

Project: SPS-G5953 Advanced UAV Based GPR Imaging Techniques for Explosive Detection

Activity: Training Seminar in the field of Ground Penetrating Radars Principles, Hardware and Software Development and Target Detection

Overview of Artificial Neural Networks based Antenna Design

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Introduction

- Analytic EM approach in antenna modelling is useful only in cases of simpler antenna geometry.
- Numerical EM approach in antenna modelling based on using **EM simulators** allows for modelling antennas of complex constructions with a high accuracy.
- The main limitation of numerical EM approach is that it requires powerful hardware resources and significant run-time for necessary calculations.
- One of the alternatives to numerical EM approach is antenna modelling by using the **Artificial Neural Networks (ANNs-based antenna modelling)**.



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Properties of ANN

- ANN represents a highly parallel distributed architecture consisting of strongly connected processing units - neurons.
- This architecture allows for modelling of previously mentioned problems by using a model based on ANN with a fast signal flow from input to output.
- ANN is not programmed to perform known functional dependencies, instead it learns about these dependencies based on a set of solved examples.



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Properties of ANN

- After successfully completed training process, ANN is capable to give solutions, not only for solved examples used during the training, but also to estimate solutions for examples not used in the learning phase.
- This property is called problem **generalization** and it allows to model problems whose physical nature is not well known (this is often the case in antenna modelling) by using ANN.



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Good property of ANN-based antenna model

- ANN-based antenna model allows for significantly faster calculation of wanted antenna characteristics for known values of geometrical and physical parameters of antenna compared to numerical EM model, while an accuracy is similar to a numerical EM model.
- This property is very important for **an optimization process of input antenna parameters** and where ANN model is potentially much faster than a classical EM simulator.
- In addition, implementation of ANN-based antenna model is significantly less demanding regarding the hardware resources than implementation of numerical EM model.

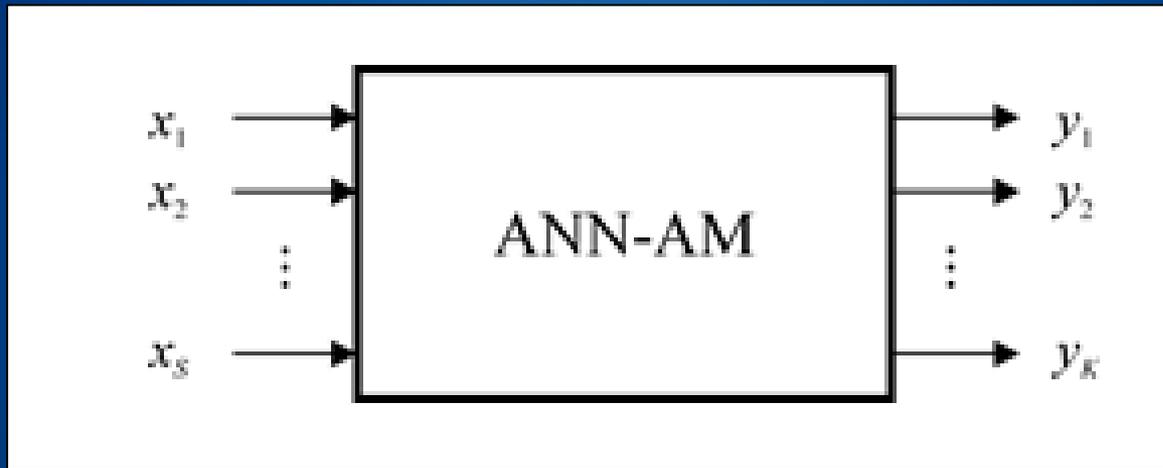


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Basic ANN-based antenna model

Black-box approach in antenna modelling



$$\mathbf{y} = f_{ANN-AM}(\mathbf{x})$$

Input parameter vector:

$$\mathbf{x} = [x_1 \quad x_2 \quad \cdots \quad x_s]^T$$

Output parameter vector:

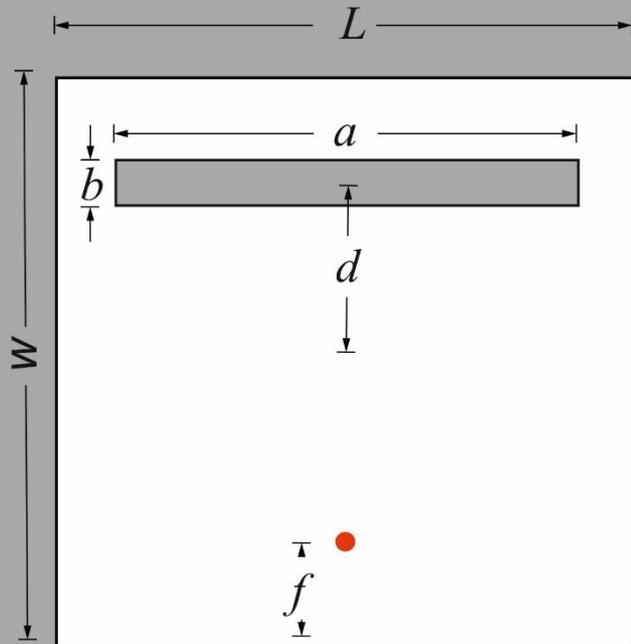
$$\mathbf{y} = [y_1 \quad y_2 \quad \cdots \quad y_k]^T$$



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Architecture of dual-band slotted square patch antenna



L – patch length

w – patch width

a – length of rectangular slot

b – width of rectangular slot

d – distance between antenna centre and slot centre

f – distance from patch edge to feed point

$$k_f = -\frac{f}{L}$$

$$k_a = \frac{a}{L}$$

$$k_d = \frac{2d}{L-b}$$

$$\frac{1}{Z_{ps}} = \frac{1}{Z_p} + \frac{1}{Z_s}$$

Z_p – patch impedance

Z_s – slot impedance

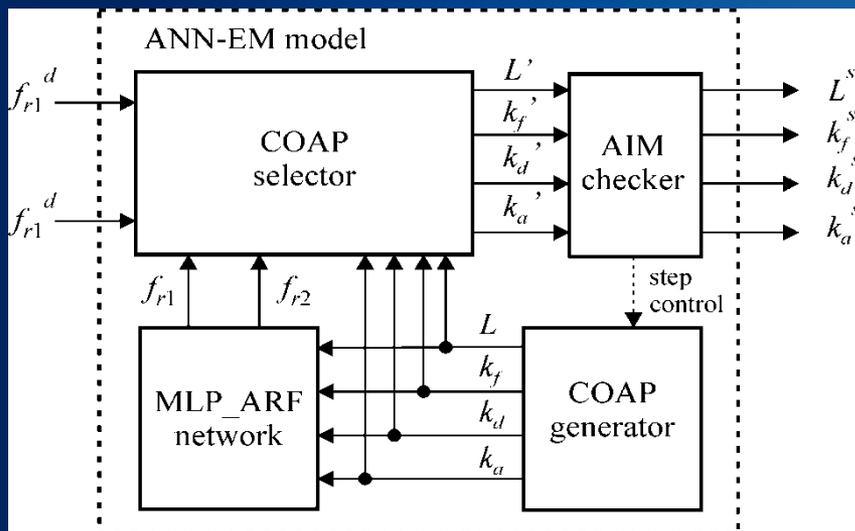


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ANN-EM model of dual-band slotted square patch antenna

The main task of ANN-EM model is to find values of physical parameters of antenna (L^s, k_f^s, k_d^s, k_a^s) for wanted resonant frequencies (f_{r1}^d, f_{r2}^d).



