ASTELCO: An Augmented Sparse Time Series Dataset with Generative Models

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Abstract: In recent years, there has been significant growth in the application of deep learning methods for classification, anomaly detection, and forecasting of time series. However, only some studies address problems involving sparse or intermittent demand time series, since the availability of sparse databases is scarce. This work compares the performance of three data augmentation approaches based on generative models and provides the code used to generate synthetic sparse and non-sparse time series. The experiments are carried out using a newly created sparse time series database, ASTELCO, which is generated from real e-commerce data (STELCO) supplied by a mobile Internet Service Provider. For the sake of reproducibility and as an additional contribution to the community, we make both the STELCO and ASTELCO datasets publicly available, and openly release the implemented code.

1 INTRODUCTION

Data augmentation has shown to be a helpful strategy for obtaining deep learning models with greater generalization capacity. This is especially crucial when tackling classification, anomaly detection, or forecasting problems involving time series (Iglesias et al., 2023; Wen et al., 2020). Efficient model design requires datasets with appropriate granularity and history to accurately capture distributions, temporal correlations, and relationships between univariate series in the context of multiple time series (Iglesias et al., 2023). The availability of varied databases, has been especially useful for training foundation models, which benefit from diverse datasets from domains, and achieve the capacity to perform well in zero-shot prediction scenarios (González et al., 2024).

Despite the recent increase in research on time series analysis, public access to databases derived from monitoring the operation of real systems, with labeled data, is not so frequent, particularly when addressing the detection of anomalies in sparse or intermittent demand series.

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Sparse time series are characterized by non-zero values that appear sporadically in time, with the remaining of the values being 0. This inherent property, coupled with the variability in the occurrence patterns across different series, poses significant challenges for forecasting (Makridakis et al., 2022). In anomaly detection, such series present an additional difficulty for detection algorithms, which often exhibit reduced performance compared to more active series (Renz et al., 2023).

The lack of more research focusing on this type of data is likely due to the limited availability of such data for training and evaluating models. Previous studies have demonstrated the effectiveness of Generative Adversarial Networks (GANs) and Variational Auto-Encoders (VAEs) in generating synthetic data from real data. For instance, (Yoon et al., 2019) proposed a GAN-based architecture and a comprehensive performance evaluation method, which we will consider as a primary reference for our work. The study evaluated performance using four metrics. Similarly, (Desai et al., 2021) introduced a VAE-based architecture, which is compared with previous metrics and other architectures (Esteban et al., 2017), showing comparable quantitative performance.

This work addresses the challenge of generating a synthetic sparse dataset through data augmentation techniques, with the aim of providing a novel dataset

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to the academic community.

This research benefited from the collaboration with the e-commerce division of a mobile Internet Service Provider (ISP), which supplied a real diverse dataset, STELCO, employed in the synthetic generation process.

In this work, we contribute with the publication of a database with sparse intermittent demand series, ASTELCO, generated from real data, STELCO, using TimeGAN (Yoon et al., 2019) and DC-VAE (García González et al., 2022). The latter is a model that has shown good performance in continuous series reconstruction and the application of anomaly detection in continuous data. The following sections describe and compare the STELCO database with other available databases. Then, the characteristics and configurations of the models used to generate the data augmentation based on TimeGAN and DC-VAE are briefly described. Finally, the performance of the generated databases is evaluated.

2 SPARSE STELCO DATASET

This section describes STELCO, a new open sparse dataset released to the community.

This dataset comprises records of invoices generated through the ISP's online commerce platform, encompassing various payment methods. Notably, certain payment methods show high levels of activity, whereas others show very little, thereby introducing a diverse range of behaviors to the whole.

In Table 1, a comparison between a set of publicly available databases (Fan et al., 2023) and our STELCO database is presented. The measure presented in Equation (1) was employed to assess the sparsity of the series.

$$sparsity = 1 - \frac{count\_nonzero(A)}{total\_elements(A)}. \quad (1)$$

Given the nature of the data in STELCO, which reflects transactions conducted at an online commerce platform, in instances where no transactions occur, no records are generated. As a result, there is an absence of null values within the dataset.

