A Multi-source Feature-level Fusion Approach for Predicting Strip Breakage in Cold Rolling

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***Abstract*— As an undesired and instantaneous failure in the production of cold-rolled strip products, strip breakage results in yield loss, reduced work speed and further equipment damage. Typically, studies have investigated this failure in a retrospective way focused on root cause analyses, and these causes are proven to be multi-faceted. In order to model the onset of this failure in a predictive manner, an integrated multi-source feature-level approach is proposed in this work. Firstly, by harnessing heterogeneous data across the breakage-relevant processes, blocks of data from different sources are collected to improve the breadth of breakage-centric information and are pre-processed according to its granularity. Afterwards, feature extraction or selection is applied to each block of data separately according to the domain knowledge. Matrices of selected features are concatenated in either flattened or expanded manner for comparison. Finally, fused features are used as inputs for strip breakage prediction using recurrent neural networks (RNNs). An experimental study using real-world data instantaneous effectiveness of the proposed approach.**

I. Introduction

Strip breakage is one of the most common and undesirable production failures during the production of cold-rolled strips [1]. This failure leads to severe consequences such as yield loss, an extended downtime caused by severe damage of rolling assets and an altered rolling performance when production resumes from a strip breakage [2-4]. Previous works on strip breakage have typically been analysed through retrospective root cause analyses after the occurrence of this failure [2, 5-7]. It is concluded that there are various causes for strip breakages from different problem spaces.

With the advancement of technologies which facilitate data acquisition and storage, various measurement devices are deployed throughout the modern steel-making process. This data-rich environment enables a handful of data-driven approaches [4, 8-10] to investigate this failure. However, firstly, these works were conducted for quality characterisation rather than prediction. Secondly, the data granularity taken in these works cannot match the temporal characteristic of strip breakage, which occurs instantaneously. Lastly, owing to organisational and technological restrictions, the consecutive steel-making processes is usually compactly deployed, and these processes are strongly correlated [11]. While in the aforementioned data-driven approaches, excluding cold rolling process data, other breakage-centric data were not considered.

New technologies have enabled the investigation of the steel-making process in multiple sources and dimensions with more accessible data. For the manufacturing of cold-rolled steel strip products, these dimensions include data from the Cold Rolling Process (CRP), incoming feedstock Hot-Rolled Coil (HRC), previous Annealing and Pickling (A&P) process and so on. In the meantime, no single data source can capture the complexity of all the factors relevant to a phenomenon such as a strip breakage [12].

In this context, we proposed a multi-source feature-level fusion approach for predicting Strip breakage. Data fusion was incorporated for breakage prediction for these reasons: firstly, since the causes of strip breakage are multifarious in problem spaces, a single measuring modality is typically inadequate. In contrast, multiple data sources can help improve the breadth of collected information [13]. Secondly, data measured on the same phenomenon from multiple sources can be combined to generate collective values, whilst potentially unnoticeable events can be fused into informative data [14]. Thirdly, multi-source heterogeneous data from the steel-making process is usually presented in large quantities. Feature-level fusion can reduce the size and dimension of the dataset by extracting useful information [15].

In this work, by harnessing heterogeneous data across the break-relevant steel-making processes, an integrative computational approach is proposed to tackle this prediction task. We start with a data collection and pre-processing stage, where breakage-centric data is collected following the production process of cold-rolled strip coils. Secondly, regarding the datasets originated from different sources, corresponding feature engineering technologies such as feature extraction and feature selection are applied based on the granularity of each data source, followed by a fusion of these features. Lastly, a sequence-to-vector Recurrent Neural Networks (RNN) architecture is used for modelling and evaluating the predictive performance.

The remainder of this paper is structured as follows. In Section II, a review of relevant studies of the strip breakage analyses and data fusion strategy from low- mid-level data fusion was first conducted. Section III outlines the flowchart of the proposed methodology for strip breakage prediction by fusing multi-source data. Section IV reports an experimental study using real-world cold rolling data to demonstrate the effectiveness of the method, followed by result analyses and discussions. Section V concludes this work.

