A Text Understandability Approach for Improving Reliability-Centered Maintenance in Manufacturing Enterprises

Theresa Madreiter, Linus Kohl, Fazel Ansari

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Theresa Madreiter[1, 2 (✉) [0000-0002-8096-2060]], Linus Kohl[1, 2 [0000-0002-3019-4403]] and Fazel Ansari[1, 2 [0000-0002-2705-0396]]

[1] Research Group of Smart and Knowledge-Based Maintenance, TU Wien
[2] Fraunhofer Austria Research GmbH
{theresa.madreiter, linus.kohl, fazel.ansari}@tuwien.ac.at

Abstract. Textual data majorly reflects objective and subjective human specific knowledge. Focusing on big data in industrial and operation management, the value of textual data is oftentimes undermined. Optimal use of data reinforces the integrative modeling and analysis of RAM (Reliability, Availability, Maintainability). Data-driven reliability engineering and maintenance management, gains benefit from textual data, especially for identifying unknown failure modes and causes, and solving problems. The scientific challenge is how to effectively discover knowledge from text data and convert it into automated processes for inferential reasoning, predicting and prescribing. This paper outlines how the reliability-centered maintenance in production systems can be improved by explicating and discovering human-specific knowledge from maintenance reports and related textual documents. Hence, a theoretical model for text understanding is proposed, which is demonstrated as a proof-of-concept demonstrator using real world manufacturing datasets. The text understanding model is represented by a three-dimensional matrix comprising three indexes, i.e. text readability, word associations within texts as well as sentiment. The implementation of the model as a software prototype involves using text mining techniques and machine learning algorithms. This paper emphasizes on the importance of knowledge extraction from text in the context of industrial maintenance, by demonstrating how an increased value of text understandability of maintenance reports correlates to an early stage detection of failure, the reduction of human failures and leads to an immense improvement of explication of human knowledge.

Keywords: Reliability, Maintenance, Human Failure, Text Mining, Industry 4.0.

1 Introduction: Unexhausted Potentials of Unstructured Data in Reliability Engineering and Maintenance

A high failure rate in an industrial system ultimately leads to high instability and low-efficiency in production, high operation costs, and poor process quality [1]. Failure rate is, therefore, a key indicator for evaluating a successful maintenance management strategy in reliability-centered manufacturing. In the era of Industry 4.0, success in terms of reliability engineering and maintenance management i) requires the reinforcement of data-driven strategies focusing on reliability, availability and maintainability (RAM), and thus ii) demands knowledge-based maintenance (KBM) strategies encompassing both predictive and prescriptive maintenance approaches [2]. KBM employs artificial intelligence (AI) for integrative analysis, modeling, predicting and reducing the likelihood of failures and thus increasing reliability and availability in production systems. Gaining benefits from multi-channel, multi-structured data sources, is thereby essential for thriving data-driven reliability engineering and KBM. Plausible implementation of data-driven reliability engineering and KBM across manufacturing enterprises, however, confront the following challenges, namely: i) inappropriate and inefficient use of multiple data sources, ii) suboptimal use of multi-structured data, iii) multimodality of data i.e. missing semantic correlation of information, iv) multiple and overlapping reliability-centered and maintenance strategy approaches, v) multidimensionality of maintenance organizations including actors and backend/frontend teams, processes and IT-systems, and vi) lack of benchmarked use-cases and economically as well as technically evaluated KBM approaches in industrial applications.

With the integration of IoT-based and embedded sensory systems in Cyber Physical Production Systems (CPPS) [3] as well as constantly evolving AI technologies, new possibilities for industrial application of data-driven reliability engineering and KBM strategies arise. However, in the literature of production and operation management, data-driven reliability engineering and KBM are mostly understood as umbrella terms referring to Condition based Maintenance (CbM) and Predictive Maintenance (PdM), i.e. applying statistical- and machine learning (ML) on structured data in order to optimize RAM [2]. Often the value of unstructured data, in particular text, is undermined or totally ignored [2]. This is mainly due to its unstructured data format, thus requiring pre-processing for converting text into machine-readable formats. Additionally, maintenance reports (e.g. log books, shift books, failure reports, repair protocols, etc.) are often characterized by informal language, incomplete sentences, incorrect syntax and technical terminologies, making knowledge extraction even more challenging. Therefore, standard text mining (TM) approaches are not sufficient for this type of text. In real-world manufacturing systems, however, the primary data type found in industrial databases is textual data, majorly reflecting objective and subjective human specific knowledge [4]. When pursing data-driven reliability engineering and KBM approaches focusing strictly on structured data, the potential of a large portion of relevant information is remained unexhausted. This reflects the fundamental problem of industrial maintenance in today's production systems, that relevant, up-to-date, and comprehensive knowledge is missing, which avoids achieving informed decisions [2]. In other words, informed decision-making should be based on multiple data sources and multimodal data, including structured and unstructured formats. In addition, optimal use of multiple data sources and multi-structured data may reinforce the integrative modeling and analysis of RAM indicators. Data-driven reliability engineering and KBM, therefore, may gain benefit from textual data, especially for identifying unknown failure modes and causes as well as improving troubleshooting processes for solving (non-routine/routine) problems and therefore lowering the human failure rate. The scientific challenge is how to effectively discover knowledge from text data and convert it into automated processes for inferential reasoning and predicting the moment of failure, and ultimately prescribing appropriate handling measures timely. In order to exploit the full potential of text and therefore, overcome the quality obstacles of maintenance reports, text understandability should be achieved, i.e. going beyond standard TM approaches (cf. Section 2).

