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Machine Learning in Applied Electromagnetics

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***Abstract*— We outline the ongoing research efforts in machine learning applied to electromagnetics at the School of Electrical Engineering, University of Belgrade, Serbia. Namely, in the past two years, our group has published multiple results regarding machine learning for antenna design and optimization, as well as applications for analyzing the emanated electromagnetic field from flat-panel monitors. We focus on finding the optimal topology of multilayer perceptron (neural) networks for the considered electromagnetic systems and assess the accuracy and efficiency of such models. The first reported example includes a dataset of up to 10 million Yagi-Uda antennas with four design parameters. The second example contains measurements of the emanated field from multiple flat-panel monitors over a time period of up to 48 hours. In both examples, we use ensembles of multilayer perceptron networks to overcome the modeling errors due to the stochastic nature of network training.**

Keywords—antennas, electromagnetics, emanated fields, machine learning, optimization

I. INTRODUCTION

While the machine learning (ML) and artificial intelligence (AI) are well-known phrases nowadays, there is a lot of misconceptions and misunderstandings about their true scientific potential [1]. They are hardly a single approach that will immediately solve all scientific problems. However, the machine-learning approach to regression problems, based on feed-forward neural networks seem to have potential to generalize the containment of large amounts of data.

We present some results about ongoing research efforts within the group for Electromagnetics, antennas and microwaves at the School of Electrical Engineering, University of Belgrade, Serbia in understanding the potentials and limits of feed-forward neural networks when applied to electromagnetic problems. Namely, analysis, design and optimization of electromagnetic systems (e.g., antennas, microwave circuits, RF hardware etc.) is challenging in a sense that present day computers are significantly limited for those problems. For example, numerical electromagnetic analysis of simplest structures lasts for about 10 ms to 100 ms on desktop computers [2], [3], while a single numerical analysis of some more complex antennas still presents a numerical challenge [4].

When applying feed-forward neural networks to any problem there are two main tasks: (a) to generate dataset for neural network training and (b) to use the appropriate depth (i.e., the number of hidden layers) of feed-forward neural network for the data regression. Namely, if the dataset for the training is too small, then there is not enough information about the problem and neural network can not be trained to accurately predicts the outputs. On the other hand, creating large datasets might last unacceptably long. If the neural network has only a few hidden layers, it might not generalize the relations between input and output data. But, if the number of hidden layers is too large, then the training time for the neural network might time too long. Finally, one has to understand that training of neural networks is a stochastic process and that in most cases each training yields different weights and biases of the neural network.

In order to illustrate those two tasks, we summarize results for two engineering examples. The first one is numerical analysis and optimization of Yagi-Uda antennas using feed-forward neural networks [3]. The second example is the identification of monitor type and state (on/off) based on AI-assisted analysis of emanated electric field from the flat-panel monitors [5].

II. NUMERICAL ANALYSIS AND OPTIMIZATION OF YAGI-UDA ANTENNAS

For numerical analysis and optimization we use Yagi-Uda antenna that consists of one reflector and three directors. It is made of perfectly conducting thin wires. In the total, there are four design variables: the length of reflector, the length of excited dipole, the length of all director (that are the same), and the distance between neighboring antenna elements. We analyzed the antenna using WIPL-D, which is based on method of moments (MoM) kernel. The primary quantity of the interest is the forward gain of the antenna, at the single frequency. All four antenna parameters are within the range of 0.1 λ to 0.4 λ, where λ is a free-space wavelength at the operating frequency. The Yagi-Uda antennas are known to be a good example for antenna design and optimization due to many minima in the optimization gain and multiple number of different antennas with similar forward gain [6].

For the insight into the design space, we provide the forward gain as a function of all four design variables in Fig. 1. The sketch of the antenna is provided in the inset of Fig. 1. One can observe that gain changes slowly with some design variables, while it has resonant behavior with others.

We generated the large dataset for training up to 10 million randomly generated antennas [7]. That dataset (or its subsets) are used for training of feed-forward neural networks and finding the optimal network topology (i.e., the total number of neurons in hidden layers, and the number of hidden layers). The detailed investigation into the topology yields that the network with three hidden layers with 20 neurons each seems to be the optimal in a sense that it can model the forward gain of Yagi-Uda antenna and that it can be trained in reasonable time.

