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Machine Learning in Production Planning and Control: A Review of Empirical Literature

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Abstract: Proper Production Planning and Control (PPC) is capital to have an edge over competitors, reduce costs and respect delivery dates. With regard to PPC, Machine Learning (ML) provides new opportunities to make intelligent decisions based on data. Therefore, this paper provides an initial systematic review of publications on ML applied in PPC. The research objective of this study is to identify standard activities as well as techniques to apply ML in PPC. Additionally, the commonly used data sources in literature to implement a ML-aided PPC are identified. Finally, results are analyzed and gaps leading to further research are highlighted.

Keywords: Machine Learning, Artificial Intelligence, Industry 4.0, Smart Manufacturing, Production Planning and Control

1. INTRODUCTION

Data generation in modern manufacturing systems has experienced an explosive growth, reaching around 1000 Exabytes per year (Tao et al. 2018). This gathered information represents a source of invaluable knowledge for manufacturers as it can lead to savings and improvements. However, the potential present in this data is insufficiently exploited (Manns, Wallis and Deuse, 2015). Consequently, various countries have proposed roadmaps to adapt their industries to the new paradigms. For instance, Germany introduced the Industry 4.0 (I4.0), the US created the Smart Manufacturing Leadership Coalition, and China proposed the plan China Manufacturing 2025 (Jinjiang Wang et al. 2018). This is leading to huge financial efforts in manufacturing research. For example, the European Union will invest around €7 billion by 2020 in Factories of the Future (Kusiak, 2017).

In the context of I4.0, PPC can be defined as an approach that determines the flow of work through each work centre and monitors the production process by enabling real time synchronisation as well as customized fabrication of products (Tony Arnold, Chapman and Clive, 2012; Kohler and Weisz, 2016).

Ruessmann et al. (2015) identified nine groups of technologies enabling the realisation of I4.0. Among these nine elements, this research focuses on Big Data Analytics (BDA), and more specifically on ML applied in PPC. Regarding ML, the definition that will be considered is the one proposed by Mitchell (1997), which refers to a computer program capable to learn from experience to improve a performance measure at a given task.

Even if there are efficient analytical solver methods to perform PPC, the proposed solutions become rapidly unfeasible in the execution phase due to uncertainty (machine breakdowns, scrap rate, etc.) and to the stochastic nature of manufacturing processes. Furthermore, Enterprise Resource Planning (ERP) systems perform poorly at the operative level (Gyulai, Kádár and Monosotori, 2015). Additionally, current volatile markets with a strong tendency towards mass customization and strict respect of delivery dates impose a complexity that has to be addressed through an robust PPC (Reuter et al. 2016). ML could improve PPC's robustness since knowledge included in data may help to handle predictable and unpredictable events.

Having recognized the potential contribution of ML to PPC, the aim of this paper is to conduct a systematic review of scientific literature about the use of ML in PPC under the context of I4.0. Two research questions were addressed: **which are the activities and techniques currently employed to perform ML-aided PPC?** And **which are the currently used data sources to implement a ML-aided PPC?**

The first question relates to the research objective of this study, while the second question will provide insights about data sources used to train ML models in recent applications. In fact, data sources represent an important aspect at the core of ML, because the meaningfulness of the results greatly depends on the quality and source of the data used to train the models.

The rest of this paper is constructed as follows. Firstly, the methodology of the systematic review is described in Section 2. Section 3 introduces the analysis framework to be used. Section 4 presents and analyses the results of the review. Finally, Section 5 deals with the conclusion and further research perspectives.

2. RESEARCH METHODOLOGY

To address the proposed questions and meet the research objective, a full investigation of the bibliography is carried.

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Therefore, a systematic review following the bibliographical research method proposed by Tranfield, Denyer and Smart (2003) was performed. This literature review focuses exclusively on applications of ML in PPC under the context of I4.0.

The queries were performed between 10/10/2018 and 05/11/2018 in two databases: ScienceDirect and SCOPUS. Additionally, to assure the context requisite, only papers published in and after 2011 were considered, as this year corresponds to the formal introduction of I4.0 at the Hannover Fair. The following keywords conducted the research in *titles, abstracts and keywords*:

- ("Deep Learning" OR "Machine Learning") AND ("Production scheduling")
- ("Deep Learning" OR "Machine Learning") AND ("Production control")
- ("Deep Learning" OR "Machine Learning") AND ("Line balancing")
- ("Deep Learning" OR "Machine Learning") AND ("Production planning")

Additionally, from the year restriction (year >= 2011), only publications corresponding to "Research Articles" in ScienceDirect and "Conference Paper" OR "Article" in SCOPUS were considered. Then, a review of the abstracts allowed the selection of only empirical applications of ML in PPC. Next, duplicates were removed. Finally, a full text analysis of the initial article selection enabled the construction of the short list of papers that were used to perform the analysis. Figure 1 depicts the search strategy.

