Available online at www.sciencedirect.com
ScienceDirect
Procedia Computer Science 232 (2024) iii-xxi
Procedia Computer Science
www.elsevier.com/locate/procedia

# Table of Contents

Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 232 (2024) 1259–1268

Procedia Computer Science

www.elsevier.com/locate/procedia

5th International Conference on Industry 4.0 and Smart Manufacturing

# Leveraging Natural Language Processing for enhanced remote troubleshooting in Product-Service Systems: A case study

Roberto Sala[a]*, Fabiana Pirola[a], Giuditta Pezzotta[a], Sergio Cavalieri[a]

[a]University of Bergamo, Department of Management, Information and Production Engineering, Viale Marconi, 5, Dalmine (BG), 24044, Italy

**Abstract**

In Product-Service System (PSS) offerings is crucial to deliver services in the shortest time to maximize customer satisfaction. One of the first contacts that customers have with the provider is usually through remote assistance delivered via telephone or email. Thus, the development of a structured troubleshooting procedure is fundamental for fast problem identification and resolution. While customers exchange with help desk technicians are saved in a company database, they are often lacking proper structure and, thus, are rarely analyzed. This poses a challenge since aggregated data can provide valuable insights for knowledge extraction and reuse, benefiting PSS lifecycle management and improvement (e.g., enhancing troubleshooting, maintenance service, or PSS design). The paper presents a case study where the textual data collected from the customer ticket database have been analyzed to extract the most recurrent problems and the frequently suggested solutions and improve remote troubleshooting.



*Keywords:* Product-Service Systems (PSS); Maintenance; Natural Language Processing (NLP); Troubleshooting

## 1. Introduction

In the current industrial context, the capability of improving and delivering services efficiently and effectively is crucial to be competitive. To do so, it is necessary to extract knowledge generated by daily activities, summarize it, and turn it into something useful, such as a set of procedures, guidelines, or standardized processes that allow employees to do their job most easily and clearly. Such a scope requires understanding the process that needs to be improved, identifying its flaws, understanding how to overcome them, and working toward their implementation [1].

* Corresponding author. Tel.: +39-0352052005
*E-mail address:* roberto.sala@unibg.it


10.1016/j.procs.2024.01.124

Such an approach can be applied to many processes to optimize their flow and ensure the expected outcomes. For instance, in the case of manufacturing companies, this can be translated into the process of managing and delivery maintenance, especially in the case of market offerings based on product-service bundles, usually referred to Product-Service Systems (PSS) [2]. In this kind of offering, the relationship between the industrial asset/product provider and the customers is not limited to the moment of the sale but continues over time thanks to the service provision. The durability of this relationship is subject to service quality and economic sustainability [3, 4].

Service delivery is not an easy task and requires considering service and asset integration since the designing phase [5]. It is very uncommon that the service design result in the optimal configuration after the first iteration since new elements emerge over time while the customers use the asset and the provider gains experience in the service delivery process [6]. For this reason, the collection and analysis of data on the service execution and delivery are required to continuously improve these aspects [7].

Using the maintenance service as a reference, multiple authors highlighted the need to continuously learn from the data collected to know if, when, and what maintenance should be delivered [8]. This knowledge can stem from the analysis of numerical (e.g., vibrations, production, quality rates) [9] or textual data (e.g., maintenance reports, maintenance tickets) [10] that must be analyzed with the most appropriate methods depending on their nature. Leveraging on the knowledge extracted, companies can update their internal processes to improve the execution of maintenance and the management of the PSS lifecycle [8]. One of the most important phases of the maintenance delivery process is the initial one, where the customer contacts the provider requiring support. The fast and correct identification of the problem allows for a timely problem resolution and guarantees higher satisfaction for the customer and optimized resource usage for the provider. Thus, the definition of proper remote troubleshooting is required to offer reliable maintenance services, and the knowledge generated through the information exchange with the customer can constitute a base for this.

Being usually in the form of unstructured written text, it is hard for companies to summarize it in a fast and efficient way [11]. In this regard, recent years have seen the development of research on the topic of Natural Language Processing (NLP), and related applications in the industry context for text summarization, information discovery, and others [12]. The adoption of NLP can be a means for companies to summarize information collected in the exchange with customers and transform the knowledge extracted into useful troubleshooting procedures.

This paper is not aimed at introducing new NLP models but aims to demonstrate how NLP approaches could be included in a wider PSS lifecycle management process that is aimed at improving service execution (i.e., maintenance and help desk) and future design [5]. In particular, this paper presents a case study where the ticketing data of an Italian company has been analyzed with NLP-based approaches to extract knowledge targeted to the improvement of the troubleshooting phase for the maintenance help desk.