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II. Literature Review

A. Strip Breakages in Cold Rolling

Cold rolling, as an essential process in the metal processing of sheets and strips, is widely applied due to its production rate and high efficiency [16]. Cold rolling is one of the primary metal forming processes in the production of steel strip. Strip properties such as surface smoothness, tensile strength, yield strength and hardness are enhanced by changing the microstructure and thickness of the steel [8]. Cold rolling can encounter inevitable failures such as edge cracking, central burst, surface defects and buckling [17]. Among these failures, strip breakages require special attention since it does not only significantly increases production costs and cycle time but also cause severe damage to mill accessories [18].

As a common and undesired production failure, plenty of work has been conducted on strip breakage in cold rolling. However, previous research on strip breakage has been performed in a retrospective manner focusing on root causes analyses. There are diverse causes of strip breakage in cold rolling as proved in [1, 2, 4, 6-9, 16, 19]. We can generally classify the causes into four categories such as feedstock property, equipment malfunction, improper rolling process operation and other causes.

Firstly, strip breakages can be caused by the chemical and physical properties of the feedstock, which is the hot-rolled coil (HRC) [20, 21]. By analysing and comparing the surface and mechanical defects of HRC, it is considered that there are two reasons for the strip breakage during cold rolling. One is the protective slag involved in the steel-making process, and the other one is the oxide scale pressed into the hot rolling process [21]. Secondly, equipment malfunction has also been analysed as a common cause of strip breakage. For instance, a high-pressure fluctuation results from servo-valve malfunction can lead to inter-frame tension deviations. The deviations crush the strip to one side, which causes strip breakages [1]. Thirdly, inappropriate operation parameter settings is another critical aspect accounts for strip breakage. The parameters such as levelness, the perpendicular position of the deflector rolls, diameter disparity between the top and bottom work rolls, levelness of the bottom work roll and convexity degree of the work rolls have been discussed as the significant strip breakage causes [2].

B. Data Fusion Strategies

As reviewed in Section II-A, there are various causes for strip breakages in the cold rolling process. In other words, the problem of strip breakage needs to be investigated in multiple dimensions that include feedstock properties, equipment malfunction, improper rolling process operation and other causes. In this case, no single data type can capture the complexity of all breakage-centric factors describing the phenomenon of strip breakage. Therefore, as an integrative method, a data fusion technique that combines data from multiple problem spaces should be considered.

The taxonomy of data fusion is defined as the methods to the analysis of multiple data sets jointly, and these methods are dating back to the 1990s [22]. For now, there are several definitions of the term "data fusion" presented, which mainly differ in the specific research areas [23]. For the case herein presented, the data fusion gathers enhanced information about strip breakage phenomena which are observed from different problem spaces. Therefore, the definition reported in [24] is preferred: "Data fusion is a formal framework expressed as means and tools for the alliance of data originating from different sources."

Besides the definition of data fusion, three levels were defined to represent at which level fusion is operated [25]. Low-level data fusion is directly applied to data sets at an observational level. Mid- or feature- level is where data fusion operates on extracted features from pre-processed data in more general terms. High- or decision- level is where the outcomes of the models based on each data source are fused [23].

To be specific, firstly, data fusion at low-level may be conducted by simply concatenating different data blocks or by applying various joined or coupled methods on data blocks. The main advantage of low-level data fusion is the possibility to interpret and backtrack the results from the original variables [26]. Secondly, regarding data fusion at mid-level, two approaches are typically applied, 1) feature selection methods, and 2) decomposition techniques [22]. When feature selection is applied, the model interpretation regarding the original variables is straightforward. In contrast, when a decomposition technique such as principal component analysis (PCA) is applied, it requires a back-linking between the salience of each feature to its pattern. Thirdly, the fusion of modelling results from each independent data block is defined as the high- or decision- level fusion. Therefore, the role of each data set from different sources is not investigated while the focus on the final performance of the disjoint modelling on each data set is performed [23].

