Natural Language Processing applications in manufacturing: a systematic literature review

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Abstract: Among the manufacturing sector several applications of Natural Language Processing (NLP) are emerging. NLP is a branch of Artificial Intelligence (AI) aimed at understanding, interpreting, and manipulating human language through computer-based data processing. This application is quite powerful and prospective in manufacturing context, considering the ever-increasing amount of data available within the organizations, often unstructured, non-standardized, and free text. Therefore, human analysis to extract information and useful knowledge results in a long and tedious task with limited added value. The automation of these activities moves workers to more meaningful and value-added activities; it improves efficiency in searching for and extracting information, with benefits for decision-making processes. The paper presents a systematic literature review concerning NLP applications in manufacturing, conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement methodology. Basing on the documents retrieved, a comparative analysis of the literature is presented. The analysis is carried out following two different rationales: an objective analysis, which highlights and compares the different purposes with which NLP is applied in the manufacturing field, such as knowledge base, ontology, predictive maintenance, human machine interaction and decision support system. The second analysis investigates NLP applications by exploring different production process phases involved in manufacturing activities. The research identified mature NLP applications, transversally implemented in several production process phases, with specific objectives. The paper provides a comprehensive and in-depth overview on the topic. Finally, possible future directions of development of NLP in manufacturing were defined.

Keywords: Information Extraction; Text analysis; Smart Manufacturing; Machine Learning; Industry 4.0

I. INTRODUCTION

Over the last decade, the topic of Natural Language Processing (NLP) has gained much attention and a considerable number of studies about different NLP applications in the production context has been accumulated. The increased need to reduce both cost and delivery time forces today's industrial business environment to define and employ adequate NLP applications to meet these demands [1]. NLP techniques imply the automatic processing of written or spoken information of natural language by means of an electronic calculator [2]. NLP applications support organizations in processing a large quantity of data with various objectives, ranging from information extraction, summarizing information to emotion detection [3]. As these innovations continue across industries, the manufacturing industry has also begun to gain benefits. Specifically, NLP applications are going alongside the best-known technologies typical of Industry 4.0. Its fields of application are the most varied: from the analysis of fault reports or machine logs to summarizing documents relating to production processes or the design of human-machine voice systems [4], [5]. Several reviews have been proposed: some were focused on the application of machine learning in production context [6], and others focused on Robotic Process Automation and AI [7] or specific NLP approaches such as knowledge extraction [8]. Nonetheless, as observable from the previous paragraphs, there is still a lack of a review current research trends, and industry applications of NLP. For this reason, the scope of this review is expected to gather approaches available in multiple modern industrial settings to favour a cross-domain approach. For the objective of the study a scoping review is developed, adopting a systematic approach for defining eligible studies, in line with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [9]. The remainder of the paper is organized as follows Section 2 details the database and query used for the analysis and the systematic approach followed for the review. Section 3 presents a bibliometric analysis of documents considered for review. Section 4 details a synthesis of main interpretative findings. Finally, the conclusion summarizes the review and underlines the open research questions.

II. MATERIALS AND METHODS

This review investigates articles and conference papers following the PRISMA guidelines, given in [9]. PRISMA guidelines define a systematic process of study identification, screening, eligibility, and inclusion. The detailed process followed for this study is described in the workflow shown in Fig. 1.

