Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 55-2 (2022) 522–527

NLP-based insights discovery for industrial asset and service improvement: an analysis of maintenance reports

Roberto Sala*, Fabiana Pirola*, Giuditta Pezzotta*, Sergio Cavalieri *

** Department of Management, Information and Production Engineering, University of Bergamo, Viale Marconi, 5, Dalmine (BG), 24044, Italy (email: roberto.sala@unibg.it, fabiana.pirola@unibg.it, giuditta.pezzotta@unibg.it, sergio.cavalieri@unibg.it)*

Abstract: Even if usually filled in the form of unstructured text, maintenance service reports can be an important source of information for manufacturing companies providing field and remote maintenance services to their customers. By analyzing their content, companies can discover hidden knowledge that can be used for improvement purposes. By exploiting Natural Language Processing (NLP) techniques, this paper wants to show how an Italian company producing machinery can extract new knowledge from its maintenance database. The company under analysis started a servitization journey and need to understand how to improve the maintenance service delivery. By using the information extracted, the company can define improvement plans linked to both the maintenance service delivery and the asset design.

Keywords: Product-Service System, Servitization, Maintenance, Text Mining, Industry 4.0, Natural Language Processing, Knowledge Extraction, Artificial Intelligence, Topic Modelling, Latent Dirichlet Allocation

1. INTRODUCTION

Manufacturing companies are offering more frequently combinations of products and services, known as Product-Service Systems (PSS), to their customers (Kamal *et al.*, 2020). The scope is creating long and profitable relationships by changing how customers see them – no more as simple vendors but as trustable partners for their business. This explains why, in the current manufacturing scenario, the offering of services on top of products is spreading. Consequently, the way services are offered characterizes the competitiveness of companies, which should be able to guarantee high responsiveness to customers' requests.

Among services, maintenance is one of the most diffused when dealing with manufacturing companies. As stated by Reslan *et al.* (2021) *"Maintenance is a life-long skill where maintainers constantly learn new techniques and maintain new equipment"*. Thus, the storage and reuse of information and lesson learnt generated during maintenance service execution impact the effectiveness of the learning phase.

Usually, detailed information and feedback of maintenance activities are described in reports stored by the companies in their internal information systems. Navinchandran et al., (2019) suggest that this large amount of knowledge generated by the technicians can be relevant to understand why some failures happen and how to solve them. In addition, as discussed by Xin *et al.* (2018), knowledge generated during the Middle of Life could be reused at the various levels of the company operations to modify something in the maintenance service delivery process or the asset design (e.g., to simplify the task execution, to reduce specific failures, or to increase the asset useful life).

Despite the availability of such noteworthy information in the reports, many companies do not use it to perform extensive analyses. This can be due to the lack of resources allocated to this task, but also to the lack of skills and knowledge about instruments and tools that can facilitate the analysis and extraction of insights from text-intensive maintenance reports. However, in most cases, this information is never intended to be used, and it is stored only with a legal scope (e.g., in case of dispute with the customer).

From the research perspective, this paper wants to demonstrate how the application of text-mining techniques, such as topic modelling executed using Natural Language Processing (NLP), can generate new knowledge for the actors dealing with maintenance service. In particular, the aim is to show how, from the analysis of maintenance reports, companies can extract information that can impact both the maintenance service delivery and the asset design, feeding thus a dual perspective improvement. To do so, the paper describes an application in an Italian manufacturing company producing bottling machines. For the company, the application of text-mining techniques on its maintenance report database aimed to: a) understand the intervention distribution in terms of typology/content; b) extract valuable hints concerning the nature of the most common interventions performed by maintenance technicians; c) identify weaknesses in the assets installed; d) identify weaknesses of the maintenance service delivery process and the asset components; e) define improvement plans for the maintenance service delivery process and the asset design.

The paper is structured as follows: Section 2 provide a short theoretical background. Section 3 describes the research approach adopted for this paper, while Section 4 presents the application case and the results. Section 5 provides a

10.1016/j.ifacol.2022.04.247

discussion on the insights extracted from the analysis. Section 6 concludes the paper and depicts the next steps.

