Bringing Advanced Analytics to Manufacturing: A Systematic Mapping

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Abstract. Advanced analytics has the potential to redefine manufacturing. However, practical implementation is in its infancy. One reason is a lack of management tools that enable decision-makers to choose suitable techniques from advanced analytics for domain-specific problems in manufacturing. This paper uses a systematic mapping review in order to identify seven application areas to which analytics can add substantial value. Each area is then matched with suitable techniques from the field of advanced analytics. The resulting systematic map provides a novel management tool for the purpose of identifying promising analytics projects in manufacturing and thus facilitates decision-making.

Keywords: Smart Manufacturing · AI Applications · Advanced Analytics · Systematic Mapping Review

1 Introduction

Advanced analytics offers new ways to improve and innovate manufacturing processes [5,10]. Steady progress in terms of computing power and storage capacity, as well as the rapid development of advanced algorithms, has equipped companies with unprecedented possibilities to generate knowledge and business value from large datasets [13,24]. In this way, analytics changes the basis of competition [10].

In order to thrive in today's competitive market environment, manufacturers can use advanced analytics to streamline complex operations while improving quality and reducing costs [22,25]. The manufacturing sector can benefit greatly from the use of advanced analytics, since data is abundantly available [16], providing a still largely untapped potential for process improvement and innovation. Manufacturing strategies, such as Industry 4.0 in Germany, Industrial Internet in the United States, and the Made in China 2025 initiative, recognize the strategic importance of utilizing data in order to enhance manufacturing competitiveness [21,22]. However, manufacturers are not exploiting the full potential of data and analytics. Recently, McKinsey speculated that less than 30 % of the potential has been captured so far [10].

A main barrier that prevents manufacturers from harnessing the full potential of analytics is a lack of management tools that enable decision-makers to choose suitable techniques from advanced analytics for domain-specific problems in manufacturing. While research has brought forward various techniques capable of solving complex problems in manufacturing, little has been done to equip practitioners and decision-makers with the necessary management tools to implement these techniques on an operational level [7,23,25].

This paper uses a systematic mapping review in order to identify seven application areas to which analytics can add substantial value. Each area is then matched with suitable techniques from the field of advanced analytics. The resulting systematic map provides a novel management tool for the purpose of identifying promising analytics projects in manufacturing and thus facilitates decision-making. To the best of our knowledge, such a management tool, one that matches application areas in manufacturing with analytics, does not yet exist.

2   Background

Several authors have attempted to define the vague term "analytics" and yet there is no universally accepted definition. In this paper, we adopt the definition put forward by Davenport et al. [6, p. 7], characterizing analytics as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions." With the term "advanced analytics", we subsume methods originating from statistical learning, e.g., data mining techniques, as well as methods stemming from artificial intelligence research, in particular machine learning algorithms.

Previous work in the field of analytics applications for manufacturing has predominantly been limited to systematic literature reviews [3,4,9,12,18,19]. The available systematic literature reviews generally neglect to consistently systematize and link application areas with suitable analytics techniques in a structured and visually appealing way. A notable exception is Köksal et al. [12]. However, a drawback is the limited focus on quality improvement tasks, rather than considering additional important application areas such as production planning, product inspection, or machinery maintenance.

Flath and Stein [8] have developed an adapted data mining process model for manufacturing prediction tasks, proposing guidelines for modelling, feature engineering, and interpretation. However, similar to already existing generic process models, such as the cross-industry standard process for data mining (CRISP-DM), their work does not provide decision support for the selection of suitable analytics techniques.

Villanueva Zacarias et al. [23] propose a framework that automatically recommends suitable analytics techniques with respect to a domain-specific problem at hand. Similarly, Lechevalier et al. [14] present a framework for the semi-automatic generation of analytical models in manufacturing and a proof-of-concept prototype that allows practitioners to generate artificial neural networks

for prediction tasks through a user interface. Both frameworks represent promising approaches tackling the problem of automated analytics technique configuration in the manufacturing domain. However, these concepts do not pursue the goal of identifying promising combinations of analytics and application areas in the first place. Therefore, both approaches are unsuitable for decision-making at the managerial level.

Table 1 stresses the research gap by reporting on related key literature. We explicitly searched for articles focusing on the fusion of both manufacturing application areas and analytics techniques. Evidently, existing solutions are either unsatisfactory or inadequate to facilitate the selection of suitable techniques from analytics for domain-specific problems in manufacturing. Although scholars have addressed the lack of decision support [7,25], no research has yet been devoted to comprehensively combining analytics with application areas in manufacturing.

Table 1. Selected key literature on analytics applications for manufacturing. Full circle indicates compliance with the respective criterion.