The paper is structured as follows: Section 2 briefly discusses the literature on the topic, and Section 3 details the methodology used. Section 4 describes the case study used for this research. Section 5 discussed the outcome of the analysis. Section 6 concludes the paper also delineating future research.

## 2. Literature background

Product-Service Systems (PSS) offerings gained considerable attention in the manufacturing sector over the years. To be effective, they need to be built upon strict integration of product and service components that should be designed in a way that allows providers to deliver satisfactory services to customers in a sustainable way (especially considering the economic aspect) [4]. To do so, researchers clarified the need to constantly improve the offering through data collection and analysis targeted to summarize knowledge to be reused for product or service redesign, especially because of the unprecedented data availability that characterizes the modern industrial scenario [13–15].

In this context, maintenance is among the most common services that companies offer to customers given the considerable effect that poor execution may have on the performance of an asset or a plant, leading to a reduction of its productivity that goes from 5% to 20% according to [16]. Another frequent service the companies offer to customers is the help desk, which consists in supporting remotely the customers in solving some problems that may occur with the machine [17, 18]. This process is strictly tied to the maintenance one since, based on the identification of specific problems in the asset, a maintenance intervention might be scheduled. In turn, to avoid useless interventions and reduce the downtime of the assets, companies must define reliable troubleshooting procedures that help employees in identifying the problems and the related solutions [19].

The Natural Language Processing (NLP) literature proposed a plethora of contributions related to the application of such an approach to the industry. Such contributions span from the fault log text classification [20], to the support for staff assignment [21], to the topic modeling for discovering frequent problems [10], or to the correction of manual classification [22]. These approaches are all interested in understanding how the data and information entered in maintenance reports might be summarized through automatic means and translated into knowledge to be later reused for improvement.

While [23] proposes a custom word embedding model targeted at extracting knowledge from maintenance reports, [24] addresses the problem of adapting NLP approaches to technical text, also discussed by [25, 26].

From this brief literature background, it emerges the interest that NLP applications gained in the maintenance field, with various applications that should be further deepened to show the benefits that a wider adoption could have on the companies' improvement processes. In doing so, this paper embeds its research contribution in the PSS context, where actors can learn from previous experience to build new products and services and improve the current ones.

## 3. Research approach

Company A is an Italian manufacturing company producing equipment and plants for the food and beverage sector. The company realized in recent years the necessity of moving towards a more structured maintenance offering because of the higher competitiveness that emerged in the market and the possibility of instantiating new revenue streams through PSS offerings, beneficial for internal investments and future expansion.

The research aimed to verify whether the use of Natural Language Processing (NLP) on a dataset of claim records from customers could be used to improve the maintenance service by achieving more efficient maintenance execution and effective remote troubleshooting. The dataset, structured in a tabular format, was composed of a main column "Contact message", a second column "Suggested activities", and other numerical or categorical columns useful to have more detail on the operators carrying out the support of the customer requiring assistance.

The methodological steps followed to carry out the research are the following (also shown in Figure 1):

1. *Data collection*. Where data from the company database were extracted in .csv format.
2. *Data pre-processing* ("Contact Message"). Where the .csv files were merged into one, and standard pre-processing steps (e.g., dataset translation, tokenization, stop-words removal, Part-of-Speech tagging, lemmatization, n-grams identification) were applied. This phase was carried out using Python 3.9 code and Python packages such as nltk [27] and spaCy [28].
3. *Feature extraction* ("Contact Message"). Where weights were assigned to the pre-processed dataset to identify the most important features for the following step.
4. *Topic modeling* ("Contact Message"). The pre-processed messages were clustered into topic arguments to allow distinguishing them based on their content. To carry out this phase, Latent Dirichlet Allocation (LDA) [29] method was used through genism [30]. The result was saved in a model to be used in step 6.
5. *Topic validation* ("Contact Message"). The validity of the topics was evaluated through mathematical indexes like Perplexity and Coherence [31] and manual checks of the topics' content.
6. *Topic assignment* ("Contact Message"). Once validated the topics, the model created in step 4 was used to assign, to each message, one or more topics.
7. *Topic clustering*. Based on the results of step 6, messages were clustered according to the topic assigned.
8. *Data pre-processing* ("Suggested Activities"). As in the case of the "Contact message" column, the "Suggested activities" column underwent a pre-processing phase to uniform the content and favor the analysis.
9. *Frequency analysis* ("Suggested Activities"). Following the pre-processing phase, the authors analyzed the content of the suggested activities connected to each "Contact message" to identify the most common resolution strategies suggested. This phase was carried out through simple frequency analysis due to the requests of the company.

