAQ10: Does the study provide value for academia or industrial practice?

The answers were scored as “No“ = 0, “Partial“ = 0.5 and “Yes” = 1. For each selected paper, data regarding the topic, e.g. title, key words, main area and related topics mentioned, the authors, the source, the study type, the methods used as well as the quality evaluation were extracted.

3. Results

The literature research resulted in 62 papers addressing the use of ML methods in the context of the prediction of delivery dates. 33 (53%) papers appeared in scientific journals, while 29 papers (47%) were published in conference proceedings. The papers were classified based on the five main categories:

- negation processes
- time periods
- methods
- data
- PPC tasks

Each paper could be assigned to several main and sub categories.

3.1 Topics and methods

As high logistic performance is a relevant purchasing criteria for today's customers, the adherence to delivery dates is a highly discussed topic in the literature. The complexity of related topics such as scheduling and routing is enhanced by the uncertainties in sales forecasting, production problems and delays in delivery existing in industrial practice. The delivery date is strongly influenced by these uncertainties. Nevertheless, the delivery date prediction is mainly considered to be a subordinate aspect of the logistic performance. Therefore, papers calculating due dates while mainly focusing on the optimization of a system, e.g. order release, scheduling or inventory management to minimize costs, were excluded from this study. In case the determination of specific time periods of orders was conducted to negotiate the delivery date with the customer the papers were considered relevant for the topic. Figure 2 shows the distribution of the papers regarding addressed time periods and PPC tasks (RQ1).

Sorting the papers by the time period addressed revealed that the delivery time is mainly an important feature regarding last mile delivery, such as package delivery or shipment processes, and the negotiation processes between manufacturers, suppliers and customers. The prediction of the throughput time and its components processing time and inter-operation time are the main topic focused within the context of delivery dates. In addition, a few authors highlight unexpected delays, for example due to machine breakdowns and the related determination of safety times. The highly varying interest in time periods also reflects in considered interrelationships with related PPC tasks. The acceptance or rejection of an order depends on the negotiation process and its features such as the price per unit und the delivery time. Therefore the amount of papers dealing with the order acceptance is similar to the ones focusing directly on the delivery time. In a standard Make-to-Order production the lot size is equal to the size of the customer order and there is no semi-finished or finished goods store. Therefore, the PPC tasks lot sizing and inventory planning are not directly relevant for the determination of the delivery time. Nevertheless, they are a few times addressed in the context of the dispatch time as well as an influencing factor during scheduling. As the throughput time and its components are the mostly investigated topic, the directly related PPC tasks scheduling and capacity planning occur in various studies.

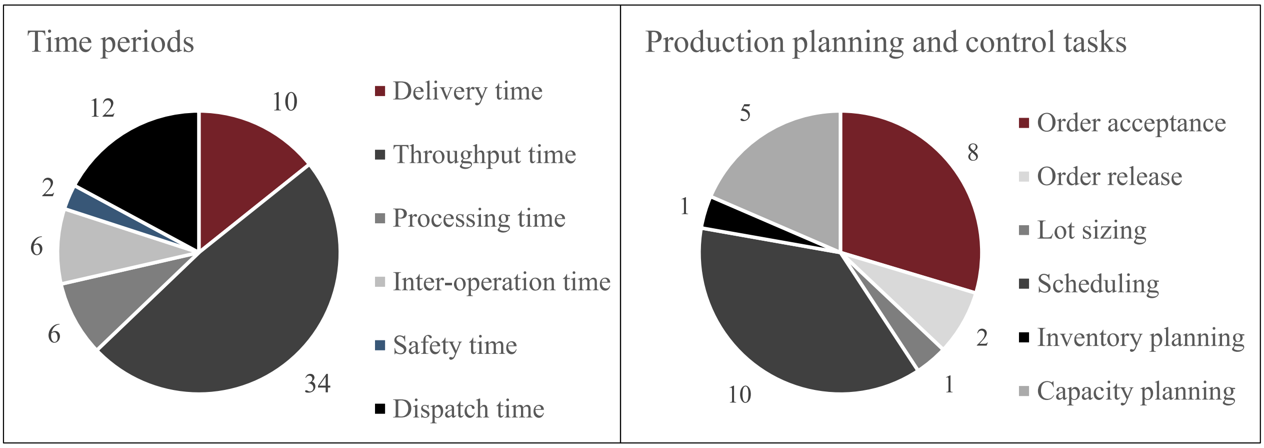

Figure 2: Papers assigned by the addressed time period and the related production planning and control tasks

The applied methods are as broad as the addressed time periods and PPC tasks (RQ3). They range from fundamental mathematical models to concepts based on a combination of different ML methods. Neural networks are the most used method as various versions of them appear in 45% of the papers. However, this high percentage can be explained by the fact that most of the authors present a comparison of several methods for a specific problem (79%) rather than a new universal approach (21%). In cases where ML methods were compared with conventional methods, they generally performed better (RQ4). However, most of the approaches considered only a few or even just one objective.