Considering the discussion above the following research question emerges, “How can text understandability (TU) in industrial maintenance contribute to an increased reliability and thus, a lowered failure rate?”. The objective of this paper is, therefore, to i) propose a concept for TU in the context of industrial maintenance, focusing on creation of an objective function representing multidimensional TU and ii) provide a proof-of-concept software prototype for demonstrating plausible industrial application of the aforementioned concept.

The rest of the paper is structured as follows: Chapter 2 provides a literature review on the necessity of TU in maintenance. Chapter 3 introduces the concept of TU, its industrial proof-of-concept implementation and expected industrial impact. Finally, Chapter 4 concludes the discussion and identifies the pathways for future research.

2 State-of-the-Art and -Practice: Why Does Text Understandability in Maintenance Matter?

Knowledge extraction and discovery from text is used to discover hidden patterns and valuable information using AI algorithms [4]. Where knowledge discovery focuses on identifying and understanding valid, novel and useful patterns in data [5], TM applies this approach to machine supported analysis of text. TM involves information retrieval and extraction technique as well as natural language processing (NLP) combined with algorithms from machine learning and statistics to process and analyze unstructured data sources [6]. This enables (semi-)automated identification of relevant words in those texts using Named Entity Recognition (NER) and Part-of-Speech (POS) Tagging. Linking these words to quantitative information (e.g. costs, production quantities) can further enhance text understanding and therefore lead to increased knowledge gain [7]. These matched entities can then be used in subsequent steps to enrich databases and ML models further [8]. A typical TM pipeline for extracting relevant knowledge from one or more data sources includes the following steps: i) extracting the text from documents or web pages [9], ii) preprocessing and iii) extracting domain-specific information using advanced techniques like NER [8]. This entity relation extraction allows linking entities labelled by domain-specific tags and the information related to them.

However, a major challenge for the extraction of knowledge from maintenance reports is their unique form, often not meeting standard text quality measures in terms of syntax and semantics. Maintenance reports often feature informal language, special characters, individual abbreviations, domain (company) specific expressions and incomplete sentences [7, 10, 11]. Additionally, maintenance reports are often multilingual featuring English as well as non-English expressions and thus the quality of reports often depends on the qualification and competence level of maintenance operators [7].

Effective knowledge extraction requires handcrafted solutions for measuring associations, and the structured representation of domain-specific context [11]. In order to overcome the limitations of current approaches, the human (expert) ability to understand text should be reproduced by algorithms. Therefore, the knowledge extraction from maintenance reports requires text understandability methods, rather than a standard TM pipeline.

Despite foreseeable advantages of text understandability, the body of literature in maintenance mainly reflects knowledge extraction and discovery from textual data, using TM. The majority of the state-of-the-art approaches restrictively aims to extract specific information from text rather than fostering TU. Notable examples are summarized in Table 1, which consider textual maintenance data in various industries, trying to extract specific information, e.g. the time of failure or frequent occurring incidents.

Table 1. Research considering TM in maintenance

Key statement	Extracted Information	Industry
increased accuracy of failure times for reliability using TM [12]	time of failure	energy industry food industry
detection of causalities and comprehension of incident progress patterns using NLP [13]	flows of events of accidents	space industry
extraction of information about component failure patterns using TM, which enables the identification of frequent warning and failure incidences [14]	components causing frequent warnings/failures	facility management
frequent incidents detection in building sectors based on characteristics using text analytics [15]	frequent incidents	facility management

In order to fully comprehend textual data in maintenance and exploit the comprised knowledge, a close to human-like TU model for the analysis of textual documents should be established. According to psycholinguistics, the human's TU is a complex and dynamic process, that takes place on various levels, including a syntactic and a semantic level [16]. In order to comprehend text, humans build and access a complex inner dictionary, storing syntactic and semantic information as well as generated inference, by linking previously gained knowledge with information from recent events [17, 18]. As a first approach a compositional framework for text understanding has been introduced by Ansari [7], focusing on text analysis in industrial maintenance.

