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Predicting fine blanking process signals from sheet metal thickness

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Abstract. In sheet metal forming and blanking processes, the direct assessment of process conditions and product quality poses a challenge due to high production rates and the inaccessibility of the tool. In this context, the process signals generated by the manufacturing process, such as force and acoustic emissions, have the potential to serve as a valuable source of information, containing important insights into the quality of the final product as well as the complexity of the process itself. To date, it is not yet fully understood how these process signals depend on different influencing factors, such as process parameters. However, knowing how process signals, which reflect the process state, change with influencing factors is relevant to put observed signals into context and make informed decisions with respect to parameter adjustments. Conditional generative AI models, such as conditional generative adversarial networks (CGANs) offer a promising approach to the aforementioned issue by generating probable process signals based on specified conditions. In this study, thin metal sheets with three different thicknesses were provided into a fine blanking process, and corresponding punching force signals were measured. With these signals, a conditional-deep convolutional GAN (C-DCGAN), a model that combines the principles of both CGAN and deep convolutional GAN (DCGAN), is trained with sheet metal thickness specified as a condition. The trained generator is employed to predict process signals for different sheet thickness values. The presented model is evaluated with respect to thickness values that were known during training time as well as with thickness values that were not presented to the model during training.

Introduction

Sheet metal forming and blanking processes are widely used in the automotive and aerospace industries due to their high production rates and stable quality, making them suitable for high production rates. Fine blanking, specifically, stands out with its capability to create a high proportion of smooth cutting surface [1], enabling its use in production of safety-related products, such as automotive seat belt tongues. Given the applications of the products resulting from this process, it becomes significant to monitor the tool's condition and strive to extend the tool's lifespan. While direct assessment of this condition is difficult due to their high production rates and the inaccessibility of tools [2], it has been recognized that indirect assessments based on process signals show potential in tackling these challenges. In wear monitoring, Unterberg et al. [3] analyzed acoustic emission (AE) signals in an industrial-grade fine blanking process and revealed potential correlations with the surface roughness of scrap webs, as a proxy for tool wear.

They suggested an approach for developing models that predict tool wear based on extracted features from AE signals. In another publication, Kubik et al. [4] presented a machine learning (ML)-based inline wear state quantification model using torque and force signals in the roll forming – fine blanking process chain. They classified the abrasive wear states of the punch into five stages, and based on this classification, they trained a ML model that is able to predict the wear states.

Despite recent research of indirect assessment of the process state through process signals, adjusting process parameters based on these signals still remains a challenge. Difficulties arise due to the lack of knowledge regarding how the changing values of process parameters impact the state of the process. Simulations are developed to tackle these problems, but simulation models often face a trade-off between high accuracy and computational complexity [5]. However, the fact that process signals reflect process states suggests an approach to overcome this problem associated with utilizing reference process signals. For example, by considering the shape of a process signal that mirrors the desired process state as a target, process parameters can be adjusted to align the current process signal with the target process signal while monitoring corresponding changes in the current process signal. However, in the absence of a thorough comprehension of the behavior of the process signal, it becomes challenging to make such informed adjustments to process parameters. To comprehend the complex dynamics of process signals, a thorough analysis must be attempted with signals generated with a wide variety of parameters [6]. Unfortunately, the current scenario in production lines is characterized by signals generated within restricted parameter ranges, primarily due to safety constraints or economic considerations, such as tool breakage. These limited and frequently imbalanced datasets hinder a thorough understanding of the process signal behavior, therefore results in the selection of right target parameters and the adjustment of their values becoming complex tasks. In order to overcome these limitations, exploiting synthetic process signals in yet unexplored or scarce parameter spaces becomes an essential step.

In recent study in manufacturing, generating synthetic data using deep learning models are actively investigated. Their ability to generate synthetic, but realistic data has already been demonstrated, for instance, in the context of predicting SEM images of a material's microstructure using a CGAN under previously unknown processing conditions [7]. Analogously, the work by Link et al. [8] conducted a comprehensive investigation into the metamodeling of deep drawing processes. Their study demonstrated the feasibility of employing CGANs in sheet metal forming for predicting sheet thickness of forming result from finite element simulations, achieving high precision with limited data and robustness against varying input parameters. The study by Molitor et al. [9] addressed the challenges of data efficiency in the context of utilizing deep learning models for tool wear classification in stamping process. Using various types of GANs, their work demonstrated the effectiveness of data augmentation techniques to improve classification accuracies of deep learning models even with low data availability. However, most of the existing research does not utilize conditional generative models for the synthesis of time series process signals, but rather focuses on image data. Those for time series have primarily emphasized the balancing of dataset through categorical conditions of the machine state [10] or the models are used to predict missing data by leveraging relationship within and between input data, rather than relying solely on modifying condition to obtain them [11].

