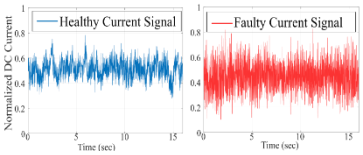
Signal Generation using 1d Deep Convolutional Generative Adversarial Networks for Fault Diagnosis of Electrical Machines

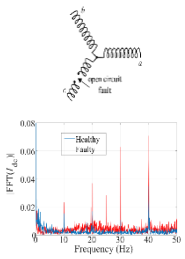
Russell Sabir[1 2], Daniele Rosato[1], Sven Hartmann[1] and Clemens Gühmann[2]

[1]SEG Automotive Germany GmbH, [2]Chair of Electronic Measurement and Diagnostic Technology & Technische Universität Berlin

1. Introduction and Motivation

- Synchronous Machines Faults





- 1-D convolution neural network with Wavelet Packet Transform **98.8% accuracy**
  (I. Kao, W. Wang, Y. Lai and J. Perng, "Analysis of Permanent Magnet Synchronous Motor Fault Diagnosis Based on Learning," in IEEE Transactions on Instrumentation and Measurement)
- Stacked Autoencoder with softmax layer **96.4% accuracy**
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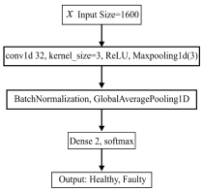
- Challenges with Deep Learning Algorithms
  - Deep Learning methods require large amounts of data
  - Algorithms don't generalize with large data

2. Fréchet Inception Distance (FID)

$$FID = \|\mu_1 - \mu_2\|^2 + Tr(C_1 + C_2 - 2(C_1C_2)^{1/2})$$

where, μ_1 and μ_2 are the feature wise mean
C_1 and C_2 are the covariance matrices
And Tr is the trace of the matrix

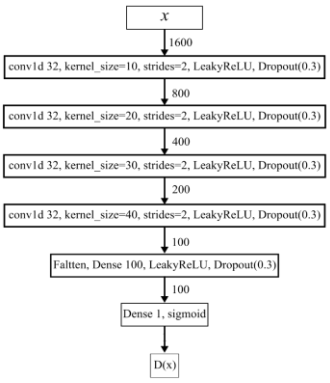
FID Threshold: 5 x 1E-5



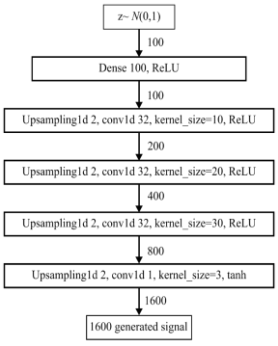
3. Training Parameters

- Training Data: 1400 Healthy and 1400 Faulty Current Signals
- Sampling Frequency: 100 Hz
- Learning rate of 0.0002 and beta of 0.5
- Discriminator Loss Function: binary cross-entropy
- Generator Loss Function: sparse categorical cross-entropy
- Adam Optimizer

4. 1d DCGAN Architecture

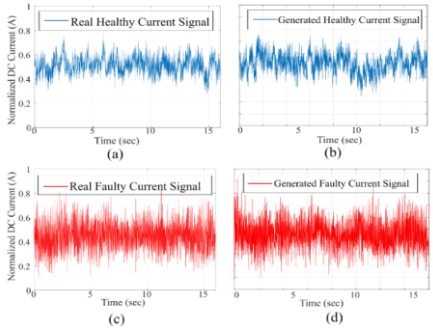


Discriminator



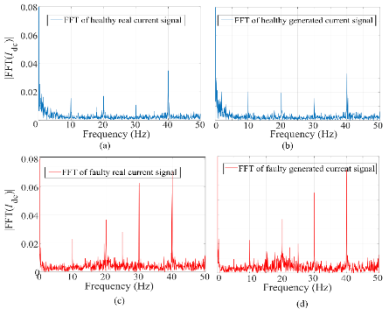
Generator

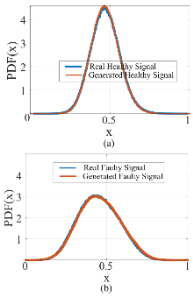
5. Generated Results



Normalized (between 0 and 1) E-Drive DC (a) Real current signal of Healthy Machine (b) Generated current signal of healthy machine
(c) Real current signal of faulty machine (d) Generated current signal of faulty machine

6. Evaluation of results





- **Creativity:** The generated signals are not duplicates of the real signals.
- **Diversity:** The generated signals are not duplicates of each other.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

