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# Predicting Noise Power in Gm-C Filters through Machine Learning

Malinka Ivanova



Technical University of Sofia  
College of Energy and Electronics

[m\\_ivanova@tu-sofia.bg](mailto:m_ivanova@tu-sofia.bg)



# THE AIM

A novel approach for predicting the total noise power in biquad low pass second order Gm-C filter through application of machine learning algorithms to be presented



# GM-C FILTERS

- The increased interest to the continuous-time Gm-C filters is connected to their features like:
  - high bandwidth
  - possibilities for parameters tuning in large frequency diapason
  - very low passive sensitivity
- Their successful applications are:
  - in high frequency computers
  - communication systems
  - bio-medical devices



# NOISE IN GM-C FILTERS

- Noise depends on the design of the transconductor cell and on the Gm-C filters topology
- The research efforts are focused on minimization the noise level in the filters that will lead to the larger dynamic range and higher ratio signal/noise
- The dominant noise in Gm-C filters is thermal noise, but flicker noise is also taken into consideration
- The sources of noise are MOS transistors:
  - thermal noise (white noise) is generated in the channel as consequence of random charge carriers movement
  - flicker noise (or pink noise) is product of random mobile carriers trapping and detrapping in the channel and in the gate oxide



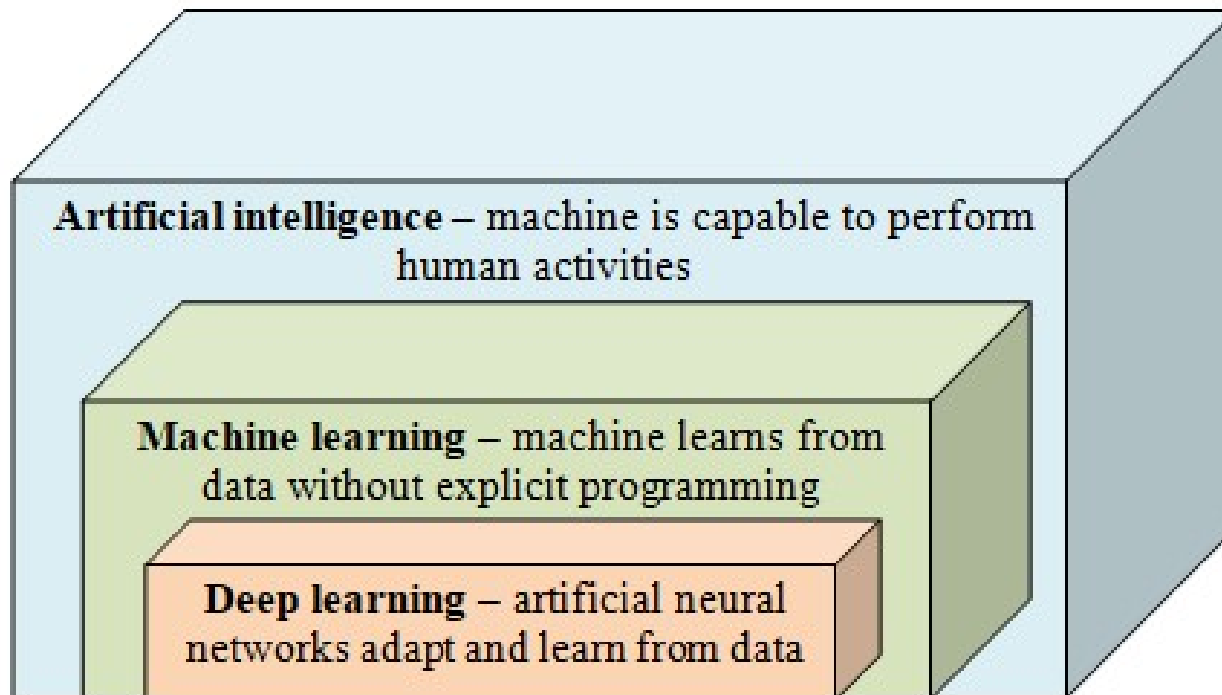
# NOISE MODELING

- Several methods are known for description the noise features and Gm-C filters noise behavior
- All of them are based on noise analysis for a concrete filter solution
- Exception is the general method proposed in (S. Koziel, S. Szczepanski and R. Schaumann, 2003) - such approach is suitable for implementation in the form of CAD tools

