Lead time forecasting in smart manufacturing context: emerging research trends and perspectives

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Abstract: Forecasting lead times (LT) is a very challenging task in Production Planning and Control (PPC). LT is one of the most important elements to bear in mind because it can provide guidance on how to allocate jobs among available machines and affect the date assignment of jobs and the adjustment of priorities. The extent to which plans are implemented depends mainly on the ability to accurately predict the lead time. In today's competitiveness-driven markets, it is important not only to shorten but also to provide reliable lead times to improve customer satisfaction and on-time delivery. Furthermore, with the advent of the Industry 4.0 paradigm, the availability of data and high computing power have made Big Data Analytics (BDA) appealing solutions to predict LT in complex manufacturing systems overcoming the limits of traditional approaches. To the best of the authors' knowledge, a complete overview of this topic is missing in the literature. For this reason, this paper, methodologically based on a systematic literature review, aims to identify research trends in manufacturing lead time prediction considering the last 20 years and systematizing the current research gaps. Specifically, we provided an overview of the main methods/approaches developed by researchers from analytical to Artificial Intelligence (AI) based ones and their related advantages and drawbacks, the types of data needed and their source, and the specific type of manufacturing system. The findings of this study revealed that for lead time prediction, which remains a topic of great interest for make-to-order (MTO) and engineering-to-order (ETO) production environments, the analytical methods are frequently outperformed by AI-based methods. At the same time, complete frameworks for supporting the choice of the best method, according to the needs and the available data for the specific type of manufacturing system, are still missing.

Keywords: Lead time estimation; Production Planning and Control; Prediction methods; Artificial Intelligence; Machine Learning.

I. BACKGROUND AND MOTIVATION

In production systems, the time between an order's arrival and its completion on the shop floor is defined as lead time (LT). It is also called internal LT to distinguish it from external LT, which refers to the duration from an order's arrival to the delivery of the product [1].

Today, globalization, changing demands and more tailored customer requirements establish serious challenges for manufacturers. It is essential for companies, not only to shorten but also to appropriately quote LT when an order is received by the customer to improve the level of customer service and performance of on-time delivery. Under the increasing pressure of competitiveness, the time needed for quotations should be short and the reliability of fulfilling on-time delivery should be high [2]. Accurate LT forecasting allows to meet customer expectations and become more competitive but also affects shop floor management practices and improves Production Planning and Control (PPC) processes [3–5]. It is essential to know how much time a product might take to get through the manufacturing system for good planning, which allows to achieve high flexibility of processes and resources and makes scheduling more predictable, agile, and flexible [4]. For industries with high product variability, planning is based on the knowledge of product LT and the degree to which the plan is executed depends largely upon the ability to accurately predict it [4,6]. A forecasting system could be extremely beneficial to a plant manager since it can demonstrate alternative actions that can be done to maintain an effective throughput through the optimization of the available resources [7]. Over the past few decades, many different problems have emerged to deal with this challenge: predictive maintenance, demand planning, scheduling, and LT forecasting [8]. Companies are forced to modernize and update their equipment as well as their PPC methodologies due to the rapid advancement of technology. The customer's interest in the ordering process extends beyond product requirements to include the time by which the product will be finished. As a result, companies are interested in forecasting an appealing but also reliable LT even if the complexity of this process, which should include lots of variables such as equipment failures, material shortages, lack of workers, or employees with insufficient skills. The production schedule must take into account the available production capacity, technological limitations, due dates, and the system condition to establish the job's LTs [3]. The more complex the manufacturing system, the more it has to be considered the limited capacities as well as the nonlinear relationship between capacity utilization, work-in-process, and LT [9].

Traditionally, the PPC function determines the order's LT based on the knowledge of the processes and the shop-floor status. In most cases, experience drives managers in the estimation of production LT [10]. However, even when the order specification is the same as that of a previous one, the status of the shop floor may not be identical to the previous one. Since it's difficult to consider all the elements, there could be inaccuracies in the LT estimation, which would increase the overall cost. Therefore, academic researchers and industrial practitioners have been paying more attention to this problem and trying to develop more sophisticated approaches to reduce forecasting errors [11].