2. THEORETICAL BACKGROUND

Over the years, many researchers worked to propose methodologies and processes able to capture information and data generated by the PSS to reuse them for improvement purposes (Machchhar and Bertoni, 2021).

For companies, it is frequently hard to generate value from text-intensive maintenance service reports since they are usually filled with unstructured text, which requires a long time to be adequately analyzed (Hodkiewicz and Ho, 2016). Limitations in data analysis could derive not only from the format used to create the reports, but also from their content which, as Mahlamäki et al. (2016) discuss, can be affected by typos, missing data fields, and other errors that lower the maintenance data quality. As suggested by Sexton and Fuge (2019), another problem frequently present in the reports is due to the jargon used by technicians while compiling the report, which may be different from the one used by other actors of the organization like engineers or designers. In response, the same authors discuss the possibility of using ontologies to overcome this problem and create appropriate tags to classify the text, as confirmed by the research of Akhbardeh *et al.*, (2020) and Brundage *et al.*, (2021).

Literature also developed text-mining approaches, mainly focusing on the definition of instruments and methodologies to support information extraction from the maintenance reports (Bird *et al.*, 2009; Honnibal *et al.*, 2020). In this sense, Abramovici *et al.*, (2018) discuss the importance of quality reports for generating new knowledge in the PSS context for companies who want to improve maintenance service delivery.

In this perspective, this paper wants to investigate the adoptability of an NLP-based text-mining approach to extract valuable knowledge from maintenance service reports aimed to improve maintenance service management and delivery. The selection of NLP has been motivated by the fact that such an approach is widely used in science and industry working with unstructured texts or user comments and is commonly used to search and identify important part of text, summarize texts, group information, identify the sentiment of user comments, answering queries or developing chatbots. To do this, a real case application has been carried out. The next section describes the research approach adopted for the paper development.

3. RESEARCH APPROACH

The approach used to conduct the research is shown in Figure 1 and it is composed of six macro-phases, which can be composed of additional sub-phases. The analyses were run using Python 3.9 and some of the most popular modules for text-mining such as NLTK (Bird *et al.*, 2009), gensim (Řehůřek and Sojka, 2010) and spaCy (Honnibal *et al.*, 2020).

3.1 Data collection

This phase is required to have a corpus of text on which to execute the analyses. The aim is to collect maintenance reports and transpose them in an analyzable form (e.g., Microsoft Excel®, JSON). If possible, the aim is to use files containing both the description of the intervention (subject of the NLP-based analysis) and additional data related to the interventions. By doing so, it would be possible to run also analyses involving spatial and time-based perspectives, adding more information to the study.

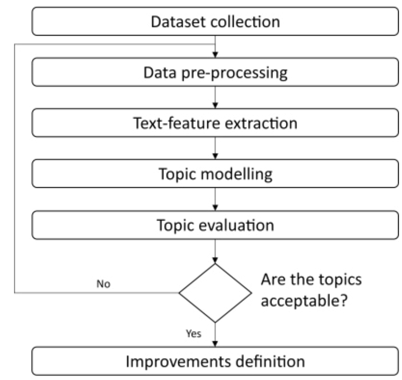

Figure 1. Research approach.

3.2 Data pre-processing

The data pre-processing phase requires executing the following activities:

- *Dataset translation.* If the maintenance reports are written by technicians working in different parts of the world, these may be written in different languages. The adoption of automatic translators (e.g., Google translate) allows to uniform the language of the descriptions.
- *Tokenization.* It consists in separating the texts into linguistic units (i.e., the words and the punctuation) and removing the punctuation. It is important to clarify that a set of tokens constitutes a document, while a set of documents compose a corpus (which is the ensemble of text that will be analyzed).
- *Stop-words removal*. It consists of the removal of specific words from the corpus of the analyzed text. The words to be removed consist of the most common words found in the language of the corpus. Additional words can be defined and added to the list if necessary.
- *Part-of-Speech (POS) tagging and Lemmatization*. POS consists of tagging each token according to its role in the sentence (e.g., verb, noun, adjective). Then, lemmatization uses the POS to reduce each token to its root form (e.g., transforming plural forms into singular forms, changing the tense of each verb to infinite form).
- *N-grams.* It allows analyzing the frequency in the text of words couples, triplets, quartets and so on. Using this technique makes it possible to check how frequently a certain sequence of words (of length n) appears in the text.