10. *Troubleshooting process improvement*. Based on the results of step 9, a troubleshooting procedure, in the form of required checks was defined for each topic identified in step 4.

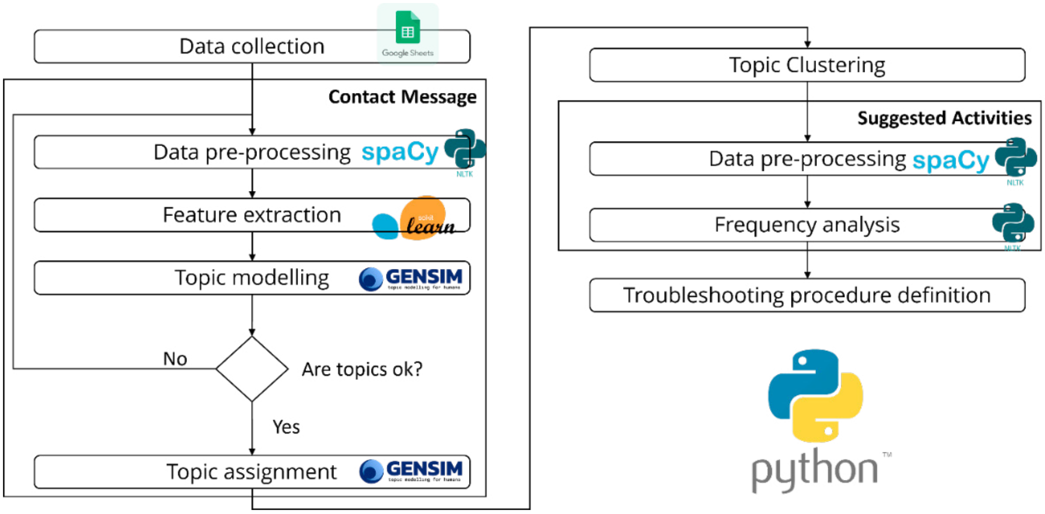


Figure 1 - Research Approach

## 4. Case Study

Starting from the methodological description provided in section 3, section 4 aims at presenting its application to the case of Company A.

As anticipated in the previous section, data were extracted from the company database in the form of .csv files. Two main files were extracted. One ("Contact messages") contains the message that started the conversation between the company and the customer, and another one ("Suggested Activities") contains the message exchange that followed between the two actors. The extraction of two files instead of one was due to the structure of the database, which did not allow a single extraction. Using the numerical identifier stored in the column "Intervention ID", it was possible to create a single file for analysis. The file was structured with the following columns "Intervention ID", "Customer", "Location", "Subsidiary", "Status", "Contact Message", "Suggested activities", "Start date", "Closure date", and others. It must be clarified that the "Suggested activities" column contains not only the message(s) sent by the technician but contains the whole conversation with the customer (apart from the initial message).

### *4.1. Pre-processing and features extraction*

The pandas library [32, 33] was used to create the file for analysis. The joined dataset was composed of almost 15000 rows, each one corresponding to a ticket. Before moving to the analysis of its content, the dataset was cleaned through the removal of rows missing fundamental information for the analysis (e.g., the content of the "Contact message" or "Suggested activities" columns), leading to a final set of 13000 rows. If the "Contact message" was missing, it was not possible to assign the corresponding "Suggested activities" info to a specific topic. The same goes if the "Suggested activities" content was missing since it was not possible to improve the troubleshooting phase on the assigned topic without that information.

As a first activity, the "Contact Message" and "Suggested Activities" columns were translated into English using Google Sheets and the GOOGLETRANSLATE function to achieve higher uniformity in the analysis. This passage was executed in accordance with the company after evaluating the potential risk of information loss due to mistranslations.

Following, *Tokenization* took place and allowed the separation of the sentences into single words (tokens) while removing the punctuation and white-spacing from the messages. It is important to clarify that the spaCy library was modified to avoid removing negative words (e.g., no, not) to avoid problems of interpretation (e.g., "work" vs "does not work"). Once tokenized, the *stop-words removal* phase took place. In this phase, the tokens were compared against a list of common words widely used in the English language. If the token matched one of the stopwords, it was removed from the list. If not, it was kept in the dataset.

