Predicting Noise Power in Gm-C Filters through Machine Learning

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Abstract—**Noise level in Gm-C filters is connected to the dynamic range and to the ratio signal-noise. Noise depends on the design of the transconductor cell and filter topology. Predicting the noise power before filter realization could save engineers efforts and resources. The aim of the paper is to present a novel approach for predicting the total noise power in biquad low pass second order Gm-C filter through application of machine learning algorithms as data is taken from synthesized filter topology and filter mathematical model. Five machine learning algorithms: Artificial Neural Networks, Decision Tree, Random Forest, Gradient Boosted Trees, Support Vector Machine are applied for data training and they are evaluated in order to find the most suitable for this problem. The results show that the best solutions for solving this engineering task are Artificial Neuron Networks and Decision Tree algorithms, which are characterized with the best performance and high accuracy.**

Keywords - machine learning; Gm-C filter; noise power; predictive model; signal flow graph

I. INTRODUCTION

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 and very low passive sensitivity, as well as their successful applications in high frequency computer, communication and bio-medical devices and systems [1]-[3].

The most discussed Gm-C filters are realized through CMOS technology as the main building block is the transconductor (OTA – operational transconductance amplifier), which is implemented in the form of differential amplifier, cascodes or folded cascode [4]. Thus, the filter properties in significant way depend on the OTA design.

The minimal input signal is limited by the input referred noise and the maximum input signal is connected to the transconductor nonlinearity. The output dynamic range is related to the total output noise and the maximal value of output linear voltage swing. So, the topics about noise reduction and transconductor linearity are still under extensive investigation.

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 as thermal noise (white noise) is generated in the channel as consequence of random charge carriers movement and flicker noise (or $1/f$, or pink noise) is product of random mobile carriers trapping and detrapping in the channel and in the gate oxide.

Another question under exploration is related to the noise modeling and analysis and 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 [5][6]. The authors have developed a general structure of Gm-C filter that is a base for deriving any particular topology and analytical description. Such approach is suitable for implementation in the form of CAD tools. Nowadays, the most utilized methodology for Gm-C filters noise analysis (that is used in this work) consists of four steps: (1) identification the noise sources and noise spectrum Sn; (2) discovering the transfer function H from the noise source to the filter output; (3) calculating the output noise spectrum taking into account all noise sources; (4) calculating the total noise power as an integral over the frequency band of noise spectrum.

One contemporary approach for modeling and analysis of electronic circuits and their parameters relays on algorithms in the areas of artificial intelligence, machine learning and deep learning [7][8], which scope is presented on Figure 1.

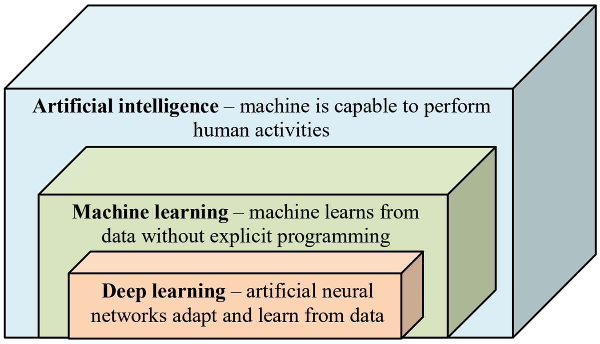

Figure 1. Scope of artificial intelligence, machine learning and deep learning

Artificial intelligence utilizes programs to reproduce human behavior and typical human activities. Machine learning is an application of artificial intelligence where machines are capable to learn from data without explicit programming. Machine learning algorithms are used for solving classification and clustering tasks with aim some items, events and processes to be predicted and analyzed [9]. Deep learning is part of machine learning and it is based on Artificial Neural Networks usage that is inspired by brain functionality of biological systems. Among the advantages of algorithms for deep learning are learning from data in an easy way, correct features selection and pattern recognition. Recently, machine learning approach is applied in support of electronics engineers, facilitating and automating tasks related to computer-aided design and analysis of electronic circuits [10].

