

Knowledge Based Grey Box Modeling of Inaccessible Circuits for System EMC-Simulation in Time Domain

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Keywords

«Neural network», «Passive Filters», «Modelling», «Discrete-time», «EMC/EMI»

Abstract

Time domain simulations are important to efficiently optimize function and EMC of electrical circuits in one setup together. Knowledge based grey box modeling is a promising approach for modeling inaccessible circuits which enables simulations of whole electrical systems. Grey box modeling combines the advantages of white and black box modeling. This work examines and evaluates the application possibilities in the field of EMC considerations. Furthermore, perspectives for future work are given.

Introduction

In a product development process, electromagnetic compatibility (EMC) is just as important as the function of the electrical circuit [1]. Prototype-based design iterations can be highly time-consuming, so simulations are aimed. A time domain simulation is suitable to cover aspects of EMC and circuit function in one single simulation setup. The circuit function has to be monitored and preserved during EMC optimization process. Electromagnetic emissions (EME) are part of the EMC and in the application focus of this work. As being the initial source for EME, voltage and current spectra are used as modeling evaluation criteria in the following considerations. These spectra are calculated by fast Fourier transform (FFT) from time domain results. EME results are not presented, because they can only be determined for a whole system including other circuits, the environment and measurement equipment, not for a single component. So only the component modeling capability of low and high frequency, small and large signals at the same time will be examined by spectra of voltages and currents.

Models of electrical components have to be built if they are not available or not sufficient for the simulation of function and EME-relevant spectra. In general, there are two different modeling approaches: White and black box modeling. Pure white box modeling by physical insight can be quite complicated and costly. Pure black box modeling suffers from other disadvantages: Previously known model parts are not included, so available knowledge is neglected. Furthermore, the learned behaviour can be limited to the used training data, extrapolation for example demands for new approaches [2] and the amount of

required training data can be a practical problem. Grey box modeling combines the advantages of these two general modeling approaches: Previous knowledge and physical insight can be implemented. Very complex or unknown behaviour can be represented by trained black box model parts. Compared to a pure black box model, less training data is needed and the extrapolation possibilities are better [3]. Furthermore, some components are not accessible, so measurement and characterization of internal parts are not possible. The grey box modeling approach is applied to model components with limited insight. So EME considerations by simulations with inaccessible components are thus aimed to be made possible by knowledge based grey box modeling. In Fig. 1, this topic is shown in context of a development process. For developing such an approach, nonlinear passive filter circuits are useful application examples. They are widely spread in power electronics applications, are important for the function and EME of electrical circuits and can have strong nonlinearities. Furthermore, they can have a significant time dependent behaviour due to their energy storage elements. Some characteristics are previously known and can be directly implemented in the model. The remaining amount of the overall behaviour can be trained to and represented by a black box model part. The knowledge based grey box modeling approach based on equivalent circuits is introduced. The modeling results are compared to an existing pure neural network model implementation of the same filter application example [6]. In future work, the grey box approach should be applied to an integrated DC-to-DC-converter.

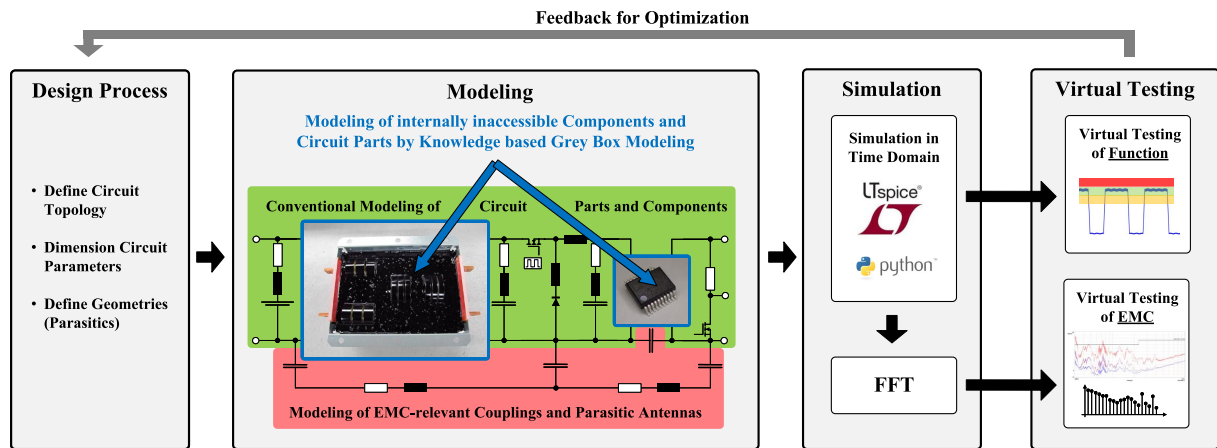


Fig. 1: Modeling of internally inaccessible components and circuit parts by knowledge based grey box modeling in context of a development process (LTspice- and Python-Logo from [4] [5])

The filters are simple and well known examples to explain, implement and verify the knowledge based grey box modeling approach. They are used as a placeholder for much more complex components and thus are assumed to be inaccessible. Only the rated component values without nonlinearities are known. The goal is to achieve the modeling of existing inaccessible components to enable the EMC simulation of a whole system. It is not intended to apply knowledge based grey box modeling for filter design optimization.