Then, using spaCy, tokens underwent the Part-of-Speech (POS) tagging phase and the following lemmatization. POS tagging consists in assigning the grammar meaning and classification to each token (e.g., verb, noun, adjective), while the lemmatization is used to convert a word in its root form (e.g., from plural to singular, form conjugated to the infinitive) and allow the following model to better perform. *Stop-words removal* took place once again to ensure the removal of all the non-useful words. In addition, the stop-words list was customized to include additional words that the company experts considered non-significant. Then, n-grams, which are a set of words (e.g., two for bigrams, three for trigrams, and so on) that frequently appear in the text, were identified in the scope of better contextualizing some problems.

### *4.2. Topic modeling and validation*

Topic modeling is a text-mining technique that is aimed at analyzing the content of a set of documents (corpus) to identify recurrent patterns that can be later generalized into topics. More in detail, topic modeling is based on an unsupervised approach, where documents that were previously not labeled, are labeled based on their content and the content of the corpus under analysis. To maximize the probability of identifying topics accurately, the dataset was pre-processed, as described in the previous sub-section. To run the analysis, the Latent Dirichlet Allocation (LDA) algorithm was used. The LDA algorithm uses a statistical and probabilistic approach to cluster documents into a set of topics that require to be validated. Methodologically, the validation of the topics follows the use of two mathematical indexes, the Perplexity (the lower, the better), and the Coherence (the higher, the better), as well as a manual check to ensure the correctness of the topics' content.

The algorithm provided in the genism package can be customized by setting the values of specific parameters (e.g., number of topics, chuck size, iterations). In the case of analysis, 14 topics were identified as the optimal number considering the perplexity score (113) and the coherence (0.65). It must be clarified that these scores are the ones that minimize the perplexity and maximize the coherence. Since the literature does not provide a clear indication of the optimal values for these indexes but only gives general indications for evaluation (the lower the perplexity the better, the higher the coherence the better), authors, after an evaluation of the topics content, considered the result satisfiable. The LDA algorithm provides as output a table with the topic number and the topic keywords, while the topic name must be manually defined by the user. Table 1 provides an overview of the topics and the related keywords as well as a short explanation of its content.

The table reports only part of the keywords associated with a topic. The more the keywords are explored, the more words can be found, even crossing other topics, which is something expected since there is the possibility that a customer might have a request involving multiple problems. The acceptance of these 14 topics followed the fact that their content was well clustered and no excessive overlapping took place. Once acquired the topics and validated their content, a model, able to categorize messages according to these topics, was created and saved. Following, the same model was used to analyze the single messages in the "Contact Message" column in the scope of assigning a topic to each message. One of the problems with the LDA algorithm is that it does not return the simple belonging of a message to one topic but returns probability scores that can be used to understand to what topic the message belongs. For instance, it might assign a probability of 75% to belong to the topic "Trigger code", 24% to belonging to the topic "Format", and another probability of 1% split over the 12 remaining topics because, due to the way it is designed, it must assign a probability to each topic. Once assigned the probabilities score for each message, the "main topic" was identified for each one. The identification of the main topic follows the selection of the maximum score value assigned to the message (e.g., if the maximum value assigned by the LDA model is 75% for Topic_01, it means that the message deals with the "Trigger code" topic).

Following, the records in the dataset were clustered according to the main topic identified for each one of them. Then, the authors analyzed the "Suggested Activities" column, as discussed in the next subsection.

Table 1. Topics, keywords, and topics explanation

| Topic Number | Topic | Keywords | Topic explanation |
|---|---|---|---|
| Topic_01 | Trigger code | Code, trigger, trigger code, request, code request | It deals with problems related to the code required to make the machine function after certain problems occurred. |
| Topic_02 | Ring | Problem, ring, problem ring, communication problem, fiber | It deals with problems related to the item that connects the various components of Company A's machines through high-speed signal interchange. |
| Topic_03 | Oven | Oven, oven problem, alarm, machine error, error oven | It deals with problems in the oven, that cover a fundamental phase in the production process. |
| Topic_04 | Format | Format, request format, problem format, format machine | It deals with problems related to the kind of product produced. Different formats lead to the production of different products. |
| Topic_05 | Password | Request, password, password request, change, request change | It deals with problems related to the password requested to modify some parameters in the machine. |
| Topic_06 | Communication | Communication problem, communication error, communication, oven communication | It deals with the problems related to the ability of the machine to communicate internally (e.g., between components) or externally (e.g., with the company cloud) |
| Topic_07 | Level | Level, need, level request, password level, send password | It deals with problems related to the password requested to access some functions of the machine. |
| Topic_08 | Warranty | New, warranty, reported, request warranty, installation, new format | It deals with problems related to the request for maintenance under or outside warranty. |
| Topic_09 | System | System, installation, change system, install system, request system | It deals with problems related to the software installed on the machine. |
| Topic_10 | Terminal | Terminal, error, terminal error, terminal installation, change terminal | It deals with problems related to the terminal used to control the machine. |
| Topic_11 | Film | Film, start, program, problem film, replacement film | It deals with problems related to the film used for the packaging of the products. |
| Topic_12 | Alarm | Replacement, alarm, change, warranty, send | It deals with some problems related to some alarms shown by the machine. |
| Topic_13 | Machine | Machine, start, start machine, system, error | It deals with some general problems related to the machine functions. |
| Topic_14 | Customer | Problem, oven, customer problem, communication customer, request | It deals with generic problems described by the customers |