The aim of the paper is to present a novel approach for predicting noise power in Gm-C filter through application of machine learning algorithms as data is taken from synthesized filter topology and filter mathematical model. Five machine learning algorithms: Artificial Neural Networks (ANN), Decision Tree (DT), Random Forest (RF), Gradient Boosted Trees (GBT), Support Vector Machine (SVM) are applied for data training and they are evaluated in order to find the most suitable for this problem, e. g., those with the best performance and high accuracy. The rest of the paper is organized as follows: 2nd section describes the research method, the 3rd section explains the filter modeling with noise sources, the 4th section presents predictive modeling through machine learning, and the final section includes conclusion and future work.

II. Research Method

The proposed method for predicting the noise power in Gm-C filter is shown on Figure 2 and it consists of the following steps:

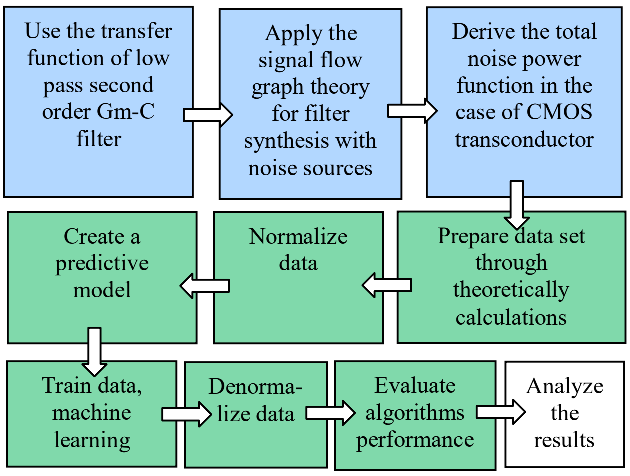

Figure 2. Used research method

(1) Derive the mathematical description of the filter noise power as before that the filter synthesis with noise sources is performed through the filter transfer function and signal flow graphs; (2) Form data set according to the filter mathematical description and data pre-processing; (3) Create a predictive model, train data, and apply machine learning algorithms; (4) Evaluate the performance of machine learning algorithms and analyze results.

III. Filter Modeling with Noise Sources

The literature examination shows that enough efficient noise models could be received after assumption that the capacitors in the Gm-C filter configuration are noiseless. Also, 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 $S_n(f)$ as it is presented on Figure 3 [11]-[13].

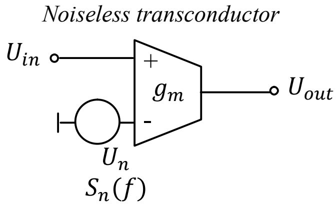

Figure 3. Noise model of an OTA [11]-[13]

In the same literature sources, it is shown that the spectral density $S_n(f)$ of one input referred noise voltage source U_n can be modeled with two components that define the influence of thermal $\frac{S_{th}}{g_m}$ and flicker $\frac{S_f}{f}$ noises:

$$S_n(f) = \frac{S_{th}}{g_m} + \frac{S_f}{f} = \frac{8kT}{3g_m} + \frac{A}{C_{ox}WLf} = K' + \frac{K''}{f}, \quad (1)$$

where $k = 1{,}38.10^{-23} J/K$ - Boltzmann constant, T - absolute temperature, A is a flicker noise coefficient that depends on the CMOS process and its value is about $10^{-25} V^2 F$ (according to [14]), W and L are channel parameters of MOS transistors, C_{ox} - oxide capacitance per unit area. The total output noise voltage spectral density taking into account the Gm-C filter topology can be calculated through the following formula:

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

where H_i is the noise transfer function from this noise source to the filter output. The total noise power of noise spectrum is the integral over the frequency band:

$$P_{nout} = \int_0^\infty S_{ntotal}(f) df . \quad (3)$$

To demonstrate the noise modeling in Gm-C filters, the signal graph flow theory [15] is used. Some scientific works discuss the utilization of signal flow graph for RC and Gm-C filters design [16] [17], but here, it is applied in the context of noise power formulation, that is a new approach. The transfer function of low pass second order biquad Gm-C filter is used [18]:

$$T(s) = \frac{U_{out}}{U_{in}} = \frac{a_o}{s^2 + b_1 s + b_0} = \frac{\omega_o^2}{s^2 + \frac{Q}{\omega_o}s + \omega_o^2} . \quad (4)$$

The filter synthesis is performed after several transformations of (4) and drawing the corresponding signal flow graph.