In this paper, the C-DCGAN model is trained using sheet metal thickness as the conditioning parameter, employing stamping force signals obtained from a fine blanking machine. We demonstrate the effectiveness of the trained generator in learning the distinctions between force signals for specific sheet thicknesses and show its ability to generate synthetic force signals accurately under these conditions. These synthetic signals are then compared to real signals to assess the feasibility of employing an approach that utilizes synthetic process signals for signal-based parameter adjustments in the manufacturing process under specific parameter conditions. In this context, the following research questions are outlined:

RQ1. How effectively can the generated process signals align with real process signals across different thickness classes?

RQ2. How effectively can the generated process signals align with conditions that were not presented to the model during training?

Methods

In the experiment of this study, a 16MnCr5 (AISI 5115) thin metal sheet with three different thicknesses was provided to the Laboratory for Machine Tools and Production Engineering (WZL) of RWTH Aachen University. The sheet underwent processing through the fine blanking process line at a stroke speed of 30 strokes per minute, as illustrated in Fig. 1.

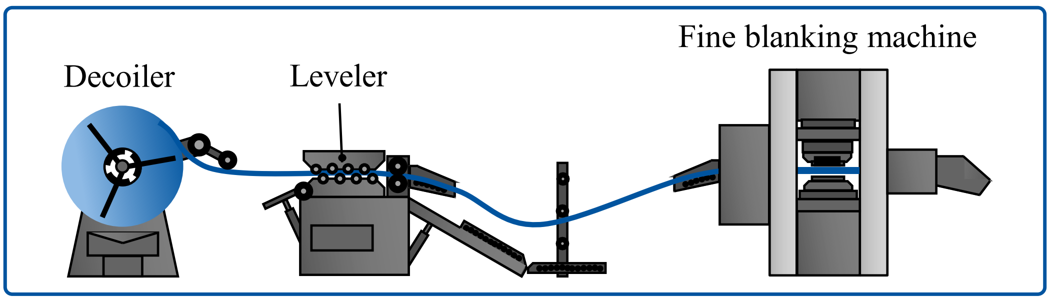

Fig. 1. Fine blanking process line

The stamping force is measured via four in-tool piezoelectric force sensors integrated into the fine blanking machine. Each sensor captures signals at a sampling rate of 10 kHz, and the acquired signals are segmented based on the stroke. This yields a multivariate time series for each sensor, where each time series of 10,500 data points varies with the number of strokes. The start and end parts of each stroke are adjusted to attain zero force values, and these corrected force signals from the four sensors are averaged to create a unified multivariate time series. This led to in total of 287, 270 and 181 time series for each thickness class: 3.95 mm, 4.00 mm and 4.05 mm, respectively.

For a detailed analysis of force signal variations concerning sheet thickness, the shearing and stripping stages are isolated from the overall time series. This isolation yields 2,000 data points of the shearing stage and 1,201 data points of the stripping stage. The time series for these isolated stages are then aligned along the time-axis with specified reference points, which are identified as the maximum peaks for shearing and minimum peaks for stripping within each stage's time series.

To reduce the amount of data points per time series for model training, each stage is further divided into two segments for shearing and three segments for stripping, respectively. On one hand, these segments are scaled, resulting in each data point across the time series being scaled to have a mean of 0 and a unit variance. Each scalar model is saved before training phase (Fig. 2 (a)) and utilized for the rescaling of the generated data in the after training phase (Fig. 2 (c)). In the training phase (Fig. 2 (b)), the total of 738 scaled segments are employed as the training data for the model. For balanced training across each class, the training data is complemented by randomly sampling additional training data from each class, which leads to 288 time series for each class. On the other hand, average time series from the non-scaled segments are computed for each thickness class. These average time series serve as the ground truth for selecting trained models based on time series plots, as depicted by x_{ground_truth} in Fig. 2 (c).