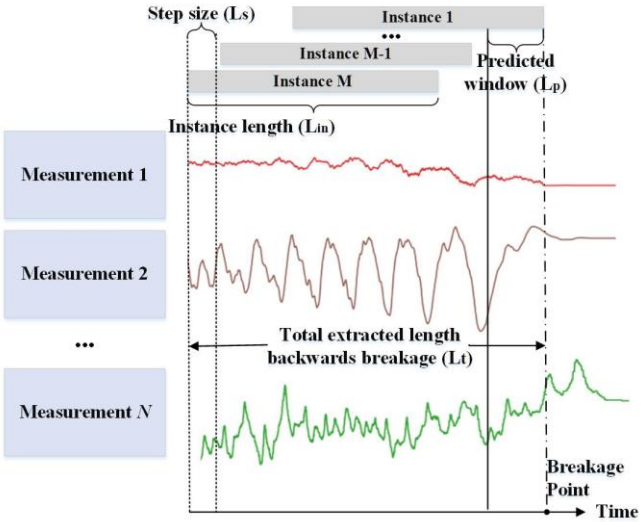
III. Methodology

In this paper, a multi-source feature-level fusion approach for predicting strip breakage in cold rolling is proposed, as shown in Figure 2 below. Breakage-centric data is collected following the production process of cold-rolled strip coils in stage 1. For the next stage, regarding the datasets originated from different sources, feature extraction and feature selection are applied based on the granularity of each data source, followed by a fusion of these features. In stage 3, a sequence-to-vector RNN architecture is applied for modelling and evaluating the predictive performance.

A. Data Collection and Pre-processing

As reviewed in Section II-A and suggested by the domain experts, the preparatory processes before cold rolling should be deemed as potentially relevant with strip breakage. It should be noted that regarding the collection of CRP data, which is typically recorded in a multivariate time-series manner, the concept of recency should be incorporated. Since strip breakage is an instantaneous failure, the temporal observations that extend far from the breakage point into the past are believed to be less informative than breakage-recent observations [27]. In this context, data was collected in a run-to-failure manner, from the strip breakage time point backwards in time to obtain the most recent observations of breakage. Besides, a segmented time window conveys more information than a single time point; a sliding window strategy is adopted to segment the raw time-series data into a collection of pieces, as illustrated in Figure 1.

Figure 1. Illustration of proposed sliding window strategy



Through this sliding window strategy, an instance is a two-dimensional matrix containing $\mathbf{L_{in}}$ sampling points (i.e. the window length) with **N** attributes. By sliding window backwards in time from the breakage point following a selected step size Ls, the total window length is segmented into **M** instances. The label of each instance is determined by the interval between the last sample point and the strip breakage point. If the interval is wider than the predefined predicted window length $\mathbf{L_p}$, the corresponding instance is labelled as "good" representing no breakage. Otherwise, if the interval is within the pre-set predicted window length, the corresponding instance is labelled as "break", which represents the coming breakage. Under this manner, the label is a binary class representing whether the strip will break within the specific predicted time window.