Firstly, the transfer function (4) is presented in the form $U_{out}(s^2 + b_1 s + b_0) - a_o U_{in} = 0$ and obtained expression is multiplied to the variable $\frac{1}{s^2}$. The received formula

$$U_{out} = \frac{a_0}{s^2} U_{in} - \frac{b_1}{s} U_{out} - \frac{b_0}{s^2} U_{out} \quad (5)$$

is a base for signal graph construction (Figure 4a and b).

Further, equivalent transformation of the flow graph from Figure 4 is presented on Figure 5, where $a_o = b_o = \omega_o^2$ and $b_1 = \frac{Q}{\omega_o}$ (taking into account (4)).

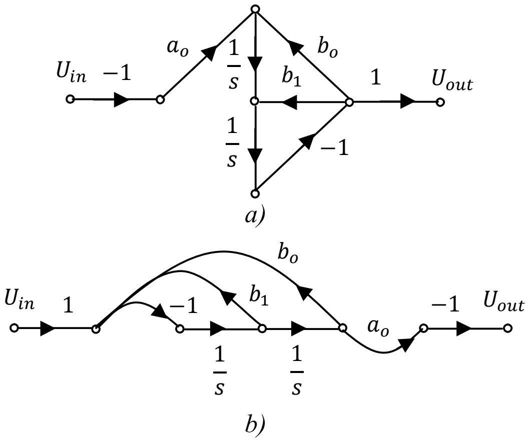

Figure 4. Signal Flow Graph of second order buquad filter: a) direct representation of (5); b) equivalent transformation

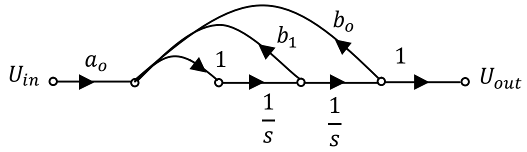

Figure 5. Equivalently transformed signal graph

The circuit implementation of this graph could be realized in different ways. One approach is shown on Figure 6, which includes two lossy integrators and a current injection source. Such topology for first time is reported in [19]. The method of current injection node is chosen because of its design flexibility and possibility for construction filters with different complexity. The first lossy integrator consists of g_{m_2}, g_{m_5}, g_{m_6}, C_1 and characterizes with the transfer function

$$H_1(s) = \frac{\frac{g_{m_2}}{C_1}}{s+\frac{g_{m_2}g_{m_5}}{C_1\ g_{m_6}}} = \frac{g_{m_2}g_{m_6}}{sC_1g_{m_6}+g_{m_2}g_{m_5}} \tag{6}$$

and noise voltage spectral density

$$S_{out1}(f) = \frac{g_{m_2}^2 S_{n_2}(f)+g_{m_5}^2 S_{n_5}(f)+g_{m_6}^2 S_{n_6}(f)}{(2\pi f C_1)^2 g_{m_6}^2+g_{m_2}^2 g_{m_5}^2}. \tag{7}$$

The second lossy integrator is implemented with g_{m_3}, g_{m_4}, C_2 and has the transfer function

$$H_2(s) = \frac{\frac{g_{m_3}}{C_2}}{s+\frac{g_{m_3}g_{m_4}}{C_2\ g_{m_3}}} = \frac{g_{m_3}}{sC_2+g_{m_4}} \tag{8}$$

and noise spectral density

$$S_{out2}(f) = \frac{g_{m_3}^2 S_{n_3}(f)+g_{m_4}^2 S_{n_4}(f)}{g_{m_4}^2+(2\pi f C_2)^2} \text{ [20].} \tag{9}$$

The injected current source is realized through single OTA with transconductance g_{m_1}, which transfer function is

$$H_3(s) = \frac{g_{m_1}g_{m_3}g_{m_5}}{C_1C_2g_{m_6}} \tag{10}$$

and noise spectral density

$$S_{out3}(f) = \frac{g_{m_1}^2 S_{n_1}(f)+g_{m_3}^2 S_{n_3}(f)+g_{m_5}^2 S_{n_5}(f)+g_{m_6}^2 S_{n_6}(f)}{(2\pi f C_1)^2(2\pi f C_2)^2 g_{m_6}^2}. \tag{11}$$

