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

By

Russell Sabir, Daniele Rosato, Sven Hartmann and Clemens Gühmann

SEG Automotive Germany GmbH

Technische Universität Berlin

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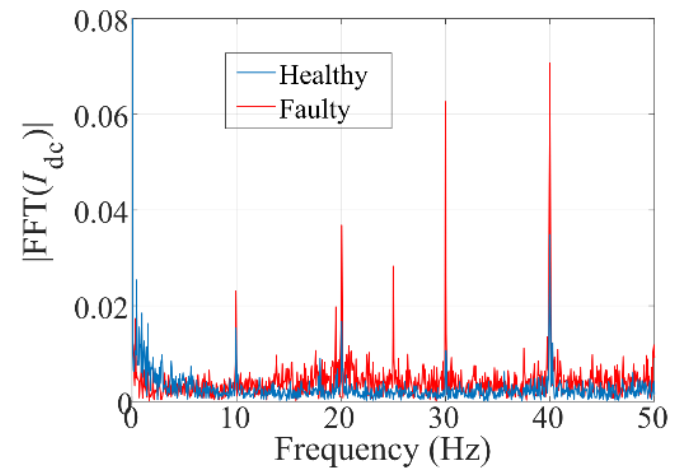
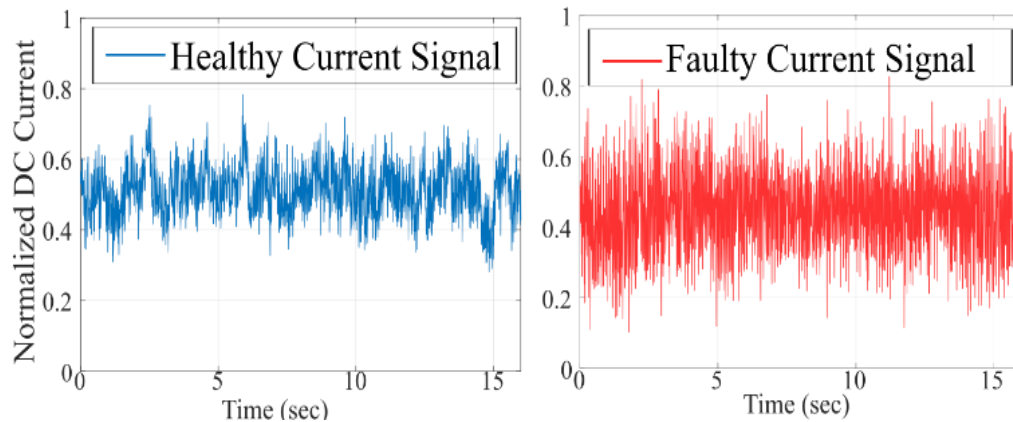
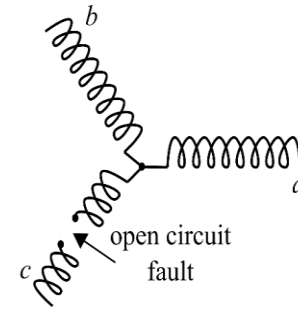
SIGNAL GENERATION USING 1D DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS FOR FAULT DIAGNOSIS OF ELECTRICAL MACHINES

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Motivation

SIGNAL GENERATION USING 1D DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS FOR FAULT DIAGNOSIS OF ELECTRICAL MACHINES

► Synchronous Machines Faults



Data generation using GAN

Problem Statement

SIGNAL GENERATION USING 1D DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS FOR FAULT DIAGNOSIS OF ELECTRICAL MACHINES

► 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**

(I. Kao, W. Wang, I. Chiang and J. Perng, "Implementation of Permanent Magnet Synchronous Motor Fault Diagnosis by a Stacked Autoencoder," 2018 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW))