B. Feature-level Data Fusion

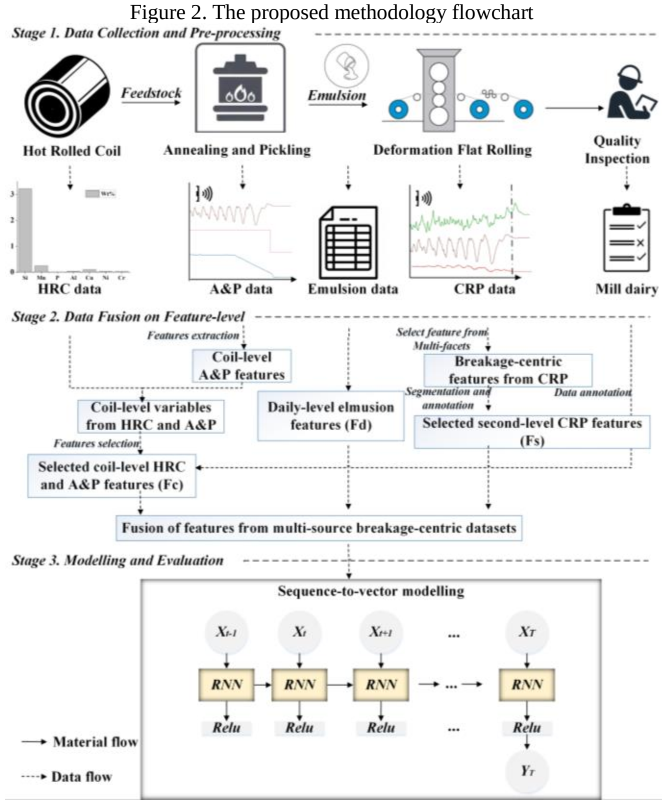
Besides the CRP data, the A&P data is also recorded in a real-time manner from the continuous annealing and pickling process. This process affects the occurrence of strip breakage from the feedstock aspect, such as strip roughness. The probability of breakage can be increased by failing to remove all the scales from HRC strip during A&P process. In this case, feature extraction is applied to transform the time-series A&P data into a feature vector representing the A&P process details of each coil. In this study, we consider a list of time-domain features to describe the A&P process characteristics.

Feature extractions are performed on A&P data to extract these data into features at a coil-level granularity. Then these features are concatenated with HRC data which is measured per coil. Subsequently, feature selection is conducted on the concatenated HRC and A&P dataset with the annotation of "good" and "break" coils to find optimal features subset Fc. Meanwhile, features Fs from CRP data are selected based on previous physics-based models and empirical knowledge of the strip breakage at the granularity of seconds. By tracking material genealogy, emulsion features Fd at the granularity of daily level are fused with Fs and Fc.

C. Modelling for Strip Breakage using Fused Features

With the fusion of features from multi-source data, the task is set to be a binary classification problem to classify whether a strip will break within a specific time window using these fused features. For this task, a supervised learning approach based on sequence-to-vector recurrent neuron networks (RNNs) architecture was proposed. To be specific, an instance entering the proposed RNNs architecture is a two-dimensional matrix containing **r** sampling points (i.e. the window length), with **N** attributes. As illustrated in Figure 2, the proposed RNNs are applied to classify the multivariate time-series. Input data for a time slice represented as a matrix instance ($\mathbf{r} \times \mathbf{N}$) is fed into the recurrent layers, and only the output of the last neuron is fed into the linear layer (the rest are ignored). This output is subsequently fed into a linear layer which embedded with an activation function to make binary predictions.

Figure 2. The proposed methodology flowchart



IV. EXPERIMENTAL STUDY

The experimental study was conducted using the historical data provided by a cold-rolled silicon electrical steel manufacturer. Compared with general low carbon steel strips, the silicon steel strips are lower in toughness due to a high silicon content [28]. In this context, strip breakages are therefore more frequently occurred in the cold rolling process of the high silicon steel strips.

A. Data Acquisition

Data from four sources are considered to be relevant with strip breakage: hot rolled coils (HRC), annealing and pickling

(A&P), emulsion and cold rolling process. The data sources for strip breakage prediction are identified in the table below.

TABLE I DATA SOURCES FOR STRIP BREAKAGE PREDICTION

Origin of data	Relationship with strip breakage	Representative features
1. HRC	The information of chemical properties and strip shape parameters are included in HRC data, while these properties are critical for strip breakage [3, 20, 21].	Chemical content, Sol Al ratio, Finishing gauge, Crown measurement.
2. A&P	Annealing significantly affects the physical properties, while pickling is crucial for the surface condition [17, 21, 28].	Annealing temperature, Pickling material, Jet flow speed.
3. Emulsion	The emulsion acts as lubrication and coolant, thus significantly influence the friction and thermodynamics between strip and roll [29, 30].	Dirt result, pH, Concentration, Heat conductivity, Chloride index.
4. CRP	The CRP data is the direct and real-time measurements of the operations before the occurrence of breakage [3, 7, 8, 31].	Rolling speed, Tension, Measured slip.