COAP (*combination of antenna parameters*) generator - generate the set of all combinations of physical parameters of antenna.

MLP_ARF (*antenna resonant frequencies*) network - network based on MLP that determines the resonant frequencies of antenna (f_{r1}, f_{r2}) for each combination of physical parameters of antenna.

COAP selector - chooses the combination of physical parameters of antenna that are close to give wanted resonant frequencies f_{r1}^d and f_{r2}^d and forms a new set of combinations

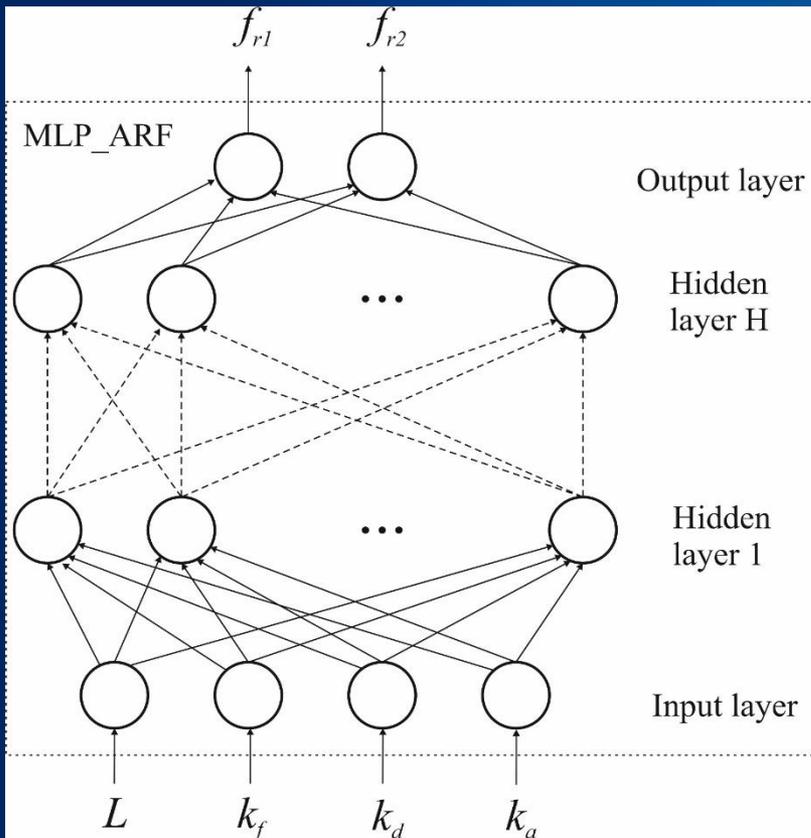
AIM (*antenna impedance matching*) checker – find the combination of physical parameters of antenna that will provide that antenna has a satisfactory match of impedances between antenna and feed line at the resonant frequencies.



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MLP_ARF network



$$[f_{r1} \ f_{r2}] = y([L \ k_f \ k_d \ k_a]^T, W, B)$$

$$\mathbf{y}_l = F(\mathbf{w}_l \mathbf{y}_{l-1} + \mathbf{b}_l) \quad l = 1, 2, \dots, H$$

$$F(u) = \frac{e^u - e^{-u}}{e^u + e^{-u}}$$

General notation for MLP neural network is $\text{MLP}_{H-N_1-\dots-N_i-\dots-N_H}$ where H is a total number of MLP hidden layers and N_i is a total number of neurons in i -th hidden layer.



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MLP_ARF network

MLP_ARF neural network is implemented in MATLAB software environment. The following sets of samples for training and testing are generated in MATLAB Antenna Toolbox..

Test and training data sets have a format $\{(\mathbf{x}^t, \mathbf{y}^t)\}$, ie. $\{([L^t \ k_f^t \ k_d^t \ k_a^t], [f_{r1}^t \ f_{r2}^t])\}$

The range of input parameters	$L[mm] \in [60, 80], k_f \in [0.36, 0.45],$ $k_d \in [0.3, 0.8], k_a \in [0.3, 0.8]$
The range of output parameter	$f_r^t = [700 - 3000] [MHz]$
Impedance of feed line	$z_f = 50 \Omega$
Training set (15 000 samples)	Random generator
Test set (300 samples)	Random generator
Training method	Levenberg-Marquardt



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MLP_ARF network - Testing results

