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Multi-sourced Modelling for Strip Breakage using Knowledge Graph Embeddings

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Abstract

— Strip breakage is an undesired production failure in cold rolling. Typically, conventional studies focused on cause analyses, and existing data-driven approaches only rely on a single data source, resulting in a limited amount of information. Hence, we propose an approach for modelling breakage using multiple data sources. Many breakage-relevant features from multiple sources are identified and used, and these features are integrated using a breakage-centric ontology which is then used to create knowledge graphs. Through ontology construction and knowledge embedding, a real-world study using data from a cold-rolled strip manufacturer was conducted using the proposed approach.

Keywords: Strip Breakage; Cold Rolling; Multi-sourced data; Ontology; Knowledge Graph

1. Introduction

As a fundamental industry sector, the steel industry is of great importance to the economy. Regarding the steel-making process of strip products, cold rolling is a secondary rolling operation after hot rolling with the aim to reduce the thickness and achieve desired mechanical properties using hot-rolled coils. During this cold rolling process, there are a number of production failures, among which the strip breakage is one of the most undesired failures resulting in severe consequences from roll damage to production delay [1]. Previous studies of the retrospective root cause analysis on strip breakages using physical or metallurgical methods have proved that the causes of strip breakage are diverse, which can be summarised into multiple facets [2-4].

With the rapid development of data collection techniques, a huge amount of data can be collected along the workflow of cold-rolled strips production. For this manufacturing process, data can be collected from multiple sources such as the hot-rolled coil (HRC), which is the incoming feedstock, annealing and pickling (A&P) process, emulsion record, the mill record during cold rolling and so on. Under this data-rich environment, to deal with this undesired production failure, the data-driven approaches [3, 5-9] is attracting attention. According to previous studies on strip breakages causes, regarding the occurrence of this failure, there are various reasons and scenarios all over the production process. In this context, the aforementioned data-driven approaches, which rely on a limited number of data sources, are usually not able to capture the complexity of such an intricate phenomenon [10]. With the aim to capture the functioning of this production failure, breakage-relevant data from multiple sources should be utilised collectively to cover the versatility of this failure.

However, breakage-relevant data are heterogeneous and are collected from a multitude of different providers along the manufacturing workflow in different formats. To incorporate multi-sourced data under the context of vast existing domain knowledge on strip breakage causes, we have proposed the use of ontology and knowledge graph technologies to create an integrated dataset for query and analysis of breakage-relevant data. Ontology is defined as a model describing structured and unstructured information through entities, properties, and the way they related to each other. As a semantic model, ontology can define and describe a wide variety of the entities, features and properties existing in a specified domain [11]. By using the knowledge concerning strip breakage analysis, a proper breakage-centric domain ontology ensures the formalisation of knowledge, making knowledge being readable for humans and computer methods [12]. Even though there are other approaches for knowledge representation such as taxonomies, logical models and topic maps, these schemas lack the ability to link between various concepts in multiple ways compared with ontology.

Subsequently, this breakage-centric ontology can serve as the representational foundation for the creation of the knowledge graph. Specific instances of each ontological relationship can be created using the tabular data as well as the breakage-centric ontology. This ontology serves as a model for the knowledge graph to capture breakage-relevant data by describing the structure of the knowledge in this specific domain. Compared with previous studies, more sources that are relevant to breakage, such as HRC, A&P, emulsion and cold rolling process, are considered in this work. With the creation of an integrated graph-structured dataset, data from heterogeneous sources can be fused under an ontological relationship. After the transformation of tabular data into the form of knowledge graphs, embedding methods can be applied to project the graph to a dense vector for breakage modelling.

The remainder of this paper is structured as follows. In Section 2, a systematic literature review of the strip breakage causes was first conducted, followed by a review on knowledge graphs creation using ontologies and knowledge graph embeddings. The flowchart of strip breakage modelling using the knowledge graph is introduced in Section 3. In Section 4, an experimental study using real-world data is reported to demonstrate the effectiveness of the proposed approach. Section 5 concludes and outline the future works of this study.

2. Literature review

2.1. Cold rolling process and strip breakage

For the manufacturing of cold-rolled strips, cold rolling is aiming at reducing strip thickness to a customer desired gauge, achieving the desired mechanical properties of the rolled strips and providing good shape with the desired surface finish. Within this process, the hot-rolled strip is rolled between two work rolls that are rotating, and a better metallurgical and mechanical property compared with the hot-rolled strip is achieved through this secondary rolling operation [13].