3.3 Text-feature extraction

For this phase, the Term Frequency-Inverse Document Frequency (TF-IDF) vectorization approach (Bafna *et al.*,

2016) can be used. Thanks to this approach, it is possible to compute the relative importance of a token inside a document with respect to the whole corpus and, thus, understand how much context and information each token could provide to the analysis. To remove the tokens with a low degree of information, it is possible to define an "inclusion threshold". Of course, depending on the threshold established, some important words may be removed. Due to this, multiple threshold values should be tested before selecting the optimal one.

3.4 Topic modelling

In this phase, the Latent Dirichlet allocation (LDA) algorithm, which is one of the most diffused algorithms for topic allocation (Syed and Spruit, 2017), is adopted. As stated in Blei *et al.* (2003), LDA is *"a generative probabilistic model of a corpus. The basic idea is that documents are represented as random mixtures over latent topics, where each topic is characterized by a distribution over words"*. The LDA algorithm assigns words to a topic with a certain probability and uses measures such as perplexity and coherence to evaluate the goodness of the topic modelled. The aim is to identify the number of topics that minimize the perplexity and maximizes the coherence by fine-tuning the parameters and hyperparameters of the LDA algorithm.

3.5 Topic evaluation

Once the optimal number of topics is identified, it is necessary to analyze their content to check their correctness. If the topics are satisfactory, it is possible to continue with the following phase. Otherwise, additional iterations of pre-processing should be performed. For example, the list of stop words may be updated, or the list of POS allowed to be part of the corpus may be changed. These pre-processing activities should be performed until the topics' content can be considered suitable for the analysis. The coherence and perplexity indexes (Morstatter and Liu, 2018) computed to evaluate the LDA model can be used to support the evaluation.

3.6 Definition of improvement actions

Once identified the topics, it is possible to perform the topic assignment to the corpus and run analyses to understand their distribution in the corpus and define improvements for the asset and the maintenance service delivery.

4. APPLICATION CASE

4.1 Company A

Company A is a manufacturing company headquartered in the northern part of Italy and producing bottling and packaging machines. The company is trying to strengthen its service offering, with particular focus on the maintenance service and with development plans related to the corrective, preventive, and predictive maintenance service offerings. To this purpose, one of the improvements that Company A is putting in place involves the extraction of knowledge from the database of field maintenance reports, which are filled by the technicians after each intervention and are based on free-text fields. Due to the nature of the reports and the lack of human resources dedicated to the task of maintenance report analysis, Company A is not able to extract information from the data stored. Thus, it decided to analyze the reports leveraging on text mining approaches, in the scope of discovering new information and use the knowledge to define asset and maintenance service-related improvement plans.

4.2 Results

The objective of the analysis was to understand the main interventions performed, in terms of problems addressed, technicians involved, and assets maintained. Company A provided a database of 340 interventions written in three different languages (i.e., English, Italian, and Spanish), distributed over seven years (2014-2021). The reports were translated into English and the methodology reported in section 3 has been followed (i.e., pre-processing, topic modelling, and topic evaluation).

The topics were evaluated only by checking the content and the coherence index since, as discussed by Chang *et al.* (2009), perplexity is a measure that might be misjudged by analysts. Thus, to improve the quality of topic modelling, the pre-processing activities were carried out recursively: by analyzing the most frequent words, the authors, supported by Company A employees, identified additional stop words as well as modified the list of POS allowed for the analysis. This recursive approach stopped when satisfiable content and coherence index were achieved.

Initially, the analysis was run on the complete corpus of interventions considering all the POS identified during the lemmatization. With this configuration, topics' content was not well defined, and the coherence showed a low value (around 0.33). Thus, the authors agreed to re-run the pre-processing, updating the stop words and the POS allowed. In particular, the authors decided to keep only words classified as "Noun" or "Verb" by the POS tagger, removing "Adjectives" and "Adverbs". This choice was crucial in terms of coherence improvement since it allowed to increase its value from 0.33 to 0.65, which is a value that the authors decided to be satisfiable for the analysis (also considering the content of the topics). As far as the authors' knowledge is concerned, there are no clear indications regarding a minimum acceptable coherence value in the literature.