The total output spectral density is calculated through equation (2):

$$S_{ntotal}(f) = S_{out1}(f) + S_{out2}(f) + S_{out3}(f). \tag{12}$$

If the suggestion is that $S_{n_1}(f) = S_{n_2}(f) = S_{n_3}(f) = S_{n_4}(f) = S_{n_5}(f) = S_{n_6}(f) = S_n(f)$, $g_{m_1} = g_{m_2} = g_{m_3} = g_{m_4} = g_{m_5} = g_{m_6} = g_m$ and $C_1 = C_2 = C$, then the total output noise power is

$$P_{nout} = \int_0^\infty S_{ntotal}(f) = \int_0^\infty S_n(f)\Big(\frac{3g_m^2}{(2\pi f C)^2 g_m^2+g_m^4} + \frac{2g_m^2}{(2\pi f\ )^2+g_m^2} + \frac{4}{(2\pi f C)^4}\Big) \approx \int_0^\infty \frac{K_1}{f^2} + \frac{K_2}{f^3}, \tag{13}$$

where $K_1 \div K_2$ are constant values.

After simplification and integration the formula (13), for the total output noise power is received (K_1' and K_2' are constants):

$$P_{nout} = -\Big(\frac{K_1'}{f} + \frac{K_2'}{2f^2}\Big). \tag{14}$$

The data about the transconductor cell is taken from [18] where for simulation is chosen $0.5\mu m\ CMOS$ technology, $W/_L = 10$, $^{\mu_n C_{ox}}/_2 = 5{,}78.10^{-5} A/V^2$, $g_m = 8{,}5.10^{-4} S$.

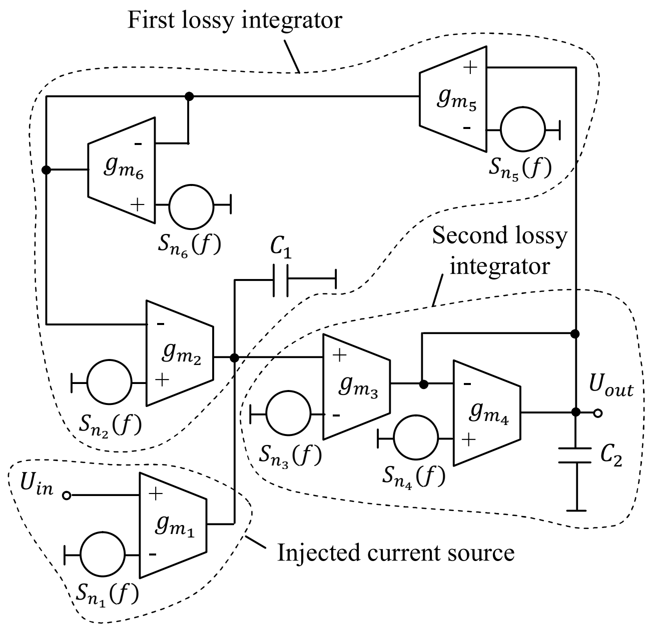

Figure 6. Gm-C filter with noise sources

Graphics of thermal and flicker noise power are presented on Figure 7. It is constructed according to obtained data of the mathematical model for noise power in

Gm-C filter. It can be seen that the flicker noise component appears at low frequency and it is much smaller (xE-25) that the thermal one (xE-17).

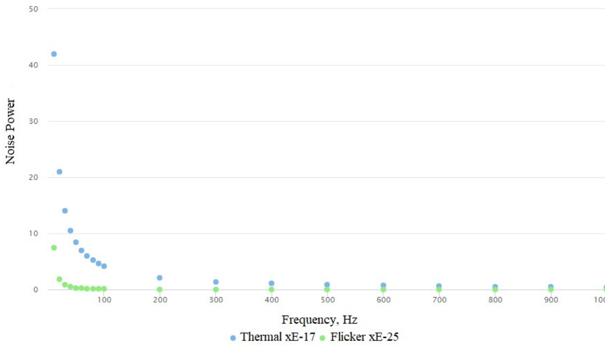

Figure 7. Thermal and flicker noise power in Gm-C filter

IV. MACHINE LEARNING AND PREDICTIVE MODELING

In this section, the development of a predictive model related to predicting the noise power in the Gm-C filter is presented. It is based on data derived theoretically from Eq. (7) and on application of supervised machine learning algorithms: ANN, DT, RF, GBT, SVM [21]-[23].