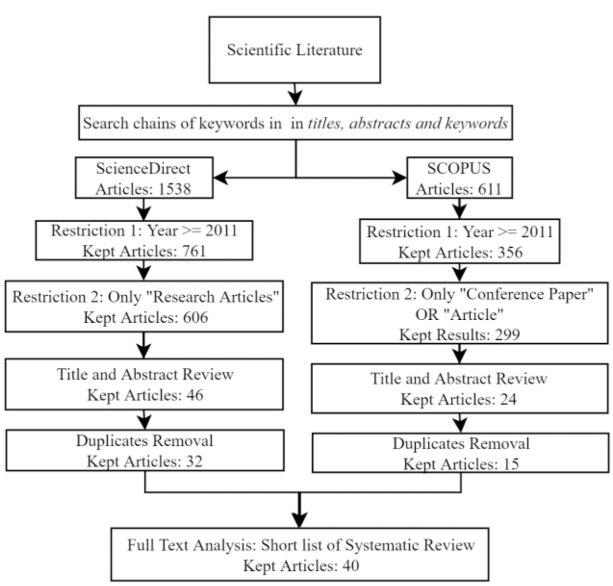

Fig. 1. Search strategy: mapping scientific literature

In such manner, the 40 kept articles were analysed under the Analytical Framework proposed in the next section.

3. ANALYTICAL FRAMEWORK

3.1 First component of the analytical framework: the elements of a method

The first research question in this paper deals with the activities and techniques used to create a ML-aided PPC model. According to Zellner (2011), these two items are related to what he proposes as the "Mandatory Elements of a Method" (MEM). These elements are:

1. A Procedure: order of activities to be fulfilled when employing the method.
2. Techniques: the way to generate the results. Activities of a procedure are supported by techniques, while tools support the latter.
3. Results: what is created by an activity.
4. Role: the point of view adopted by the person who performs the activity and is responsible for it.
5. Information Model: the relation between the four aforementioned elements.

In the scope of this research, two of the five Mandatory Elements are involved: the procedure and the techniques. The former concerns the activities, while the latter concerns the techniques themselves. More precisely, activities are related to tasks performed such as "data cleaning" or "feature selection"; and techniques are associated to used ML models such as Support Vector Machines (SVM) or Linear Regression (LR).

3.2 Second component of the analytical framework: used data sources

ML uses data as raw material to develop autonomous computer knowledge gain (Sharp, Ak and Hedberg, 2018). Therefore, it is capital to use pertinent data in order to have meaningful results. Consequently, the choice of the data source is an important dimension that has to be analysed. Tao et al. (2018) proposed a classification of data sources in manufacturing:

1. Management data, which comes from historical records stored in manufacturing information systems (MES, ERP, CRM, etc.) concerning production planning, maintenance, order dispatch, sales, etc.
2. Equipment data, that originates from Internet of Things (IoT) technologies implemented in the shop floor on machines, workstations, workers, etc.
3. User data, which derives from consumer information collected from internet sources such as e-commerce platforms or social networks.
4. Product data arising from products or service. It comes from data collected during the manufacturing process or from the final consumer. It can be related to product performance, context of use, environmental data, etc.
5. Public data coming from open databases such as university repositories, government data or data from other researchers.

The analysis of the 40 short-listed articles showed that some of them did not fit with the data sources proposed by Tao et al. (2018). These papers shared the same data origin: information generated artificially by computer by means of simulations or statistical distributions. Therefore, a sixth new data source is proposed, which is also a contribution of this paper:

6. Artificial data, which concerns information generated by computer (e.g. simulations) in order to assess applications of ML in PPC.

In such manner, both proposed analytical framework components are used to analyze the 40 short-listed articles. The next section presents the results.

4. RESULTS

4.1. First research question: activities and techniques

To identify the activities, the tasks defined to implement a ML-aided PPC in each of the 40 articles were identified. Next, a first data pre-processing was performed in order to manually group these tasks into general activities, reducing the number of results. Finally, these activities were analysed with two experts to keep the most meaningful ones. In such way, eleven standard and recurrent activities were identified:

1. Data Acquisition System Design and Integration (DA): design and implementation of IoT solutions to collect, transfer and store the data.
2. Data Exploration (DE): preliminary analysis of data to make early decisions. This can be achieved through means such as data visualization or descriptive statistics.
3. Data Cleaning and Formatting (DC): steps to make data usable to ML models.
4. Feature Selection (FS): choice of the variables to use according to domain knowledge or statistical analysis.
5. Feature Extraction (FE): creation of new and more meaningful features using the original dataset variables.
6. Feature Transformation (FT): use of techniques such as standardization, normalization or kernels to transform the features and improve the learning performance.
7. Hyperparameter Tuning (HT): adjustment of the ML parameters.
8. Model Training, Validation, and Testing (MT): as its name implies, it refers to the training, validation and testing of the proposed ML models. It also encompasses the model's performance assessment.
9. Model Comparison and Selection (MC): as there are several available ML techniques to perform the same task, this activity concerns their comparison to choose the most suitable model.
10. Contextualized Analysis or Application (CA): implementation of a solution coherent with the problem's context or the context-oriented knowledge generation from the obtained results. It goes beyond a simple assessment of the model's performance.
11. Model Update (MU): update of ML learned parameters with new data in order to adapt it to the dynamics of the manufacturing system.