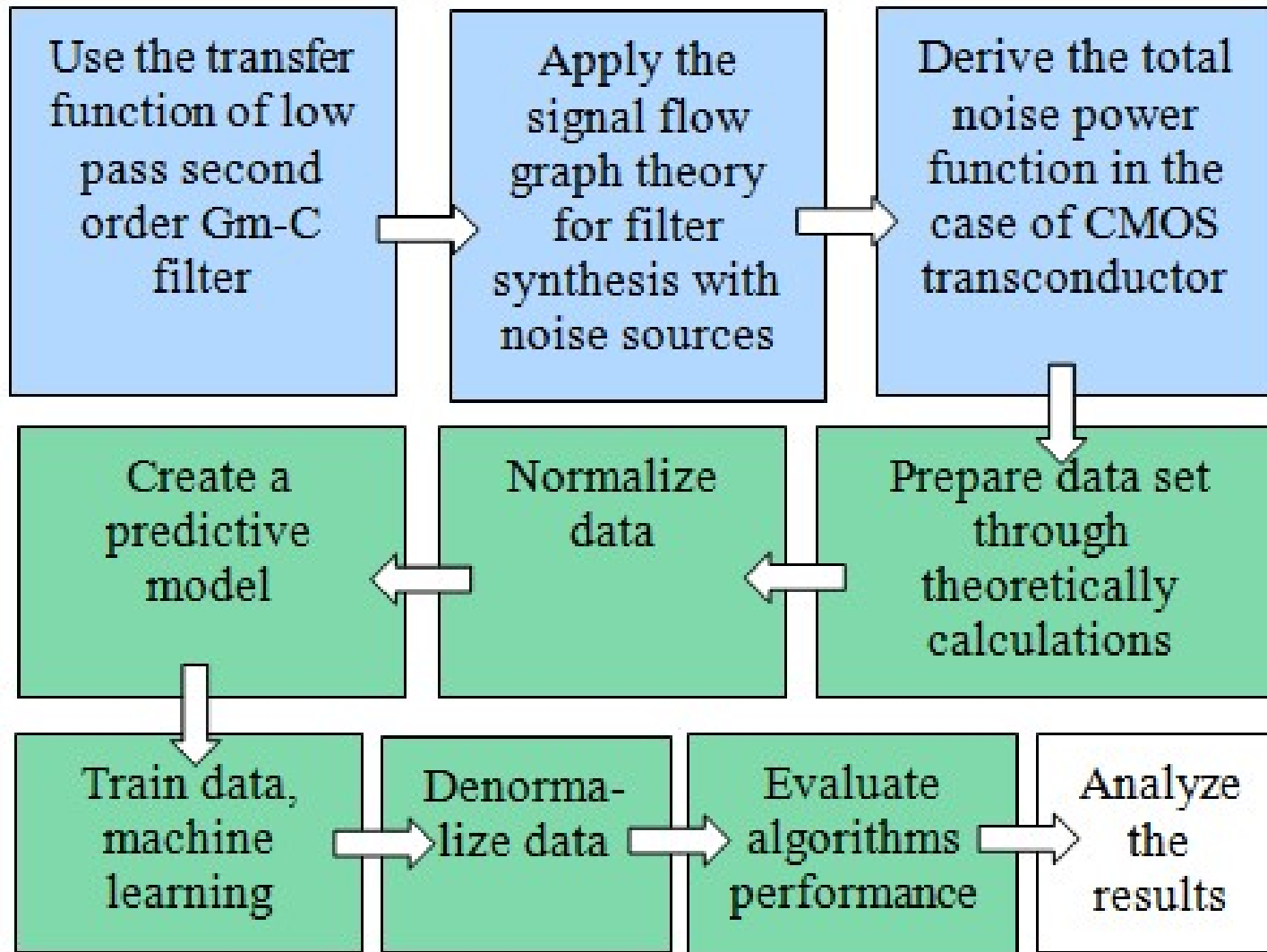


# ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN CIRCUIT MODELING

- One contemporary approach for modeling and analysis of electronic circuits and their parameters relies on algorithms in the areas of artificial intelligence, machine learning and deep learning