3 Text Understandability in Maintenance: Conception and Industrial Proof-of-Concept Implementation

3.1 Text Understandability as an Objective Function

TU is defined as an objective function representing the multidimensionality of automated text comprehension, where multiple dimensions and related criteria identified mainly from language; syntax, semantics, and context as well as target objective function (e.g. cost, quality, time, productivity, etc.) contribute to a holistic modeling of TU. In this paper, the multidimensionality of TU is limited to three dimensions i) text readability, ii) extracting hidden sentiments and iii) existing associations, where each dimension increases the comprehension of text. Thereby, text readability, assures the interpretability of textual data, sentiment analysis reveals an author's opinion towards a certain topic or event, and association measurement extracts associable terms and expressions to enable further inference generation through linking newly extracted information with previously stored knowledge. TU can, therefore, be visualized as vector in a n-dimensional space, representing the relations between its features. Fig. 1 depicts the n-dimensionality while the proposed objective function is limited to three dimensions.

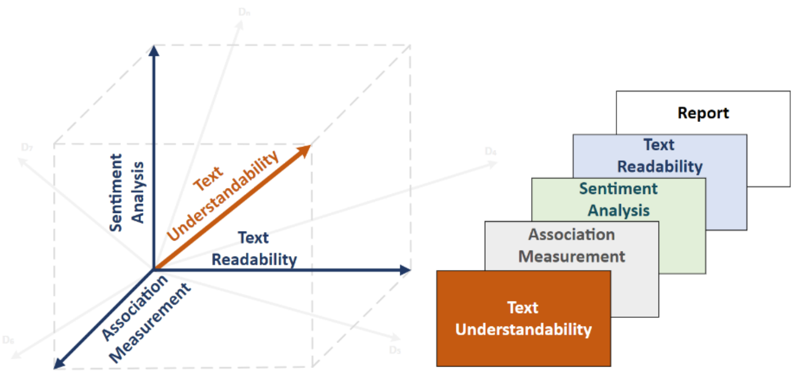

Fig. 1. Representation of a 3-D objective function for TU [19]

3.2 Procedural Model for Realizing Text Understandability

Based on the aforementioned concept, a procedural model for the realization of TU in the use case of industrial maintenance has been designed, as illustrated in Fig. 2. The concept is based on a standard maintenance process, where after the repair of failure, a maintenance report is written. Given an input maintenance report, the text readability is evaluated, since the extraction of relevant information requires the fulfillment of at least some basic readability criteria. However, readability standards applied to textual data depend on the information that needs to be extracted from text. Notably, generic quantitative measurements for text readability to evaluate the text readability from a human's perspective (e.g. Flesch-Kincaid GradeLevel Formula) assess text readability based on very limited factors (i.e. number of words and syllables) [20]. Therefore, the text readability proposed in this paper enhances and adapts existing approaches for the evaluation of human text readability [21] and additionally incorporates indicators for machine readability (i.e. unusual punctuations or spelling mistakes), that prevent the usage of automatic syntax parsers [21, 22]. In particular, text readability is evaluated through i) text length, ii) detectable language, iii) usage of special characters as well as iv) correct spelling, enabling the exclusion of uninterpretable reports, and thus a higher accuracy of recommended reports.