### *4.3. Results*

Once the clusters of “Suggested Activities” were created, they were analyzed in the scope of identifying common solutions or tests suggested by the technicians to customers. One of the main problems that Company A is facing is the lack of standardization in the way information is collected from customers and suggestions are given. This is because a common troubleshooting approach is missing, and the resolution process heavily relies on the expertise of the technicians dealing with the customer and the ability of the customer in describing the problem.

Like in the case of the “Contact Message” column, the pre-processing steps were applied to the “Suggested Activities” one. This is justified by the fact that the authors and the company evaluated the risk of losing part of the information if the pre-processing phase was not run also in this case, especially considering that this phase exploited the word-count approach as the main tool for the information extraction.

Table 2. Topics, suggested checks, and specific actions

| Topic | Suggested check | Specific action |
|---|---|---|
| Trigger code | - Trigger code request | - Send trigger code |
| Ring | - Optical fiber interruption<br>- Check power<br>- Check connected components | - Replace optical fiber<br>- Plug-in power<br>- Replace broken components |
| Oven | - Check power<br>- Check the cable connection<br>- Check the integrity of the fan, inverter, and resistors | - Replace broken components<br>- Update the database with oven specifications |
| Format | - Check the format's existence in the database<br>- Check bearings | - Replace mold<br>- Replace bearings<br>- Update available format<br>- Move gearbox |
| Password | - Check password | - Send password |
| Communication | - Check cable integrity<br>- Check the connection between components<br>- Check peripherals | - Replace cables<br>- Plug-in connectors<br>- Connect peripherals |
| Level | - Check level required | - Send the password for the level required |
| Warranty | - Check the component warranty | - Propose quotation<br>- Send spare parts |
| System | - Check system installation<br>- Check the internet connection<br>- Check sensors | - Re-install system<br>- Connect to the internet<br>- Replace sensors |
| Terminal | - Check the terminal connection<br>- Check parameters<br>- Check power voltage<br>- Check connection with other components | - Fix installation problems<br>- Update parameters |
| Film | - Check film status<br>- Check the cutting blade | - Send technical data<br>- Change film typology |
| Alarm | - Check the power connection<br>- Check led status<br>- Check system | - Send activation code<br>- Replace led<br>- Replace broken components |
| Machine | - Check the machine database<br>- Check the cable connection<br>- Check power<br>- Check the component's integrity | - Restart the system<br>- Change bearings<br>- Change belt<br>- Change engine |
| Customer | - Confirm problem | - Send technical support<br>- Send documentation |

Specifically, the aim was to search for single words but, more important, for n-grams able to give better context on the check request or executed. In particular, this phase was run using the nltk library and the FreqDist() method. In this way, authors were able to extract, for each topic, a list of suggested checks proposed and attempted that were later used to improve the troubleshooting. Table 2 summarizes the most frequent actions and checks found. Due to space constraints, it is not possible to provide examples of the questionnaire for troubleshooting that Company A started developing after the analysis.

## 5. Discussion

The analysis carried out through the NLP approach was aimed at identifying the most common requests that technicians ask customers to verify problems and suggest solutions when the customers require support. Such a scope should be considered as a step towards the improvement of the troubleshooting process, which in turn can help improve the management of the ticketing system and that, in a wider view, contributes to the improvement of the PSS offering management and service delivery [8, 10, 19]. As far as the authors' knowledge, no other case studies have been presented in the field of PSS and maintenance, with some papers discussing the problem from a more general perspective without addressing the problem as discussed in this paper [20, 34].