The HRC, A&P, Emulsion and CRP data of 1324 coils were collected, and 368 out of them were labelled as "break" while the rest were "good". The HRC data consists of 47 variables recording the physical and chemical properties of each incoming feedstock hot rolled coil. The A&P data comprised of 18 variables recording the real-time annealing and pickling process on each incoming hot rolled coil at the frequency of 50***Hz***. The emulsion data was recorded in this steel plant daily with eight variables.

The CRP data was extracted from a production data acquisition (PDA) system, which is installed on-site. Cold rolling process variables are sampled and recorded continuously at a frequency of 100***Hz***. Due to the high correlation between neighbouring data points, a lower sampling rate results in a distortion compared with a higher rate. Meanwhile, using full-resolution data enables a detailed and accurate calculation of the breakage point. Therefore, to get the most information out of CRP data, we used full resolution for further segmentation. There are thousands of measurements being recorded in the PDA system; it is necessary to select the subset of the most relevant features. The domain of the text in the dataset is also of significant influence for the choice of features. For either a specific domain or in a non-domain dependent dataset, certain features work better [32]. It was decided to determine candidate feature sets from two facets. One is the physical-based features set derived from the previous physics-based models of strip breakage failure, and the other is the empirical knowledge features set with referring to domain experts. In this context, 17 features were identified from CRP data.

B. Segmentation on CRP Data

As shown in Figure 1, based on a sliding window strategy, an overlapping segmentation was performed on CRP data. The sliding window parameters were set as follows: the total extracted length L_t is set to 30 seconds; the predicted window length L_p is set to 0.5 seconds, the instance length L_{in} is set to 29 seconds and the step size L_s is set to 0.01 seconds. To be specific, each coil set can generate 101 instances, 50 out of 101 were marked as "break", and rest were labelled as "good" under this parameter setting.

C. Feature Selection on HRC and A&P Data

Correlation-based Subset Feature Selection (CFSsub) [33] was employed in this study considering the task of finding the optimal subset of feature relevant and minimising the computational cost. For a subset S, an underlying importance score shown in Eq. 1 is used to represent the usefulness of the subset for prediction of the response class variable.

$$iScore = \frac{\mathrm{m}R_{cf}}{\sqrt{m+m(m-1)R_{ff}}} \quad (1)$$

where $iScore$ stands for the importance for subset S, R_{ff} and R_{cf} represents feature-feature correlation and response-feature correlation, respectively. As discussed in Section III-B, each the A&P variable measured at a frequency of 50Hz is extracted to 4 time-domain statistical features for each coil. Therefore, 47 HRC variables and 72 (18*4) A&P features were fused for the selected features at the granularity of per coil. By applying the CFSsub, 23 attributes were selected. To summarise, fused features were listed in Table II.