To address this issue, a resampling procedure, using the mean time difference between samples, was implemented prior to the computation of sparsity for datasets exhibiting this characteristic.

This approach effectively introduced null values into the dataset, allowing for a more meaningful calculation of sparsity.

In Table 1, it can be noted that the STELCO dataset has the shortest time interval and the largest number of samples.

To facilitate the subsequent analysis of our data, three groups of series were formed, defining them from the lowest to the highest volume of transactions. The first group (*low*) contains the series with the lowest number of transactions, the second group (*mid*) series with an average volume of transactions and the third group (*high*) series with the highest volume of transactions. To match the number of values in each group with an appropriate sampling frequency, we chose to resample the groups at intervals of 1 hour, 5 minutes and 1 minute, respectively. Thus, the number of values varied for each group accordingly: 625 values for the *low* dataset, 7,600 values for the *mid* dataset and 38,000 values for the *high* dataset.

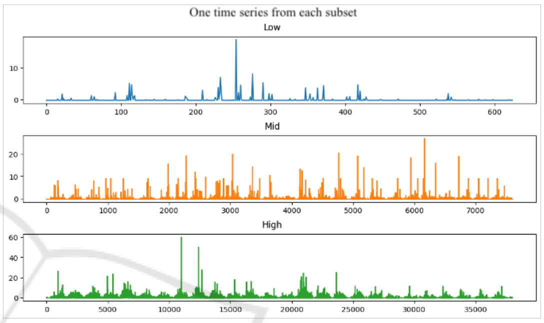


Figure 1: Example of three different time series from our dataset, sampled at different frequencies: 1 hour, 5 min and 1 min, respectively.

All the series in our set were standardized in order to preserve the confidentiality of the data. With these three sub-groups of series, the analyses presented below were carried out. An example of a series from each group is shown in Figure 1.

3 DATA AUGMENTATION

To generate synthetic data from the utilized dataset, a comprehensive analysis of various existing methods was conducted, with the objective of implementing these techniques in the context of sparse time series (Iglesias et al., 2023)(Wang et al., 2022). Among the methods employed in this study were TimeGAN and DC-VAE.

3.1 GAN-Based Generation

3.1.1 TimeGAN

TimeGAN (Yoon et al., 2019) is a method rooted in Generative Adversarial Networks (GANs), specifically designed for the generation of time series data. This model comprises a generator tasked with pro-

Table 1: Comparative table of databases with sparse series.

Database name	Time Interval	Number of series	Total number of samples	Sparsity	Description
Online Retail	1 min to 11 days Mean = 30 min	1	17,914	70.30%	Transactions for an online retail business in the UK.
Car Parts	1 month	2,674	136,374	75.90%	Demand for vehicle spare parts.
Entropy 1	1 day to 15 days	1,200	132,579	35.65 %	Demand for heavy machinery spare parts in China.
Entropy 2	1 month	57	1,938	41.90 %	Demand for parts from a vehicle manufacturing company in China.
STELCO (ours)	10 ns to 3 days Mean = 2 min	18	287,734	67.42 %	Invoicing amount in e-commerce platform.

ducing new synthetic data, which attempts to deceive a discriminator that functions to distinguish between real and fictitious data. GANs have demonstrated strong performance not only in time series generation (Brophy et al., 2023) but also in other domains, such as image generation.

A distinctive feature of TimeGAN is its incorporation of an additional embedding network that facilitates a reversible mapping between features and latent representations, thereby addressing the challenges posed by the high dimensionality of the GAN's latent space. The model employs three loss functions: one unsupervised loss associated with the GAN, another associated with the embedding network, and a supervised step-wise loss. The supervised step-wise loss utilizes real data as a reference, promoting the model's ability to capture the temporal sequential dynamics inherent in the data. This loss is minimized through the joint training of the generation and embedding networks.