LT forecasting represents a challenging task that has been a recurrent issue in the literature since the 1960s. Despite this, even in recent years, traditional approaches compute average values based on historical data causing deficiencies in PPC [12]. With the advent of the Industry 4.0 paradigm and the consequent improvement in automation and digitalization of manufacturing systems, the growing availability of data provided by cyber-physical production systems, high-computing power, and large storage capacity can enable data-driven approaches based on the strong use of data analytics and Machine Learning (ML) for LT prediction. This indicates that classical time measurement methods are not compliant with the growing complexity of manufacturing systems, which may make planning unreliable [8]. For sure, the significant and rapid improvements in data management provided new opportunities, since critical attributes in LT estimation, different job features, and patterns in data can be used to overcome the limits of the traditional approaches in LT forecasting.

To the best of the authors' knowledge, a systematic literature review on this topic, focusing on the trends in scientific research, is missing. Until now, the literature has been analysed for a specific type of manufacturing system such as Engineer To Order Systems [3] or overviews on the topic represent only the state of the art for the development of new methods or case studies [12,13]. For this reason, this paper, methodologically based on a systematic literature review (SLR), aims to identify emerging research trends and perspectives in manufacturing LT prediction considering the last twenty years and systematizing the current research gaps. Specifically, we provided an overview of the main methods/approaches developed by researchers from analytical to Artificial Intelligence (AI) based ones and their related advantages and drawbacks, the types of data needed and their source, and the specific type of manufacturing system, highlighting the main research trends and gaps in this field.

The remainder of this article is organized as follows. Section 2 describes the research methodology, whereas Section 3 reports the results of the carried-out analysis. Section 4 summarizes the main research opportunities and provides the conclusions.

II. Research Methodology

To investigate state-of-the-art of LT forecasting in the manufacturing context, an SLR approach, which mainly aims to search, screen, synthesize, and analyse the studies relevant to the specific topic, has been used [14]. The main objective of this study was to evaluate the recent trends in LT prediction in manufacturing systems and to identify all the relevant aspects. The Research Questions (RQs) that this study wants to address are:

- RQ1: What kind of techniques and methods are used to forecast LT depending on the type of manufacturing system?
- RQ2: What are the main trends in this research field and what are the not yet addressed research gaps?

To answers the RQs, a search string, which was a combination of three groups of keywords referred to the LT (1), the action to perform which is the forecasting/estimation (2), and the manufacturing context (3). The suitable keywords for our research field were chosen to answer the research question of the research study. The search string, i.e., the combinations of keywords from the groups obtained using the Boolean 'AND' operator between each group, and the 'OR' operator within each group, was used to cover the titles, keywords, and abstracts of papers in the scientific database Scopus, one of the largest scientific multi-disciplinary abstract and citation databases of peer-reviewed literature. The full string is reported below:

TITLE-ABS-KEY (("throughput time" OR "flow time*" OR "LT*" OR "delivery time*") AND ("manufacturing" OR "industry" OR "factory" OR "production") AND ("predict*" OR "forecast*" OR "estimat*"))*

The results were filtered to select only articles, conferences, and reviews, written in English, and published after 2002 to consider the last twenty years. To define the set of the eligible paper, the articles found were included or excluded according to the following exclusion criteria: papers not directly related to PPC, papers not directly related to production/manufacturing environments, duplicated, irrelevant studies, and papers with no text available. After the search of the literature, a selection screening was performed. The first stage involved reading the titles and abstracts of each paper, and papers were included or excluded according to the exclusion criteria just mentioned. The second screening involved reading the full text of the papers selected from the screening process and identification of the most relevant articles based on the same exclusion criteria. For the screening process and to manage the articles and the bibliography, Mendeley, a reference tool that can help to store, manage, and organize research data, was used. A content analysis was carried out to analyse the selected documents. A personalized and shared Microsoft Excel file was designed to organize and store the information collected by the authors after reading the full text. The main data collected, over the bibliographic, were the scientific contribution of the study (e.g., review, development of a method/model, case study, comparison of methods, etc.), the type of manufacturing system, the sector (e.g., aerospace, automotive, etc.), the type of method/techniques used, data used for the prediction and their source, the effects of LT prediction on the manufacturing system.