The research method is demonstrated in details for ANN algorithm, but the same method is applied to the other machine learning algorithms. The performance of the utilized machine learning algorithms is compared and discussed.

Before data training in RapidMiner Studio (version 9.4.001) environment [24], the data is normalized in the interval [0, 1], according to the standard min-max normalization: $x = \frac{x - x_{min}}{x_{max} - x_{min}}$.

Deep learning is realized through a multi-layer back-propagation neural network for which training is used stochastic gradient descent.

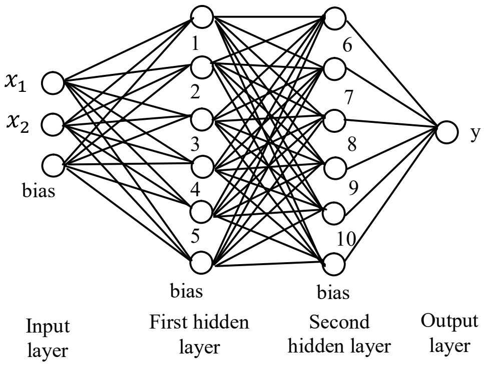

Figure 8. The constructed neural network

The artificial neural network consists of two inputs x_1 and x_2 (thermal and flicker noise power), output y (predicted noise power) and two hidden layers with five neurons in each layer (Figure 8). The neurons from the hidden layers are activated through ReLU (Rectified Linear Unit) function: $ReLU(x) = \begin{cases} 0, x \leq 0 \\ x, x > 0 \end{cases} = max\ \{0, x\}$.

Normalized and predicted data sets for noise power are presented on Figure 9.

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

Figure 9. Deep learning and predicted output

The deviation of predicted values $\hat{y}$ in comparison with the theoretically calculated y can be seen through the prediction chart on Figure 10 (the x-axis shows true values and y-axis presents predicted values).

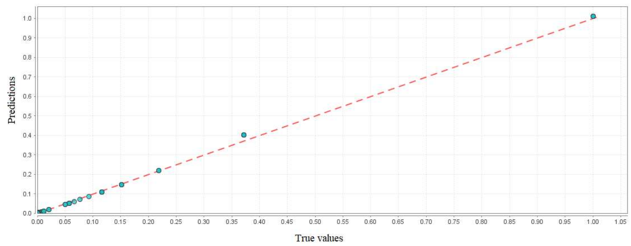

Figure 10. Deep learning – prediction chart

It can be said that the model accuracy is high, which is proved with calculation of very low errors:

- *Root Mean Square Error* (RMSE) measures the difference between N actual y and predicted $\hat{y}$ values, e. g., $RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{N}}$): 0.008 ± 0.005;
- *Absolute Error* (AE) is the average absolute deviation between predicted and actual value $\Delta y = \frac{|\hat{y}_i - y_i|}{N}, i = 1, 2, \ldots, N$): 0.005 ± 0.002;
- *Relative Error Lenient* (REL) is the average absolute deviation between predicted and actual value divided by the maximum of predicted and actual value $REL = \frac{|\hat{y}_i - y_i|}{N} \frac{1}{\max(\hat{y}_i y_i)}, i = 1, 2, \ldots, N$): $11.85\% \pm 4.51$;
- *Squared Error* (SE) is the averaged squared error:0.000.

To construct the curves of thermal noise power taking into account theoretically calculated and predicted values, the predictions are denormalized: $x_{denorm} = x_{norm}(x_{max} - x_{min}) + x_{min}$ (Figure 11).

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The prediction charts of the rest machine leaning algorithms are presented on Figure 12.

Several constructed trees through tree-based classification algorithms are shown on Figure 13 (the depicted values are normalized). The presented information through these trees could support the decision making process of designers or analysts. Following the path of the tree nodes, it is possible the decision explicitly to be explained and also the exact decision to be pointed out, concerning the values in the leafs. For example, if the tree on Figure 13b is examined and a path is followed from the root node to the leaf, it can be said that

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

The performance evaluation of the applied machine learning algorithms is shown through Table 1. The algorithm performance is important evidence about how the algorithm handles and processes the data model. The task in this work is to find the best predictive model, which is capable to solve the engineering problem related to prognosis of noise power in a Gm-C filter. Thus, an appropriate algorithm should be selected. For this purpose, the used algorithms are compared according to their accuracy (error rate), which is the most applied metrics in practice.