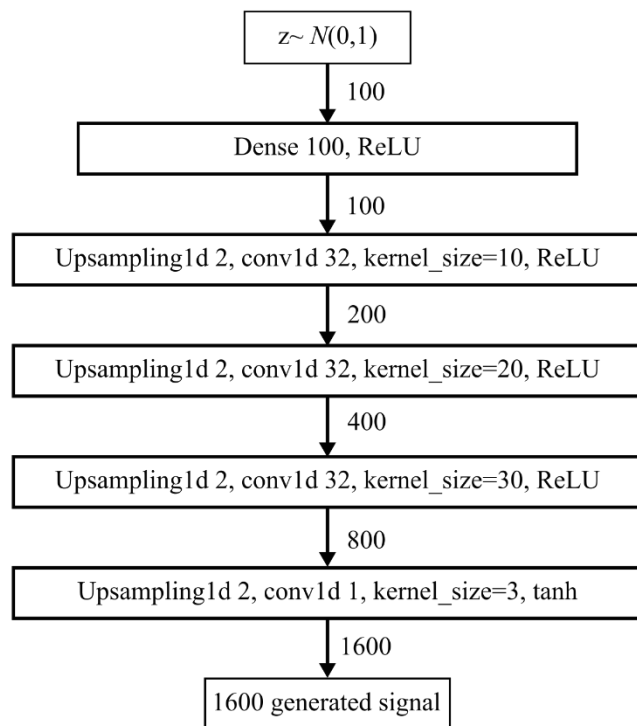
► Challenges with Deep Learning Algorithms

- Deep Learning methods require large amounts of data
- Algorithms don't generalize with large data

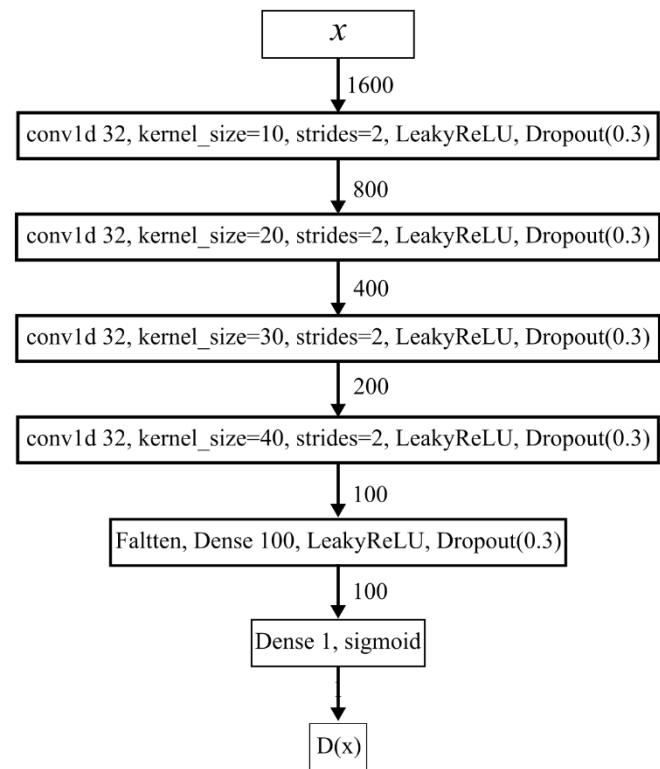
GAN Architecture

SIGNAL GENERATION USING 1D DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS FOR FAULT DIAGNOSIS OF ELECTRICAL MACHINES

Generator



Discriminator



Evaluation of GAN using FID

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► Fréchet Inception Distance (FID)

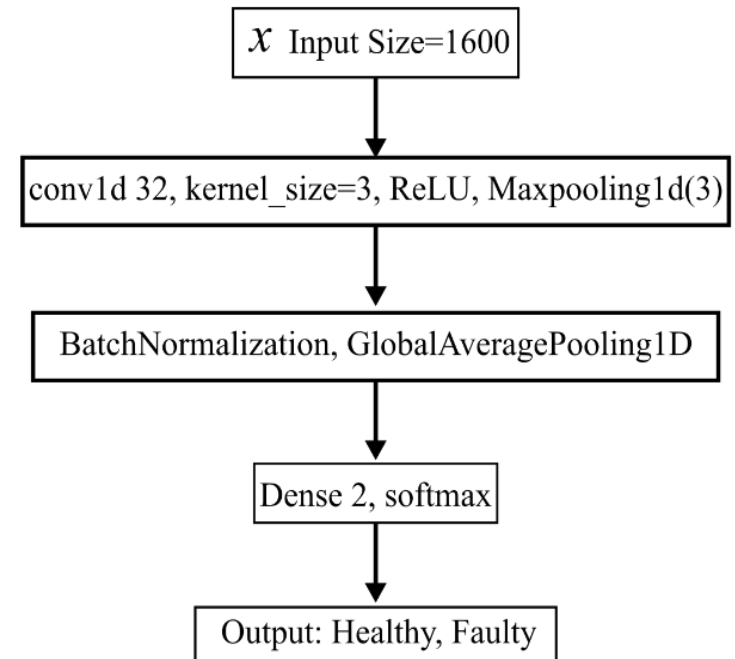
$$FID = \|\mu_1 - \mu_2\|^2 + \text{Tr}(C_1 + C_2 - 2(C_1 C_2)^{1/2})$$