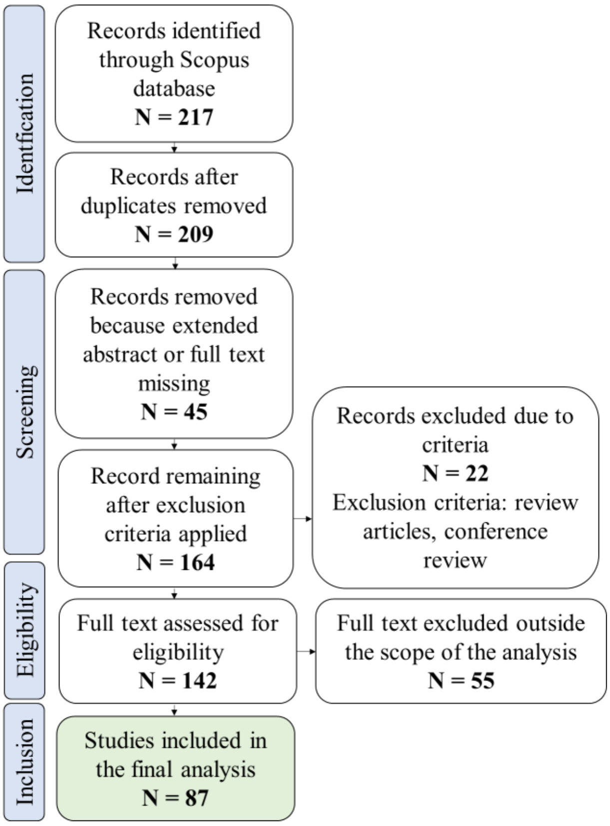

Fig. 1 Literature review strategy

A. *Identification*

The review was conducted through a search in Scopus database, of contributions indexed up to 31st February 2022. The choice of the Scopus database took into consideration its relevance in the Academia with over 75m records across 27,000 journals, sourced from more than 7000 publishers [10]. The first step of the review defined the scope of the search query. The search query looked for every paper that uses "Natural Language Processing" applications in association with "manufacturing" or "industry 4.0" to broadly collect all the articles that explore the topic. However, for the purpose of having broader inclusion criteria all the possible combinations of terms have been set to look both into Title, Abstract and Authors' Keywords. The scope of the research was limited to articles published in English. In summary, the search query for the database was:

TITLE-ABS ((nlp OR "natural language processing") AND ("industry 4.0" OR "manufacturing")) OR (TITLE-ABS (nlp) AND AUTHKEY ("industry 4.0" OR "manufacturing")) OR (TITLE-ABS ("industry 4.0") AND AUTHKEY (nlp OR "natural language processing")) AND (LIMIT-TO (LANGUAGE , "English")).

217 articles were identified through this search query. Then, 45 articles for which the full text was not available have been excluded. Therefore, the identification phase is concluded with 164 articles selected.

B. *Screening*

In the screening phase 22 review articles and conference articles were excluded. Those documents were excluded since they did not focus on a specific application but offered a general view of the topic.

C. *Eligibility*

During this phase each article full text was reviewed to evaluate if its research was adherent to the objective of the review. Among 142 articles, 55 were excluded since they did not focus on NLP applications or did not apply those techniques in an industry context.

D. *Inclusion*

A total of 87 articles were included for further analysis. The team reviewed the documents thoroughly, to allow data extraction and to synthesize the information pertinent to the scope of this review. Data were organized using a framework that helped to categorize information concerning citation information, abstract and keywords, domains of application, objectives of the studies, NLP approaches and techniques used, type of data used and production process steps in which the NLP applications have been tested.

III. BIBLIOMETRIC ANALYSIS

The bibliometric analysis described in this section identified the quantitative aspects of the research sector. Five primary aspects have been analysed: source and document type, domain of application and their evolution over time, objective of the NLP application, production process steps involved, and the type of data analysed (event log, incident reports, maintenance reports, product-process instructions etc.).

A. *Source and document type*

Documents collected highlighted a fairly balanced ratio between journal articles and conference proceedings, even though journal articles constitute approximately 58% of the total. Concerning the evolution over time of the publications, it is possible to observe in Fig. 2 a growing trend in the number of conference papers and articles related to NLP applications in manufacturing. This result is certainly linked to the spread of Artificial Intelligence applications but also to an increasing interest into the Industry 4.0 paradigm. Moreover, in detailing the articles, until 2014 most of the publications were about Human Machine Interaction, and then from 2015 the attention started to be extended to knowledge base topics.

B. *Application domain*

Natural Language Applications are today used in multiple industries [1]. However, besides some studies involving aerospace, automotive or steel and metallurgical production, 70.42% of the articles refer to general manufacturing contexts. The underlying motivation for this misalignment is that NLP applications developed in the articles, and discussed later in this paper, are viable in different industries by repurposing the same objective for different domains.

C. *NLP Application objective*

With regard to the classification for NLP Applications objectives the results show that the most relevant category is knowledge base (KB), considering both the KB for manufacturing and the KB for production process. Specifically, the Production Process category is the most well represented, including applications aimed at improving the efficiency of production process planning, new product development, assembly and production in general. Another major category is Human Machine Interaction. The use of robots & cobots and AI applications to support the operator have seen a great diffusion in the last years: voice commands and analysis of production sensors allow to make the production process more accessible and flexible, helping operators to carry out their tasks. The classification then allowed us to identify sub-goals for each item, which we have highlighted in Table I.