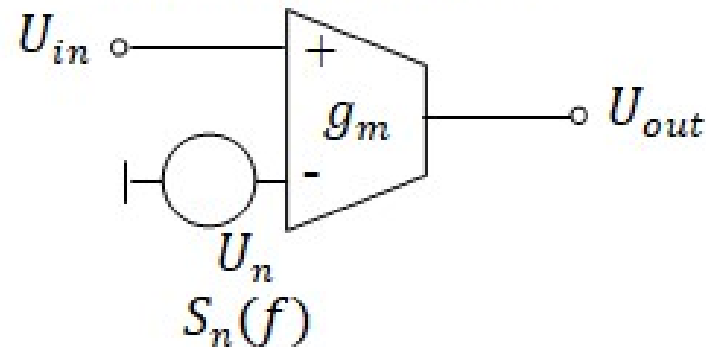
# RESEARCH METHOD



# FILTER MODELING WITH NOISE SOURCES

- Assumption
  - the capacitors in the Gm-C filter configuration are noiseless
  - noisy OTA with transconductance  $g_m$  is modeled with a noiseless transconductor and an equivalent input referred noise voltage source  $U_n$ , which spectral density is  $S_n(f)$

*Noiseless transconductor*







# FILTER MODELING WITH NOISE SOURCES

Spectral density of one input referred noise voltage source

$$S_n(f) = \frac{S_{th}}{g_m} + \frac{S_f}{f} = \frac{8kT}{3g_m} + \frac{A}{C_{ox}WLf} = K' + \frac{K''}{f}$$

The total output noise voltage spectral density taking into account the Gm-C filter topology

$$S_{ntotal}(f) = \bar{v}_n^2 = \sum_{i=1}^k S_{n_i}(f) |H_i(j2\pi f)|^2$$

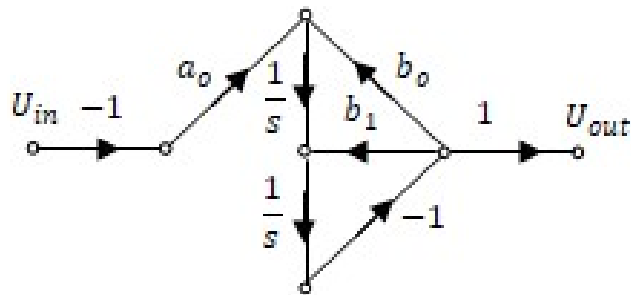
The total noise power

$$P_{nout} = \int_0^{\infty} S_{ntotal}(f) df$$

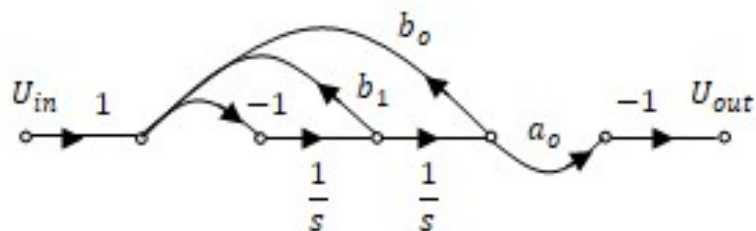
The transfer function of low pass second order biquad Gm-C filter

$$T(s) = \frac{U_{out}}{U_{in}} = \frac{a_0}{s^2 + b_1 s + b_0} = \frac{\omega_0^2}{s^2 + \frac{Q}{\omega_0} s + \omega_0^2}$$