This can also be seen in the data sets (RQ2). Only one paper described a concept without proving it by a numerical example. About a third of the authors referred to simple virtual data sets for their proof of concept, while the rest used a case study showing the applicability of their approach in industrial practice (65%). Various industries are covered through logistic companies and suppliers, typical manufacturing companies, such as automotive manufacturers, shipyards or semiconductor manufacturers, and e-commerce platforms.

3.2 Trends

Figure 3 shows the annual number of publications for the years 2002 to 2021 using a bar chart (RQ5). Although some variations are evident, there is an overall increase in the number of publications during the examined period. Starting from 2014 a continuous growth is visible. This could be related to the introduction of the term “Industry 4.0” at the Hannover Fair in 2011 and with the increased use of ML methods such as "deep learning".

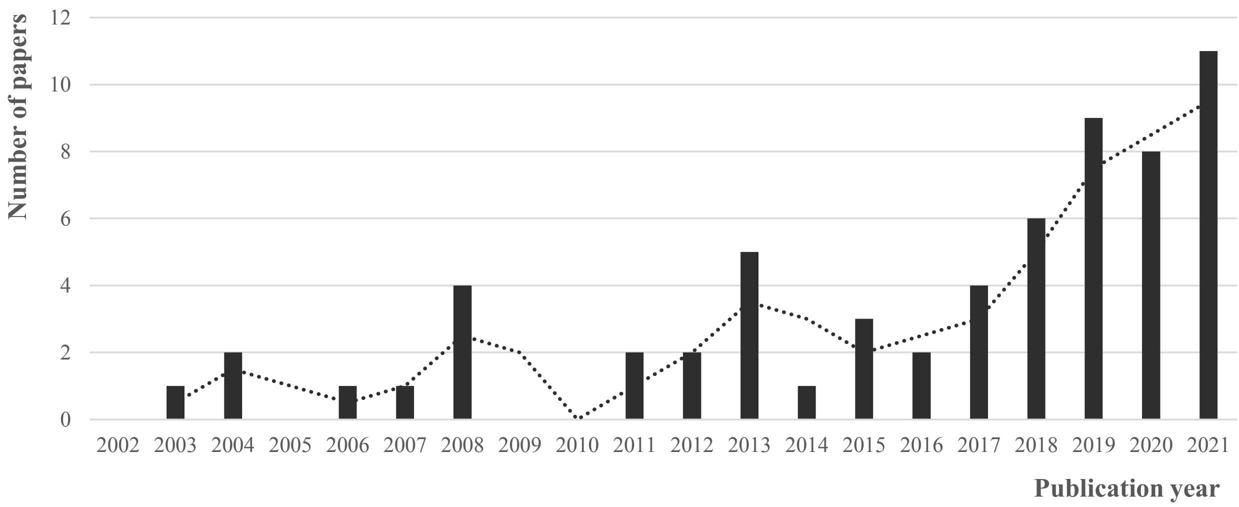

Figure 3: Distribution of papers from 2002 to 2021

The examination of the geographical distribution revealed that publications originated from a total of 24 different countries. The five countries with the highest amount of papers are Taiwan (11 papers), China (10 papers), Germany (9 papers), the United States (8 papers) and Austria (7 papers). This slight imbalance can be explained by authors presenting extensions of their own approaches and using the same data sets.

The keywords were analyzed using the software VOSviewer [34]. The so-called visualization of similarities (VOS) maps can be used to represent relationships between objects in various ways. The strength of the linkage determines the location of the keywords within the VOS maps. The size of the points assigned to the keywords correlates with the number of occurrences of the respective keyword. A keyword was considered relevant to the topic if it appeared at least two times. This assumption resulted in one group containing 133 connected keywords (Figure 4). The multiple cross-linking of the individual keywords highlights the strong connection between PPC, ML methods and the delivery time.