TABLE I
NLP OBJECTIVES

Objective	Sub objective
Knowledge Base for Production Process	Ontology
	Knowledge Graph
	Decision Support Systems
	Recommendation Systems
	Semantic Representation
Knowledge Base for Maintenance	Predictive Maintenance
Knowledge Extraction	Information Extraction and Creation
Human Machine Interaction	Ontology
	Predictive Maintenance
	Chatbot/ Virtual Assistant/ Dialogue Systems/ Q&A Systems
	Decision Support Systems

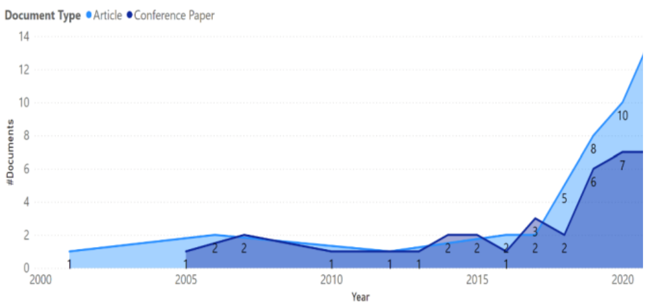

Fig 2 Evolution over time

D. *Production process steps involved*

Finally, with respect to the production process step involved, the distribution of the documents is quite homogeneous among all the steps shown in Table II. The advantages that this technology can bring range from the possibility of standardizing production rules taken from process sheets or product specifications to the possibility of analyzing maintenance documentation to reduce downtime and implement predictive maintenance strategies.

Descriptive Analysis

All the collected papers were analysed following two rationales: the NLP goal in the manufacturing sector, articulated in different sub-goals; the manufacturing process phase involved in the NLP application.

NLP goals

The literature revealed that NLP's main applications in the manufacturing sector pursue goals referable to Knowledge Base (KB) and Human-Machine Interaction (HMI) issues.

Knowledge Base

KB provides for structured construction of a comprehensive knowledge base, to manage information about products, processes, services, departments or, more generally, about a given topic. It facilitates and organizes collection and categorization of the knowledge generated and possessed by organizations, enabling, among others, more coherent service delivery, better problem-solving rates, and lower production costs. When applied to the production process, the sub-goals include such aspects: ontology, Knowledge Graph (KG), Decision Support System (DSS), Recommendation System (RS) and Semantic Representation (SR). Moreover, it can achieve maintenance sub goals, especially focusing on predictive maintenance approaches; finally, NLP can enable knowledge extraction processes. Ontology is a logical theory explaining any formal vocabulary, i. e. the set of basic terms and relations constituting a specific subject area, as well as the rules for combining terms and relations to determine vocabulary extensions. Namely, it concerns the identification of methods to simplify and facilitate the understanding of a given domain, by means of a hierarchical data structure containing all the relevant entities, the relationships existing between them, the rules, axioms, and constraints specific to the domain. In [11] the materials engineering domain is covered, which allows formalizing material properties, microstructure, process parameters and composition-process-structure-property relationships by exploiting a SNet (Siamese Network). This guarantees the proper processing of the material and the possibility to identify the suitable material for a specific processing. Further trend concerns the conversion of production/service rules into semantic ones [12], extracting formal production knowledge from unstructured text. Several algorithms are employed, including Naive Bayesian, K-means, LDA, Named Entity Recognition (NER) and Singular Value Decomposition (SVD). Additional goals are the automatic generation of feedback [13], e.g., to check whether the user input is fully or partially matching the desired input; the acquisition of knowledge from documents concerning troubles faced in production steps, such as assembly [14], resulting in modified process planning steps, even improving traditional recycling methods [15]. KGs are a knowledge base that leverage graph-structured data models or topologies to integrate data, storing interconnected descriptions of entities, objects, events, situations, or abstract concepts, encoding the semantics underlying the terminology used. As an example, graphs which transform syntactically heterogeneous data into a homogeneous version are structured to enable query systems to answer process/product queries [4]. In [16], a method for automatically extracting manufacturing knowledge and supporting the design process is proposed. DDSs consist of software systems designed to support decisions about problems not solvable by operational search models. Such as models categorize suppliers and guide decision making [17], potentially leveraging outsourcing logic and analysing the overall supply chain. RSs are content-filtering software that generates user-personalized suggestions to help in choices. Intelligent recommendation systems emerge, to identify patents and investigate technology trends in depth [18]. SR consists of a formal abstract language where meanings can be made explicit and represented, e.g., in the form of patterns. It is intended at reducing the semantic gap between CAD models and design documents [19], providing actionable information in the engineering process. Applied to the maintenance phase, the focus involves predictive thinking. The analysis of historical maintenance logs improves the current reaction to failures, allowing prediction of the fault magnitude and the maintenance action duration [20]. A methodology for generating structured knowledge models from unstructured maintenance log data is presented in [21]. Then, applications aimed at predicting the outcome of the process by following the running instance, examining events and, thus, predicting subsequent events emerge [22]. Moreover, [23] proposes a model for industrial accident prevention. Finally, Knowledge Extraction exploits existing formal knowledge or patterns based on source data for knowledge creation from structured and unstructured sources. Such knowledge can be procedural or declarative, explicit, or tacit. [24] proposes a model for transforming employee tacit knowledge into a formalized procedure for the company. To address the semantic gap between customers and designers/manufacturers, a configuration mechanism is proposed in [25].