where, μ_1 and μ_2 are the feature wise mean

C_1 and C_2 are the covariance matrices

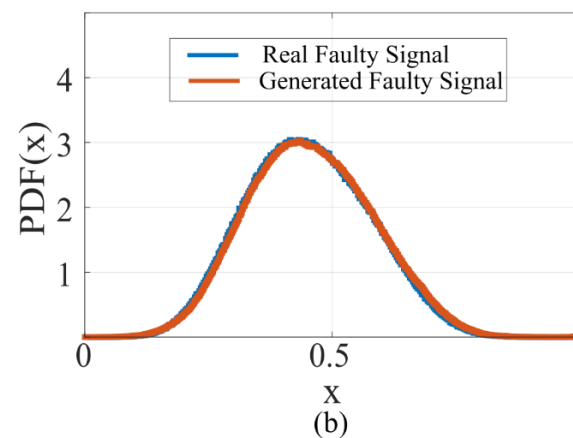
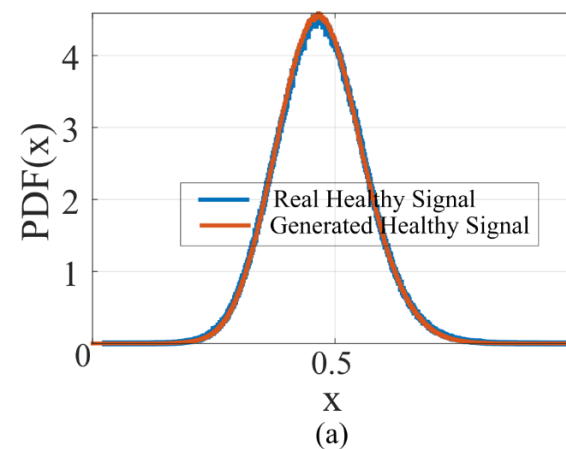
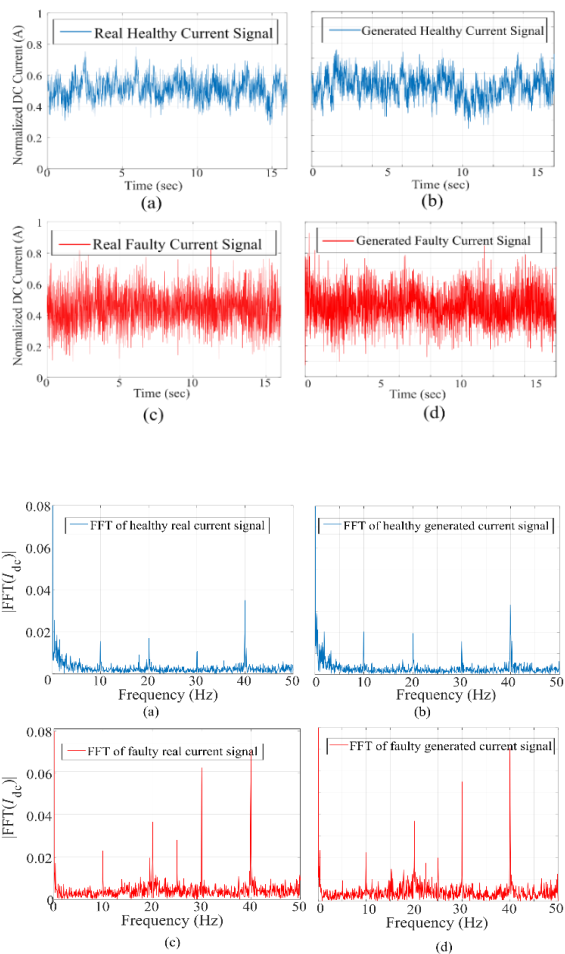
And Tr is the trace of the matrix

► Threshold: 5 x 1E-5



Generated Data Results

SIGNAL GENERATION USING 1D DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS FOR FAULT DIAGNOSIS OF ELECTRICAL MACHINES



Further evaluation of GAN

► **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

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

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

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 $i = 1, \dots, m$

Conclusion

	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

- ▶ 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

THANK YOU