The initial results using TimeGAN were obtained for the subset designated as *low* employing model parameters of 10,000 epochs and a sequence length of 24. Figures 2a and 2d illustrate windows of the time series over a specified period of time, along with histograms depicting the distributions of both the original and synthetic data. The synthetic data demonstrates a distribution that closely resembles that of the real data; however, comprehensive performance evaluations will be conducted below.

The second experiment employing TimeGAN was conducted on the subset designated as *mid*, maintaining a sequence length of 24 while increasing the number of epochs to 30,000, due to the larger volume of input data. Figures 2b and 2e show the plots and histograms of the original and synthetic data, respectively. In this case, it is seen that some of the peaks of higher values are lost and are not generated in the synthetic data.

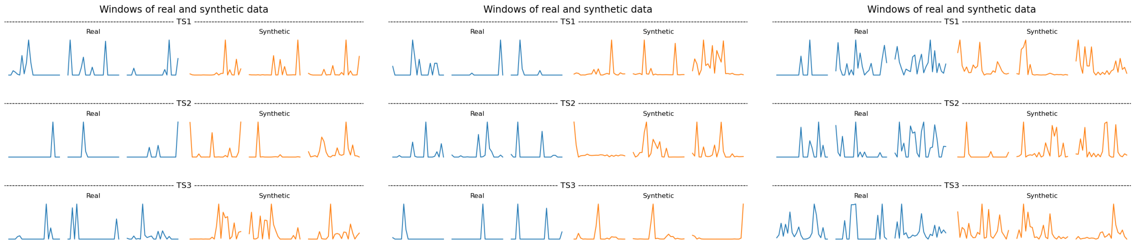
The third experiment using TimeGAN was conducted on the *high* subset, employing the same sequence length of 24 but 50,000 epochs, given the larger volume of input data compared to the other subsets. The window plots and histograms of both the original and synthetic data are illustrated in Figures 2c and 2f, respectively. Although the generated windows appear to align closely with the original data, the histograms reveal a higher density of non-zero values in the synthetic data than in the original. Furthermore, the largest values are completely absent in the generated dataset. Future investigations could benefit from a hyperparameter search to explore the effects of varying window lengths and the number of iterations on the generation process.

3.2 VAE-Based Generation

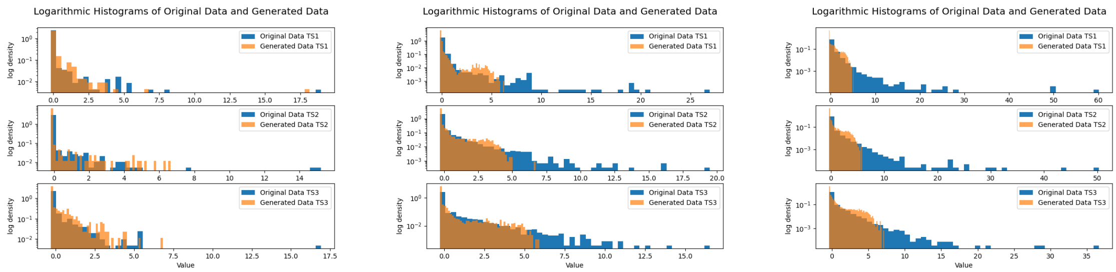
3.2.1 TimeVAE

TimeVAE(Desai et al., 2021) is a method used for synthetic generation of time-series based on Variational Auto-Encoders (VAEs). They propose an interpretable VAE architecture where they present two blocks: Trend and Seasonality, that get added to the decoder in order to add specific temporal structures to the decoding process. Thus, the output from the decoder results in the element-wise summation of the trend block output, seasonality block outputs and the residual base decoder output.