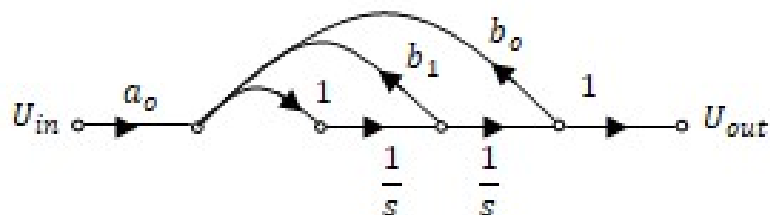
# FILTER MODELING WITH NOISE SOURCES



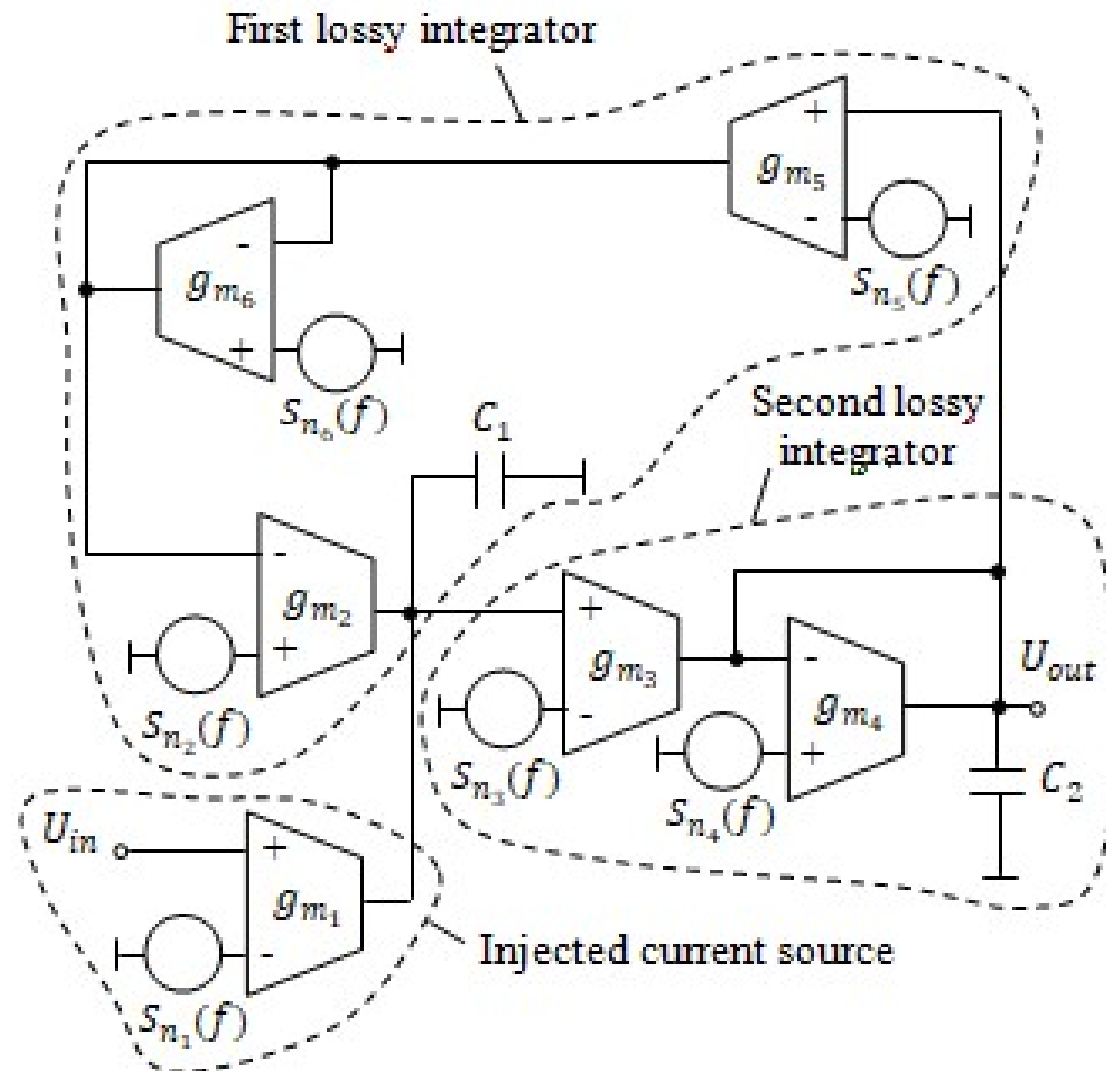
$$U_{out} = \frac{a_0}{s^2} U_{in} - \frac{b_1}{s} U_{out} - \frac{b_0}{s^2} U_{out}$$



Signal Flow Graph of second order Butterworth filter and equivalent transformations