Reference	Output	Mfg.	Analytics	Fusion
Pham and Afify (2005) [18]	Literature review	◐	◐	○
Harding et al. (2006) [9]	Literature review	●	○	○
Choudhary et al. (2009) [4]	Literature review	●	◐	○
Köksal et al. (2011) [12]	Literature review	◐	◐	◐
Cheng et al. (2018) [3]	Literature review	◐	◐	○
Sharp et al. (2018) [19]	Literature review	●	◐	○
Flath and Stein (2018) [8]	Process model	○	◐	○
Villanueva Zacarias et al. (2018) [23]	Framework	○	○	●
Lechevalier et al. (2018) [14]	Framework	○	○	●
This paper	Systematic map	●	●	●

3 Methodology

We used a systematic mapping review, following the guidelines of Petersen et al. [17], in order to design a management tool that facilitates analytics selection in manufacturing. The goal of a systematic mapping review is to build a two-dimensional classification scheme, a map, to visually structure a research area. The analysis of results focuses on frequencies of publications for categories within the scheme, thereby creating a map which can easily help transfer knowledge to practitioners [17].

We chose Scopus to search for relevant literature, since it covers a broad, interdisciplinary field of research. The search was limited to journal articles written in English and published from 2008 until the end of 2018. This time frame

of 11 years was regarded as sufficiently exhaustive, since research on analytics applications for manufacturing has only recently been addressed with growing interest [19,21,25]. Furthermore, discrete-part and assembly manufacturing that are classified into division 26-30 by the International Standard Industrial Classification (ISIC) were designated as the target domains of this work. Manufacturing companies operating in these high-tech sectors (e.g., automotive, aerospace, machinery, and electronics) are profoundly affected by digital transformation processes [15] and are, therefore, ideally suited to the adoption of analytics. However, some of the mentioned application areas also exist in continuous manufacturing processes, such as oil refining and chemicals.

Our literature search was split into two parts in order to obtain relevant research articles. The first search[1] identified seven major application areas in manufacturing to which analytics can add substantial value, namely demand forecasting, job scheduling, product inspection, process diagnostics and prediction, machine parameter optimization, diagnostic maintenance, and predictive maintenance. The second search queried each identified application area independently using appropriate keywords.[2] From the entire corpus of 1,853 articles, 81 articles that reported a successful application of at least one machine learning method were considered in order to build the final systematic map. These 81 articles were selected according to their average number of citations per year in order to include widely appreciated research articles. A stop criterion limited the number of articles per application area to 15 (or fewer if articles were cited less than three times on average per year). The reading and selection process was solely conducted by the lead author of this paper.

We only considered analytics techniques applied for the final regression, classification, or optimization task, in order to facilitate an easy interpretation of the systematic map. This is a reasonable approach, since the way data is preprocessed primarily depends on the final technique applied [1]. We agree with [25] that a promising approach to select a suitable machine learning algorithm is to look for problems of similar nature. Therefore, we are convinced that the frequency of published articles can be used as a valid proxy for the purpose of identifying suitable machine learning techniques for a specific application area.

4   Results

In the following, the main results of our research are presented. First, the identified application areas to which analytics can add substantial value are described

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[1]TITLE(manufacturing OR ``smart production'') AND TITLE(data OR ai OR analytics OR learning OR artificial) AND TITLE-ABS-KEY(application).

[2]For instance, articles regarding machine parameter optimization were queried with: TITLE-ABS-KEY(``data mining'' OR analytics OR learning OR ``artificial intelligence'' OR ``neural network'') AND TITLE-ABS-KEY(manufacturing) AND TITLE-ABS-KEY(process OR product) AND TITLE-ABS-KEY(``parameter optimisation'' OR ``parameter optimization'' OR ``parameter design'' OR ``process parameter'').

and pooled into three main groups, namely *plan*, *make*, and *maintain*. Afterwards, the map resulting from the systematic mapping review is presented.

4.1 Application Areas of Analytics in Manufacturing

Plan *Demand forecasting* and *job scheduling* are elements of the production planning processes of a manufacturing facility. Demand forecasting mostly uses historical time-series to predict future demand. Especially in large supply chains, demand forecasting can lead to a mitigated bullwhip effect [2]. Job scheduling applies optimization techniques in order to derive the actual production plan while making a trade-off between the impact of early or late completion of a task.

Make *Product inspection*, *process diagnostics and prediction*, and *machine parameter optimization* aim at optimizing manufacturing processes with regard to quality, time, and costs. Product inspection can use image data in order to analyze product states, for instance the surface quality of steel, and classifies items into scrap or good parts. Process diagnostics and prediction are two major quality improvement and control activities. Whereas process diagnostics primarily determines variables that significantly affect quality, process prediction models the relationships between input variables and output quality characteristics. Furthermore, process prediction is usually a preliminary step undertaken in order to optimize manufacturing machinery input parameters. Thus, it is closely linked to machine parameter optimization, which yields optimal machinery parameters with respect to a target quality measure, such as surface roughness, for instance. Adjusting technological processes in relation to these parameters can result in improved productivity and product quality, as well as reduced costs [21].