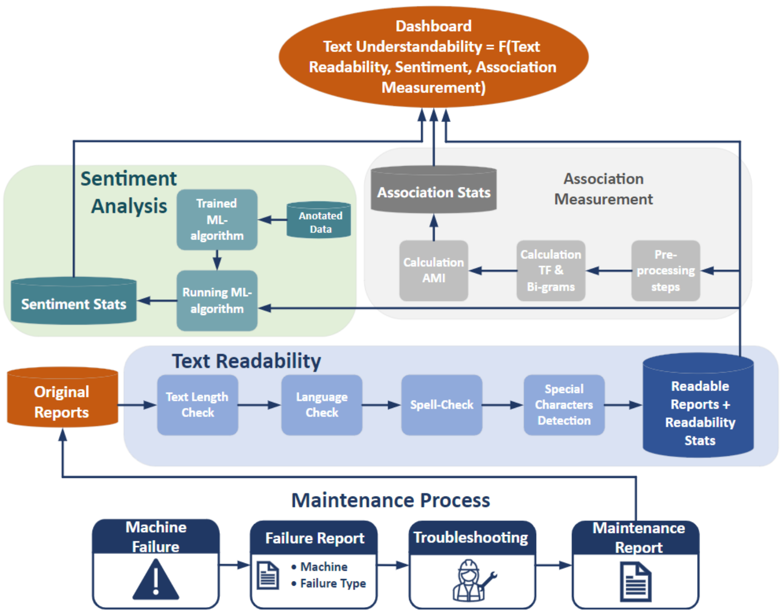

Fig. 2. Procedural model for TU in the use case of industrial maintenance [19]

Further, psycholinguistics suggest that humans achieve text comprehension and further inference generation through linking newly extracted information with previously stored knowledge. On this bases, association measurement takes place within reports to identify associative features (i.e. machine, operator, etc.). For each single report and the selected feature, comparing to all reports belonging to the selected feature, the most associable expressions and bigrams are being extracted using term-frequency (TF) and bigram-frequency (BF). The applied approach is based on term frequency – inverse document frequency (TF-IDF), a method successfully applied in the field of law to measure similarities among legal documents [23]. Due to the short texts and the initial removal of stop words, TF and BF are used due to achieving better results than TF-IDF. Within a report, the context dependent associability of used words and bigrams to a specific feature, is reflected by an Association Measurement Index (AMI) calculated based on TF and BF.

Sentiment analysis is frequently used in social media to gain insights on how users feel about certain topics [24]. However, the application of sentiment analysis is not limited to social media and can also be applied to technical documents. Applying sentiment analysis on maintenance reports reveals the opinion of maintenance employees towards certain maintenance actions and provides further information especially in terms of very short reports [7]. Due to the short text length of maintenance reports and their similarity to short social media posts, the proposed approach employs supervised ML algorithms, which are often effectively applied to determine the sentiment of tweets [24]. Certain classifiers such as Support Vector Machine (SVM), Logistic regression (LR) and Bernoulli naïve bayes (BNB) have been trained on pre-annotated test datasets. Due to achieving the highest accuracy (BNB: 78.1%, SVM: 75.0%, LR: 72.3%) on a pre-annotated test dataset, the BNB classifier is used to determine the sentiment for each processed maintenance report.

In a last step the TU is calculated based on text readability, the AMI as well as the assessed sentiment. Then the TU, as well as the extracted understandability features, are displayed in a dashboard for each report.

3.3 Development of Proof-of-Concept (PoC): TU-MARS Software

Based on the proposed procedural model, a software demonstrator for "Text Understandability by Measuring Associations, Readability and Sentiment (TU-MARS)" has been implemented. TU-MARS analyzes maintenance reports from the semiconductor industry in the format of unstructured free texts, written by maintenance operators after the fix of an incident. The to-be analyzed reports are characterized by their i) short text length, ii) incorrect syntax and iii) often-missing semantics due to being quickly written in case of incident correction. Additionally, metadata such as the affected machine and the classified down event are provided. TU-MARS analyzes previously written maintenance reports and displays its TU measures as well as its multidimensional TU aspects, including text readability statistics, the sentiment and associable terms and bigrams in a dashboard, for a chosen equipment and an occurred down event (see Fig. 3).

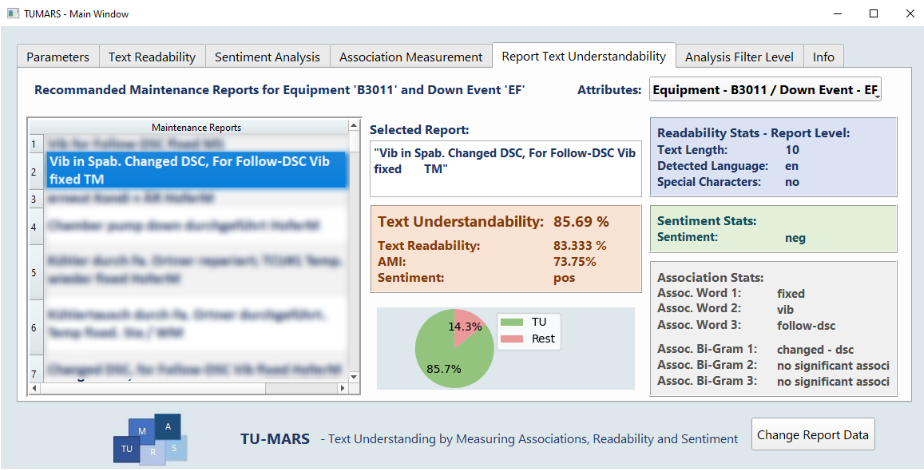

Fig. 3. TU-MARS dashboard for TU [19]