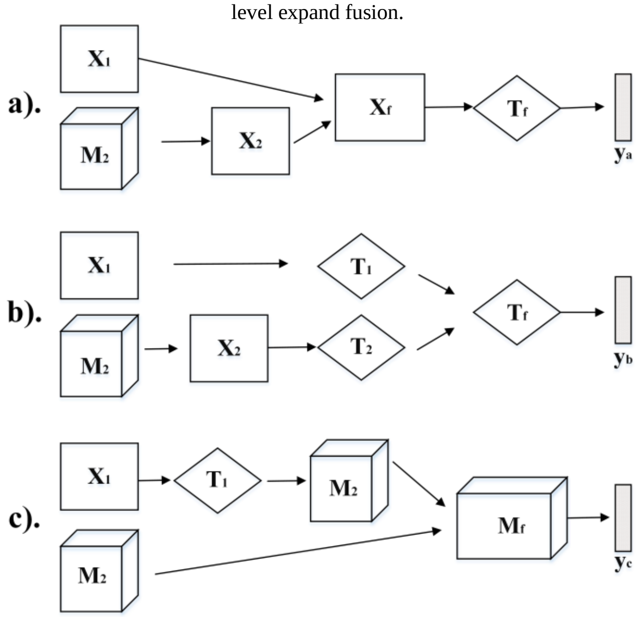
TABLE II. DETAILS OF FUSED FEATURES FROM DIFFERENT SOURCES

Origin of data	Raw data granularity	Number of selected features	Feature Granularity
1. HRC	Per coil	15	Per coil
2. A&P	Per 0.02s	8	Per coil
3. Emulsion	Per day	9	Per day
4. CRP	Per 0.01s	17	Time window covering 29 seconds

D. Experiment Design

Three different data fusion strategies were designed to reveal the merits of our proposed methodology and schematically depicted in Figure 3. Data-level or low-level flatten fusion (shown in Figure 3a) is the straightforward concatenation of different data blocks. However, in our case, the HRC, A&P and Emulsion data is batch-oriented, which means the data block is a two-dimension array shown as $\boldsymbol{X_1}$. In contrast, the CRP data is time-oriented with the data structure of the three-dimension matrix illustrated as $\boldsymbol{M_2}$. In this case, hand-crafted features were designed to extract the time-domain and frequency-domain features so that the CRP data block $\boldsymbol{M_2}$ is flattened to data block $\boldsymbol{X_2}$ which share one mode (the batch number) with $\boldsymbol{X_1}$. In this scenario, data fusion is conducted by directly fusing the data blocks. Figure 3b shows the middle level or feature level fusion of flattening features from data block $\boldsymbol{X_1}$ and $\boldsymbol{M_2}$. As feature extraction and selection of separate data blocks is conducted to generate a selected feature set $\boldsymbol{T_1}$ and $\boldsymbol{T_2}$ before fusing them, this approach can cope with large redundancy in the information from various measured variables. The Figure 3c shows the feature level fusion of expanded data where $\boldsymbol{X_1}$ is expanded to a time-oriented matrix $\boldsymbol{M_2}$ so that it can be fused with $\boldsymbol{M_1}$ to avoid information lost by time- and frequency-domain feature extraction.

Figure 1. Schematic overview of different designed data fusion scenarios: a) data-level flatten fusion, b) feature-level flatten fusion and c) feature-level expand fusion.



For scenario **a** and **b**, three conventional algorithms Random Forest (RF) [34], Support Vector Classification (SVC) [35] and Artificial Neuron Network (ANN) were deployed for breakage prediction using the open-source package Scikit-learn [36] with the default hyperparameters.

For scenario **c**, Long Short-term Memory (LSTM) network, Gated Recurrent Unit (GRU) and RNNs were applied using Pytorch [37], and Cross-Entropy is used as the loss function for this binary classification task. The efficient Adam [38] algorithm is used for optimisation. The model is fit for 100 epochs because it quickly overfits the problem.

Beside classification accuracy (ACC), the area under the ROC curve (AUC) is applied as one of the performance metrics here regarding the unbalance characterisation of the dataset [34].

E. Results and Discussions

The modelling results on different fusion strategies are shown in Figure 4 and 5. Generally, in terms of both AUC and ACC, the improvement of RNN-based models in scenario c compared to conventional approaches in scenario a and b is enormous. Since a segmented time window conveys much more information than extracted features, detailed representation of the cold rolling process using $\boldsymbol{M_2}$ surpass the flatten data block $\boldsymbol{X_2}$ in terms of strip breakage performance. This can also result from the nature of strip breakage, which occurs instantaneously; in this case, only a detailed and representation can capture the momentary pattern before breakage. However, RNN-based models are more computationally expensive than conventional approaches as a result of model complexity. Besides, a time-consuming hyperparameter selection is required for RNN-based models to achieve the desired performance.