III. FINDINGS

The search was carried out at the end of January 2023. Initially, a total of 1697 papers were identified using the search string and the initial restriction criteria. However, the first screening process allowed us to exclude 1420 articles that were not in line with the aims of this research work, at the end of the second screening process, only 43 articles were selected according to the above-described exclusion criteria.

The articles' distribution over the years per document type is depicted in Figure 1. The publication frequency distribution underlines the growing interest in this topic. 22 papers out of 43 were published in the last five years with a peak of 6 papers in 2021.

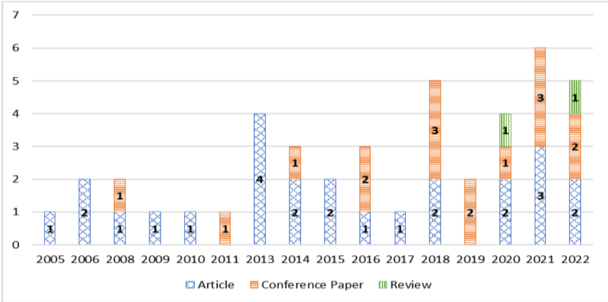

Figure 1. Distribution of articles per type of document

Most of the selected articles have been published in peer-reviewed journals (25 out of 43), mainly the International Journal of Production Research (7 papers); whereas the remaining have been presented at international conferences and were mainly published on Procedia CIRP (4 papers), Procedia Computer Science (2 papers) and IEEE International Conference on Industrial Engineering and Engineering Management (2 papers). Selected articles have been classified in Scopus as mainly related to the subject area and 'Engineering' (38,2%), 'Computer Science' (16,9 %), 'Business, Management and Accounting' (13,5 %), and 'Decision Science' (12,4%).

As part of the content analysis performed, the papers have been classified according to their innovative contributions as reported in Table I.

TABLE I. INNOVATIVE CONTRIBUTIONS

Innovative Contribution	No. Papers	References
Development of a method, model, or approach	20	[2,6,11,15–31]
Comparison of methods	8	[4,5,32–37]
Development of a framework	6	[7,9,38–41]
Case study	5	[10,12,13,42,43]
Review	2	[3,44]
Development of decision support system/tool	2	[45,46]

As expected, due to the relevance of this topic in PPC, the research attention in the last 20 years has been mainly focused on the development of methods, models, or approaches for LT forecasting and on the comparison of methods developed to identify the best one in a specific context. It is interesting to note that in 6 [11,16,21,23,30,31] out of 20 papers focused on the development of methods and in 1 [7] of the studies related to the development of a framework, a comparison of different methods has been performed by the researchers to establish the best one. Furthermore, case studies, even if not as the research focus, are reported in 5 [17,18,20,21,30] out of 20 papers focused on the development of methods, in 5 [4,32–34,36] out of 8 articles based on the comparison of methods, in 1 [38] study based on the development of a framework and in 1 study which dealt with the development of a decision support system/tool [45].

A. RQ1: LT prediction methods

To answer RQ1, the carried-out analysis focused on the type of manufacturing system, the specific sector, the methods used for LT prediction, and the main type of data used.

Regarding the manufacturing system, 12 studies focused on Make-to-Order (MTO) systems [5–7,10,15,25,27,29–32,37] and 6 on Engineering-to-Order [3,9,17,20,42,44] systems. Nowadays, many manufacturing enterprises employ MTO systems to produce various types of high-quality products within a short period of time and they require a reliable estimation of manufacturing job LTs when dealing with production orders both for due-date quotation as well as for production control decisions [31]. Given the difficulty in estimating LT resulting in this kind of system, innovative methods, considering a bigger set of system parameters influencing the LT are required and need to be developed in research [7]. In the ETO environment, instead, the engineering process represents the largest consumer of time. ETO products are generally used in large projects, and for this reason, it is common for customers to impose large cost penalties for lateness. Thus, LT accuracy and attainment are important topics for these kinds of companies [9]. For the other articles, the type of manufacturing system was not indicated, or it was only possible to distinguish between a job shop and a flow shop organization. If reported in the studies, also the specific manufacturing sector has been collected for each study analysed. LT forecasting is mainly investigated in the field of the semiconductor industry (10 out of 43 papers - [11,12,16,18,21,23,34,35,40,41]) since it has a very complex production flow [34] with products that must run on the same machines several times to build integrated circuits on the layers [12,16]. Applications have been also found in tool/mould making [10,17,20,32], shipbuilding [6,30], electromechanical [36,42], fashion [43,45] and the machining industry [33,46].