The usage of these activities in the 40 papers is summarized in figure 2.

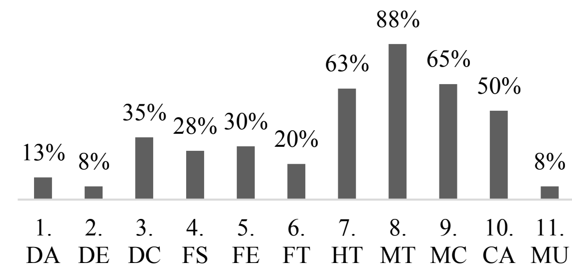

Fig. 2. Identified activities and their use percentage

From these eleven activities, three different clusters can be identified:

1. Often used activities (n°7, 8, and 9) or OUAs, applied in more than 50% of the studies.
2. Medium used activities (n°3, 4, 5, 6, and 10) or MUAs, implemented in 20 to 50% of the cases.
3. Seldom used activities (n°1, 2, and 11) or SUAs, which are used in less than 20% of the applications.

These clusters show that research is frequently focused on OUAs while the other two clusters represent potential research gaps to improve ML-aided PPC performance. Notably, MUAs mostly cover data pre-processing activities, which are capital to assure a good performance of ML models. Additionally, finding the activity n°10 in this cluster shows that it is not common to make a contextualized application or analysis of the proposed model. In fact, one out of two papers do not go further than just assessing the model's performance.

Concerning the SUAs, it was surprising to find here the activity n°1, as it represents the bridge between IoT and ML. This shows that despite the big efforts described in the introduction section, the coupling between these two subjects is far from being satisfied. Additionally, activity n°11 is fundamental to tackle the dynamics of manufacturing processes and deliver robust ML-aided PPC solutions. In fact, the unpredictable change of the statistical properties and relationships between variables over time is known as *concept-drift* (Hammami, Mouelhi and Ben Said, 2017). Models must overcome concept-drift as it can seriously damage the quality of results in a long-term horizon. Despite its importance, activity n°11 is only used in 8% of the cases, which points a gap in research.

Finally, in spite of the apparent easiness to apply the activity n°2 through means such as data visualization or descriptive statistics, it was only used in 8% of the reviewed applications.

Concerning the techniques, the number of uses of each technique family is measured. It is important to mention that, in the case of papers applying several technique families, only the one chosen by the author(s) because of its better performance was counted. Results are shown in figure 3.

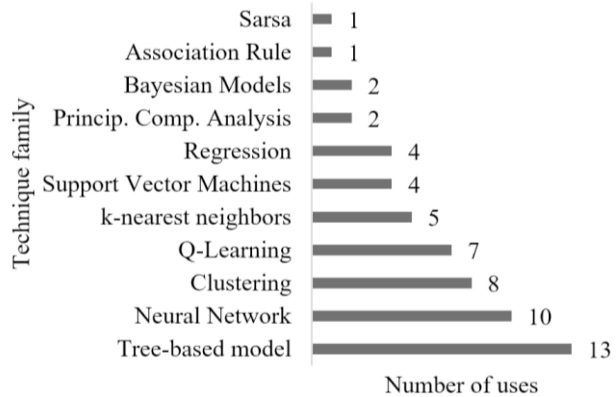

Fig. 3. Technique families and their number of uses

It is found that the Tree-based models and Neural Networks are placed in the top three most used techniques, probably because the former has a good trade-off between accuracy and interpretability; and the latter has excellent performance when dealing with non-linear datasets.

It is remarkable to find that Clustering is one of the most used techniques. In fact, they provide excellent means to deal with unlabelled data, which abounds manufacturing. Furthermore, Reinforcement Learning techniques such as Sarsa or Q-Learning were extensively used, pointing an interest on agent-based models in PPC.

Finally, it was surprising to find that Principal Component Analysis (PCA) and Association Rule are seldom used in ML-aided PPC (applied only twice and once, respectively). In fact, PCA is a useful technique allowing data denoising (included in activity n°3) as well as data pre-processing (specifically, activities n°5 and 6); and Association Rule provides interpretable results, which is convenient to generate knowledge and contextualized analysis (activity n°10).