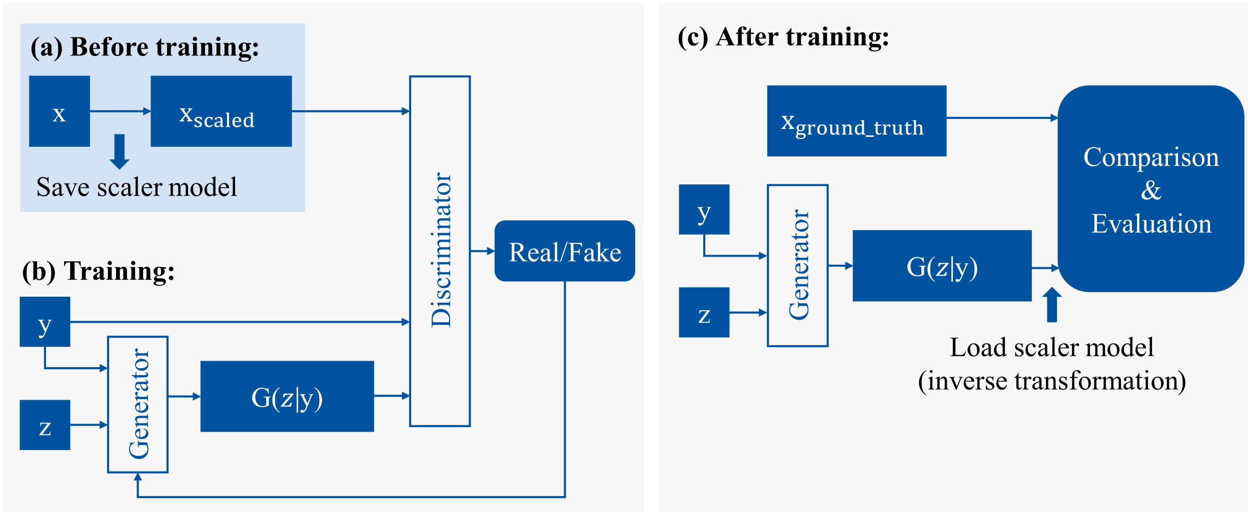

Fig. 2. Training and evaluation of the model

The model used in this paper follows the C-DCGAN architecture, which is the combination of CGAN [12] and DCGAN [13]. The generator network operates by taking input from noise z, which is composed of random numbers from the standard normal distribution. Additionally, the generator receives the label y of the real data x as the 2nd input. Both the generator and the discriminator receive this label as the auxiliary information. Under this condition y, the generator network G strives to produce realistic data G(z|y), whereas the discriminator tries to distinguish between the real data x and the synthetic data G(z|y). The model's objective function can be described as a two-player minmax game:

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x|y)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z|y)))] \quad (1)$$

where the terms $\mathbb{E}_{x \sim p_{data}(x)}[\log D(x|y)]$ denotes the expected value of the log-likelihood of the discriminator D on the conditioned real data x|y and $\mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z|y)))]$ represents the expected value of the negative log-likelihood of the discriminator D on the generated data G(z|y) [12]. In this experiment, the label y corresponds to the sheet metal thickness as a conditioning factor. These labels are encoded as 0, 1, and 2 for each thickness class.

For the training of the model, an NVIDIA Tesla V100 GPU is used. After training, the best models were selected with different learning rates and number of epochs for each segment because of the different length of the data points and the data distributions across the time series segments. Furthermore, recognition of the model's convergence through generator losses became less straightforward due to the adversarial relationship between the generator and the discriminator network, i.e., low generator losses do not necessarily mean that the generator can produce realistic data [14]. Because of these issues, training results are acquired by visually inspecting data plots, that were generated at intervals of 250 epochs, comparing generated data with the ground truth of the corresponding thickness class. Based on the adequacy of the visual inspection result from these checkpoints, the models are selected that correspond to the respective number of epochs. This resulted in five distinct generator models per research question, each trained on a different time series segment accordingly.

Results and Discussion

To address the research questions, individual training strategies are developed. For the first question (RQ1), the model is trained across all three thickness classes to investigate the fitness of the presented model by generating synthetic process signals, solely manipulating the thickness as the given condition. In the evaluation phase, the generated data from the trained generator is compared to real data within each thickness class. For each thickness class, an equivalent amount of time series is generated by the trained generator to match the number of real time series.

Fig. 3 and Fig. 4 depict time series plots for the real and generated force signals for each stage across different thickness classes. In general, the trained generators could imitate the original time series well, with the exception of the last 100 data points in the shearing stage and the data points between 950th and 1000th positions in the stripping stage, constituting part of the 2nd stripping segment. The training for the 2nd stripping segment was particularly challenging due to its small yet frequent fluctuations of the data points, in comparison to other segments' data distributions.