To perform our tests, we used the interpretable TimeVAE architecture with one Trend block, one seasonality block and the base residual decoder. The



(a) Windows for *low* subset. (b) Windows for *mid* subset. (c) Windows for *high* subset.



(d) Histogram for *low* subset. (e) Histogram for *mid* subset. (f) Histogram for *high* subset.

Figure 2: Visual comparison of original and generated data across different subsets (*low*, *mid*, and *high*) using TimeGAN.

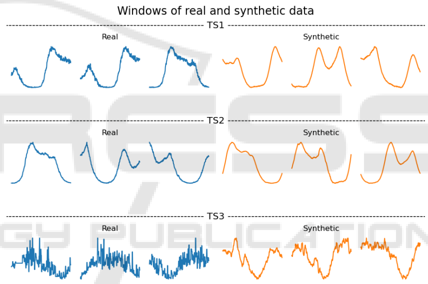
trend block was selected with 4 trend polynomials ($p = 4$). The seasonality block varied for each dataset: with $m = 7$ and d equal to the duration of a day (24 in the case of the *low* subset, 288 for the *mid* subset, and 1440 for the *high* subset); where m is the number of seasons, and d is the duration of each season.

The results obtained with this configuration are illustrated in Figure 3b, and show a difficulty in capturing the temporal dynamics of our data. This is not in accordance with the good results obtained with continuous data, with daily seasonality like TELCO, as seen in Figure 3a.

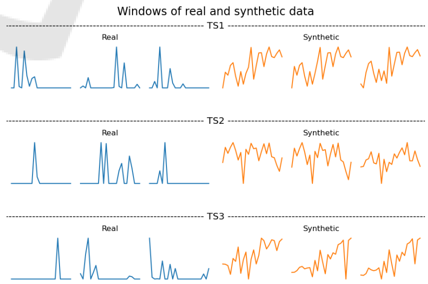
3.2.2 DC-VAE

DC-VAE (García González et al., 2022) is a method used for anomaly detection in time series, which takes advantage of convolutional neural networks (CNN) and variational auto-encoders (VAE). DC-VAE detects anomalies in time series data by exploiting temporal information without sacrificing computational and memory resources. In particular, instead of using recursive neural networks, large causal filters or many layers, DC-VAE relies on dilated convolutions (*DC*) to capture long- and short-term phenomena in the data, avoiding complex and less efficient deep architectures, simplifying learning. This method is based on the reconstruction of time series and is not used as a generative method like TimeGAN. However, we wanted to test its performance in generative tasks such as this one.

In the initial approach, the model was used to reconstruct the input series to evaluate its performance. The reconstruction of the three series of the *low* subgroup are depicted in Figure 4. A window length of 24 points was selected, corresponding to one day



(a) TELCO windows.



(b) STELCO windows.

Figure 3: TimeVAE: Real and synthetic windows for TELCO (top) and STELCO (bottom).

of activity. The model and its training process were slightly modified to shift from a multivariate approach to a global one. In this global mode, each input series was processed independently, without utilizing information from the other series for reconstruction. As illustrated in the plots, the model demonstrates a certain difficulty in reconstructing the highest activity peaks, instead primarily reflecting the mean value of each window.

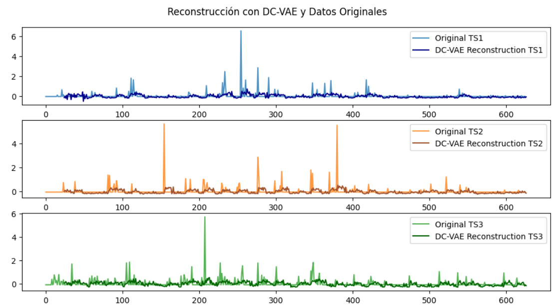


Figure 4: Reconstruction of the *low* subgroup series with DC-VAE.