Starting from the troubleshooting point of view, the results of the analysis allowed identifying a set of problems that are commonly encountered by the customers, and that require particular attention from Company A in the scope of offering a satisfactory service. While Table 2 provides a schematic overview of the results, Company A also used them to define a troubleshooting questionnaire adapted to the typology of problems that the customers have. The questionnaire is aimed at requiring specific tests, partially reported in Table 2, to check the most common causes of problems first and then check the less frequent causes. The definition of a standardized approach to the troubleshooting phase would allow for the provision of a quality service independently from the experience of the technician that is responsible for the activity. Moreover, in a wider perspective, the collection of data and statistics over the response of customers to the troubleshooting procedure (e.g., easiness in guiding them and retrieving the information, the correctness of the test required) would allow, in the long term, to update and improve the troubleshooting phase to identify in a shorter time the problem.

Similarly, this can be extended to the ticketing system, which can benefit from the creation of a list of common problems and resolution strategies both from the customer's and the technician's point of view. For the customer, it would be easier to check some control marks on the ticketing tool to better describe the problem and, following, allow the technician to identify the proper solution. On the other hand, this could also go in the direction of a more automated resolution system, where the customer enters the details of the problem through a guided procedure, and the system, depending on the problem, might immediately provide suggestions for resolution without the need of interaction with a human technician.

Eventually, the improvement of the troubleshooting procedure can be seen as part of a wider PSS offering improvement, where the analysis and collection of data related to the troubleshooting procedure could be used, as said, to make more efficient the problem identification and resolution phases but, on the other hand, could also be used in a more general improvement logic. In fact, by studying the more frequent problem requests and proposed resolution approaches, it would be possible for designers to modify the design of the product to allow for a reduced occurrence and a simplified maintenance procedure.

Thus, while on the one hand, the analysis and improvement of the troubleshooting process are targeted to provide operational benefits in terms of problem identification and resolution, thus looking at the day-by-day activities, on the other it can be considered to have an impact on the strategical and tactical level, with the re-design of certain parts of the machines, the revision of the maintenance policies (e.g., based on actual frequency of problem occurrence) and procedures (e.g., resolution approaches that might be transferred to customers instead of requiring the intervention of the technician).

## 6. Conclusions

The troubleshooting phase is one of the most important for companies offering field maintenance and help-desk services to customers. A good and straightforward troubleshooting procedure allows fast and correct identification of the problem and its cause, resulting in faster resolution and thus, short downtime, allowing the customers to continue production and maintain productivity at the expected levels. The provision of fast and reliable maintenance service is an important competitive factor for manufacturing companies dealing with the PSS business model since it is the ability to deliver service in a fast and efficient way that allows them to keep alive the relationship with the customers. For this reason, the development of a standardized and reliable troubleshooting approach, created from the analysis of historical data on causes and faults, and on the experience of technicians, is required to remain competitive.

In this context, the paper presents a case study where the NLP was used on the ticketing database of Company A, in the scope of clustering recurrent problems that customers ask for and the way technicians are used to answer them. Company A used the outcome of the analysis as a means to develop a standardized troubleshooting procedure based on a set of questions asked to customers when they encounter certain problems. Also, suggestions to solve the problems have been identified based on the content of the message exchange with customers.

Through the NLP approach, it has been possible to analyze in a short time the around 13000 customer tickets. The approach has been divided into two consecutive steps, the first one aimed at clustering problems, and the second one aimed at identifying checks/solutions. A manual analysis and classification of the whole dataset in a single session would have required days, while, once trained, the algorithm classified the whole dataset in few minutes.

From a academic and theoretical point of view, the approach demonstrated its usefulness in terms of contribution to the maintenance service improvement, especially considering a lifecycle perspective where the information collected through the tickets, in terms of problems or solutions, could be used to enhance the design of the machine (when shared with the design teams) or the way service is executed on the field (when shared with the service department and the customer service).

From a practical point of view, the case study demonstrated the validity of the approach, which allowed to analyze and summarize in a short time the content of the ticketing database, allowing to extract knowledge and define a more structured troubleshooting procedure to improve the process at the operational level. By using the knowledge extracted in terms of problems, Company A could also improve the ticketing software by adding classification fields that could be used to immediately show possible solutions to the customer or the technician, depending on how the service is structured.

The approach used in the case study could be further enhanced by deepening the analysis in the second step of the methodology, for instance by developing a LDA model specific for each problem since, as of now, the main solutions have been identified based on a simple frequency analysis. Further research, overcoming the limitations of the current research, will encompass the analysis of the ticketing solutions using the LDA as well as testing other approaches for the analysis of the database (e.g., BERT). Another major improvement to the research would be to cluster messages not only based on the topic but also based on the asset model.