μ_x is the mean value of x
μ_y is the mean value of y
σ_x^2 is the variance of x
σ_y^2 is the variance of y
σ_{xy} is the covariance of x and y
$c_1 = (k_1L)^2$ and $c_2 = (k_2L)^2$ are the variables to stabilize to the division with weak denominator
In our case $k_1 = k_2 = 0.05$, and L is the dynamic range of the signal value

$$Diversity = -\sum_{i=1}^{m} p_i \log p_i$$

where, $p_i = |C_i| / \sum_{n=1}^{m} |C_n|$
m is the number of clusters
$|C_i|$ is the number of signals in the cluster where $i = 1, \ldots, m$

$$Creativity = \frac{Number\ of\ Nonduplicate\ Signal}{Number\ of\ Signals\ in\ the\ generated\ dataset}$$

	1d DCGAN trained on Healthy signals	1d DCGAN trained on Faulty signals	Optimal values for 10000 signal dataset
Creativity	1	1	1
Diversity	9.0	8.7	9.2

7. Conclusion

- 1d signals generation using DCGAN
- Evaluation using FID distance
- Further evaluation using Creativity and Diversity
- Generated Signals are statically rich and are uncorrelated to the real signals

25th International Conference on Pattern Recognition - ICPR2020

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MDT TU Berlin

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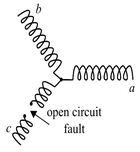

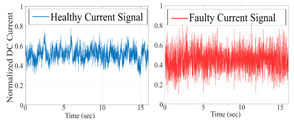

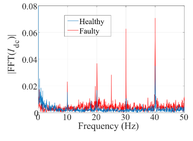

Data generation using GAN

2. Motivation

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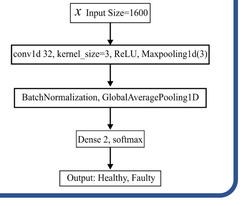

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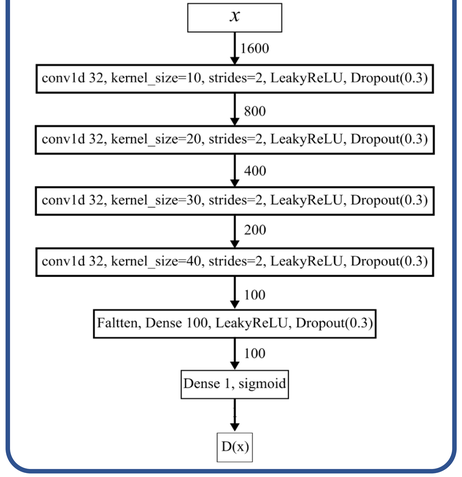

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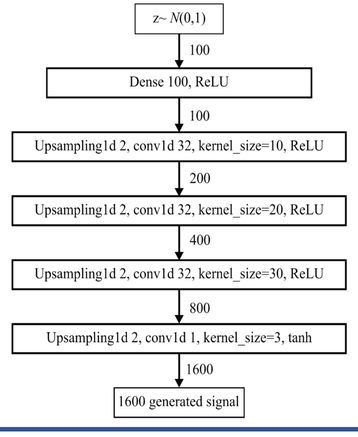

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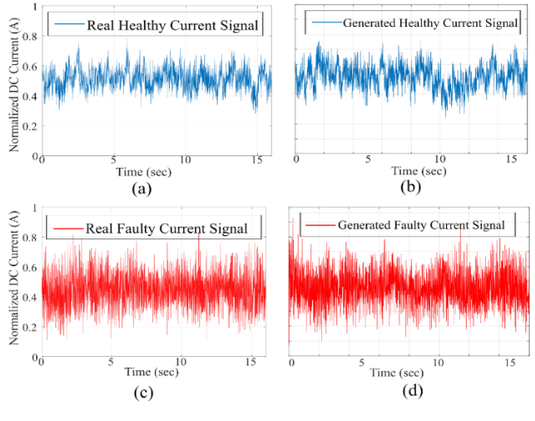
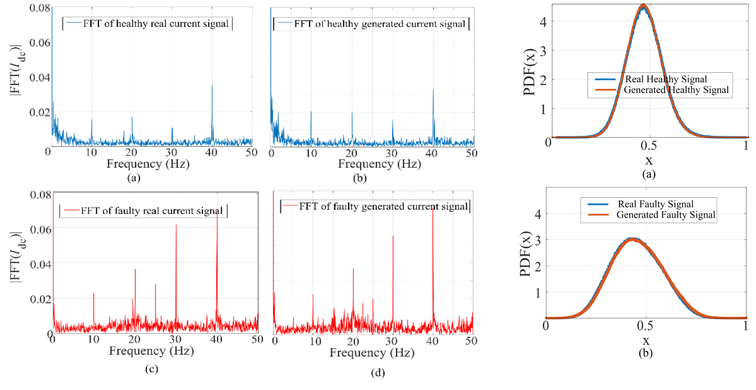


8. Results Evaluation using FFT and PSD



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