The next step was to try to generate synthetic data from the original data. For this purpose, the already trained model was used, in this case with the *low* subgroup. Vectors with a uniform distribution (0,1), of dimension equal to the dimension of the latency space of the model, were generated and passed through the decoder. Thus, a window of $T = 24$ samples is obtained at the output of the decoder. For each uniform sample of the latency space, a window is generated, which are comparable with the windows of the original series. This procedure was repeated for each subset, and Figure 5 shows the comparison of real and synthetic windows for the subset *low*.

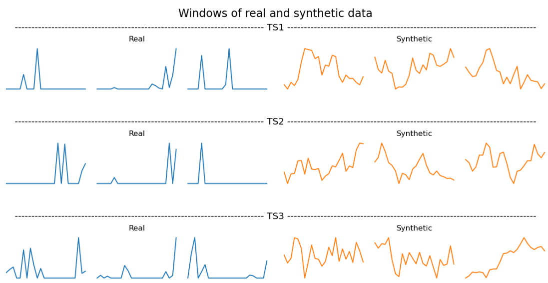


Figure 5: Comparison of windows between original data (blue color) and synthetic data (orange color), generated from the DC-VAE decoder trained with the *low* subgroup series.

It was observed that the DC-VAE inadequately captured the dynamics of the original data, resulting in generated data that lacked resemblance to the originals and exhibited a certain degree of noise. This issue may arise from several factors. Firstly, the dimensionality reduction inherent in auto-encoders tends to prioritize lower frequency data, which can lead to the loss of higher frequency components. Consequently, this results in the omission of significant peaks in our sparse data, which are crucial for our analysis.

Finally, a review of both reconstruction (4) and generation (5) results suggests that the DC-VAE is more suited for time series that exhibit higher activity levels and periodic dynamics. This is likely due to the Gaussian distribution of the DC-VAE output, which smooths the reconstruction process. In contrast, the original data does not exhibit such a distribution; rather, its values are predominantly zero, resulting in a distribution that aligns more closely with a Laplacian model. We have discussed the potential for future adaptations of the network to produce an output distribution that better fits the data, although this endeavor will require significant time and resources, and thus will be left for subsequent research.

4 PERFORMANCE EVALUATION

The metrics used to evaluate the performance of the different generative methods were inspired by RC-GAN (Esteban et al., 2017) and TimeGAN (Yoon et al., 2019). These articles present methodologies to assess the quality of the generated data based on three criteria: *diversity*: samples should be distributed in such a way that they cover the actual data; *fidelity*: the samples should be indistinguishable from the real data; and *usefulness*: the samples should be as useful as the actual data when used for the same predictive purposes.

Initially, two visual analysis methods—Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE)—are employed. These techniques allow for the visualization of the extent to which the distribution of the generated samples resembles that of the original data within a two-dimensional space. This approach facilitates a qualitative assessment of the *diversity* of the generated samples.

Secondly, a time series classification model was developed, utilizing a 2-layer LSTM RNN to differentiate between real and generated data sequences. This training is conducted in a supervised manner, with the original and generated data labeled beforehand. Then, the classification error is used as a quantitative evaluation of *fidelity*. The metric defined as discriminative score is presented in Equation (2).

$$discriminative\_score = |0.5 - accuracy|, \quad (2)$$

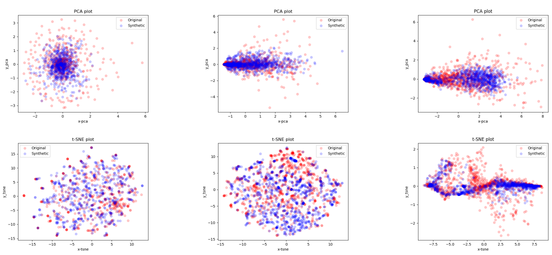
The ideal scenario, which would minimize the discriminative score, occurs when the classification accuracy is 0.5. In this case, the classifier would perceive all incoming real data as genuine and all synthetic data also as real. Therefore, half of the data would be accurately classified (the real instances) and the other half would be misclassified (the synthetic instances). This outcome suggests that the synthetic data is indistinguishable from the real data.