Arranging the keywords by year, reveals a minor change in the terms over the time. Mathematical models and decision-making based on conventional rules tends to be replaced by ML methods. The focus seems to start shifting from the throughput time to a more universal view including smaller time periods like transitions times and travel times. As the increasing customer requirements regarding the logistic performance require the accurate prediction of delivery dates, forecasting delivery times draws attention towards the handling and the quality of data.

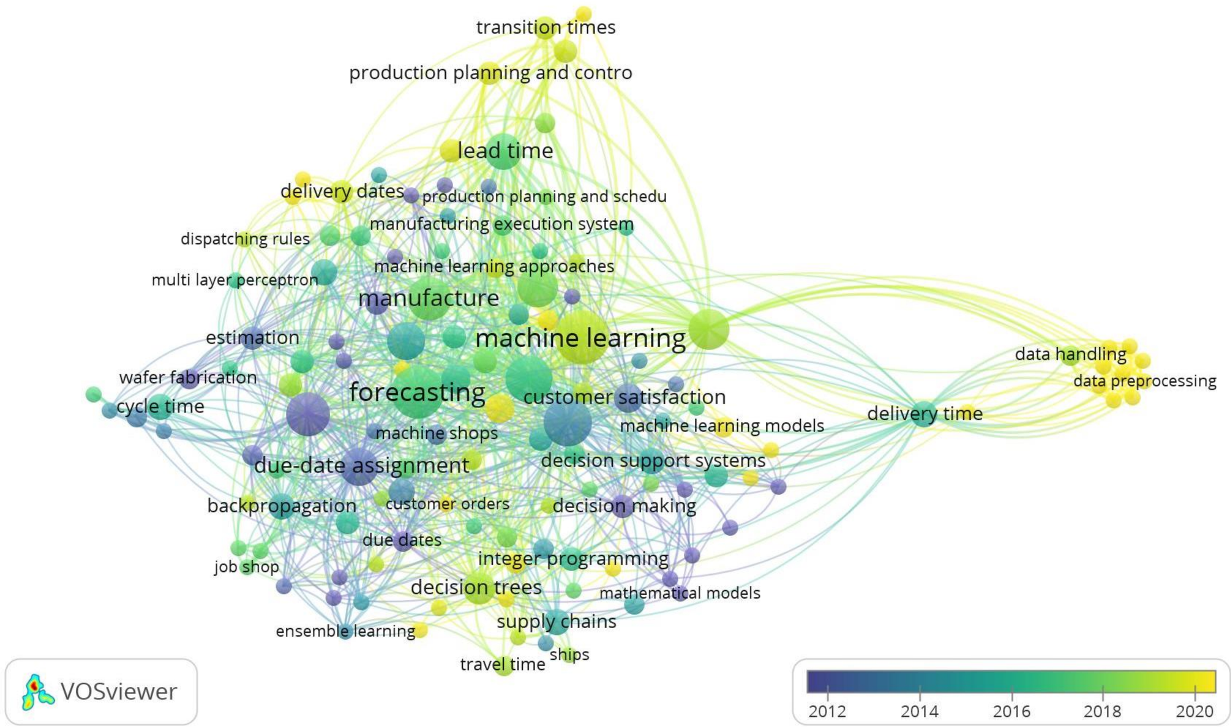

Figure 4: Results of the keyword analysis using VOSviewer

4. Conclusions and outlook

The increasing number of publications related to the prediction of delivery dates with ML methods in the last 20 years reflects the importance of this topic and the growing interest of academia and industry in it. In terms of content, the publications primarily focus on the throughput time. Nevertheless, a reorientation towards previously neglected time components of the delivery time is recognizable. This can be explained by the large number of already existing approaches concerning the determination of the throughput time and its optimization by scheduling as well as the progress made in the area of ML, and thus the simplified application to more complex problems.

In summary, a strong interrelation between the determination of delivery dates, ML methods and PPC tasks is visible. There are various fields of application and the number of publications in this area will probably keep increasing in the next years as there is still a strong imbalance leaving a research gap. Detailed analysis of the different time periods related to the delivery time as well as a holistic model for the prediction of delivery dates is required. As an initial step towards such a model, various case studies are required. There is ongoing research with partners from industrial practice on process quality, pricing, sales planning and storage dimensioning. In addition, examining the various existing interrelations with PPC tasks as well as upstream strategic decisions such as the selection of the order processing strategy or the location of production sites and warehouses could provide interesting insights. To benefit the prediction of delivery dates appropriately additional research is required in the area of forecasting customer demand and behavior as well as regarding the options offered to customers upfront like rush orders.

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