# FILTER MODELING WITH NOISE SOURCES



# FILTER MODELING WITH NOISE SOURCES

$$H_1(s) = \frac{\frac{g_{m2}}{C_1}}{s + \frac{g_{m2}g_{m5}}{C_1 g_{m6}}} = \frac{g_{m2}g_{m6}}{sC_1 g_{m6} + g_{m2}g_{m5}}$$

$$S_{out1}(f) = \frac{g_{m2}^2 S_{n2}(f) + g_{m5}^2 S_{n5}(f) + g_{m6}^2 S_{n6}(f)}{(2\pi f C_1)^2 g_{m2}^2 + g_{m2}^2 g_{m5}^2}$$

$$H_2(s) = \frac{\frac{g_{m3}}{C_2}}{s + \frac{g_{m3}g_{m4}}{C_2 g_{m3}}} = \frac{g_{m3}}{sC_2 + g_{m4}}$$

$$S_{out2}(f) = \frac{g_{m3}^2 S_{n3}(f) + g_{m4}^2 S_{n4}(f)}{g_{m4}^2 + (2\pi f C_2)^2}$$

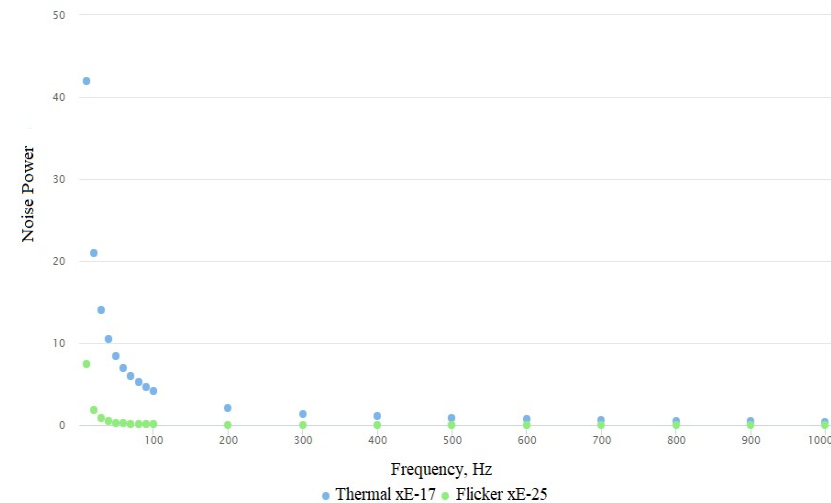
$$H_3(s) = \frac{g_{m1}g_{m3}g_{m5}}{C_1 C_2 g_{m6}}$$

$$S_{out3}(f) = \frac{g_{m1}^2 S_{n1}(f) + g_{m3}^2 S_{n3}(f) + g_{m5}^2 S_{n5}(f) + g_{m6}^2 S_{n6}(f)}{(2\pi f C_1)^2 (2\pi f C_2)^2 g_{m6}^2}$$

$$S_{ntotal}(f) = S_{out1}(f) + S_{out2}(f) + S_{out3}(f)$$

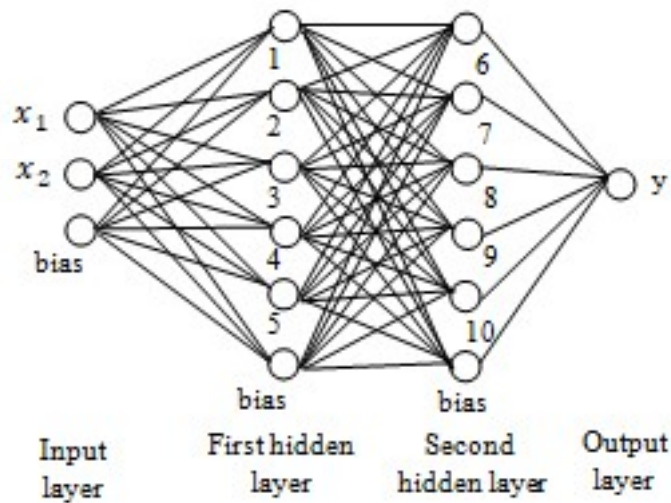
$$P_{nout} = \int_0^\infty S_{ntotal}(f) df = \int_0^\infty S_n(f) \left( \frac{2g_{m6}^2}{(2\pi f C)^2 g_{m2}^2 + g_{m5}^2} + \frac{2g_{m6}^2}{(2\pi f C)^2 + g_{m4}^2} + \frac{4}{(2\pi f C)^4} \right) df \approx \int_0^\infty \frac{K_1}{f^2} + \frac{K_2}{f^3} df$$