RMSE - mean square error

(r^{PPM}) Pearson Product Moment (PPM) - correlation coefficient

r_{avg} - average value of correlation coefficient

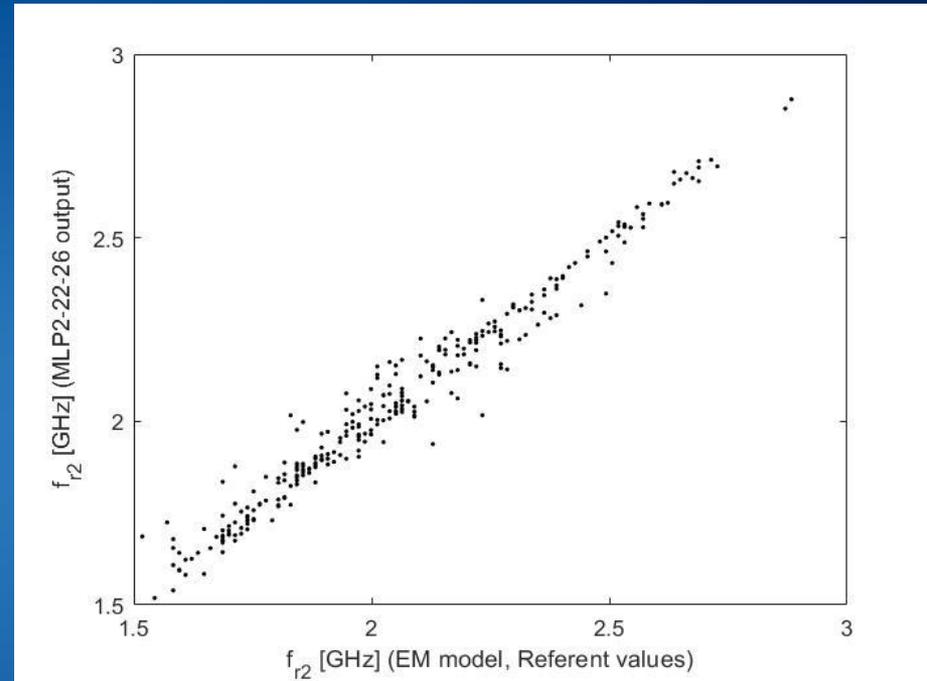
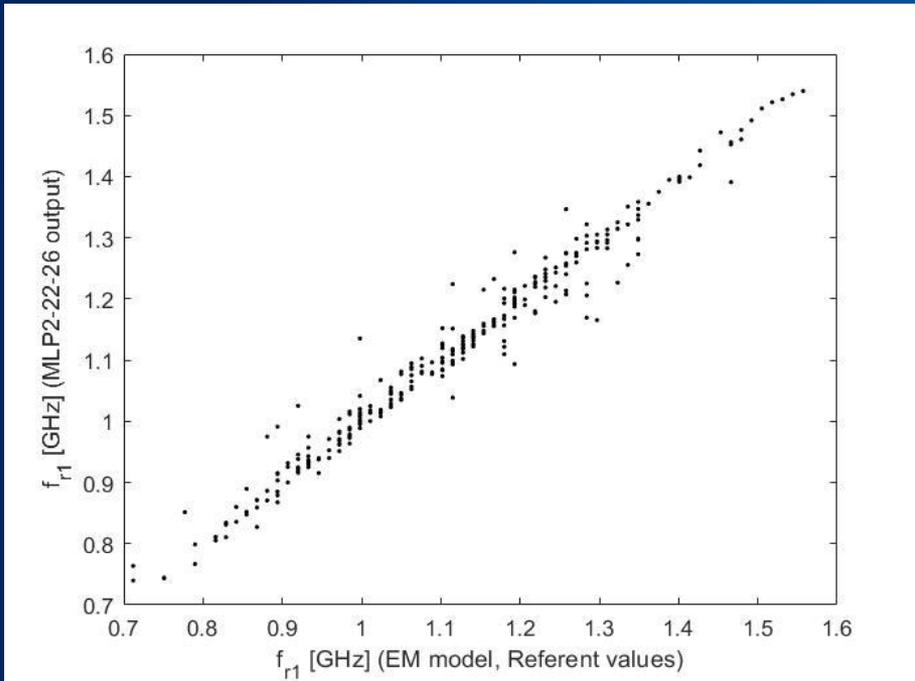
MLP_ARF network	RMSE (f_{r1})	RMSE (f_{r2})	$r^{PPM}(f_{r1})$	$r^{PPM}(f_{r2})$	r_{avg}
MLP2-22-26	0.0294	0.0527	0.9852	0.9835	0.9843
MLP2-23-20	0.0294	0.0527	0.9851	0.9835	0.9843
MLP2-20-18	0.0306	0.0512	0.9840	0.9845	0.9842
MLP2-24-19	0.0303	0.0517	0.9843	0.9841	0.9842
MLP2-22-19	0.0308	0.0520	0.9837	0.9840	0.9838
MLP2-23-19	0.0304	0.0530	0.9842	0.9833	0.9838



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MLP_ARF network – Scattering diagrams



Scattering diagram of neural model MLP2-22-26 on a test set for output f_{r1}

Scattering diagram of neural model MLP2-22-26 on a test set for output f_{r2}



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Example of using the ANN-EM model

$f_{r1}^d = 900$ MHz, $f_{r2}^d = 1800$ MHz

COAP generator:

$L_{min} = 6$ cm	$L_{max} = 8$ cm	$L_{st} = 1$ mm
$k_{fmin} = 0.36$	$k_{fmax} = 0.45$	$k_{fst} = 0.01$
$k_{dmin} = 0.3$	$k_{dmax} = 0.8$	$k_{dst} = 0.05$
$k_{amin} = 0.3$	$k_{amax} = 0.5$	$k_{ast} = 0.05$

$$A = \left\{ \begin{array}{l} (L, k_f, k_d, k_a) \mid L = L_{min} + i \cdot L_{st} \wedge L \leq L_{max} \wedge \\ k_f = k_{fmin} + j \cdot k_{fst} \wedge k_f \leq k_{fmax} \wedge \\ k_d = k_{dmin} + m \cdot k_{dst} \wedge k_d \leq k_{dmax} \wedge \\ k_a = k_{amin} + n \cdot k_{ast} \wedge k_a \leq k_{amax} \wedge i, j, m, n \in N_0 \end{array} \right\}$$

COAP selector:

$\Delta f_{r1} = 10$ MHz $\Delta f_{r2} = 10$ MHz



$$A' = \left\{ (L', k'_f, k'_d, k'_a) \mid \begin{array}{l} (L, k_f, k_d, k_a) \mid \\ |f_{r1(MLP_ARF)}(L, k_f, k_d, k_a) - f_{r1}^d| \leq \Delta f_{r1} \wedge \\ |f_{r2(MLP_ARF)}(L, k_f, k_d, k_a) - f_{r2}^d| \leq \Delta f_{r2} \end{array} \right\}$$

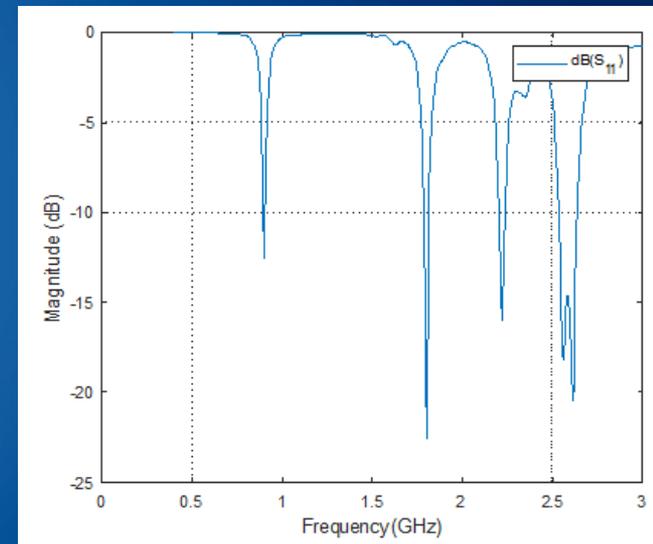
COAP generator - 25410 COAPs

COAP selector - 34 COAPs



AIM checker

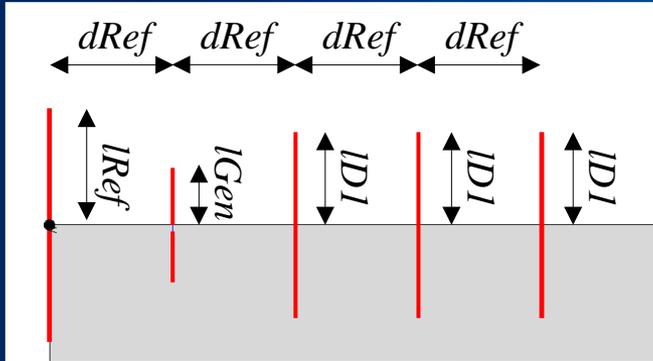
$(L_s^s, k_f^s, k_d^s, k_a^s) = (7.4$ cm, 0.41, 0.4, 0.5)