## Acknowledgements

This paper was supported by the project National Recovery and Resilience Plan (NRRP), Mission 4 Component 2 Investment 1.3 – Call for tender No. 341 of 15/03/2022 of Italian Ministry of University and Research funded by the European Union (NextGenerationEU), Award Number PE00000004, Concession Decree No. 1551 of 11/10/2022 adopted by the Italian Ministry of University and Research, CUP F13C22001230001 MICS (Made in Italy - Circular and Sustainable).

## References

[1] Morlock, Friedrich. (2015) "Service Value Stream Mapping in Industrial Product-Service System Performance Management." *Procedia CIRP*.

[2] Beuren, Fernanda Hänsch, Marcelo Gitirana Gomes Ferreira, and Paulo A. Cauchick Miguel. (2013) "Product-service systems: a literature review on integrated products and services." *Journal of Cleaner Production* **47** (**May 2013**): 222–31.

[3] Pekkola, Sanna, Minna Saunila, Juhani Ukko, and Tero Rantala. (2016) "The role of performance measurement in developing industrial services." *Journal of Quality in Maintenance Engineering* **22** (**3**): 264–76.

[4] Lee, Sora, Youngjung Geum, Hakyeon Lee, and Yongtae Park. (2012) "Dynamic and multidimensional measurement of product-service system (PSS) sustainability: a triple bottom line (TBL)-based system dynamics approach." *Journal of Cleaner Production* **32** : 173–82.

[5] Pezzotta, Giuditta, Claudio Sassanelli, Fabiana Pirola, Roberto Sala, Monica Rossi, Sophia Fotia, et al. (2018) "The Product Service System Lean Design Methodology (PSSLDM)." *Journal of Manufacturing Technology Management* **29** (**8**): 1270–95.

[6] Mourtzis, Dimitris, Sophia Fotia, Marta Gamito, Rui Neves-Silva, Ana Teresa Correia, Philipp Spindler, et al. (2016) "PSS Design