$$P_{nout} = -\left( \frac{K_1'}{f} + \frac{K_2'}{2f^2} \right)$$



# MACHINE LEARNING AND PREDICTIVE MODELING

- Demonstration of the research method with ANN algorithm



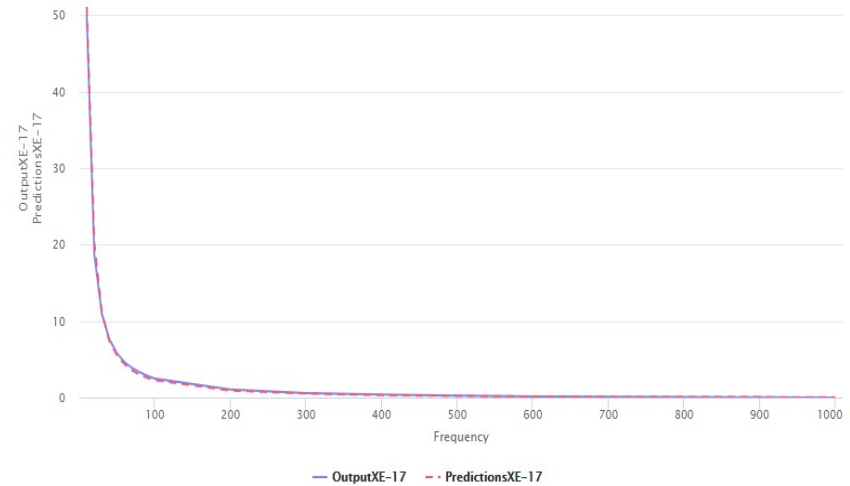
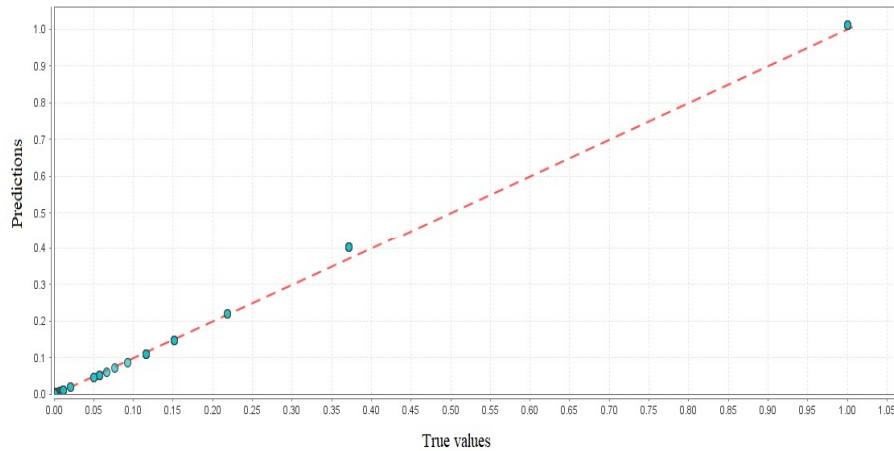
The constructed neural network

Row No.	output	prediction(o...	input1	input2
1	0.372	0.403	0.495	0.250
2	0.219	0.220	0.327	0.111
3	0.152	0.146	0.242	0.062
4	0.116	0.109	0.192	0.040
5	0.077	0.070	0.134	0.020
6	0.066	0.059	0.116	0.015
7	0.057	0.051	0.102	0.012
8	0.008	0.006	0.015	0
9	0	0.001	0	0
10	0.116	0.109	0.192	0.040