4.2. Second research question: data sources

Table 1 summarizes the results concerning the second research question (i.e. data sources).

Table 1: Summary of data sources for the short-listed articles

Reference	M	E	U	P	Pb	A
(Altaf et al. 2018), (Li et al. 2012)				X		
(Diaz-Rozo, Bielza and Larrañaga, 2017), (Kho, Lee and Zhong, 2018), (Kruger et al. 2011), (Rostami, Blue and Yugma, 2018), (Yang, Zhang and Chen, 2016), (Zhong, Huang and Dai, 2013)		X				
(Dolgui et al. 2018), (Kartal et al. 2016), (Lai and Liu, 2012), (Lingitz et al. 2018), (Mori and Mahalec, 2015), (Reboiro-jato et al. 2011), (Reuter et al. 2016), (Schuh et al. 2017), (Tong et al. 2016), (Wauters et al. 2012)	X					
(Gyulai et al. 2018), (Leng et al. 2018), (Manns, Wallis and Deuse, 2015)	X			X		
(Gyulai, Kádár and Monosotori, 2015)	X	X				X
(Gyulai, Kádár and Monostori, 2014)	X					X
(Hammami, Mouelhi and Said, 2016), (Ji and Wang, 2017), (Li, Wang and Sawhney, 2012), (Qu et al. 2016), (Shahzad and Mebarki, 2012), (Stricker et al. 2018), (Wang et al. 2015), (Waschneck et al. 2018)						X
(Junliang Wang et al. 2018)	X				X	
(Lubosch, Kunath and Winkler, 2018)					X	X
(Lv et al. 2018)	X				X	X
(Palombarini and Martínez, 2012), (Tian, Zhou and Chu, 2013), (Tuncel, Zeid and Kamarthi, 2012), (Wang, Zhang and Wang, 2018)					X	
(Solti et al. 2018)				X		X
(Zhang et al. 2011)	X					X
Number of times applied	**18**	**7**	**0**	**6**	**7**	**14**

M: Management data, **E:** Equipment data, **U:** User data, **P:** Product data, **Pb:** Public data, **A:** Artificial data.

The most commonly used data sources were, by far, the Management data and Artificial data. This indicates two things: first, researchers extensively use the historical data stored in enterprise information systems, which is favourable for companies as they benefit from their records. Second, despite the extensive use of Management data, there are still issues to retrieve real information, which obliges the use of Artificial data. These issues are mainly related to difficulties to collect the information.

There are some applications using Equipment and Product data (7 and 6 papers, respectively). These two data sources are directly related to IoT technologies implemented *inside* the factory. This means that manufacturers are starting to benefit from data generated by IoT in their facilities. However, it is not the case for the use of IoT *outside* the factory environment. This is concluded with the fact that no paper used User data as source. Therefore, there is an important gap in the use of customer analytics applied in I4.0.

5. CONCLUSION AND FURTHER RESEARCH

This research paper studied the activities, techniques and data sources used to perform ML-aided PPC in the era of I4.0 through the analysis of 40 empirical application papers. Three clusters of activities were identified: OUAs, MUAs, and SUAs. The last cluster needs further research as it mainly contains activities positioned as key enablers for I4.0. Specially, it is possible to highlight the low percentage of papers using activities n°1 and 11, which are directly related to connected factories to collect and exploit real time data. In that sense, activity n°1 is presented as the way to capture this real-time data and activity n°11 can be proposed as a solution to adapt the ML model to the dynamics of the manufacturing systems and overcome the concept-drift issue.

The usage of six data sources (from which one is proposed by this study) is analyzed. Results indicate that Management and Artificial data dominate the current horizon of applications. On the other hand, IoT related data sources such as Equipment, User and Product data are until now rarely used, pointing a research gap. This shows that despite the efforts launched to develop the I4.0, there are few applications integrating ML with IoT technologies.

Concerning the identified techniques, there is a prevalence of Tree-based models, Neural Networks and Clustering. However, further exploration of the use of PCA and Association Rule in the context of I4.0 must be done to tackle the lack of data pre-processing and contextualized application activities (MUAs cluster). Notably, Association Rule is considered as a method able to discover and deliver knowledge from databases, an important characteristic that must be exploited.

Further research will concern, at a first stage, the development of a methodology to implement ML-aided PPC. In such manner, three important steps must be performed: first, identify tools and link them to techniques; second, link the techniques to activities; and third, stablish a logical order between activities to create a procedure. At a second stage, the domains in PPC where ML has been applied are to be identified. This will provide an insight about which areas need further development.

Finally, at a third stage, an application is to be performed in one of the PPC domains labeled as a gap in order to test the methodology proposed in the first stage. Ideally, a successful application will settle solid basis to explore further solutions to the concept-drift issue in manufacturing.

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