Figure 2. AUCs of models with the best performance in predicting strip breakage in different scenarios

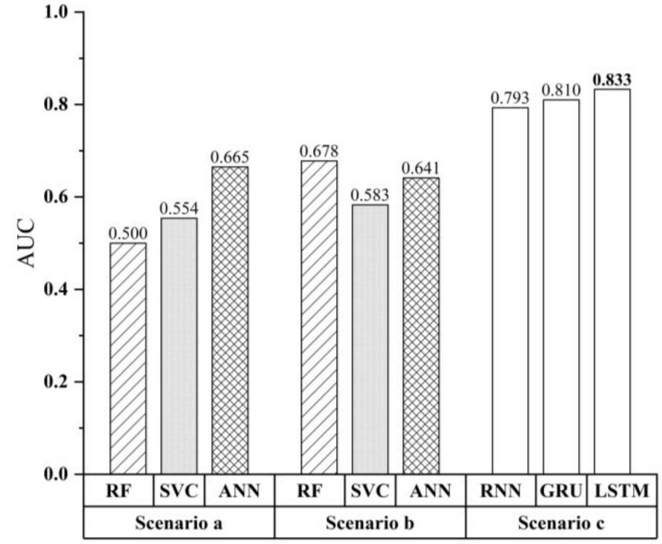
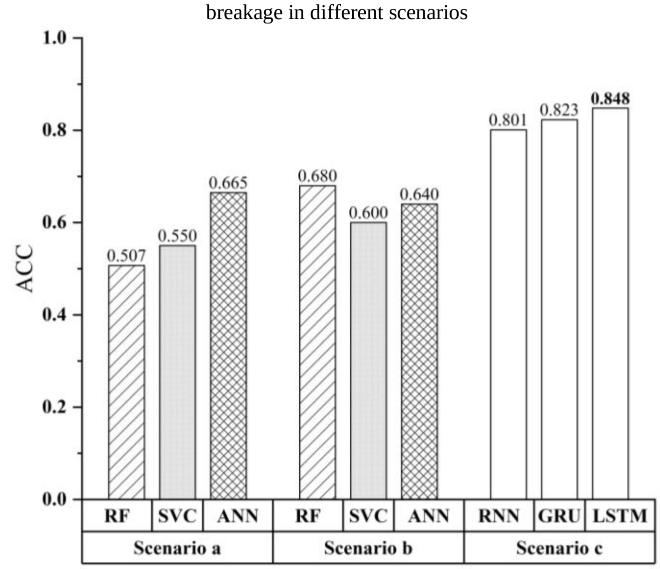


Figure 3. ACCs of models with the best performance in predicting strip breakage in different scenarios



Compared with low-level data fusion strategy, feature-level fusion is much less computationally expensive. Since low-level fusion is usually confronted with a large dataset after concatenation, it is less challenging to handle due to a lower-demanding memory and computation time. By comparing the results between scenario **a** and **b**, feature-level fusion strategy outperforms data-level strategy in terms of AUC and ACC. For conventional classification algorithms, mid-level fusion, which overcomes the difference in information density by extracting the predictive information from the blocks, performed better than low-level data fusion. However, feature-level fusion is demanding in terms of validation since it requires the application of feature selection algorithms for each data block from a different source.

V. CONCLUSIONS

We have demonstrated the effectiveness of feature-level fusion approach using selected HRC, A&P and Emulsion features and segmented time-window CRP data in terms of breakage prediction performance. Besides, feature-level fusion surpasses data-level fusion in terms of both computational cost and classification performance. Moreover, in terms of feature-level fusion through feature selection, extraction and identification, less effort is required to interpret the results compared with latent variable approaches. The cold rolling mill operator can benefit from utilising this prediction approach to their contingency mitigation strategies. According to the predicted information, a planned stop action can be taken to avoid damage from an unplanned fast stop. Understanding the likelihood of strip breakage soon can also be critical for post-analysis, such as determining what countermeasures should use.

Meanwhile, this approach did not recognise how different levels of granularity can result in regularities in the data. It is believed that different features and relationships emerge at different granularities. Further work will focus on trying to take advantage of this fact in designing more effective data fusion strategies for strip breakage prediction.

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