Deep learning and predicted output

# MACHINE LEARNING AND PREDICTIVE MODELING

Deep learning – prediction chart

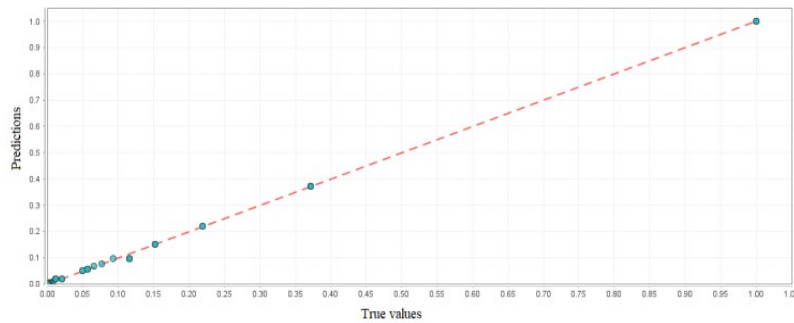


Theoretically calculated and predicted noise power

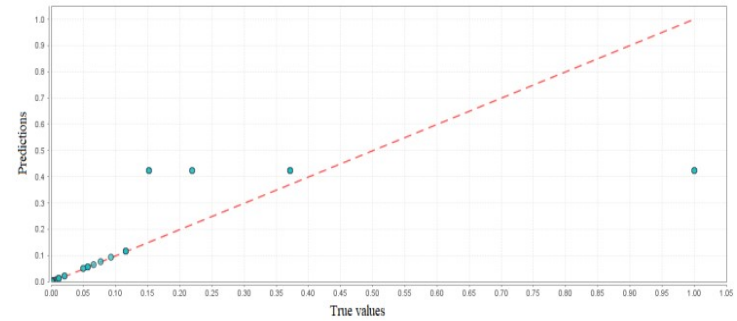


# MACHINE LEARNING AND PREDICTIVE MODELING

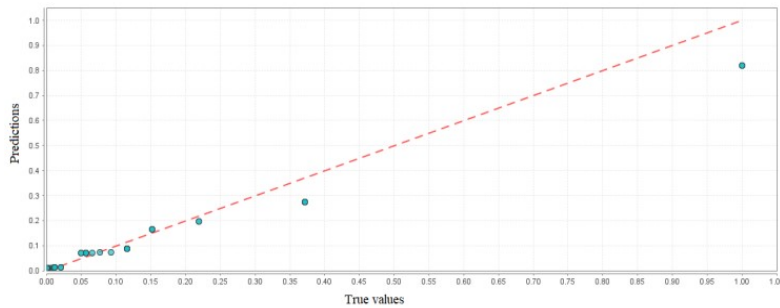
Prediction charts



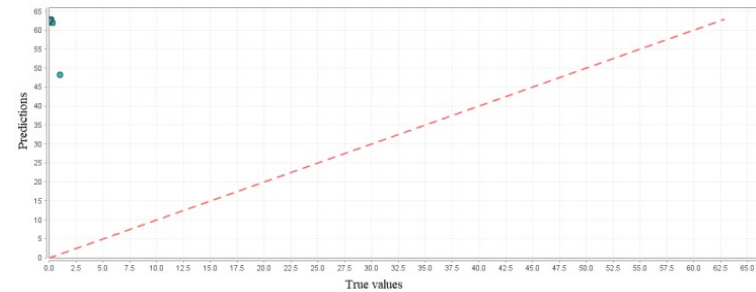
Decision Tree



Random Forest



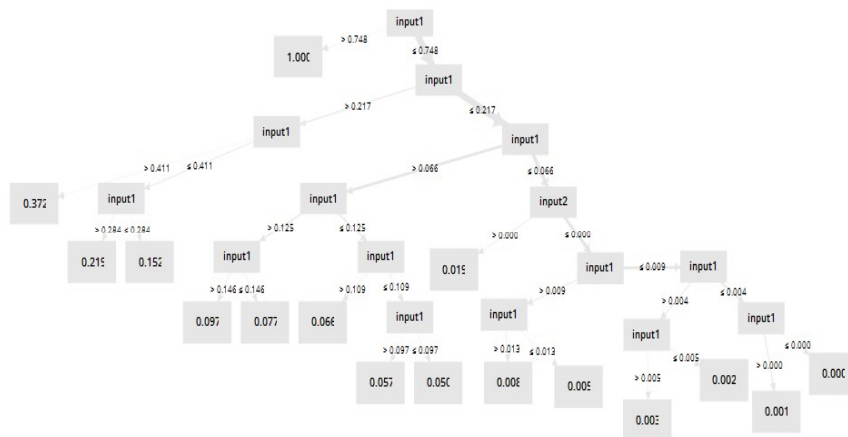
Gradient Boosted Trees



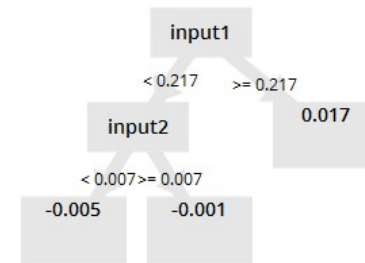
Support Vector Machines

# MACHINE LEARNING AND PREDICTIVE MODELING

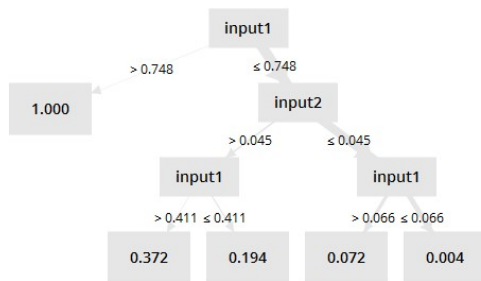
- Constructed trees



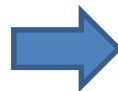
Decision Tree



Gradient Boosted Trees



Random Forest



*IF  $0.411 < input1 \leq 0.748$  AND  $input2 > 0.045$  THEN the predicted output IS 0.372*



# MACHINE LEARNING AND PREDICTIVE MODELING

- Performance of machine learning algorithms

Algorithm	Criterion			
	RMSE	AE	REL	SE
ANN	0.008 ± 0.005	0.005 ± 0.002	11.85% ± 4.51%	0.000
DT	0.007 ± 0.004	0.004 ± 0.002	6.52% ± 3.99%	0.000
RF	0.036 ± 0.029	0.025 ± 0.016	32.60% ± 10.59%	0.002 ± 0.003
GBT	0.113 ± 0.078	0.051 ± 0.033	14.94% ± 10.76%	0.018 ± 0.018
SVM	61.947 ± 0.997	61.901 ± 1.098	99.80% ± 0.13%	3838.173 ± 122.279

→ ANN and Decision Tree algorithms are the best solutions for predicting the noise power in Gm-C filters. They are characterized with high accuracy.



# MACHINE LEARNING AND PREDICTIVE MODELING

- Processing time

Algorithm	Criterion		
	Training time	Scoring time	Total time
ANN	3s	109ms	895ms
DT	61ms	65ms	251ms
RF	140ms	152ms	962ms
GBT	3s	43ms	17s
SVM	1s	65ms	4s



# CONCLUSION

- **Machine learning** that is described as a field of artificial intelligence proposes **powerful techniques** and **algorithms** for electronic circuits' analysis and design
- Studying the circuits' behavior through data about them allows a wide variety of **predictive and analytical models** to be created in support of engineers for decision making and problems solving