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DNN model of Yagi antenna



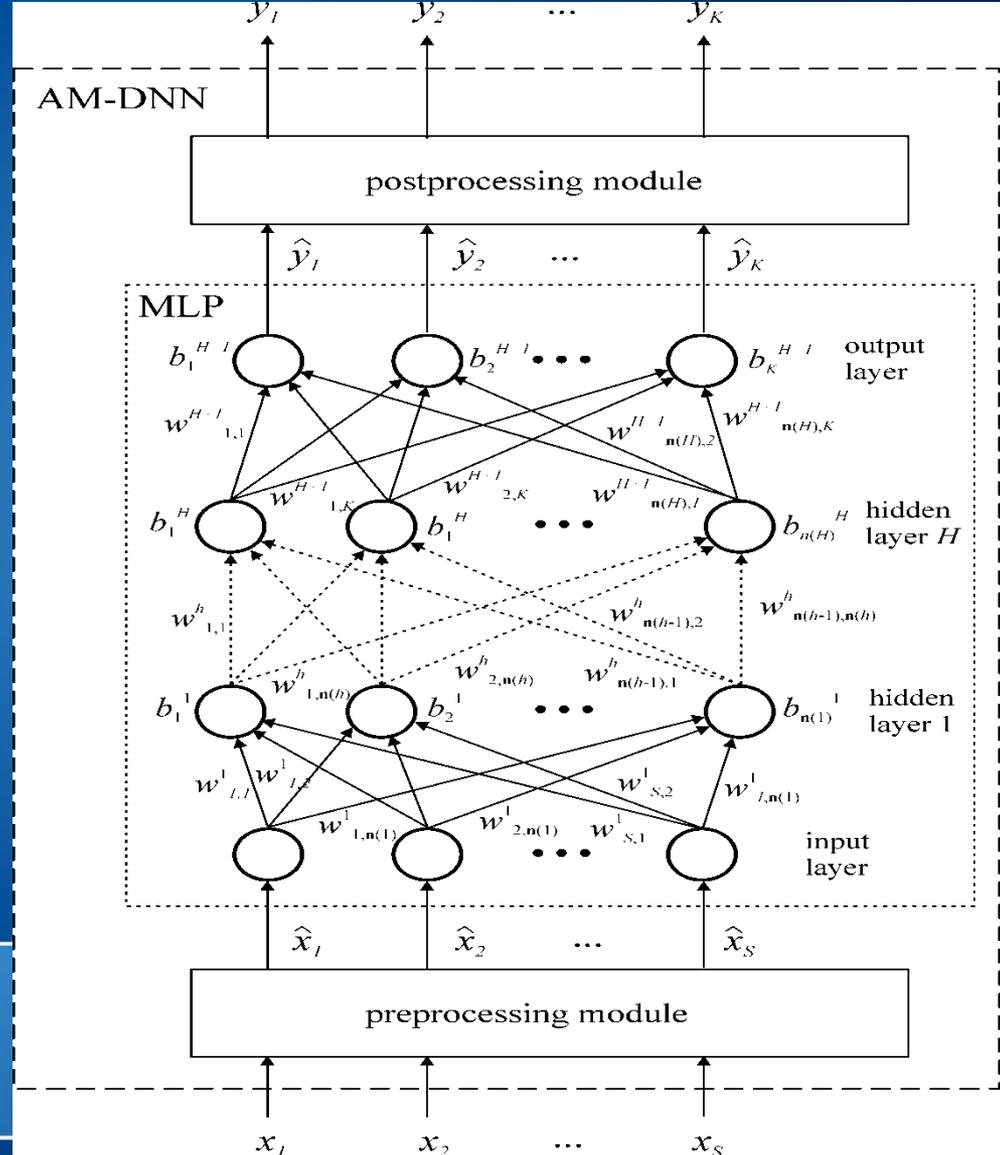
$$\mathbf{x} = [lGen \ lRef \ lD1 \ dRef] \quad \mathbf{y} = [G]$$

$$\mathbf{h}^0 = \mathbf{x}$$

$$\mathbf{h}^l = F_h(\mathbf{w}^l \mathbf{h}^{l-1} + \mathbf{b}^l) \quad l = 1, 2, \dots, H$$

$$\hat{\mathbf{y}} = \mathbf{h}^{H+1} = F_o(\mathbf{w}^{H+1} \mathbf{h}^H + \mathbf{b}^{H+1})$$

$$F_h(u) = \frac{e^u - e^{-u}}{e^u + e^{-u}} \quad F_o(u) = u$$



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Finding the optimal architecture for DNN model of Yagi antenna

- In order to find an optimal architecture of DNN model with respect to the number of hidden layers and number of neurons per hidden layer, the training of a number of different configurations of MLP network is performed (**the number of hidden layers: 2-6, the total number of neurons in hidden layers: 30, 60, 120**).
- MLP network training is performed on a training set with **100k** samples with a random distribution, generated by using the WIPL-D simulator, and with **wanted MSE 10^{-4} i $10^{-4.5}$** .
- Training algorithm is the Levenberg-Marquardt algorithm.
- Test set contains **5k** random samples.