Finally, a sequence prediction model was trained using a 2-layer LSTM RNN to forecast the time vectors of the next step in each input sequence. Specifically, for a sequence of data ranging from 0 to T, the objective is to predict the value of the series at time T+1. This model was trained on the generated data and evaluated on the original data. Its performance is quantified using the mean absolute error (MAE) as defined in Equation (3), thereby providing a quantitative assessment of *usefulness*.

$$MAE = \sum_{i=1}^{D} |x_i - y_i| \tag{3}$$

where x and y are series of dimension D, corresponding to the predictions and the real data. For both the fidelity and utility metrics, the procedure is repeated 10 times, with the average of all iterations presented as the *predictive score* in Table 2 for each subset.

Figure 6 shows the PCA and t-SNE plots for the experiments performed with TimeGAN on the subsets *low*, *mid* and *high*, respectively. It illustrates that the generated data (blue) closely ressembles the real data (red), as evidenced by the similar spatial distributions observed in their PCA and t-SNE plots. This similarity is particularly notable for the *low* and *mid* subsets.

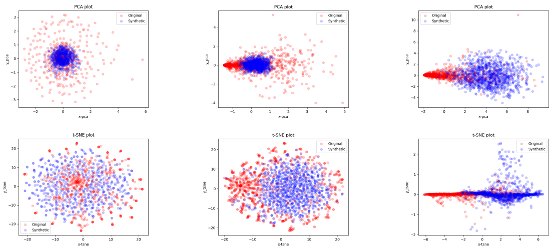


(a) *low*. (b) *mid*. (c) *high*.

Figure 6: TimeGAN: PCA (top) and t-SNE (bottom) plots.

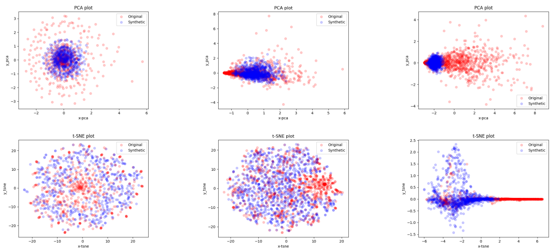
Additionally, to facilitate a comparison between the synthetic data generated by DC-VAE and the original data, the PCA and t-SNE plots for this model are presented in Figure 7.

Another factor that should be taken into account when comparing methods is the time they take to train and generate the synthetic data. This is where DC-VAE excells, since its VAE architecture is quite small and presents fast computing times. TimeGAN, on the other hand, is quite slow, performing at its worst with large amounts of data and large window sizes. In Table 2, the elapsed training time is shown for each method using an NVIDIA GeForce RTX 3090 with 24.5GB of GPU memory.



(a) *low*. (b) *mid*. (c) *high*.

Figure 7: DC-VAE: PCA (top) and t-SNE (bottom) plots.



(a) *low*. (b) *mid*. (c) *high*.

Figure 8: TimeGAN concatenated windows: PCA (top) and t-SNE (bottom) plots.

Figure 9: TimeGAN: concatenated windows for the *low* subgroup.

Table 2: Comparison of model performance for the 3 subsets of data evaluated.

Metric	Method	Data subset		
		low	mid	higih
Discriminative Score	DC-VAE	**0.2496 ± 0.0256**	0.2644 ± 0.0193	**0.2497 ± 0.0239**
	TimeGAN	0.2678 ± 0.0828	**0.2486 ± 0.1307**	0.2694 ± 0.0447
Predictive Score	DC-VAE	0.5254 ± 0.0059	0.6871 ± 0.1036	**0.5541 ± 0.0042**
	TimeGAN	**0.5186 ± 0.001**	**0.5204 ± 0.0017**	0.7377 ± 0.0043
Time to train and generate	DC-VAE	**79 s**	**678 s**	**1,634 s**
	TimeGAN	5,624 s	30,494 s	65,220 s

Table 3: Comparison of window concatenation performance for the 3 subsets of data evaluated.