# CONCLUSION

- Also, machine learning gives huge opportunities for **automation of engineering tasks** decreasing the needed time, efforts and resources
- Such approach could be implemented in CAD and EDA software in order to present a technique for design and analysis of electronic circuits and devices that could decide engineering problems with high quality and efficiency





# CONCLUSION

- Some machine learning algorithms like tree-based ones not only **point out the final solution**, but also **describe one or several paths** for its achievement
- Other algorithms for deep learning which are based on artificial neural networks allow flexible and accurate approach for **resolving the complexity of the problems**
- It seems that some machine learning algorithms are suitable for performing a given engineering task while the others cannot deal with it



## CONCLUSION

- This work explores the capabilities of machine learning to predict the noise power of Gm-C filters and it is proved that the learning algorithm should be precisely chosen for obtaining the best results
- Also, it is proved that a predictive model with high accuracy can be created to facilitate the performance of prognostic and analytical engineering tasks

# CONCLUSION

- The future work will be focused on further exploration the capability of machine learning algorithms to facilitate engineering tasks, proposing possibilities for better understanding the behavior of electronic circuits
- The development of predictive and analytical models will be performed, exploring their valuable meaning in support of
  - Gm-C filters design – how the filter building blocks and elements to be chosen and arranged to form operable topology
  - filter analysis – what will be the filter and its building blocks reaction at different input stimuli

Picture is taken from: <https://www.ansys.com/blog/what-is-crosstalk-electromagnetic-challenges-trends-electronics>