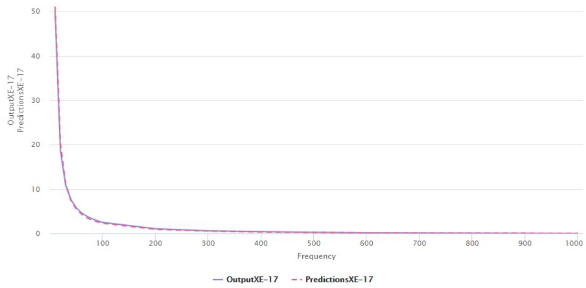
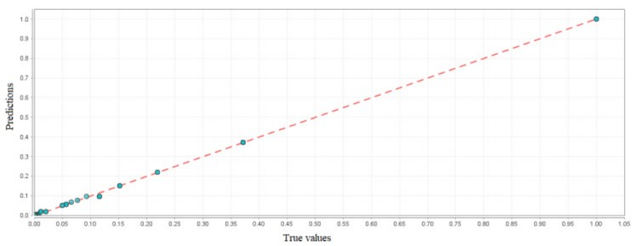


Figure 11. Theoretically calculated and predicted noise power



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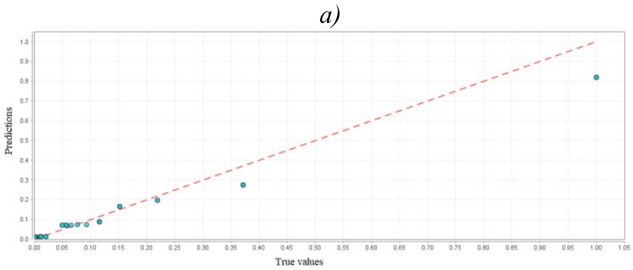

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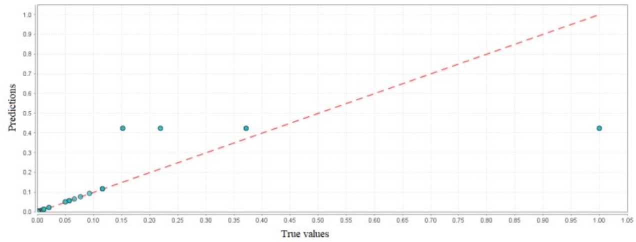

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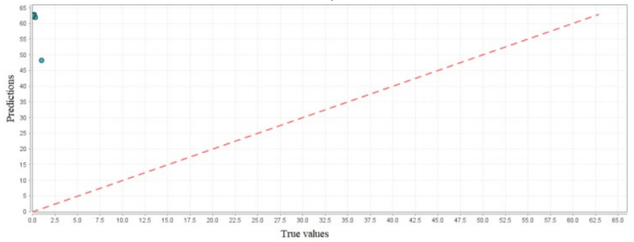
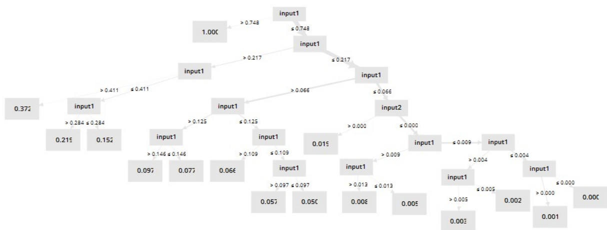


d)

Figure 12. Prediction charts of machine learning algorithms: a) Decision Tree; b) Random Forest; c) Gradient Boosted Trees; d) Support Vector Machines



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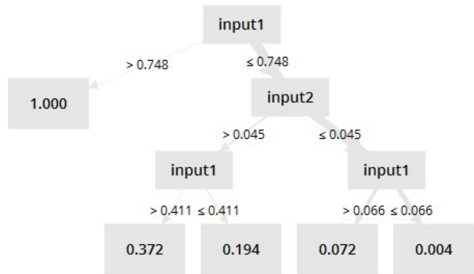

b)

c)

Figure 13. Constructed trees through applying: a) Decision Tree; b) Random Forest (one of 20 constructed trees); c) Gradient Boosted Trees (one of 150 constructed tress)

TABLE I. PERFORMANCE OF MACHINE LEARNING ALGORITHMS

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

The comparison of prediction charts (Figure 10 and Figure 12) and data about the performance of machine learning algorithms from Table 1 point out that the ANN and DT algorithms are the best solutions for predicting the noise power in Gm-C filters. They are characterized with high accuracy.