During the cold rolling process for strip products, several undesired production failures could occur. Among these failures, strip breakage has severe consequences such as work and backup rolls damage, yield loss and production delay [8]. By summarising related studies on the cause analysis of strip breakage, the causes can be concluded into four different facets.

The first type of possible breakage causes is material related issues. The hot-rolled coil (HRC) is the feedstock of the cold rolling process. The undesired physical or chemical properties of HRC can result in a breakage [14]. To be specific, previous work has discovered that there is a higher possibility for coils to break if any non-metallic material such as protective slag or oxide scale is inclusion in steel during the hot rolling process [15]. For the impurity of the strip, it was proved that the impurity has a negative impact on the homogeneity of the steel strip, which can contribute to a breakage [4]. Another work discovered that the material hardness and hardening through the deformation of cold rolling have an impact on the yield stress, which is an essential parameter when considering breakage [16]. In terms of the incoming HRC, apart from the chemical and physical properties, the surface condition, shape, and flatness of the strip derived from the roll gap model are the potential causes of strip breakage as well [17]. Other than HRC, the emulsion which acts as the coolant and lubrication also plays an important role in the occurrence of strip breakage according to the friction model, which describes the friction between the roll surface and strip using parameters such as strip speed, roll and strip surface roughness and lubrication [18]. Moreover, the conditions of stability and reliability of the hot rolling process are also proved to be influential with possible strip breakage [19].

Specifically, for electrical steel, the strips are annealed and pickled before cold rolling. For this process, hot-rolled coils anneal followed by water quench to control the precipitation of grain growth inhibitors. In addition, shot blast and pickle will be conducted to remove the scale of the strip, which will have an impact on the strip surface condition as well [20].

Secondly, equipment malfunction, especially the rolling mill, is proved to be another facet for breakage causes. In a previous case study [21], the strip is broke and crushed to the other side due to an inter-frame tension deviation resulted from mill malfunction. Another research [22] discover that the levelness and verticality of the steering roll of the uncoiler and the piston rod elongation of the hydraulic gauge control (HGC) system are potential causes for strip breakage. In addition, strip breakage can be caused by an unexpected high servo valve adjustment resulting from the defects of backup roll bearing [23]. Under this unexpected adjustment, the pressure fluctuations on both entry and exit sides are different, which results in tension deviation, which is a significant cause for breakages.

Thirdly, rolling operation such as inappropriate parameter settings were analysed to be the representative causes for strip breakage in some recent works. It has been concluded that the opposite effect will occur with the reduction of rolling speed, which can increase the risk of a strip breakage [4]. In a related study [23], the authors discovered that an inappropriate tension match between the entry and exit side leads to a large deformation on one side of the strip. Another study discovered that inappropriate tension and roll separating force setting caused by unreasonable HGC control is the main cause for breakage [24]. Moreover, the variation of specification such as maximum gauge, width and yield stress should be compensated during the rolling operation; otherwise, the breakage is more likely to occur [25].

Fourthly, the rolls such as the work rolls and backup rolls of the mill are proved to relevant with breakage in related works [3, 22, 26]. The roll wear applies an adverse effect on the shape of strips, which can further result in a strip breakage [3].

According to the roll wear model, which calculates the time-dependent thermal contours of the rolls [26], the roll contour and roll temperature have an impact on the roll wear. In terms of the roll contour, the bending model, which describes the roll bend, roll contour and flattening between the work roll and support roll, should all be taken into consideration for the calculation of bending. In addition, both the convexity degree and diameter disparity of the work rolls have been discovered to be possible causes for strip breakage [22]. Another research discovered that imperfections of the backup rolls and working rolls could result in uncontrolled mill resonance, which is the main cause for strip breakage [27].

2.2. Knowledge graphs creation using ontologies

In terms of knowledge representation and management, ontology utilised pre-defined classes and properties to express knowledge and relationships in an understandable format for both machine and human [28]. However, only the general entities or concepts that share the same properties are described in an ontology rather than the description of a specific individual in a specified domain. Ontologies have been applied in a number of works, from the recommendation system [29] to product family design [30, 31].