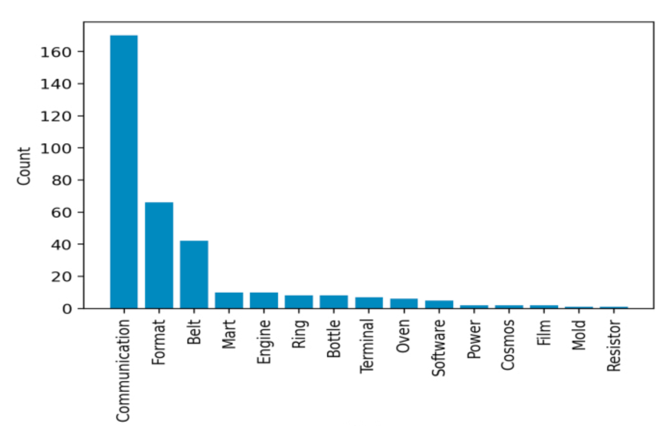

Figure 2. Topic frequency in the corpus.

Table 1. Topics identified

Topic	Keywords
Communication	communication, leave, damage, perform, recommend, card, review, report, course, result
Engine	engine, request, number, movement, finish, indicate, motor, screw, reformatte, note
Format	rod, air, mold, valve, cam, unit, wheel, blow, adjust, bearing
Mart	change, mart, belt, pass, form, com, transport, chain, die, serial
Resistor	area, seem, counter, hour, help, resistor, keep, parcel, expect, conditioner
Oven	try, oven, send, fan, block, console, want, say, install, miss
Software	program, version, place, update, fault, monitor, proceed, discard, mst, hath
Terminal	device, relay, wire, error, pc, create, terminal, power, panel, lose
Ring	ring, fiber, serco, decide, fiber_optic, assembly, measure, interruption_ring, problem, image
Mold	mold, close, lock, pin, backlash, locking, min, ndolo, ntc, observation
Belt	need, run, belt, instal, temperature, day, chain, pack, part
Bottle	speed, filler, decrease, carousel, fill, stock, problem, bottle, blow, blower
Film	film, print, track, ndolo, ntc, kick, lanea, min, inrush, nom
Power	replace, power_supply, fact, message, pilz, command, lanea, min, ndolo, ntc
Cosmos	make, stop, note, start, take, climb, button, board, year, cosmos

The LDA model used by the authors defined the 15 topics listed in Table 1. Once configured, the LDA model was used to perform the topic allocation on the corpus. To simplify the understanding, a single label was associated to each topic describing the type of intervention carried out (Table 1). After this activity, it has been possible to investigate the frequency for each topic, as shown in Figure 2. It must be clarified that Figure 2 shows the number of times a specific topic has been identified as the "*dominant topic*" in the corpus (in terms of the number of words belonging to that topic found in the description). This means that, in the frequency analysis, each topic "gained a point" only if the topic was identified as dominant for that intervention, neglecting minor or additional problems that occurred to the asset. Even if this could limit the information collected from the analysis, it allows extracting an overview of the major problems causing each intervention request, that represented the objective of the analysis.

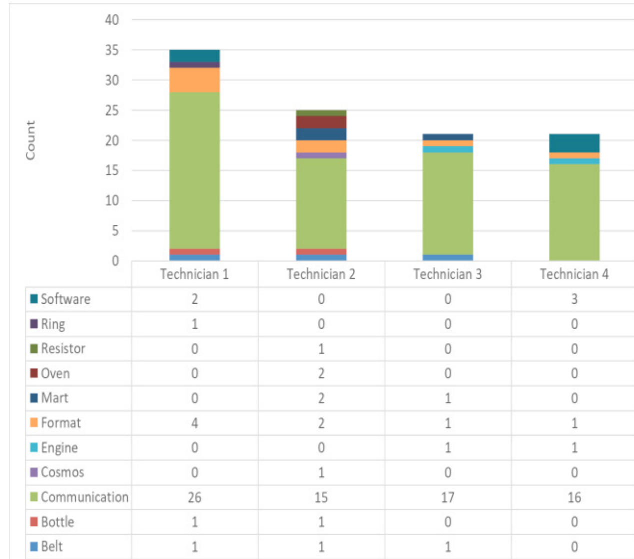

Figure 3. Technician vs Topic.