Moreover, we used the same datasets (of 10k, 100k and 1M samples) and the same neural network topology (3 hidden layers, 20 neurons per layer) in order to investigate the division of the training dataset into smaller batches and speed up the

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training. The results are shown in Fig. 2. The batch sizes are shown as power of two. We used TensorFlow library for this experiment [8].

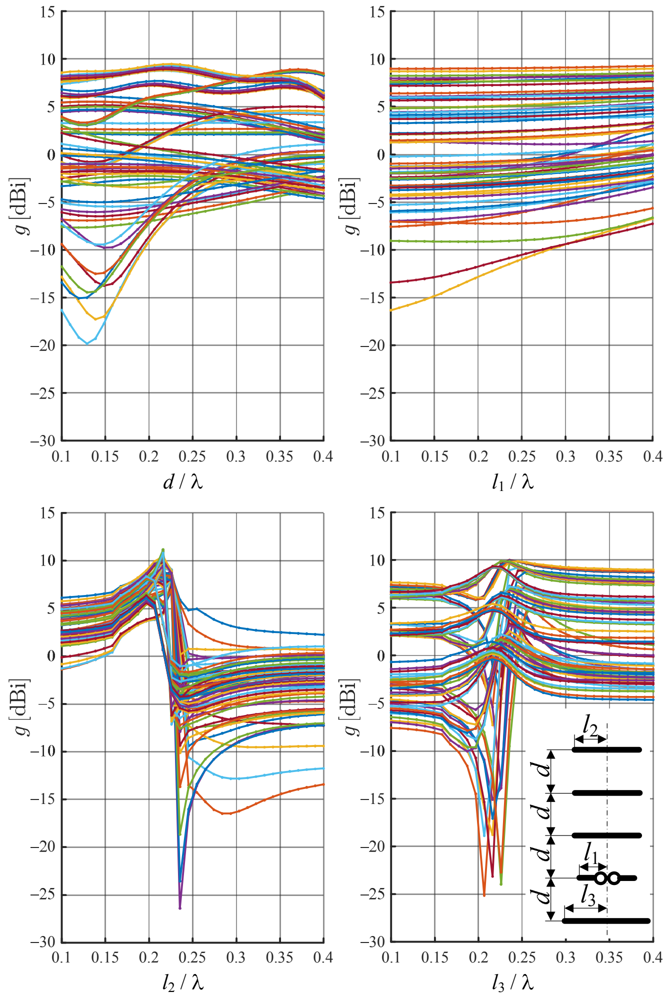

Fig. 1. Forward gain as a function of design variables of Yagi-Uda antenna [3]. The antenna model is shown in the inset in the lower right corner.

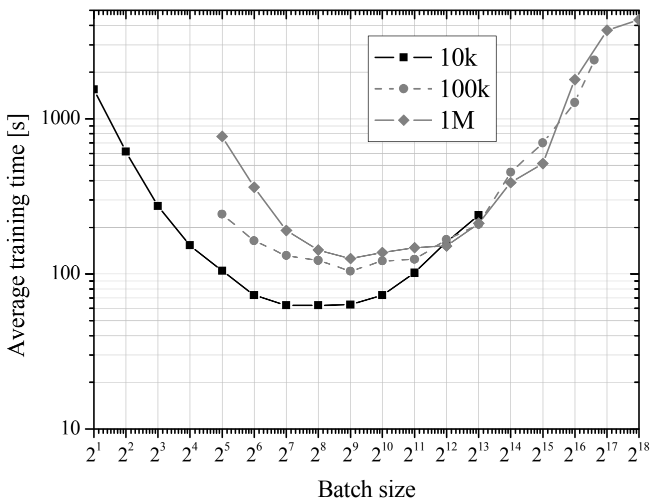

Fig. 2. Average training time as a function of the batch (subset) size [7].

The results shown in Fig. 2 demonstrate that for each topology of the feed-forward neural network there is optimal batch size that leads to the shortest (average) training time. However, that batch size seems to depend also on the total size of the data set used for training.