Compared with ontology, the knowledge graph is the manifestation of the ontology to the specific content. It is a specialised graph of the things we want to describe by capturing related data with ontological relationships. This graph can link multi-sourced data with the integration of structured and unstructured information [32].

Even though there are differences between ontology and knowledge graph, an ontology that serves as a framework to model the content of multiple data sources can be applied to create a knowledge graph. Recently, ontology has been used as a solid tool to construct a knowledge graph in a lot of works [33-36]. Accepted terminologies and genomic reference versions are used as sources for knowledge graph creation [33]. In this work, the creation process is defined as a data integration system for these sources. Subsequently, the RDF mapping language (RML) and the Function Ontology (FnO), which define how the ontology concepts are populated with data from the sources, were used among data sources and domain ontologies for knowledge graph creation. In another work on drug-drug interaction prediction [35], an integrated knowledge graph was used as a tool to incorporate multiple data sources. The creation of this knowledge graph was conducted by fusing information from existing knowledge bases and scientific literature. Moreover, an air traffic management (ATM) knowledge graph was created using the ATM ontology constructed by NASA [36]. This ontology defines key classes of entities for the management of the air traffic system and serves as the representational foundation for the subsequent knowledge graph. By populating a huge amount of historical infrastructure, flight, and weather data into this ATM ontology, a corresponding knowledge graph was generated with instances derived from real-world ATM data sources.

2.3. Knowledge graph embeddings and their application in machine learning

By transforming the knowledge into latent vector space representations, knowledge graph embedding algorithms enable an easy way to feed knowledge into machine learning algorithms and improved the modelling performance by introducing connected features [37]. Typically, embedding algorithms are divided into two different approaches, which are semantic matching-based models and transitional distance-based algorithms. In terms of the former approaches, a semantic transitional distance is used to capture the relational semantics of the knowledge graph embeddings. For the latter, entity and relation vectors interact via addition and subtraction.

Typically, the machine learning tasks on knowledge graph can be divided into four main categories, which are node classification, link prediction, community detection and graph classification [38]. For node classification, the objective is to predict the missing types of the nodes given the relationships network and node features. For link prediction, the goal is to predict whether there is a connection between two nodes [39]. In terms of community detecting, the task can be regarded as clustering of the nodes within a single graph [40]. For graph classification, multiple instances of different graphs are given to train the model on them [38].

3. Methodology

In this paper, as shown in Figure 1, a multi-sourced modelling approach for strip breakage using ontology and knowledge graph is proposed. In the first stage, a multitude of breakage-relevant data from different sources is collected. Then, based on our previous work [2], the breakage-centric features were identified and used as the concepts for ontology construction. By a systematic review of breakage causes, a lightweight breakage-centric ontology is generated in stage 2. Lastly, by populating the multi-sourced data into this ontology, the graph-structured data are embedded for graph classification.

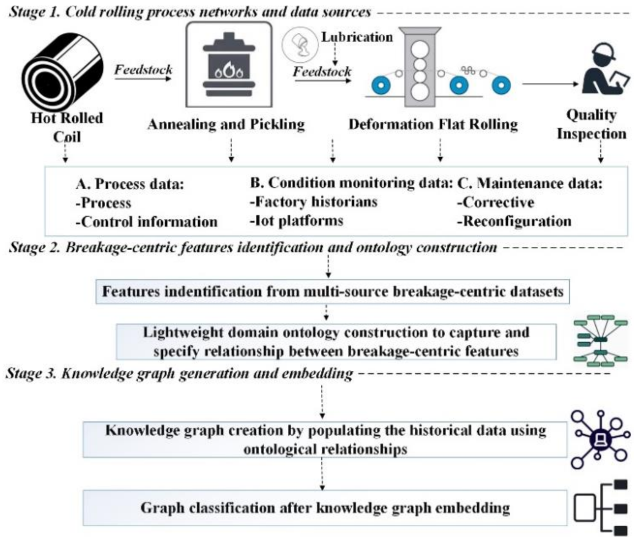

Fig.1. The flowchart of the proposed methodology.