Regarding the analysis from the technician's point of view, it emerged a considerable disparity in the maintenance reports available for the analysis. The 340 reports available were written by 76 different technicians but, among these, 102 were written by only 4 of them. This first result highlights the problem related to the willingness of many technicians to fill their maintenance reports. The authors chose to analyze the distribution of topics among the intervention of these 4 technicians. As shown in Figure 3, the interventions linked to the "Communication" topic constitutes a significant part of the interventions. In terms of variety, with 8 different topics, technician 2 seems to be the one who deals with the greatest variety of problems. On the other hand, technician 4, with only 4 topics, seems to have the lowest variety among the group in terms of dominant topics. This opened discussions in the company concerning the specialization of some technicians and/or the lack of skills of others and, thus, about the necessity to activate training courses.

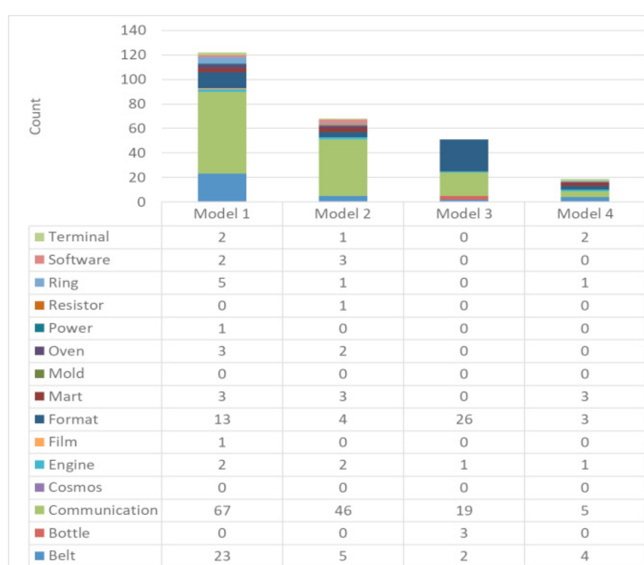

Figure 4. Model vs Topic

Another interesting aspect for Company A was the analysis of the intervention distributions by asset model (i.e., the product family the assets belong to). Figure 4 shows the topic distribution for the four most cited models. They cover 260 interventions out of the 340 composing the corpus. Requests coming from assets belonging to Model 1 accounts for 122 interventions, while for Models from 2 to 4 are 68, 51, and 19, respectively. As in the case of the previous analysis, it is interesting to notice how the variety of the interventions changes according to the model analyzed. Model 3 see only 5 types of interventions, mainly focused on the "Format" topic. On the contrary, the other models see the "Communication" topic as most frequent. Despite the consistent number of interventions focused on topics related to "Communication" and "Belt", Model 1 and Model 2, also thanks to the high number of interventions reported, show an interesting variety in terms of number of topics. Looking at Model 4, it is possible to notice an almost uniform distribution for the interventions, without a clear predominance of one topic over the others.

5. DISCUSSION

The analysis of the topics allows opening the discussion regarding the possible uses of the information extracted (partially reported in this paper due to space limitations). Indeed, the knowledge extracted from the analysis could be used to: a) improve the maintenance service delivery; b) define improvements plans for the technicians; c) improve the assets' design; d) offer customized services for customers.

5.1 Improve the maintenance service delivery process

One of the first outputs was a significant improvement in the knowledge related to the problems affecting the assets, based on an objective analysis of the company's interventions. This would help the company to re-engineer the maintenance service delivery process, both improving the efficiency and effectiveness of the process itself (e.g., providing technicians with some checklist or guided troubleshooting procedure based on the problem identified and the asset) or enabling new maintenance service provision modes (e.g., through remote support). For example, through the analysis of the words used by the technicians, Company A was able to identify a specific problem affecting multiple models (Figure 4) of its portfolio (i.e., related to communication components) that would prevent from offering satisfiable remote monitoring services. This could have badly influenced the relationship between Company A and its customers, possibly causing the loss of the customers. To solve this, Company A decided to redesign the component and study the causes behind the failure.