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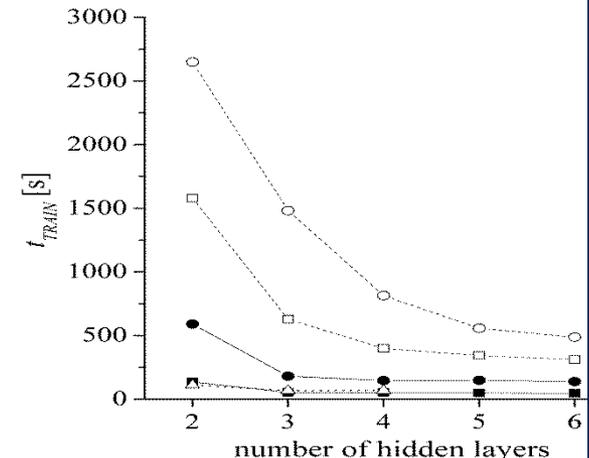
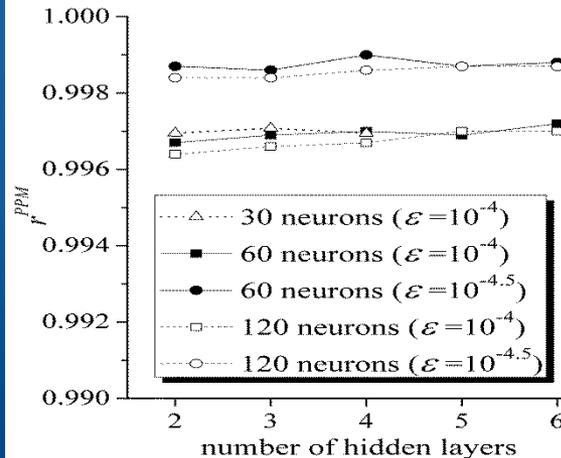
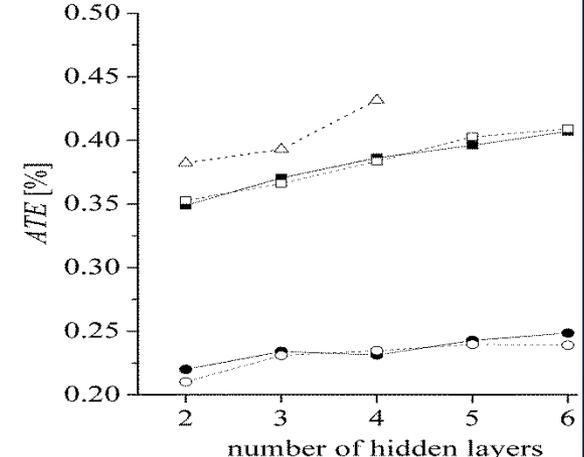
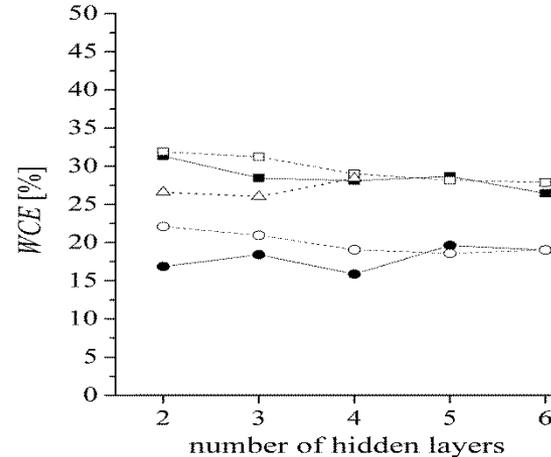
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Error of DNN model of Yagi antenna and the training time vs. the number of hidden layers and number of neurons in them

(WCE)
Max test error

(ACE)
Average test error

(r^{PPM})
Pearson Product
Moment (PPM)
correlation coefficient



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Determination of optimal number of training samples for referent DNN model of Yagi antenna

- Analysing the results and taking into account the compromise between accuracy and duration of training time for **referent DNN model of Yagi antenna**, MLP network with three hidden layers and with 20 neurons in each hidden layer is chosen (**MLP3-20-20-20**).
- In order to find an optimal number of samples for the training of referent model, its training is performed on the training sets with **4k, 10k, 100k and 1M** samples with uniform and random distribution, generated by using the WIPL-D simulator, and with **wanted MSE 10^{-4} and $10^{-4.5}$**
- Training algorithm is the Levenberg-Marquardt algorithm.
- Test set contains **5k** random samples.



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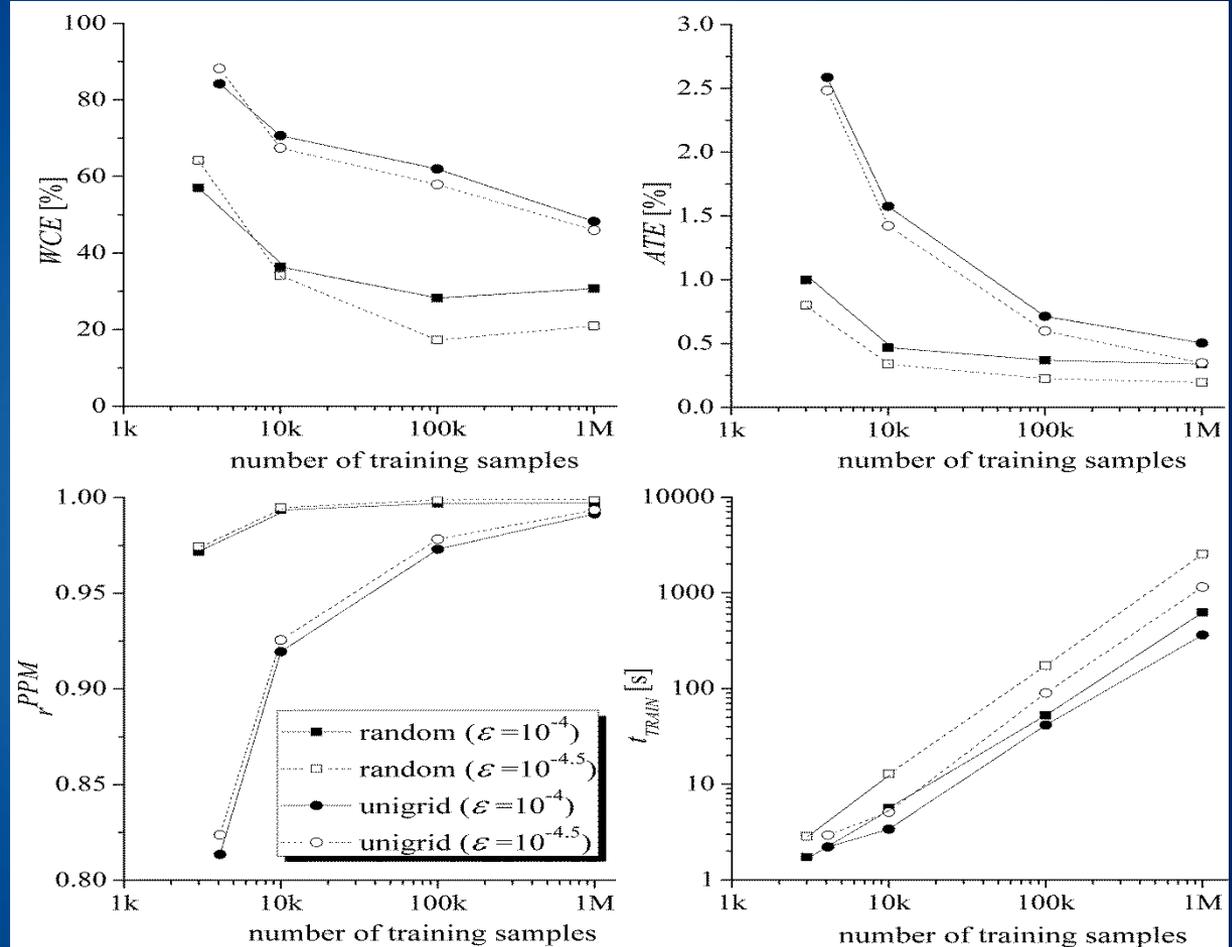
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Error of DNN model of Yagi antenna and the training time vs. the number of training samples and type of their distribution