Maintain *Diagnostic* and *predictive maintenance* are two application areas that strongly build on each other [20], aiming to reduce downtime of manufacturing machinery and tool equipment. A new maintenance paradigm, condition-based maintenance, has gained considerable attention in recent years [19]. Condition-based maintenance utilizes online condition variables to detect, identify, and forecast potentially detrimental fault conditions. Current condition-based plans, designated as diagnostic maintenance, assess the current state of the system in real-time and perform maintenance when a triggering event occurs, such as the growth of a fault frequency beyond a particular threshold. However, a major drawback of diagnostic maintenance is that it cannot anticipate a breakdown well ahead of time. To overcome this, predictive maintenance looks at the current and past states of the system, as well as its expected future operational load, to predict how much remaining useful life a system has [19]. This temporal information advantage helps maintenance engineers to proactively order important spare parts that might not be immediately available.

4.2   Systematic Map

The resulting systematic map is shown in Fig. 1. The vertical axis presents all seven application areas, while the horizontal axis reports on techniques from advanced analytics that are classified in a two-level taxonomy.
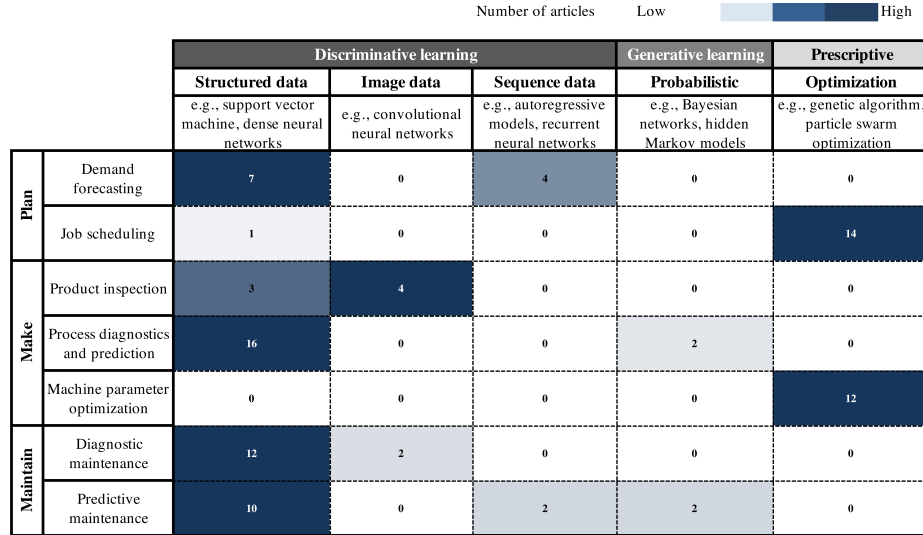
		Discriminative learning			Generative learning	Prescriptive
		Structured data	Image data	Sequence data	Probabilistic	Optimization
		e.g., support vector machine, dense neural networks	e.g., convolutional neural networks	e.g., autoregressive models, recurrent neural networks	e.g., Bayesian networks, hidden Markov models	e.g., genetic algorithm, particle swarm optimization
Plan	Demand forecasting	7	0	4	0	0
Plan	Job scheduling	1	0	0	0	14
Make	Product inspection	3	4	0	0	0
Make	Process diagnostics and prediction	16	0	0	2	0
Make	Machine parameter optimization	0	0	0	0	12
Maintain	Diagnostic maintenance	12	2	0	0	0
Maintain	Predictive maintenance	10	0	2	2	0

Number of articles   Low ▮▮▮▮ High

Fig. 1. Systematic mapping of techniques from advanced analytics (horizontal axis) to seven application areas in manufacturing (vertical axis). Color intensities represent the relative frequency of proposed analytics techniques with respect to an application area. The sum of the matrix is greater than 81 (number of reviewed articles) because some articles compared multiple analytics techniques.

Since most analytics techniques applied in manufacturing are of a supervised nature [25], we chose to differentiates between discriminative learning, generative learning, and prescriptive techniques on a first level [1,11]. On the second level, discriminative learning techniques are further subdivided into structured, image, and sequence data-based models to allow for a more granular interpretation of the map. Examples of the most commonly encountered techniques are given below. For each application area, color intensities represent the relative frequency of proposed analytics techniques.

Empirical evidence from 81 reviewed journal articles shows that optimization techniques have thus far been applied in the areas of job scheduling and machine parameter optimization. Discriminative analytics techniques based on image data, e.g., convolutional neural networks, have become the primary tool for automated product inspection. Discriminative analytics techniques that rely on structured data are mainly used for demand forecasting, quality diagnostics and prediction, as well as diagnostic and predictive maintenance.

5   Conclusion

Advanced analytics is expected to have a significant impact on manufacturing. However, practical implementation is still in its early stages. One reason is that decision-makers have lacked management tools to choose suitable techniques from advanced analytics for domain-specific problems in manufacturing.

This paper applied a systematic mapping review to identify seven application areas to which analytics can add substantial value. Each area was then matched with suitable techniques from the field of advanced analytics. The resulting systematic map provides a novel management tool to identify promising analytics projects in manufacturing and thus facilitates decision-making.

Furthermore, the presented systematic map organizes interdisciplinary knowledge in a structured manner to serve as a means for common understanding in analytics projects. This is particularly helpful in order to bridge the gap between domain-specific manufacturing contexts and general-purpose analytics practices. In this way, collaboration between different stakeholders, e.g., domain experts and data analysts, can become a less complex and time-consuming task.

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