5.2 Define improvement plans for the technicians

The analysis of the typology of interventions executed by each technician can be used to understand the skills owned by each one as well as their level, to check the match between the interventions assigned by the planner and the skills declared and define possible improvement paths. Furthermore, by integrating topic analysis with time-based analysis of the intervention, it would be possible to gain further insights on the technician performance and skills. Based on this, Company A decided to introduce a periodic check to verify the typology of interventions executed by the technicians to define, when necessary, improvement paths that would allow to cover gaps, allow technicians to acquire new competences, and/or strengthen specific ones.

5.3 Improve the assets' design

The analysis of the most frequent failures affecting the assets (or the assets' model) could be used to identify design problems and induce components' redesign to guarantee a higher availability for production. By combining this with a time-based perspective, failures can also be clustered according to the lifecycle phase (e.g., separating infancy failures from wearing ones). In addition, a geographical-based analysis can provide information on the failures' distribution, creating connections between failures and environmental conditions useful to redesign components accordingly. Such an analysis could be used to feed instruments and methodologies designed to identify and keep track of criticalities in the assets and their components. An example is the Failure Modes, Events and Criticality Analysis (FMECA) methodology (Chen *et al.*, 2012), which can use the knowledge emerging from such analyses to update the Risk Priority Numbers (RPNs) dynamically. In the case of Company A, the asset-based perspective allowed to identify a common problem for all the models due to the communication components. On the other hand, it allowed noticing that the assets belonging to model 3 had major problems in the "Format" topic. Thus, Company A decided to redesign these components to prevent their failure and allow reliable remote services.

5.4 Offer customized services for customers

Cross analyzing the topics with the customers requiring maintenance may reveal additional services that may be sold to them depending on the interventions' content, frequency, and evolution. For example, services linked to the training of the customers' operators may be offered. Additionally, information linked to the spare parts consumption may be extracted by deeply analyzing the topics content and intervention descriptions. For example, Company A noticed a recurring problem for the format produced by the asset due to wrong regulations made by the customer. Following this, Company A decided to offer additional consultancy and training to some of its customers.

6. CONCLUSIONS

The generation of new knowledge is fundamental for companies who want to market competitive PSS offerings. Text-based maintenance reports, even though filled in an unstructured form, can be a great source of information, but companies need to find reliable ways to process them. In this scope, this paper proposes a series of steps and methods that companies may apply to process textual data and create improvement loops for their assets and maintenance service delivery processes. To verify the usefulness of such an approach, the paper presents an application case conducted on a dataset of maintenance reports from Company A. The application allowed to cluster the interventions according to the content of the textual description, unlocking new knowledge linked to the interventions executed.

The reports have been processed using standard approaches, fine-tuned to improve the result of the analyses. Starting from the results, Company A defined actions for improvement linked to the main problems. The analysis allowed suggesting the redesign of components and allowed introducing improvement plans for the maintenance resources. Anyway, additional improvements linked to the analysis approach could be introduced. For example, by ameliorating the way text is pre-processed (e.g., spell-checking, jargon removal). Also, the topic classification may be improved by feeding the model with additional reports. Additionally, investigating other topics appearing in the description instead of only focusing on the dominant ones, could help visualize what topics, and how frequently, present together. Additional data may be added to the analysis by converting hand-written reports using image recognition tools and then including them in the dataset.

The improvements brought to the model will be the starting point for creating new procedures and instruments to better support customers. Future research will address the analysis of the customer service tickets to cluster the customer requests and better support the problem identification starting from the customers' words. Following this, and merging the results of this analysis, a troubleshooting tool will be developed.

REFERENCES

Abramovici, M., Gebus, P., Göbel, J.C. and Savarino, P. (2018), "Semantic quality assurance of heterogeneous unstructured repair reports", *Procedia CIRP*, Elsevier, Vol. 73, pp. 265–270.