The best performance and fastest total time (Table 2) shows the DT machine learning algorithm (the experiment is done on local computer with processor Intel(R) Core™ i7-5500U @ 2.40GHz, RAM 8GB). The worse case is the algorithm SVM that cannot deal with this predictive task. Its performance is very poor and the accuracy is small.

The comparison of the tree-based algorithms outlines that the smallest errors are introduced by DT algorithm and the biggest by GBT.

TABLE II. PROCESSING TIME

	Criterion		
Algorithm	**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

V. CONCLUSION

In this paper, a predictive model regarding noise power in Gm-C filter is proposed. It is created according to the designed research method. The filter synthesis with noise sources is performed through usage of its mathematical description and through applying signal flow graph theory. The derived equation for noise power allows data sets to be prepared for further statistical and machine learning processing. Five machine learning algorithms - ANN, DT, RF, GBT, and SVM are used for data training with predictive purpose. The performance of these algorithms is evaluated and they are compared according to two groups of criterion: accuracy and timing. The results show that the DT algorithm is characterized with the best performance: $RMSE = 0.007 \pm 0.004,\ AE = 0.004 \pm 0.002,\ REL = 6.52\% \pm 3.99\%,\ SE = 0.000,\ training\ time = 61ms,\ scoring\ time = 65ms,\ total\ time = 251m$. Another suitable algorithm is ANN, which is capable to predict the noise power values with very high accuracy.

It can be said that 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. 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.

Learning through big data is a method that leads to better understanding the functionality and topology of electronic circuits and particularly the analog filters. 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. The explanation of a given solution is valuable knowledge in engineering practice. 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.

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.

The lessons learned and challenges can be summarized as follows:

- At the stage of data gathering – suitable step for data collection should be chosen.
- At data model preparation – the designer should assess the data value, choosing the correct data set, ignoring the redundant data.
- At pre-processing stage, suitable format for data set processing should be selected.
- At data processing stage, several machine learning algorithms should be applied and compared for receiving the required output. The algorithms parameters should be precisely defined, because it reflects on the accuracy at the task solving.
- The predictive model should be evaluated and improved, when the obtained results are not satisfactory.

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, as well as in assistance of filter analysis – what will be the filter and its building blocks reaction at different input stimuli.

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REFERENCES

[1] M. A. Bhuiyan, M. B. Omar, M. M. Reaz, K. N. Minhad, and F. H. Hashim, “A review on CMOS Gm-C band pass filters in RF application,” Journal of Theoretical and Applied Information Technology, 61(1), pp. 17-23, 2014.

[2] B. Saidulu, A. Manoharan, and K. Sundaram, “Low Noise Low Power CMOS Telescopic-OTA for Bio-Medical Applications,” Computers, 5(4), 2016, https://doi.org/10.3390/computers5040025.

[3] S. K. Arfin, S. Mandal, and R. Sarpeshkar, “Dynamic-Range Analysis and Maximization of Micropower Gm–C Bandpass Filters by Adaptive Biasing”, IEEE International Symposium on Circuits and Systems, pp. 2954-2957, 2009.

[4] M. Akbari and O. Hashemipour, “Design and analysis of folded cascode OTAs using Gm/Id methodology based on flicker noise reduction,” Analog Integrated Circuits Signal Processing, 83, pp. 343–352, 2015.

[5] S. Koziel, S. Szczepanski and R. Schaumann, “A general approach to continuous-time Gm-C filters,” International Journal of Ciruit Theory and Applications, pp. 361-383, 2003.

[6] S. Koziel, R. Schaumann and Haiqiao Xiao, “Analysis and optimization of noise in continuous-time OTA-C filters,” IEEE Transactions on Circuits and Systems I, 52(6), pp. 1086–1094, 2005, doi:10.1109/TCSI.2005.849142.