It contemplates customer requirements and maps them in terms of product specifications useful in the design phase.

Human-Machine Interaction

Referring to the interactions between users and machines/computers/robots, HMI requires the design and development of usable and reliable interactive systems to support human activities. Applied to ontology issues, it guarantees an intuitive interaction enabling workers to actively participate in production despite not possessing a specific technical background. Moreover, workers can capture and retrieve knowledge content derived from the process. [26] proposes Ontology Filtering System (OFS) to formalize natural language content in a systematic way so that operator instructions can be translated into a machine-understandable language. Therein, by means of an ontological network, generic terms used in human-computer interaction (HMI) are reduced to a set of standardized terms to generate unambiguous, machine-specific commands. [27] introduces an integrated software environment for the rapid exploration of design alternatives, with the goal of identifying and managing requirements to produce suitable solutions more efficiently. Applied to predictive maintenance issues, HMI optimization improves the collection and analysis of data from sensors to generate insights for maintaining and securing processes and equipment. Such data can prevent accidents, detect failures [28], and help increase production efficiency by detecting production unexpected events in real time [29]. [30] presents a model whereby natural language operator queries are input and transformed into SQL, allowing the user to explore the database containing production sensor data and thus find the appropriate response for specific queries. Further applications involve the implementation of interactive digital virtual assistants (VAs). In [31] a VA is deployed featuring an intelligent and robust interface, incorporating conversational strategies to create a more natural and humanized environment. [32] presents a chatbot to ensure adherence to procedures, trained by comparing a set of operator questions with the text of digital procedures. In [5] a dialogue-based virtual assistant is introduced to manage order processing and production execution. [33] illustrates an integrated chatbot with virtual reality (VR) and immersive user interfaces logic, allowing users for product design changes while querying the system on specifications and standards. Considering DSS, Question & Answering mechanisms emerge, to help the user by offering recommendations for actions to be performed [34]. (Sanz, 2003) describes a system to support operations in a cement plant when operators are acting alone, needing to independently and real-time decision making. A summary table of the described results is provided below.

E. Production process steps involved in NLP applications

The literature review found applications of NLP established in product design, process planning and design, manufacturing, assembly, maintenance, monitoring, and control phases (Table II).

Product design

NLP is applied to integrate models and/or customer specifications to identify problems in a preventive manner. The main applications are aimed at: reducing process time and cost by integrating CAD models with customer specifications [19]; preventing intellectual property violation [36]; identifying and solving problems to ensure efficient processes and suitable products [8].

Process planning and design

NLP is implemented to standardize processes and make them easily reusable even by non-expert users [37]. Such modelling prevents problems and unexpected events [22], limiting costs and time related to process iterations. Furthermore, the association between production and design variables, allows to pre-emptively assess whether a given design meets manufacturability constraints, and to contextually explore various production alternatives [27].