Once the training is performed the question arises how accurate is the gain (output) of the trained neural network? There is no analytical expression or standardized approach that quantifies such error. Hence, instead of using a single neural network we use multiple independent neural networks in a so-called consensus arrangement illustrated in Fig. 3. The idea is to predefine a threshold and calculate the output of all used neural networks. If the calculated estimations of forward gain of all networks are within the threshold, we have a confidence in that output and use it. Otherwise, we neglect the output and use 3D EM simulation instead. Consensus flag in Fig. 3 is used as an indicator (flag) that signal if the results among all used neural networks are within the predefined threshold.

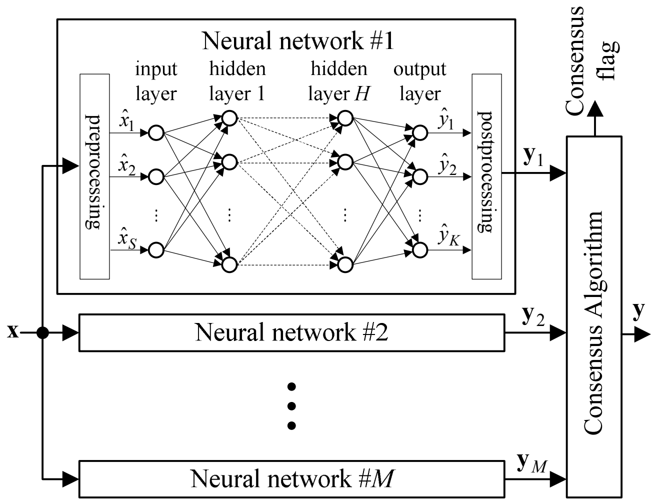

Fig. 3. Illustration of the consensus approach for multiple neural networks.

For this particular antenna we set the threshold to 0.5 dB since we estimate that such deviation in gain estimation is acceptable. However, in general case the final user of the data must make a decision on the threshold having in mind the particular application at hand.

We summarize the results of efficiency η of using results generated by neural networks and the deviation of the gain, from the actual gain calculated with 3D EM solver, i.e, $\Delta g = \left| g_{\text{neural\_network}} - g_{\text{WIPL-D}} \right|$. The efficient $\eta = 100\%$ corresponds to the case when all results generated by neural networks are used, while $\eta = 0$ corresponds to the case when all results generated by the neural networks would be discarded. In order to use the neural network efficiently, we would like to have as close η as possible to 100%. On the other hand we would like to have Δg as close to zero, since that corresponds to the case when there is no discrepancies between the results obtained by neural networks and from the 3D EM solver. The results for η and Δg as a function of number of used neural networks is shown in Fig. 4. It can be seen that by increasing the total number of used neural networks both η and Δg decrease. Therefore, in practical applications there is a compromise between η and Δg that one must count on. Also, it is worth noting that using a single neural network leads $\eta = 100\%$ but Δg is hard to estimate.

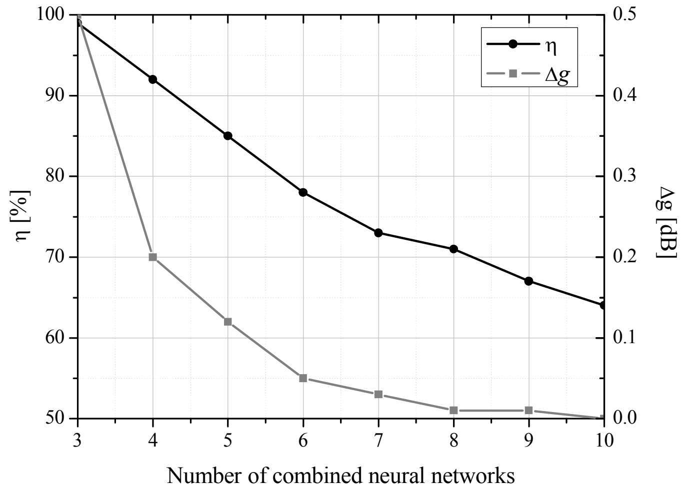

Fig. 4. The efficiency (η) and error in gain (Δg) as a function of the total number of neural network used for consensus [3].