(WCE)
Max test error

(ACE)
Average test error

(r^{PPM})
Pearson Product
Moment (PPM)
correlation coefficient



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Consensus DNN model of Yagi antenna

- Analysing the results and taking into account the compromise between accuracy and duration of training time for referent DNN model of Yagi antenna as well as realization of advanced consensus DNN (C-DNN) model of the same antenna, **100k set is recommended**.
- C-DNN model of Yagi antenna represents the set of M DNN networks that have the same architecture, but trained with different (random) starting values of network weights and biases.
- Output of C-DNN model is obtained by averaging outputs of all DNN networks models under condition of established consensus and where the average output values, which deviate from the average output value for more than max tolerated deviations ξ , are not taken into account.



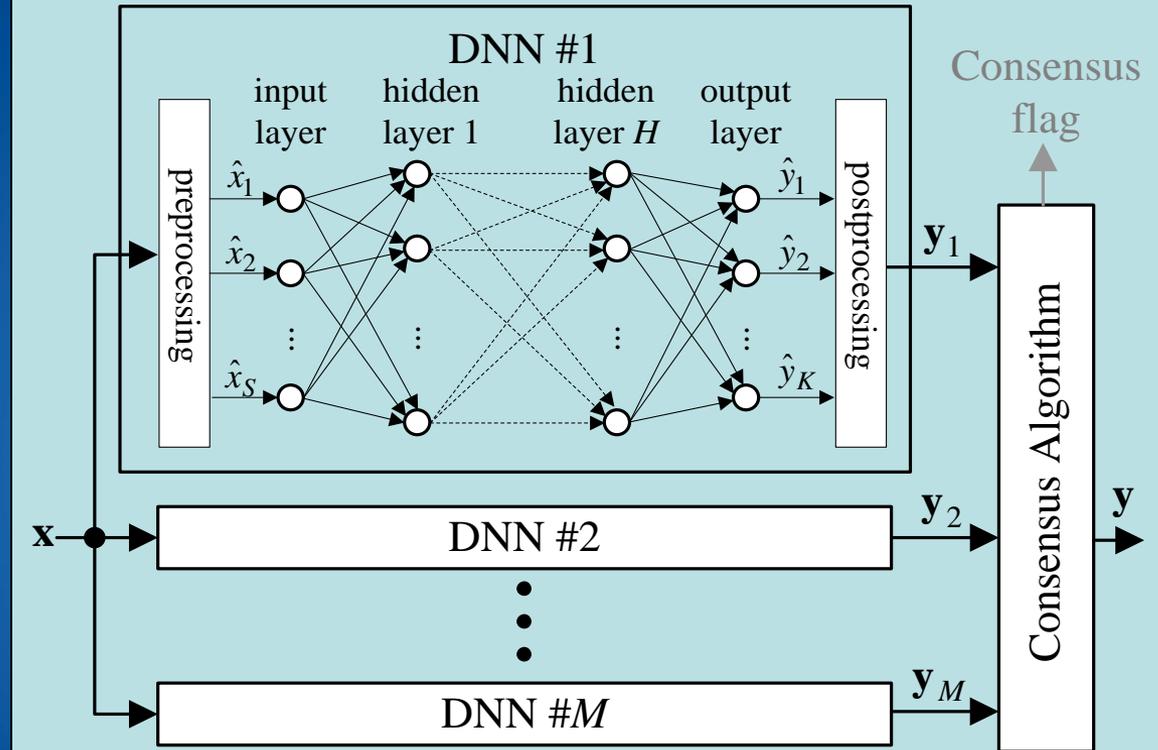
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Architecture of C-DNN model

Konsezus algoritam:

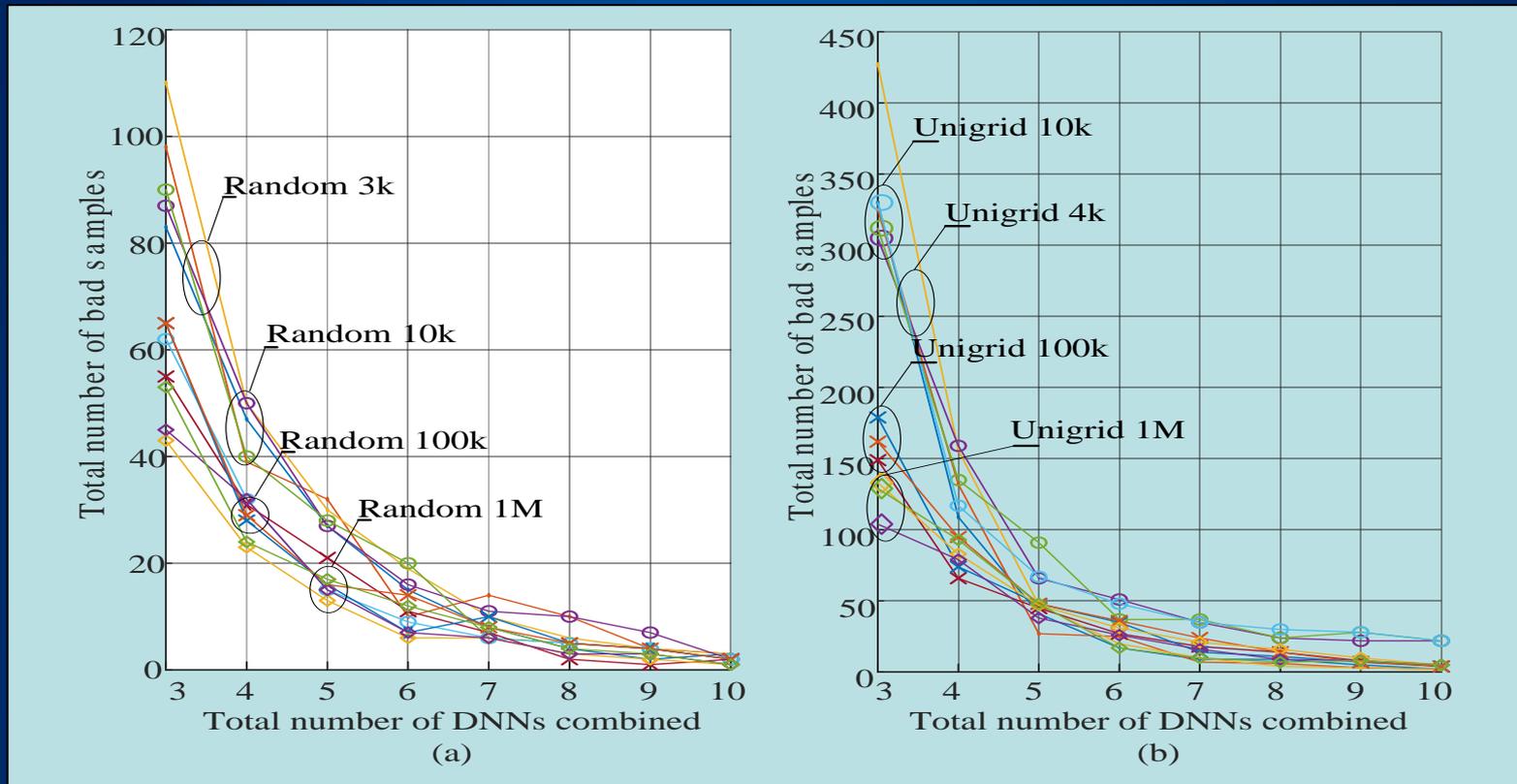
1. Calculate arithmetic mean of all networks outputs (ASI).
2. Check if there are deviations of networks outputs from ASI that are higher than ξ . If there are not any, go to step 5.
3. Throw away the network output that deviates the most from ASI and whose deviation is higher than ξ .
4. Calculate ASI for outputs that are not thrown away and go to step 2.
5. Consensus is achieved and algorithm is finished (Consensus flag = 1).