3.4 Potential Impact of TU in Industrial Maintenance

Through determining the TU of maintenance reports, knowledge from text can be included in informed decision-making processes, positively affecting industrial maintenance decisions and planning measures. A maintenance process usually starts with the occurrence of an incident on a specific machine and the classification of the failure by a machine operator. TU-MARS is able to identify highly interpretable and relevant previously written reports that have led to successful troubleshooting in the past, based on TU. For a specific machine and the occurred down event, maintenance operators are provided with the most fitting maintenance reports, based on their TU. Considering the displayed TU-measures in Fig. 3, the selected recommended report shows a TU of 85.69% due to the high interpretability (text readability: 83.33%), high relevancy (AMI: 73.75%) as well as a successful outcome (sentiment: pos) of the report. Based on the displayed associable maintenance actions and the domain specific knowledge of the maintenance technician, efficient maintenance operations for the current failure event can be derived and adopted. The proposed solution is based on the same dataset used by Ansari et. al. [25], where the authors were able to increase the uptime by 6.7% and the mean failure detection time by 97.3%, based on word recommendations for a classified failure event, and recommending the best-fitting maintenance operator. TU-MARS does not only provide word recommendations, but also previously written reports featuring a high interpretability, that lead to successful maintenance operations in the past and are highly associable to the current failure. Therefore, it can be expected, the mean failure detection time will increase by at least additional 10%, while also lowering the human failure rate up to 15%, by providing guidance during the maintenance operation. Thereby, each TU dimension contributes valuable information, enabling an increase of knowledge exploitation and potentially leading to a reduced equipment downtime, lowered human failure rate and earlier failure detection (cf. Fig. 4).

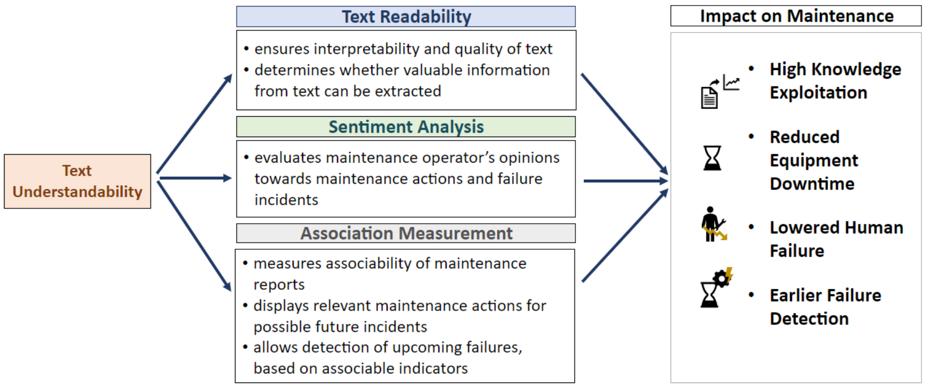

Fig. 4. Impact of TU on industrial maintenance

4 Conclusion and Future Research Agenda

This paper introduces a transferable and scalable concept and PoC for TU, demonstrating the potential of AI-enhanced text analytics in industrial maintenance. Compared to already existing approaches, TU offers a novel approach of knowledge extraction from text, by enabling multilevel text comprehension. TU-MARS displays beneficial maintenance reports and relevant technical terms, specifically for affected machines and occurred incidents, which the maintenance technician has to repair. The proposed concept is capable of reducing the human failure rate and time to failure detection, thus achieving an increased reliability, by effectively using hidden knowledge stored in maintenance reports. It ultimately enhances informed decision making in maintenance and production planning. Although, the proposed concept addresses the opportunities provided by TU in maintenance, the proposed approach needs to be further developed and verified dealing with the following industry-oriented and scientific challenges:

- *Exploring economic significance of text analytics in maintenance*, so that information from textual data are incorporated in production and maintenance planning and knowledge loss is prevented,
- *Establishing context specificity for text analytics in technical environments,* since standard TM solutions are not suitable to handle context-specific terminologies or abbreviations, and
- *Implementation of feedback loops,* so that the analytical results can be validated by domain experts in order to increase the value of proposed results of TU-MARS.

Finally, yet importantly, TU-MARS will be further developed by introducing further syntax-, semantic-, language- and context-specific dimensions focusing, but not limited to, industrial maintenance.

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