III. AI-ASSISTED IDENTIFICATION OF MONITOR STATE AND TYPE

As the second example we measure emanated electric field in the presence of multiple monitors that can be either turned on or off. One of the measurement setups that we use is shown in Fig. 5, where monitors, log-periodic antenna used for measurements and the computer used to gather the measured data from spectrum analyzer can be seen.

Fig. 5. Measurement setup for emanated electric field from monitors [5].

The emanated field is relatively large in nowadays flat monitors due to the unshielded flat cable used for low-voltage differential-signaling (LVDS) used to present data to the panel [5]. The emanations are measured in the frequency range from 10 MHz to 500 MHz, since the experiments showed that most of the emanation is in that range. We use up to 12 different monitors and three different antennas in total – two printed custom-made Vivaldi antennas and one professional log periodic antenna for EMC measurement. The example of a measurement setup is shown in Fig. 5. Used antennas and their reflection coefficients are shown in Fig. 6. We use multiple antennas to experimentally demonstrate the influence of different reflection coefficients of antennas to the proposed approach.

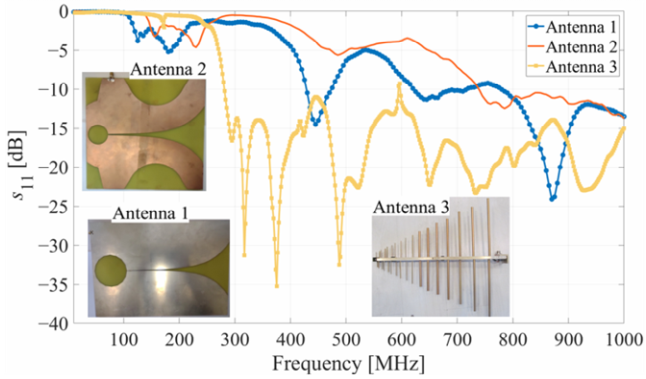

Fig. 6. Measured reflection coefficients of the used antennas [5].

Typical measured results for one Vivaldi antenna (antenna #1 in Fig. 6) are shown in Fig. 7. Namely, for a single monitor turned on we performed 500 consecutive measurements of received signal on the antenna. Moreover, we measured the present electromagnetic noise (all monitors are turned off), since all experiments are performed in the presences of real-life noise.

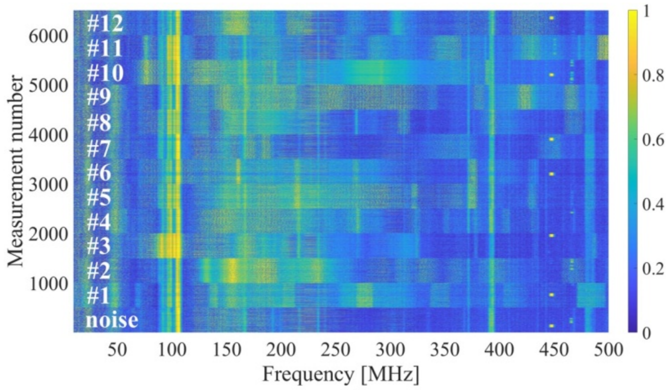

Fig. 7. Measured emanations of each monitor and the present noise [5].

From Fig. 7 it can be seen that each among 12 used monitors has distinct pattern of electromagnetic emanation. However, it is not clear how to establish (numerical) relation between the monitor type and the measured emanation. In order to solve this problem we use feed-forward neural networks.

Somewhat surprisingly the results show that feed-forward neural network with a single hidden layer with 200 neurons yields the shortest training time. The inputs to used networks are 501 measured frequency samples (in the range from 10 MHz to 500 MHz) and the output is binary (0/1) for each monitor. The output 1 means that the monitor of that type is turned on, while the output 0 means that the monitor is turned off.

Those trained feed-forward neural networks were able to identify the monitor state and type with the accuracy of 99%!

Note that we performed initial measurements and the training of the feed-forward neural networks with identical displayed picture on all monitors (see Fig. 5). However, in the subsequent measurements we used different displayed pictures. Those pictures are specifically chosen to have different colors and different content as much a possible from original picture. However, the trained feed-forward neural networks again identified the monitor type and state with the accuracy of 98%.