Metric	Method	Data subset		
		low	mid	high
Discriminative Score	TimeGAN	0.2678 ± 0.0828	0.2486 ± 0.1307	0.2694 ± 0.0447
	TimeGAN-concat	0.219 ± 0.101	0.2466 ± 0.0654	0.3341 ± 0.1234
Predictive Score	TimeGAN	0.5186 ± 0.001	0.5204 ± 0.0017	0.7377 ± 0.0043
	TimeGAN-concat	0.5239 ± 0.0004	0.5197 ± 0.0005	0.7373 ± 0.0006

5 COMPLETE TIME SERIES SYNTHESIS

A common factor with the models evaluated is that the generation of data is done on a window-by-window basis. This inhibits the models ability to reconstruct the dynamics of the original series sample by sample. The lack of temporal coherence between windows undermines their concatenation, making it challenging to establish continuity. The correlation between one window and the next depends on the relationship between one random uniform vector and another, which are not necessarily close to one another.

In this case, given the sparsity of the time series analyzed in this study, it would be worthwhile to investigate whether retaining only the last value from each window and concatenating them could yield an entire synthetic time series, that not only matches the input data in length, but also in its temporal dynamics.

This approach would not work for continuous time-series since each window presents a specific dynamic that would not be so easily concatenated. An example of windows from a continuous time series from the TELCO(García González et al., 2023) dataset is illustrated in Figure 3a. However, in sparse series such as STELCO, given the low probability of occurrence of peaks, it could be argued that their concatenation could yield an entirely new time series that preserves the original distribution of the data.

In order to assess this aspect, the same performance evaluation procedure was applied to the concatenated windows generated using TimeGAN, and the results are presented both in Table 3 and in Figure 8. As we can see in this results, it seems to be possible to generate an entire time series, when they are sparse enough. So that is what we did for the low subgroup, giving the result illustrated in Figure 9. An issue still persists with the less frequent high value peaks, that are not represented in the generated series. Future work will focus on adapting the concatenation method to effectively capture these dynamics and facilitate appropriate complete series generation.

6 CONCLUSIONS AND FUTURE WORK

One of the main conclusions of our work is that it was possible to successfully generate a new synthetic sparse dataset through the augmentation of our real dataset using generative methods.

In contrast to previous works that restrict the generation to limited windows, this study demonstrates the capability to generate complete synthetic sparse time series that match the size of the original series. Notably, the performance scores achieved are comparable to those obtained from individual windows.

In the comparison of the methods based on GAN with those based on VAE, it is observed that while the performance metrics are similar, the visual analysis of the generated series indicates superior performance from TimeGAN relative to VAE-based methods. In the case of DC-VAE similar prediction, discrimination, PCA and t-SNE scores are obtained, with notoriously lower execution times. However, across all methods, a common challenge is the difficulty in accurately reproducing the most prominent peaks in the data.

Future lines of work include lifting the Gaussian assumption in VAE-based models. This would involve, for example, a detailed examination of the model architecture to assess possible modifications aimed at better aligning the output distribution with the characteristics of our data.

Additionally, introducing conditioning mechanisms in the generation of consecutive windows would be extremely valuable. This could involve implementing a more sophisticated method for concatenating windows that preserves the temporal correlation between them.

Finally, it is important to emphasize that we make the STELCO dataset and the generation procedure for ASTELCO publicly available, along with the accompanying code.

7 CODE AND DATASETS

We provide access to all materials utilized for conducting the experiments, including both the real and generated datasets: the code used to run the experiments with TimeGAN [1] and DC-VAE [2], the metrics used to evaluate the performance of the models [3], and both STELCO and ASTELCO datasets [4].

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