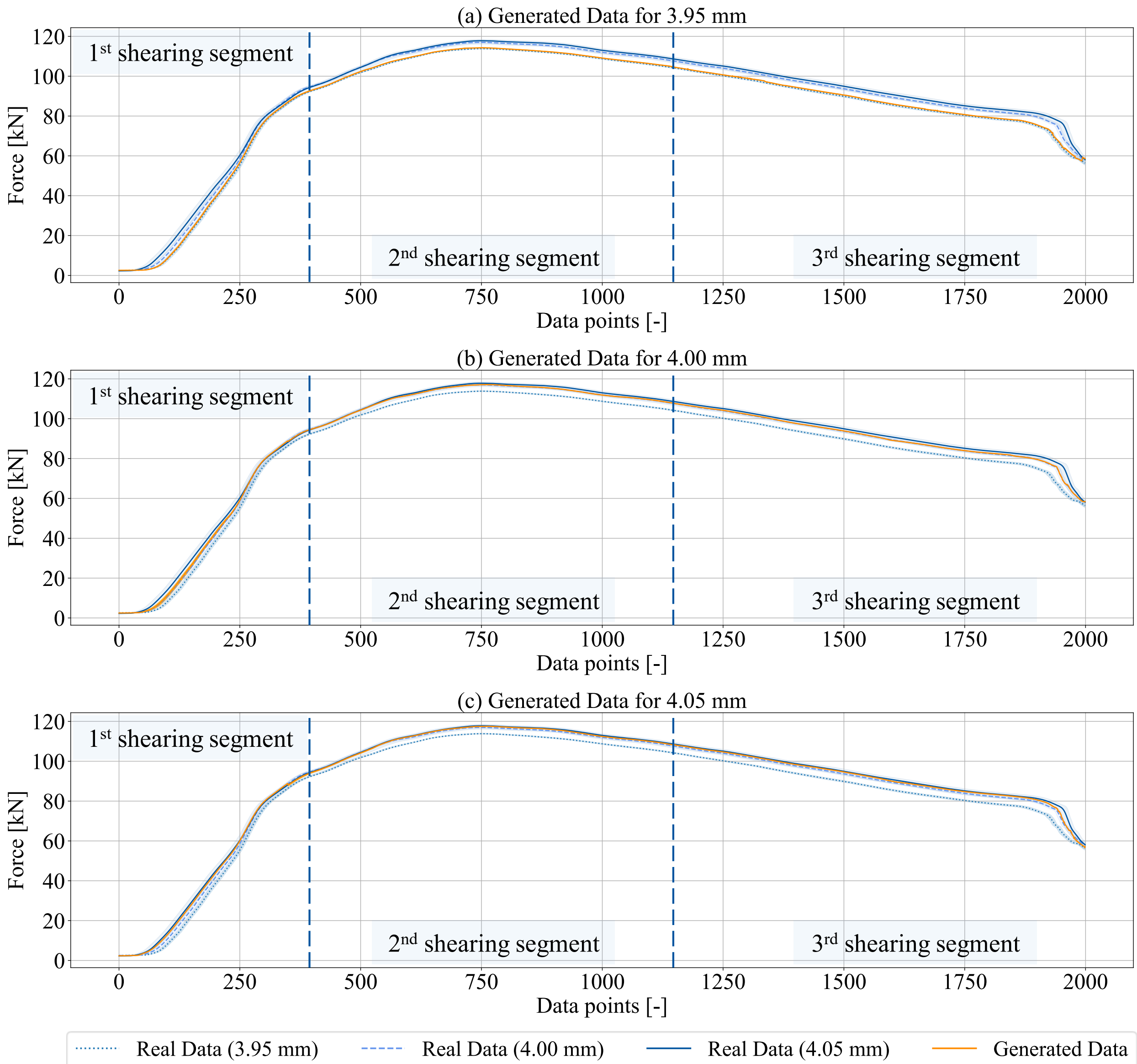

Fig. 3. Real and generated force signals (shearing stage) – RQ1

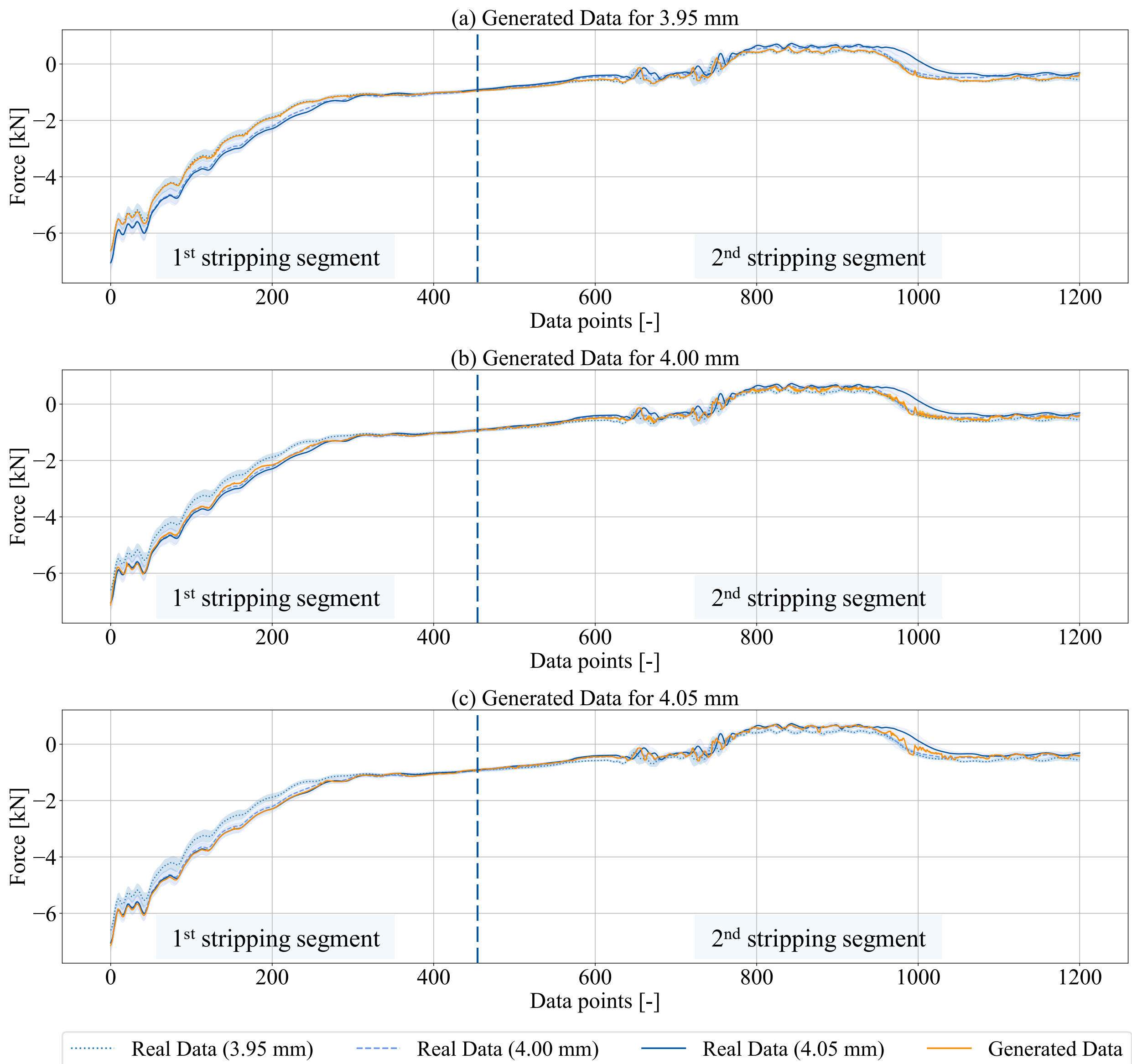

Fig. 4. Real and generated force signals (stripping stage) – RQ1

This could be observed in Fig. 5 (e) as well, which is the violin plot of the 2nd stripping segment. In the following Fig. 5, each region corresponds to a Gaussian kernel density estimate (KDE), depicting the density of respective values. The horizontal dashed line within each violin indicates the median, while the dotted lines indicate the first and third quartiles. The shapes of KDE for generated signals look similar to those of real signals. Although there are some deviations in the medians for 4.00 mm and 4.05 mm, the scale of the 2nd stripping segment is still smaller than that of shearing segments. This is because the real time series of the shearing stage cover a much broader range of force values compared to that of the stripping stage.