[7] E. Rosenbaum, “Machine Learning: An enabling technology for electronics modeling and design optimization,” 2017. [Online]. Available from: http://publish.illinois.edu/advancedelectronics/files/2017/02/DesignCon_rosenbaum_keynote-Feb-1-2017-web-.pdf

[8] T. L. Hemminger, “A Neural Network Approach to Transistor Circuit Design,” Global Journal of Computer Science and Technology, 16(1), 2016, Online ISSN: 0975-4172, Print ISSN: 0975-4350.

[9] L. Rokach, A. Feldman, M. Kalech and G. Provan, “Machine-learning-based circuit synthesis,” IEEE 27th Convention of Electrical and Electronics Engineers in Israel, Eilat, pp. 1-5, 2012, doi: 10.1109/EEEI.2012.6377134.

[10] Machine Learning in VLSI Computer-Aided Design, Eds. Ibrahim (Abe) M. Elfadel, Duane S. Boning, Xin Li, Springer International Publishing, 2019, doi: 10.1007/978-3-030-04666-8.

[11] T. Deliyannis, Y. Sun, and J. K. Fidler, “Two Integrator Loop OTA-C Filters,” Continuous-Time Active Filter Design, Boca Raton: CRC Press LLC, 1998, https://doi.org/10.1201/9781439821879.

[12] T. Deliyannis, Y. Sun, and J. K. Fidler, “Single Operational Transconductance Amplifier (OTA) Filters”, Continuous-Time Active Filter Design Boca Raton: CRC Press LLC, 1998, https://doi.org/10.1201/9781439821879.

[13] A. Brambilla, G. Espinosa, F. Montecchi and E. Sanchez-Sinecio, “Noise optimization in operational transconductance amplifier filters,” IEEE International Symposium on Circuits and Systems, Portland, OR, vol.1, pp. 118-121, 1989, doi: 10.1109/ISCAS.1989.100305.

[14] Telehealth and Mobile Health, Eds Halit Eren and John G. Webster, p. 627, CRC Press, 2015, ISBN-13: 978-1482236613.

[15] G. S. Moschytz, “Analog Circuit Theory and Filter Design in the Digital World,” chapter “An Introduction to Signal-Flow Graph Theory,” Springer Nature Switzerland AG, 2019, pp. 85-100, doi: 10.1007/978-3-030-00096-7.

[16] P.-M. Lin, “Signal Flow Graphs in Filter Analysis and Synthesis,” Circuit Analysis and Feedback Amplifier Theory, W.-K. Chen (Ed.), 2006, https://doi.org/10.1201/9781315220567.

[17] L. A. Sánchez-Gaspariano et al., “CMOS Analog Filter Design for Very High Frequency Applications,” Electronics 2020, 9, 362, doi:10.3390/electronics9020362.

[18] K. Kaewdanga and W. Surakampontorn, “A balanced output CMOS OTA with wide linear current tunable range,” International Journal of Electronics and Communications (AEÜ) 65, pp. 728–733, 2011.

[19] G. Espinosa, F. Montecchi, E. Sanchez-Sinencio and F. Maloberti, “Noise performances of OTA-C filters,” IEEE International Symposium on Circuits and Systems 3, Espoo, Finland, pp. 2173-2176, 1988, doi: 10.1109/ISCAS.1988.15374.

[20] E. Sanchez-Sinencio, R. L. Geiger and H. Nevarez-Lozano, “Generation of continuous-time two integrator loop OTA filter structures,” IEEE Transactions on Circuits and Systems, 35(8), pp. 936-946, 1988, doi: 10.1109/31.1840.

[21] M. A. Stošović and V. Litovski, “Applications of Artificial Neural Networks in Electronics,” Electronics, 21(2), pp. 87-94, 2017.

[22] T. Wu, H. Zhao, F. Liu, J. Guo, and H. Wang, “Machine Learning Approach for Device-Circuit Co-Optimization of Stochastic-Memristive-Device-Based Boltzmann Machine,” 2019. [Online]. Available from: https://arxiv.org/ftp/arxiv/papers/1905/1905.04431.pdf.

[23] M. Kubat, “An Introduction to Machine Learning,” Springer International Publishing AG, 2017, doi: 10.1007/978-3-319-63913-0.

[24] RapidMiner, RapidMiner Studio Manual, 2014. [Online]. Available from: https://docs.rapidminer.com/downloads/RapidMiner-v6-user-manual.pdf.