TABLE II
APPLICATIONS AND PRODUCTION PROCESS STEPS

Application	Production process step
Intellectual property violation prevention	Product design
Integration of CAD models and customer specifications	Product design
Identification and troubleshooting	Product design
	Process planning and design Manufacturing
	Assembly
	Maintenance
	Monitoring and Control
Process standardization	Process planning and design
	Manufacturing
	Assembly
Voice interfaces to assist operators	Manufacturing
Translation process rules	Assembly
Fault prediction	Maintenance
Compliance check	Monitoring and Control

Manufacturing

NLP helps to detect and resolve faults, reducing downtime [32], and standardizing the process to make it large-scale reusable, through text processing of production manuals [38], even performing productibility analysis [39]. Moreover, applied to interfaces to support operators, it assists them during tasks, reducing issues arising from the industrial environment, such as the presence of noise that hinders voice interaction and leads to misunderstandings [5].

Assembly

Applications to translate rules into different languages and make them reusable across manufacturing sites in different countries emerge [40], as well as to standardize the process by defining fixed and optimized assembly procedures [41].

Maintenance

Smart maintenance leverages data from manufacturing systems to better react to production failures by predicting the magnitude and timing of a machine breakdown [42] as well as the duration of maintenance action, benefiting production scheduling and decision making [20]. Such applications enable increased awareness of equipment and process health [43], and predict remaining lifetime of industrial equipment [42].

Monitoring and Control

This phase includes all activities from raw material and component input to the final product. The main applications of NLP involve compliance checks, aiming at ensuring quality, safety, and interoperability [29] as well as suitable working environments, also preventing accidents [23]. These objectives are sometimes pursued by designing appropriate HMIs [30]. A summary table of the results obtained is provided below.

IV. DISCUSSION AND CONCLUSION

The paper presents a novel literature review regarding NLP applications in manufacturing, still not provided by the literature. To date, a fragmented literature on this topic still exists. Then, most of the literature deals with theoretical aspects showing how NLP still faces challenges in gaining its ground in this field notwithstanding several potential benefits. As the applications illustrated show, NLP has great potential in the manufacturing sector, generally improving process knowledge, which plays an increasingly key role in modern production systems. It allows to enhance and exploit the huge amount of data owned by organizations, a priceless knowledge resource. Without proper analysis and contextualization tools and techniques, the usefulness of the data is severely limited. With few exceptions, NLP shows high adaptability, where similar applications are reusable throughout the production cycle, whatever the type of production and product. To date, new methods that combine standard text processing techniques with deep learning algorithms are becoming increasingly accessible to enterprises. However, there is an emerging need to combine multiple models in an increasingly integrated way, thus enhancing the cross-disciplinary nature of NLP outputs. Moreover, a need to increase the engagement rate of operators emerges, making these techniques widely accessible, not requiring specific experience and knowledge. Barriers related to proactive, cross-cutting use of data also emerge. The use of non-standardized terminology often limits interoperability and the definition of complex formal knowledge bases. Future developments must include the definition of scalable and coherent models for application across domains and capable of processing any-sized dataset. This includes, among others, defining "universal" language models and implementing unsupervised or supervised training strategies with small, annotated datasets. NLP is also still limited by the issues surrounding the identification and understanding of implicit relations present in unstructured texts. These relationships are often ambiguous and non-intuitive. To overcome this obstacle, new approaches integrating knowledge from cognitive science and neuroscience are emerging to create conversational systems able to simulate high-level cognitive functions. Such approaches foster experience-based learning and interaction between machine, human, and external environment. Further future developments include intelligent product customization, an increasingly central requirement in manufacturing. Therein, besides behavioural indicators, such personalization must incorporate perceptive aspects, both improving customer satisfaction rates and reducing new product introduction time.

V. LIMITATIONS AND FUTURE STEPS

The most critical issues related to the research presented included the challenge in identifying applications of NLP in the manufacturing sector by means of a specific query. The results seem more theoretical rather than concrete applications in the context of Industry 4.0. This caused spending great effort in analyzing the papers to find concrete results. Therefore, it is necessary to extend the current research with more specific queries. For instance, building upon the objectives and sub-objectives identified with this review, more targeted and specific research queries searching for applications in the emerged contexts might be built. Once a narrower scope has been defined, the research could also include other scientific databases, and add backward and forward snowballing methods. Mover, other industries than manufacturing could be investigated, with the goal of providing the most extensive yet well-focused results.

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