For each study, the methods used for LT prediction have been collected and the most frequent have been reported in Table II.

TABLE II. LT PREDICTION METHODS

Method	**No. Papers**	**References**
Artificial Neural Network	14	[10–12,18,23,25,29–31,33,36,39,40,42]
Linear Regression Model	9	[4,7,12,23,30,33,36,40,41]
Decision Tree	8	[4,5,7,12,13,18,23,45]
Random Forest	7	[4,7,12,30,33,39,45]
Analytical	5	[19,20,22,26,46]
Total WorkLoad	5	[5,13,15,23,31]
Support Vector Machine	5	[4,6,12,33,45]

Artificial Neural Networks (ANNs), which are deep learning-based models, that can perform regression tasks predicting a continuous value, represent the most investigated method to predict the LT. ANNs, like many AI-based methods, can model nonlinearity and complexity that exist in the relationship between system operations characteristics and LT and consistently achieved higher forecasting accuracy compared to other models in [11,18,39] representing an alternative to existing static and reactive approaches [29].

The second most investigated method is Linear Regression (LR), which assumes an approximately linear relationship among the variables. LR, whose main aim is to predict the value of a variable based on the value of another variable or set of them, has been investigated in 9 papers and only in one study a multivariate regression model was applied [40].

For LT prediction, also tree-based models, which are inherently non-linear, have been applied in the analysed studies. Decision Tree (DT), a supervised learning technique that can be used for both classification and regression problems [45], was first reported in the study [5]. However, DT applications generally were not very accurate unlike Random Forest (RF). RF, known as an ensemble ML method, instead, represents an extension of decision tree regression and uses randomly created multiple decision trees to make predictions [45]. RF performed better than the tree-based methods in [4,7,12,33,45].

Also, analytical, or ad-hoc methods have been developed in 5 studies, e.g., a method is proposed to give a practical solution to small-scale companies which cannot count on performing big data analytics [26], an analytical expression is derived for flexible manufacturing cells [19], and an approximation for cycle time is developed in [46].

Support Vector Machines (SVM), i.e., a supervised learning model which can be used for both classification and regression [45], are mainly used for comparing the accuracy of different models but they did not outperform the other methods used. In [6] an optimization of the parameter of an SVM is present which overcomes the blindness in parameter selection for the overall improvement of the model performance.

It is worth noting that traditional due-date assignment rules were mainly used for comparison. Most of them are equations that sum up the total processing time and waiting time of a job inside the production system [2]. For example, Total Workload (TWK), where the LT is predicted based on a job’s processing time or its dynamic counterpart, the Dynamic TWK (DTWK). One of the main drawbacks of these kinds of approaches is that they assume pre-specified factors (i.e., job and shop attributes) and are based on estimating model parameters [45]. The equations designed are based on rationale, but they might not be suitable for the estimation of the LT in all types of manufacturing systems [15].

Nowadays, the significant and rapid improvements in data management make AI and ML very powerful tools in manufacturing [39] which can overcome the limits of the traditional approaches. They have the great advantages of exploring the patterns in data, determining critical attributes in LT estimation, and efficiently considering the different job features [4]. It is interesting to note that in the decade 2002-2012, researchers have mainly focused on analytical methods [19,20,22] and TWK [5], while in the second decade of the timespan covered by our analysis, and especially in the last five years, researchers have been much more focused on AI/ML-based methods than traditional or analytical approaches. This highlights the increasing interest in innovative approaches which can return more accurate predictions and benefit from the availability of data provided by smart manufacturing environments.

Furthermore, the relationship between the methods used and the type of manufacturing systems has been also investigated. For the MTO environment, ANN [10,25,29–31], regression models [5,7,30], decision tree [7,30], and random forest [7,30] have been mainly used whereas, for the ETO environment only an application of Neural Networks application has been identified [42].