For numerical comparison, the first Wasserstein distances are calculated between real and generated time series across different thickness classes to measure the similarity of two time series. Given i.i.d. samples $X_1, \ldots, X_n \sim P$ and $Y_1, \ldots, Y_m \sim Q$, the first Wasserstein distance between two probability distributions P and Q is defined as the minimum cost of transforming one distribution into the other, i.e.:

$$W_1(P,Q) = \inf_{\pi \in \Gamma(P,Q)} \int_{\mathbb{R}\times\mathbb{R}} |X - Y| \, d\pi \tag{2}$$

where $\Gamma(P,Q)$ is the set of all joint probability measures on $\mathbb{R} \times \mathbb{R}$ [15].

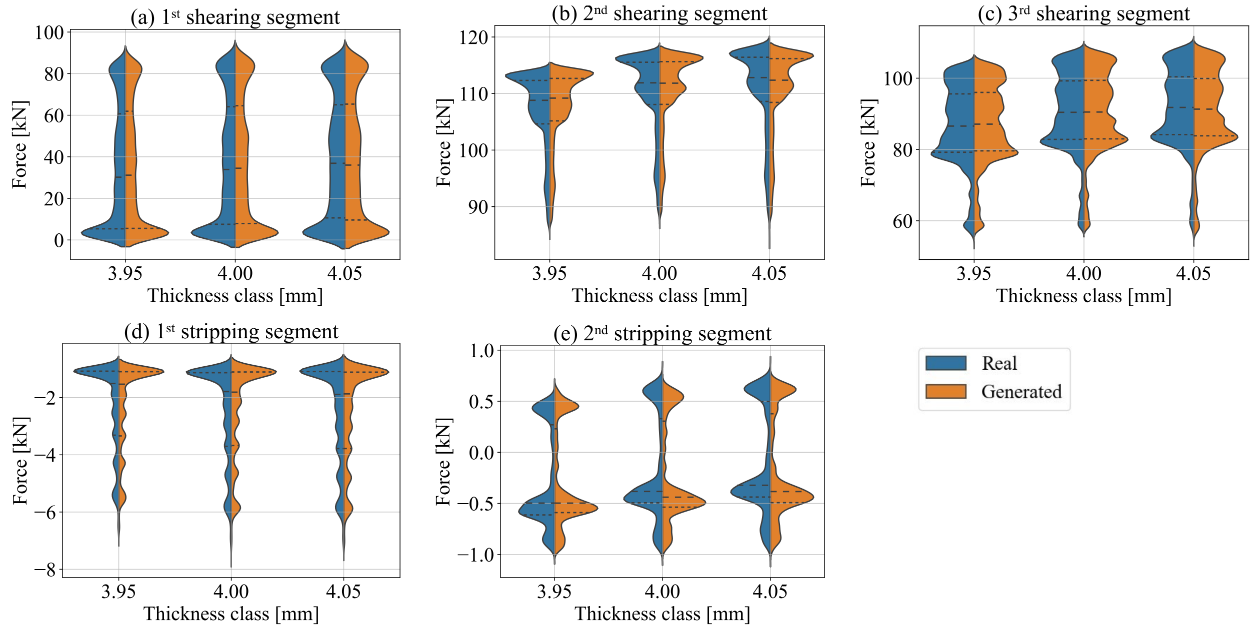

Fig. 5. Violin plot for Gaussian KDE of real and generated force signals – RQ1

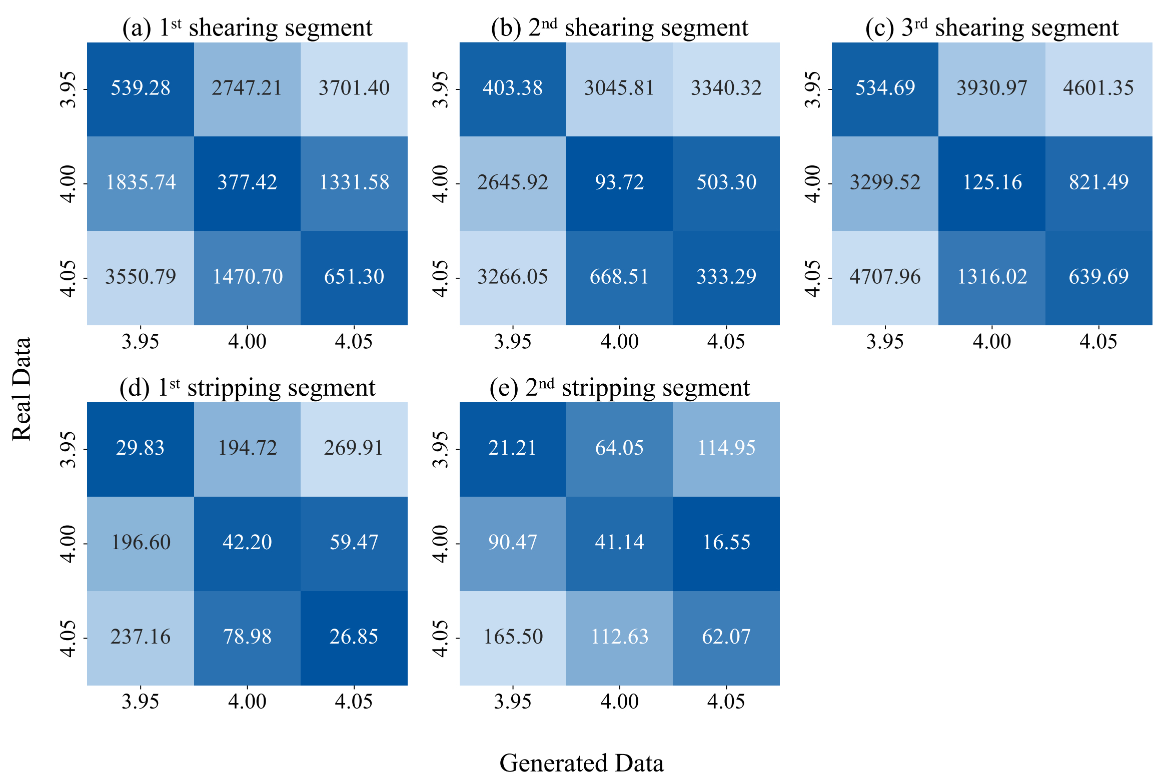

Fig. 6. Heatmap of Wasserstein distance between real and generated force signals – RQ1

The heatmaps with Wasserstein distance in Fig. 6 visualize the calculated results, rounded up to two decimal places. Lower value indicates high similarity between real and generated time series. When examining the heatmap in Fig. 6 derived from the generated data side, it becomes apparent that the darkest color within the values corresponding to each thickness class aligns with the thickness classes of the actual real data, except for the 2nd stripping segment. However, considering that there is a significant scale difference between the shearing stage (Fig. 6 (a), (b) and (c)) and the stripping stage (Fig. 6 (d) and (e)), the dissimilarity in thickness between 4 mm and 4.05 mm for the 2nd stripping segment is not deemed critical. Nevertheless, despite of that the last 100 data points generated by targeting a thickness of 4.05 mm in the third shearing segment appeared closer to thickness 4.00 mm (refer to Fig. 4), the Fig. 6 (c) reveals that the Wasserstein distance still indicates a greater proximity of the data generated with a target of 4.05 mm rather than 4.00 mm. This implies that, despite the last 100 data points aligning more closely with thickness 4.00 mm, when considering the entire dataset comprising approximately 2000 points, this favorable alignment consists only a small fraction.

For RQ2, training is exclusively conducted on two thickness classes, namely 3.95 mm and 4.00 mm, to explore the capability of the trained generator in producing synthetic process signals for thickness classes that were not included in the training set. The generator, trained under this specific setting, is employed to generate data conditioned on all thickness classes, including 4.05 mm. Subsequently, the generated data is compared to real data in this previously unseen condition. Owing to the difficulties in visually comparing using time series and violin plots that illustrate differences between the results of two research questions, only the numerical comparison using the Wasserstein distances is presented for RQ2 as Fig. 7.