Therefore, the results show that displayed picture does not have any significant influence on the presented approach. This can be explained with the fact that the electrical signals transmitted through flat cable for low-voltage differential signaling have practically the same frequency spectrum no matter what actual picture is displayed.

Moreover, we repeated the experiment with the same antennas and the same monitors one year afterwards and the results were again the same [5].

From Fig. 7 one can observe that some of the sub-ranges in the measurements have larger significance for identification of monitor state and type than the others. In order to find out that sub-ranges, we trained multiple feed-forward neural networks with the same training dataset. The coefficients and biases of those networks are different due to the stochastic nature of training procedure. Then the ensemble of those networks are combined together as it is illustrated in Fig. 8. Each network is used to estimate importance of each of 501 frequency (spectral) sub-ranges, and then all calculated outputs are averaged in order to obtain spectral sub-range importance.

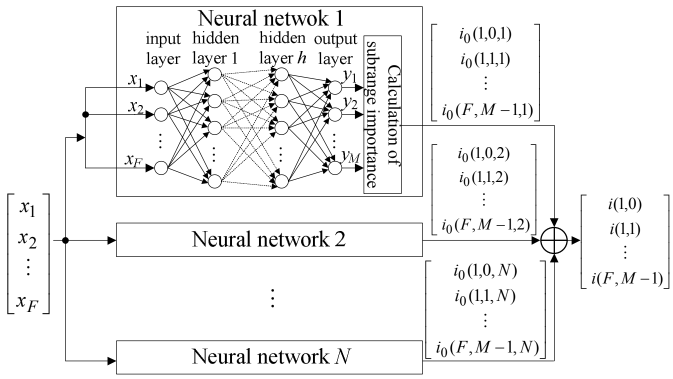

Fig. 8. Topology of ensemble of neural networks used for calculation of spectral sub-range importance.

The obtained results are shown in Fig. 9. Those results show that for different monitors there are different sub-ranges that have high significance, while the other sub-ranges can be even avoided in measurements. Note that frequency sub-ranges between 90 MHz and 100 MHz do shown up for all monitors in Fig. 9. In those sub-ranges there were a lot of noise due to FM radio. Therefore, we use trained neural networks to analyzed and pinpoint the significant frequencies for the task at hand.

By using only the selected frequencies for identification the accuracy was the same as in the case when all measurements were used. However, the speed up of up to 7 times can be achieved if only the significant sub-ranges are actually measured [5]. Finally, in order to correlate the found significant sub-ranges with actual emanation from the monitors, we measured monitors in anechoic chamber of Idvorsky laboratories. The results show that identified significant spectral sub-ranges correspond well with the actual peaks in emanations of the monitors.

Finally, note that the average training times of used neural networks on a desktop computer Intel® Core™ i7-9700 CPU @3 GHz with 16 GB RAM, are a minute and a half on average.

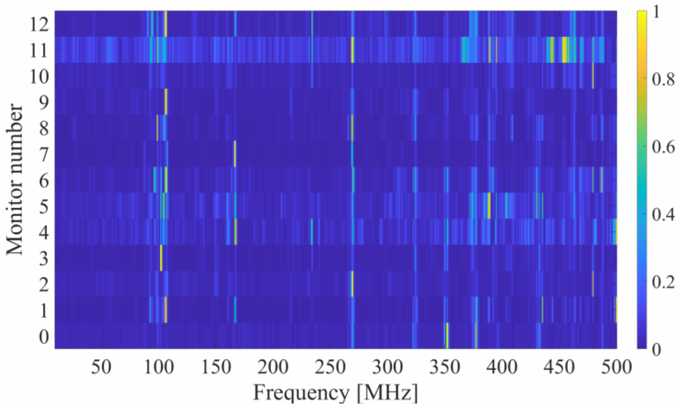

Fig. 9. Importance of each spectral sub-range with respect to the networks' ability to accurately recognize the monitor under test [5].

IV. Conclusions

The machine learning regression is used for the two exemplary problems of applied electromagnetics. While it is not straight forward to choose which topology of feed forward neural network to use, if correctly chosen those neural networks can be trained to provide usable outputs very quickly. Finally, one has to be careful neither to underestimate nor to overestimate the usability of machine learning in applied electromagnetics.

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