Several types of data have been used for LT prediction and they have been classified in: order data (i.e., dates, quantities, type of product, etc.); machine/process data (i.e., operational parameters, etc.); system status data (i.e., level of stock, utilization, etc.); and material data (i.e., geometry, weights, etc.). According to this classification, the results related to the data used by the most investigated methods are reported in Table III.

TABLE III. DATA CLASSES FOR DIFFERENT LT PREDICTION METHODS (A=ORDER, B=MACHINE/PROCESS, C=SYSTEM STATUS AND D=MATERIAL)

Method	**A**	**B**	**C**	**D**
Artificial Neural Network	[10-12,18,23, 25,29–31,39,42]	[10,12,18, 25,29,30, 33,39,40]	[10–12,23,25, 29,31,36, 39,40]	[10,18, 30,33,42]
Linear Regression Model	[4,7,12, 23,30,41]	[4,7,12,30, 33,40,41]	[4,7,12, 23, 36,40]	[4,30,33]
Decision Tree	[4,5,7,12, 18,23,45]	[4,5,7, 12,18,45]	[4,5,7, 12,13,23]	[4,18,45]
Random Forest	[4,7,12, 30,39,45]	[4,7,12, 30,33, 39,45]	[4,7, 12,39]	[4,30, 33,45]
Analytical	[19,20, 22,46]	[19,20, 26,46]		[26]
Total WorkLoad	[5,15, 23,31]	[5,15]	[5,13, 23, 31]	
Support Vector Machine	[4,6, 12,45]	[4,12, 33,45]	[4,12]	[4,33,45]

The results related to the data classes revealed a prevalence in the use of order, machine, and system status data. Material data, instead, are less included in the prediction methods. Data also need to be collected for the application of the methods. Regarding the source of data, they were mainly the results of simulation (21 studies - [2,5,7,11,13,15,16,19,23,24,25,27–29,31,35,37,39–41,43]). In 19 studies [4,6,9,10,12,17,18,20–22,26,30,32,33,36,38,42,45,46] real data (from specific ERP or with no clear source reported) has been used and only 1 study [34] combined both real and simulated data.

B. *RQ2: Trends and research gaps*

To answer RQ2, the main trends and research gaps of the selected studies have been identified through the analysis of the papers.

- Generally, the human factor is not included in the LT prediction. For example, researchers often underestimated factors outside of the order parameters, like production load or workforce availability [27] or human actions are not always included in the simulation of real manufacturing systems [34].

- Moreover, there is a need to use data obtained from the field, such as the Internet Of Things (IOT) data and features of machines used in production instead of only simulated data [11,27,45]. The effect of machine breakdowns, variable processing times, and other dynamic conditions needs to be considered in LT prediction [13,36,43].
- As reported in the literature, LTs can be set by reacting on earlier flow times (reactive approach), by using past data and the current system state (proactive approach), or by using past data, the current system state, and an anticipated future system state to prevent arising issues of future periods (predictive approach). The latter has been not enough investigated until now [25,41].
- Regarding the choice of the method to apply, no rules or frameworks for selecting a model or algorithm to predict LT are provided in the literature, but generally a comprehensive analysis is needed to be performed beforehand and the single case needs to be analysed in detail [7,19].
- Lastly, estimates of LTs, especially in small and medium enterprises, are generally based on employees' experience and this can be misleading [20]. For this reason, new approaches for this kind of company that provide practical solution needs to be well developed [12,32].

IV. Conclusions

The accurate estimation of LT is fundamental for improving production planning and control processes and making decisions. An SLR approach has been adopted to (1) investigate the main methods and frameworks for lead time prediction and (2) identify the gaps in the existing research literature.

The main results of the carried-out analysis are reported below.

- In recent years, researchers have developed increasingly complex methods and tools for forecasting LT, mainly based on AI and ML, to support decision-making processes.
- Most of the research studies have made use of simulated data. Obtaining real data to validate the developed approaches is still a struggle.
- Frameworks that help in the choice of the best LT prediction method according to the specific needs of the systems are missing in the literature.
- Human elements and characteristics are generally not included in the methods even though manual activity is still significant in some manufacturing contexts.

In conclusion, this research, even though presents some limitations that could be solved in the future (e.g., only one scientific database was used for identifying the set of eligible papers and the search string could have not included all the useful keywords), can assist researchers in finding new topics to focus on in this field.

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