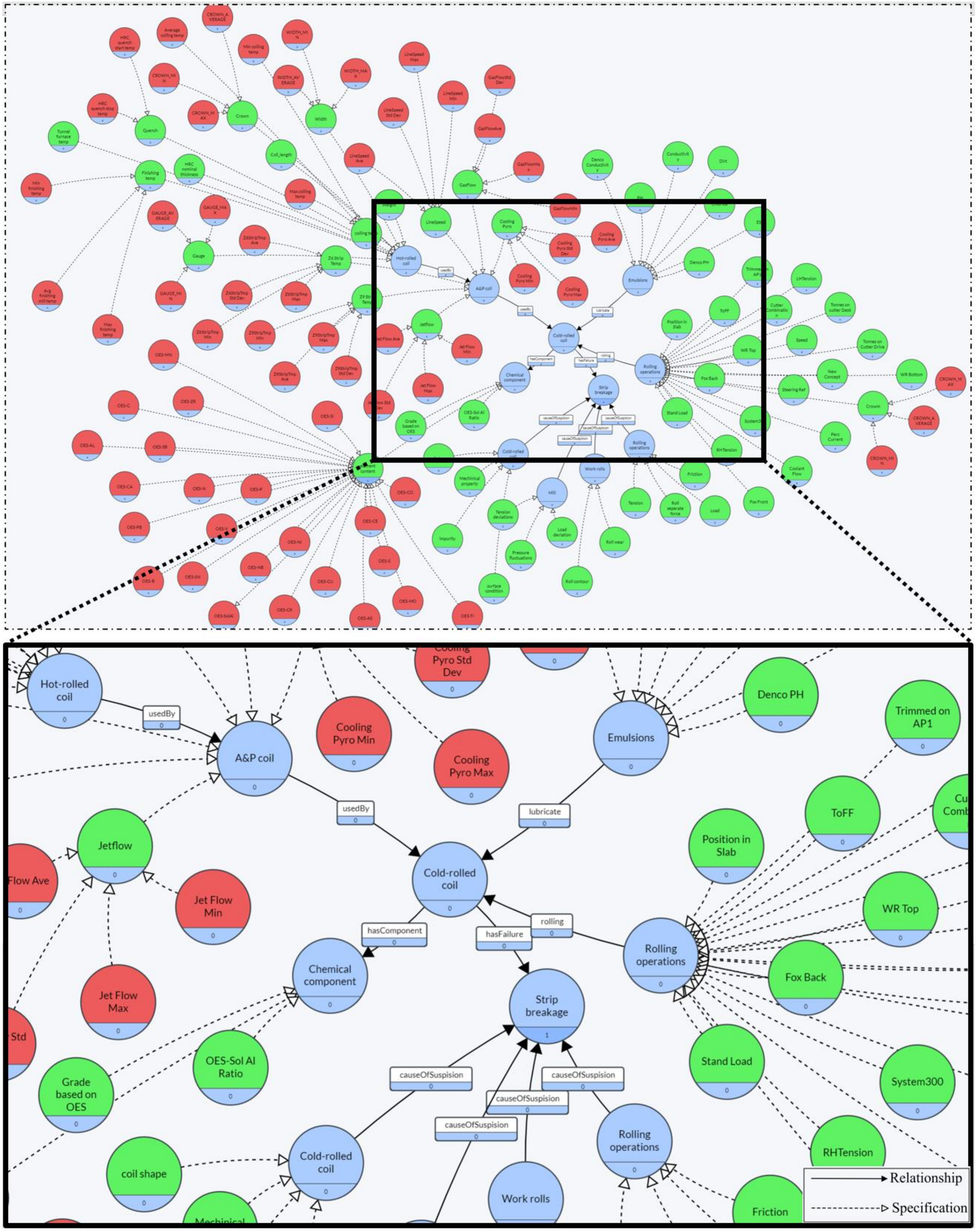

Fig.2. The whole and a zoom-in fragment of the lightweight breakage-centric ontology

4. Case Study

4.1. Data description

In this experimental study, the data was provided by an electrical steel manufacturer where a reversing mill is equipped for the cold rolling process. The grain-oriented electrical steel (GOES) is an iron alloy with a high silicon content (up to 3%). This element reduces magnetic losses by increasing the electrical resistivity of the material. As a higher concentration of silicon results in brittleness of the strip during cold rolling, breakages are more likely to occur for the manufacturing of these strips [3].

According to our previous study [2], data sources considering relevant with breakage are identified in Table 1.