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Performance analysis of C-DNN model when used to determine the gain of Yagi antenna



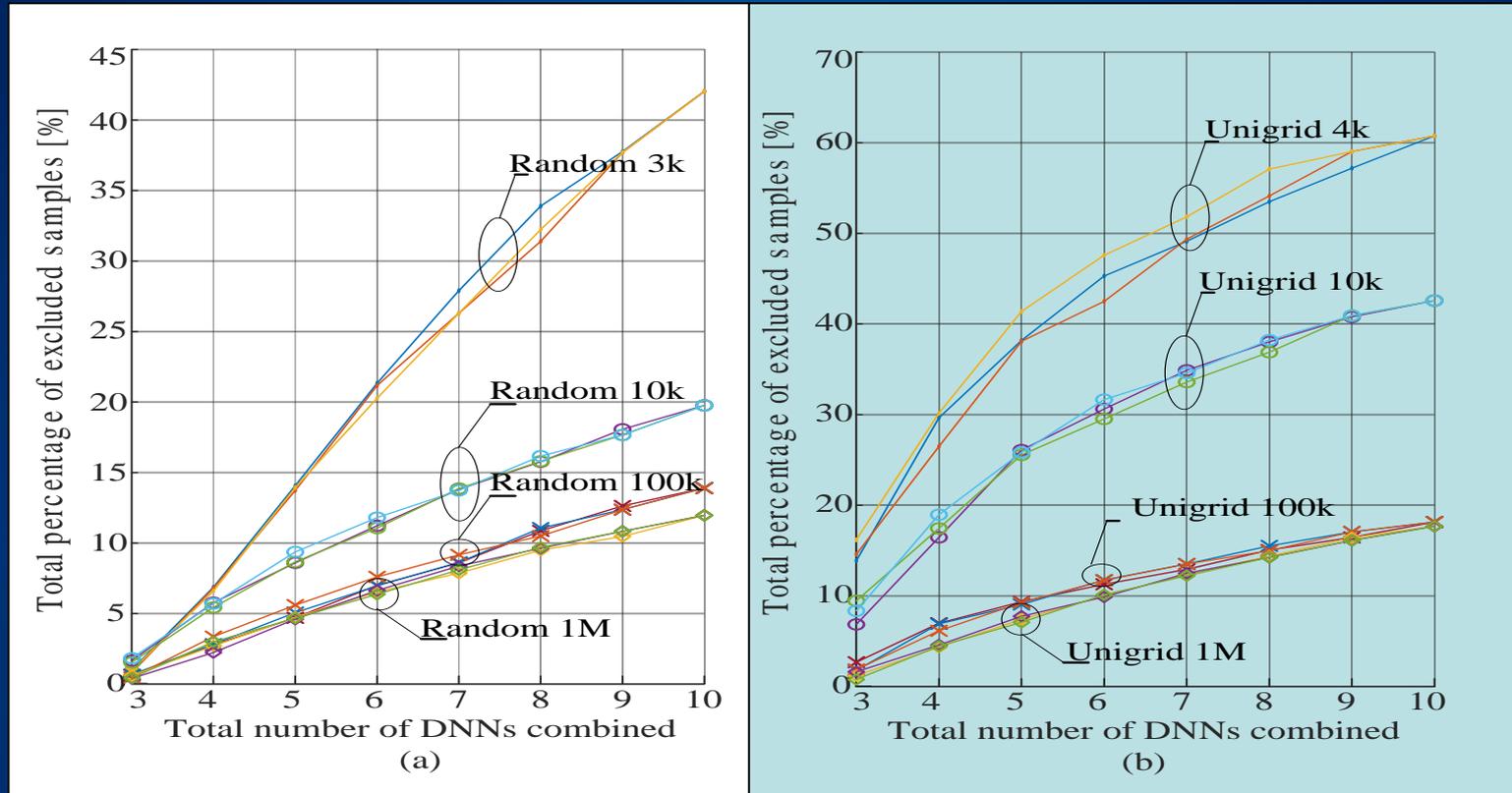
Dependence of the number of „bad samples“ on the number of DNN networks in consensus model for (a) random i (b) uniform distribution of samples ($\xi = 0.5$ dB)



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Performance analysis of C-DNN model when used to determine the gain of Yagi antenna



Dependence of the percentage of „thrown away samples“ on the number of DNN networks in consensus model for (a) random i (b) uniform distribution of samples ($\xi = -0.5$ dB)



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Optimization of Yagi antenna by using C-DNN model

- By using C-DNN model, optimization of geometrical antenna parameters (length of reflector, director and active dipole as well as their mutual distances) is performed in order to achieve the wanted antenna gain.
- C-DNN model is implemented in WIPL-D 3D solver, and iterative twostep optimization method is used: In the first step, for 1000 random combinations of parameters, antenna gain is calculated by using C-DNN model as well as the deviation from wanted gain, minimal deviations are selected and among them 50 best minimal deviations are chosen. In the second step, for each minimum, the Nelder-Mead simplex algorithm is started with 150 iterations for fine tuning of antenna parameters.