Considering Feedback from the Entire Product-service Lifecycle and Social Media." *Procedia CIRP* **47** : 156–61.
[7] Bertoni, Alessandro, and Tobias Larsson. (2017) "Data Mining in Product Service Systems Design: Literature Review and Research Questions." *Procedia CIRP* **64** : 306–11.
[8] Sala, Roberto, Fabiana Pirola, Giuditta Pezzotta, and Sergio Cavalieri. (2022) "Data-Driven Decision Making in Maintenance Service Delivery Process: A Case Study." *Applied Sciences* **12** (**15**): 7395.
[9] Carvalho, Thyago P., Fabrízzio A.A.M.N. Soares, Roberto Vita, Roberto da P. Francisco, João P. Basto, and Symone G.S. Alcalá. (2019) "A systematic literature review of machine learning methods applied to predictive maintenance." *Computers & Industrial Engineering* **137** : 106024.
[10] Sala, Roberto, Fabiana Pirola, Giuditta Pezzotta, and Sergio Cavalieri. (2022) "NLP-based insights discovery for industrial asset and service improvement: an analysis of maintenance reports." *IFAC-PapersOnLine* **55** (**2**): 522–7.
[11] Lee, Shenae, Maria Vatshaug Ottermo, Stein Hauge, and Mary Ann Lundteigen. (2023) "Towards standardized reporting and failure classification of safety equipment: Semi-automated classification of failure data for safety equipment in the operating phase." *Process Safety and Environmental Protection* **177** : 1485–93.
[12] Naqvi, Syed Meesam Raza, Mohammad Ghufran, Safa Meraghni, Christophe Varnier, Jean-Marc Nicod, and Noureddine Zerhouni. (2022) "Cbr-based decision support system for maintenance text using nlp for an aviation case study." in *2022 Prognostics and Health Management Conference (PHM-2022 London)* IEEE; p. 344–9.
[13] Bertoni, Alessandro, and Marco Bertoni. (2018) "PSS cost engineering: A model-based approach for concept design." *CIRP Journal of Manufacturing Science and Technology*. Available from: https://linkinghub.elsevier.com/retrieve/pii/S1755581718300464
[14] Cibat, Janis, Thomas Süße, and Uta Wilkens. (2017) "An Ecosystem Approach as a Design Principle for a PSS-Specific Business Simulation." *Procedia CIRP* **64** : 223–8.
[15] Bertoni, Marco, and Alessandro Bertoni. (2022) "Designing solutions with the product-service systems digital twin: What is now and what is next?" *Computers in Industry* **138** : 103629.
[16] Coleman, Chris, Satish Damodaran, and Ed Deuel. 2022 "Predictive maintenance and the smart factory." [Internet]Deloitte; Available from: https://www2.deloitte.com/us/en/pages/operations/articles/predictive-maintenance-and-the-smart-factory.html
[17] Kolling, Camila, Janine Fleith de Medeiros, José Luis Duarte Ribeiro, and Donato Morea. (2022) "A conceptual model to support sustainable Product-Service System implementation in the Brazilian agricultural machinery industry." *Journal of Cleaner Production* **355** : 131733.
[18] Maleki, Elaheh, Farouk Belkadi, Eric Bonjour, Ali Slayman, and Alain Bernard. (2019) "Interface modeling for product-service system integration." *Systems Engineering* **22** (**6**): 471–84.
[19] Liang, Jeremy S. (2020) "A process-based automotive troubleshooting service and knowledge management system in collaborative environment." *Robotics and Computer-Integrated Manufacturing* **61** (**July 2019**): 101836.
[20] A, Darlington-Njoku Chidinma, Bhupesh Kumar Mishra, and Will Sayers. (2022) "Fault Log Text Classification Using Natural Language Processing And Machine Learning For Decision Support." in *2022 14th International Conference on Software, Knowledge, Information Management and Applications (SKIMA)* p. 98–103.
[21] Mo, Y., D. Zhao, J. Du, M. Syal, A. Aziz, and H. Li. (2020) "Automated staff assignment for building maintenance using natural language processing." *Automation in Construction* **113** .
[22] Hong, Sungil, Junghyun Kim, and Eunhwa Yang. (2022) "Automated text classification of maintenance data of higher education buildings using text mining and machine learning techniques." *Journal of Architectural Engineering* **28** (**1**): 04021045.
[23] Bhardwaj, Abhijeet Sandeep, Akash Deep, Dharmaraj Veeramani, and Shiyu Zhou. (2022) "A Custom Word Embedding Model for Clustering of Maintenance Records." *IEEE Transactions on Industrial Informatics* **18** (**2**): 816–26.
[24] Dima, Alden, Sarah Lukens, Melinda Hodkiewicz, Thurston Sexton, and Michael P. Brundage. (2021) "Adapting natural language processing for technical text." *Applied AI Letters* **2** (**3**): e33.
[25] Akhbardeh, Farhad, Travis Desell, and Marcos Zampieri. (2020) "NLP Tools for Predictive Maintenance Records in MaintNet." in *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* p. 26–32.
[26] Brundage, Michael P., Thurston Sexton, Melinda Hodkiewicz, Alden Dima, and Sarah Lukens. (2021) "Technical language processing: Unlocking maintenance knowledge." *Manufacturing Letters* **27** : 42–6.
[27] Bird, Steven, Ewan Klein, and Edward Loper. (2009) "Natural language processing with Python: analyzing text with the natural language toolkit." O'Reilly Media, Inc.;
[28] Honnibal, Matthew, Ines Montani, Sofie Van Landeghem, and Adriane Boyd. (2020) "spaCy: Industrial-strength Natural Language Processing in Python." [Internet]Zenodo; Available from: https://doi.org/10.5281/zenodo.1212303
[29] Blei, David M., Andrew Y. Ng, and Michael I. Jordan. (2003) "Latent dirichlet allocation." *the Journal of machine Learning research* **3** : 993–1022.
[30] Řehůřek, Radim, and Petr Sojka. (2010) "Software Framework for Topic Modelling with Large Corpora." in *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks* Valletta, Malta: ELRA; p. 45–50.
[31] Morstatter, Fred, and Huan Liu. (2018) "In search of coherence and consensus: measuring the interpretability of statistical topics." *Journal of Machine Learning Research* **18** (**169**): 1–32.
[32] team, The pandas development. (2020) "pandas-dev/pandas: Pandas." [Internet]Zenodo; Available from: https://doi.org/10.5281/zenodo.3509134
[33] McKinney, Wes. (2010) "Data Structures for Statistical Computing in Python." in Stéfan van der Walt and Jarrod Millman (eds.) *Proceedings of the 9th Python in Science Conference* p. 56–61.
[34] Iyer, Naresh, Nurali Virani, Zhaoyuan Yang, and Abhinav Saxena. (2022) "Mixed Initiative Approach for Reliable Tagging of Maintenance Records with Machine Learning." in *Annual Conference of the PHM Society*.