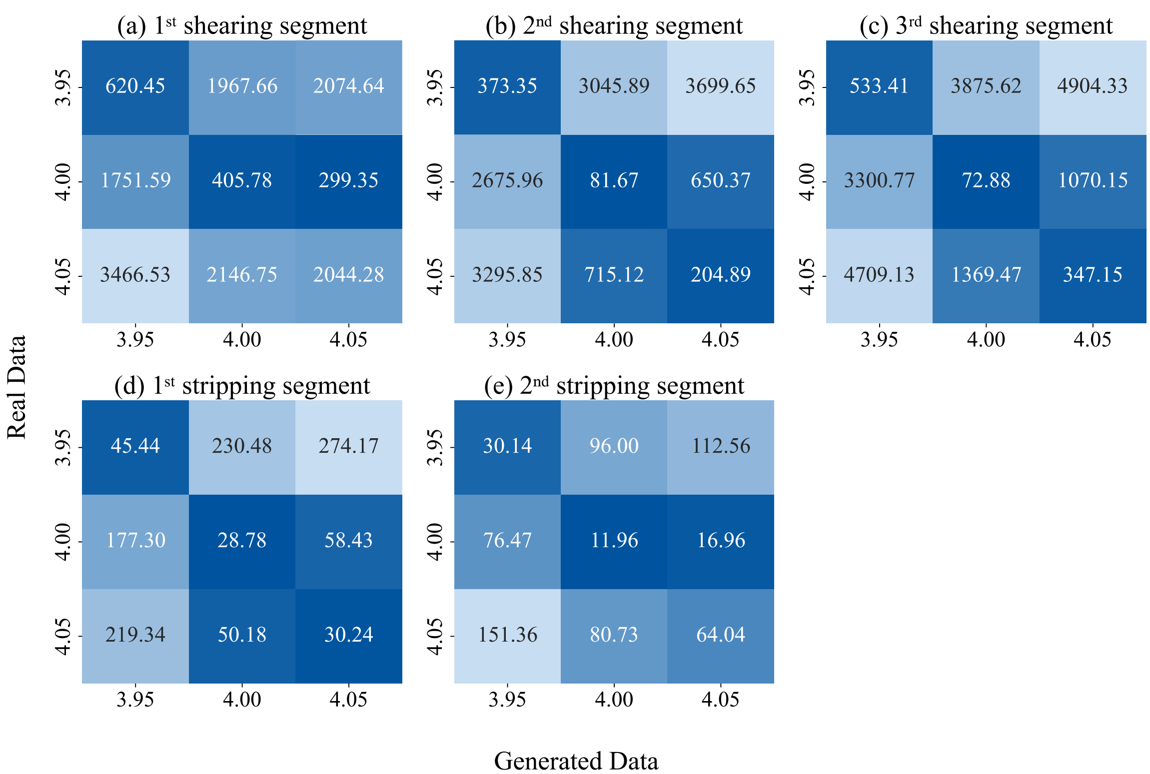

Fig. 7. Heatmap of Wasserstein distance between real and generated force signals – RQ2

As illustrated in Fig. 7 (b), (c) and (d), the generators trained under limited conditions can predict the time series for 4.05 mm with some degree of error, yet the predictions are still closer to the target time series compared to those for 3.95 mm and 4.00 mm. This also further validates the extrapolation ability of conditional GANs, as demonstrated by Fu et al. [16]. Although the model failed to predict accurate time series for the 1^{st} shearing segment and the 2^{nd} stripping segment (Fig. 7 (a) and (e)), an interesting point is that these generators exhibit even better prediction results than when trained with all thickness classes (compared to Fig. 6 (b), (c) and (d)). This might be due to the typical problems of deep learning model such as overfitting or catastrophic forgetting, implying that the model performance can be improved through fine-tuning of the hyperparameters.

Summary

This study explores the application of C-DCGAN in generating synthetic process signals for sheet metal forming processes, particularly in fine blanking. In the context of process parameter adjustments, synthetic process signals have the potential to serve as the baselines for understanding complex dynamics of the process signals with given parameter conditions. This research addresses two main questions: examining the effectiveness of generated process signals across different sheet thickness classes (RQ1) and assessing the model's ability to predict signals for conditions not presented during training (RQ2). For RQ1, the trained generators demonstrated the capability to approximate the original time series for three different thickness classes: 3.05 mm, 4.00 mm and 4.05 mm. This suggests that the selected conditional generative model can predict process signal by employing the given influencing parameter as the condition. For RQ2, training under limited conditions on two thickness classes allowed the generator to predict time series for previously unseen condition. This extrapolation capability of conditional generative models can be further utilized to generate synthetic process signals by exploring as-yet-unknown process parameter spaces.

This paper serves as a feasibility study to determine the potential for generating synthetic yet realistic process signals under specified conditions. The generated synthetic process signals can be utilized as the baselines for further analogy experiments related to understanding process signal behavior. While environmental factors or system parameters (e.g., sheet thickness) are beyond the scope of in-line control, leveraging the synthetic process signals can be extended to signal-based adjustments of in-line controllable process parameters. Hence, evaluating the model conditioned on in-line controllable process parameters has to be considered as main focus of future work. A more efficient model selection metric could also be considered to reduce the manual labor in selecting the best models. In addition, to further assess the validity of the synthetic process signals, additional statistical tests measuring (dis)similarity of two probability distributions could be considered, such as the Kolmogorov-Smirnov test [17].

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