Akhbardeh, F., Desell, T. and Zampieri, M. (2020), "NLP Tools for Predictive Maintenance Records in MaintNet", *Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing: System Demonstrations*, pp. 26–32.

Bafna, P., Pramod, D. and Vaidya, A. (2016), "Document clustering: TF-IDF approach", *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)*, presented at the 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), pp. 61–66.

Bird, S., Klein, E. and Loper, E. (2009), *Natural Language Processing with Python: Analyzing Text with the Natural Language Toolkit*, O'Reilly Media, Inc.

Blei, D.M., Ng, A.Y. and Jordan, M.I. (2003), "Latent dirichlet allocation", *The Journal of Machine Learning Research*, JMLR. org, Vol. 3, pp. 993–1022.

Brundage, M.P., Sexton, T., Hodkiewicz, M., Dima, A. and Lukens, S. (2021), "Technical language processing: Unlocking maintenance knowledge", *Manufacturing Letters*, Vol. 27, pp. 42–46.

Chang, J., Gerrish, S., Wang, C., Boyd-Graber, J.L. and Blei, D.M. (2009), "Reading tea leaves: How humans interpret topic models", *Advances in Neural Information Processing Systems*, pp. 288–296.

Chen, Y., Ye, C., Liu, B. and Kang, R. (2012), "Status of FMECA research and engineering application", *Proceedings of IEEE 2012 Prognostics and System Health Management Conference, PHM-2012*, IEEE, pp. 1–9.

Hodkiewicz, M. and Ho, M.T.W. (2016), "Cleaning historical maintenance work order data for reliability analysis", *Journal of Quality in Maintenance Engineering*, Emerald Group Publishing Ltd., Vol. 22 No. 2, pp. 146–163.

Honnibal, M., Montani, I., Van Landeghem, S. and Boyd, A. (2020), *SpaCy: Industrial-Strength Natural Language Processing in Python*, Zenodo.

Kamal, M.M., Sivarajah, U., Bigdeli, A.Z., Missi, F. and Koliousis, Y. (2020), "Servitization implementation in the manufacturing organisations: Classification of strategies, definitions, benefits and challenges", *International Journal of Information Management*, Vol. 55, p. 102206.

Machchhar, R.J. and Bertoni, A. (2021), "Data-driven design automation for product-service system design: framework and lesson learned from empirical case studies", *Proceedings of the Design Society*, Cambridge University Press, Vol. 1, pp. 841–850.

Mahlamäki, K., Niemi, A., Jokinen, J. and Borgman, J. (2016), "Importance of maintenance data quality in extended warranty simulation", *International Journal of COMADEM*, Vol. 19 No. 1, pp. 3–10.

Morstatter, F. and Liu, H. (2018), "In search of coherence and consensus: measuring the interpretability of statistical topics", *Journal of Machine Learning Research*, Vol. 18 No. 169, pp. 1–32.

Navinchandran, M., Sharp, M.E., Brundage, M.P. and Sexton, T.B. (2019), "Studies to predict maintenance time duration and important factors from maintenance workorder data", *Proceedings of the Annual Conference of the PHM Society*, Vol. 11.

Řehůřek, R. and Sojka, P. (2010), "Software Framework for Topic Modelling with Large Corpora", *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*, ELRA, Valletta, Malta, pp. 45–50.

Reslan, M., Hastings, E.M., Brundage, M.P. and Sexton, T. (2021), "A Data-Driven Framework for Team Formation for Maintenance Tasks", *International Journal of Prognostics and Health Management*, Vol. 12 No. 1.

Sexton, T. and Fuge, M. (2019), "Using Semantic Fluency Models Improves Network Reconstruction Accuracy of Tacit Engineering Knowledge", *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Vol. 59186, American Society of Mechanical Engineers, p. V02AT03A051.

Syed, S. and Spruit, M. (2017), "Full-text or abstract? examining topic coherence scores using latent dirichlet allocation", *2017 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*, IEEE, pp. 165–174.

Xin, Y., Ojanen, V. and Huiskonen, J. (2018), "Knowledge Management in Product-Service Systems – A Product Lifecycle Perspective", *Procedia CIRP*, Vol. 73, pp. 203–209.