Table 1. Details of breakage-relevant data sources

Data sources	Number of selected features	Representative features
Hot-rolled coils	15	Chemical content, Gauge, Crown, quench temperature.
Annealing and Pickling process	8	Annealing temperature, Jetflow speed.
Emulsion	9	Dirt result, pH, Conductivity, Chloride index.
Cold rolling process	17	Rolling speed, Tension, Measured slip.

A subset of the historical data, which was stored in a tabular format covering the production period of six months, was collected. For this dataset, 1324 coils were collected; 368 of them were labelled as "break" while the rest were "good".

4.2. Lightweight breakage-centric ontology construction

It can be concluded from the comprehensive review of breakage causes in Section 2.1 that the causes of strip breakage are varying considerably. Hence, in terms of modelling strip breakage using a data-driven approach, it is necessary to fuse data from multiple sources to generate collective information on this production failure. Given all the domain knowledge on the causes of strip breakage, it is possible to integrate data from various resources using this knowledge.

Typically, without close collaboration with domain experts, it is not easy to construct an ontology under a domain environment from scratch [41]. To specify domain knowledge, a lightweight breakage centric ontology is created by a systematic review on the cause's analysis of this failure.

The ontology was build using the Grafo software. The aim is to create an ontology to populate the tabular data from multi-sourced breakage-relevant data. The fragment of lightweight breakage-centric ontology based on the manufacturing process of cold-rolled electrical strips is shown in Figure 2.

In this study, the proposed ontology is in a three-layer concept hierarchy. The upper-most layer of the concept categories is constituted with concepts of the top-level breakage-centric ontology, which is the blue circles showing in the figure. The domain concepts relating to the breakage causes are subtypes of these meta-categories, represented in the green circle. For the bottom level, the application concept categories (i.e., the identifies features) are instances of the breakage-centric domain concept.

4.3. Generating knowledge graph using breakage-centric ontological relationship

The breakage-centric knowledge graph is constructed from four different structured data sources consisting of different data formats, which are databased tables, spreadsheets, and tab-based text format. These data were transformed into resources description framework (RDF) triples compatible with the breakage-centric ontology using the Grafo software.

Subsequently, these triples were loaded into the triple store using GraphDB software. GraphDB is a graph database software compliant with RDF and SPARQL specifications. It supports open APIs based on project and enables fast populating of linked data [36]. Multi-sourced breakage-relevant data was populated into this ontology using this software. The knowledge is represented by the subject-predicate-object format triples. Within these triples, the predicate indicates the relationship between an entity pair which is the subject and the object.

4.4. Knowledge graph embedding and Graph classification

With the aim to transform the information from this graph in a format suitable for the breakage modelling using machine learning, embedding techniques should be applied to transform the graphs into a vector space representation. Since the scope of this study is to propose the overall approach for KG generation and modelling rather than algorithms exploration, one popular approach, GRAPHSAGE [42] with global mean-pooling, was selected for knowledge graph classification. To be specific, the batch size was set as "32" with a learning rate of "0.01", the optimizer was set as the "Adam", and the loss function was section as the "binary cross-entropy".

In the context of graph classification, given a labelled graph dataset G where y_i is the label of G_i, the purpose of the task is to learn a function $f: G \rightarrow y$ that maps the graph to its label.

Compared with the coils under smooth-rolling operations, the coils which broke during rolling can be regarded as the minority. Therefore, considering the imbalance of the dataset, the area under the ROC curve (AUC) was applied as the performance metrics [43].

After fusing data from different blocks using the ontological relationships, the GRAPHSAGE graph-based approaches using graph classification achieved a performance of "0.603" in terms of AUC. Even though the data from multiple sources are integrated under the ontological relationship, the classification performance is barely satisfactory.

One possible reason could result from the relationship of a lightweight breakage-centric ontology, where the structural information between identified features has not been fully exploited yet. In addition, as a preliminary study using knowledge graph, the configuration of the various graph classification approaches needs to be further explored.

5. Conclusions and future works

In this study, we have described the process towards developing a knowledge graph resource using a lightweight domain-specific ontology for the modelling of a multi-faceted production phenomenon in the cold rolling process, including a preliminary case study on the classification of graphs generated through this approach.

In terms of our future works, connected graph features that represent the structural characteristics of the graph will be considered to enhance machine learning performance. Besides, to enhance the ability of linking and reasoning for a complicated situation, future work will focus on extending the breadth and depth of breakage-centric ontology.

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