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Quality optimization metrics using C-DNN model

- During the optimization process by using C-DNN model, in each iteration, when for given combination of input parameters, consensus was not reached, EM solver was called to be run in order to calculate antenna gain, instead of neural models, which significantly slows the optimization.
- Efficiency of optimization η is introduced as a ration of the number of iterations in which the C-DNN model is only called and the total number of iterations (calls for C-DNN model + calls for EM solver).
- After optimization, for optimized geometrical parameters of antenna, EM solver is called to check how much is the gain of such optimized antenna deviates from wanted gain (Δg).



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Performance analysis of C-DNN model in optimization of Yagi antene

Run	g [dBi]	N _{iter}	g ₀ [dBi]	Δg [dB]	η [%]
1	12.12	1974	12.14	0.02	88
2	12.31	1676	12.14	0.17	97
3	12.34	1846	12.25	0.09	89
4	12.34	1667	11.96	0.38	96
5	12.36	1656	12.19	0.17	96
6	12.30	2054	12.17	0.13	88
7	12.36	1730	12.19	0.17	91
8	12.34	2183	11.96	0.38	87
9	12.35	2308	12.24	0.11	91
10	12.33	1665	11.98	0.35	92
Avg.	12.32	1876	12.12	0.20	92

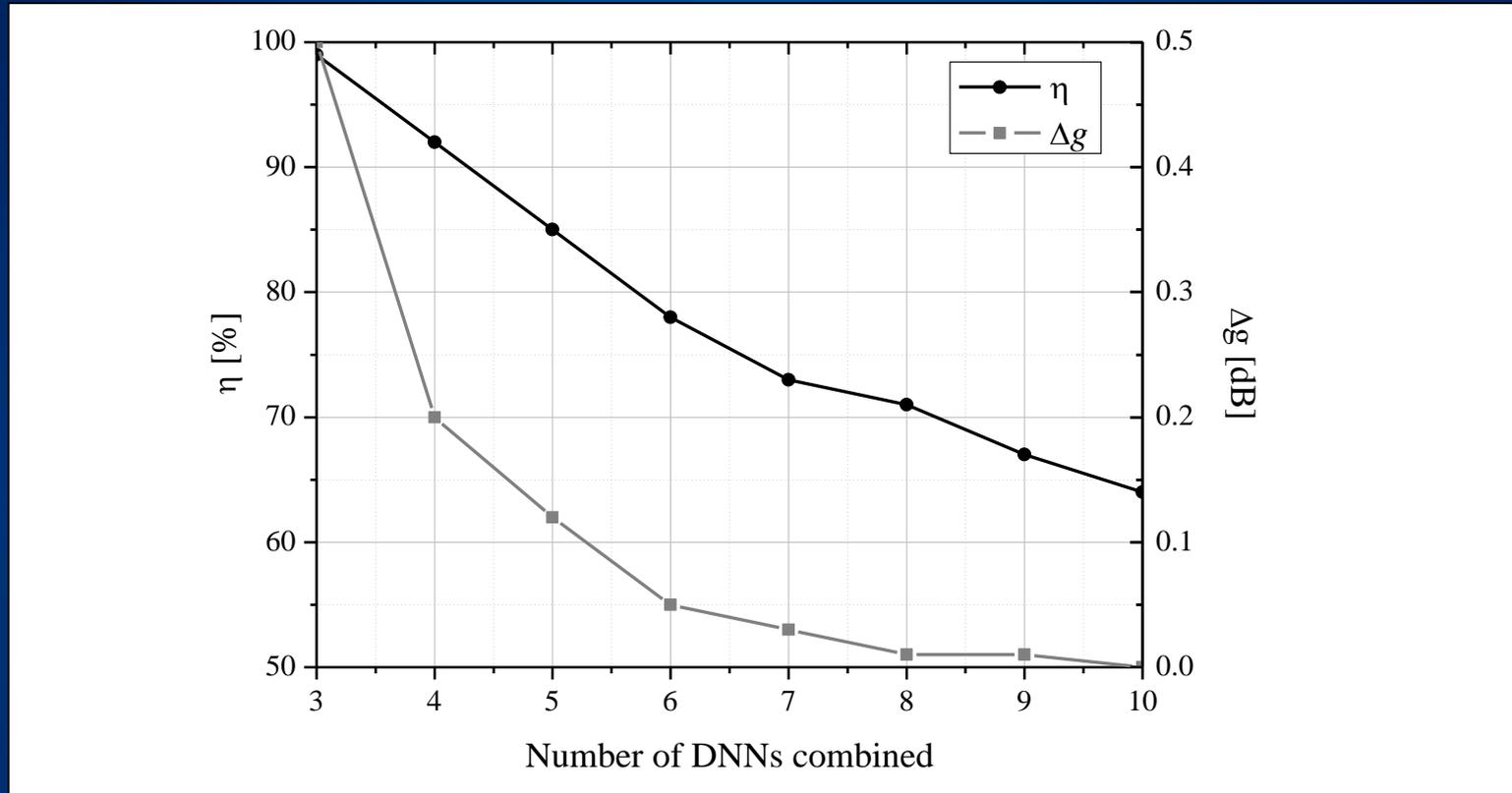
Results of optimization obtained by using the C-DNN model with 4 DNN networks



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Performance analysis of C-DNN model in optimization of Yagi antene



Efficiency of optimization η and the errors of found solution Δg vs. the number of DNN networks combined in the C-DNN model



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Reference

- K. Pesic, Z. Stankovic and N. Doncov, "ANN-EM Model of Dual Band Square Patch Antenna with a Floating Rectangular Slot," *2021 15th International Conference on Advanced Technologies, Systems and Services in Telecommunications (TELSIKS)*, 2021, pp. 153-156, doi: 10.1109/TELSIKS52058.2021.9606409.
- Z. Ž. Stanković, D. I. Olćan, N. S. Dončov and B. M. Kolundžija, "Consensus Deep Neural Networks for Antenna Design and Optimization," in *IEEE Transactions on Antennas and Propagation*, doi: 10.1109/TAP.2021.3138220.



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Conclusion

- ANN-based antenna models are significantly faster than the numerical EM models based on EM simulators, while the accuracy of ANN model is close to numerical EM models.
- In optimization processes of physical parameters of antenna, when ANN models are not able to completely solve the problem, they can be combined with the numerical EM models and such hybrid approach can be still faster compared with independent numerical EM model.
- In addition of fast calculation speed, ANN models require modest hardware resources for implementations compared to numerical EM models.
- All these previously mentioned benefits suggest that ANN models can significantly speed up the design process of antennas.



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