The research questions (RQ) addressed in this paper are:

- Are knowledge based grey box models suitable to model partly known and internally inaccessible circuits for time domain simulations of EME-relevant voltage and current spectra (by easily understandable and representative example of nonlinear filters)? (RQ1)
- Do knowledge based grey box models of partly known and internally inaccessible circuits lead to better modeling results than pure neural network models (from just as little training data)? (RQ2)
- Is there a simulation speed advantage? (RQ3)

State of the Art

In this section, different filter modeling approaches are introduced to show the difference between the general modeling approaches. Filter modeling is used here as a well known example. Conventional filter

modeling is briefly summarized without any claim of completeness. Neural network (filter) modeling is presented by literature overview. The used nonlinear filter application examples and neural network modeling methods in the mentioned reference paper [6] are addressed after that. Finally, knowledge based grey box modeling with neural networks is explained.

Conventional Filter Modeling

A conventional filter modeling approach is the usage of an equivalent circuit (EC). An EC is a simplification which represents the major physical dependencies. The complexity of the circuit structure determines the grade of simplification. Including parasitics and nonlinearities, the EC model has to represent the filter behavior across all required operating points and frequencies. Depending on the application, there can be a huge amount of operating points to be linearized by small signal measurements. Such nonlinearities like a current dependent inductance and a voltage dependent capacitance are described in the LTspice documentation [7]. LTspice is one of many suitable possibilities to simulate EC models and used here exemplary. Ideas for specific modeling procedures can be found in literature, e.g. in [1] [8]. Every component feature has to be known for applying ECs. Even frequency dependent inductances can occur. So all relevant internal components have to be accessible for measurements with e.g. vector network and impedance analyzers. The biasing for nonlinear component measuring can be a practical problem, especially by limited accessibility. On the one hand, the usage of finite element programs is limited by available component information. On the other hand, finite element programs can be too costly and extensive for a wide industrial application.

Neural Network (Filter) Modeling

In literature, neural network modeling is applied to different kinds of circuits. A waveguide and a microstrip low-pass filter is modeled by a recurrent neural network (RNN) [9]. Nonlinear circuits in time domain (CMOS-Receiver, integrated power amplifier and integrated CMOS-Logic) are modeled by a deep RNN [10]. Long short-term memory (LSTM) networks are applied to power amplifiers [11]. Different kinds of RNN are applied for fast simulation of high-speed channels [12]. It may be useful to also apply these modeling approaches from the field of high frequency, low power communications technology to power electronics and its EME. In [6], a LSTM network is applied for modeling of nonlinear filters in discrete time domain. This is the pure neural network reference example for comparison. The nonlinear filter examples, the training details and the results will be summarized later.

Knowledge Based Grey Box Modeling with Neural Networks

There are several approaches concerning knowledge based grey box modeling with neural networks. In [13], existing RF and microwave knowledge is combined with neural networks. This includes the integration of knowledge into neural network structures and the combination of circuit models with neural networks. The last approach can be realized e.g. by the source difference method (SDM), the prior knowledge input method (PKI) and space-mapped neural models (SMN). In the SDM, the neural network models the difference between the original and the equivalent circuit model behaviour. Previously unknown behaviour is added to the EC model by the neural network. In the PKI, the neural network is used to map the EC output to the desired, original output behaviour. In SMN, the neural network is used to map the original problem input-space to a coarse model (e.g. equivalent circuit). There, all desired model behaviour has to be considered by the chosen coarse model structure. Additional output mapping is proposed in [14].

Further approaches, like physics-informed neural networks (PINN), neural networks with transfer functions (neuro-TF) [3] and the combination of equivalent circuits, neural networks and state-space-equations (EC-SSE-NN) [16] and state-space neural networks [15] are not considered here. State-Space neural networks are time discrete state-space equations with neural network functions instead of typical matrices [15]. The modeling capability of neural networks is combined with well-known properties of state-space equations such as stability criteria and internal state estimations.

Solution Approach

In this section, the solution approach using knowledge based neural grey box models is presented. The chosen types are based on equivalent circuits, because of the transparent implementation of previous knowledge. Due to the author's best knowledge, they are applied for the first time to strongly nonlinear and discretely constructed filter circuits in discrete time domain. The filters are only simple application examples to introduce the approach. In future work, it should be applied to more complex circuits. The desired goal of such an approach is a smaller modeling error compared to a pure neural network modeling with the same little amount of training data. This data is available from [6] and applied in the following. State-space neural networks are also a promising approach but proposed for future work.

Equivalent Circuit Based Neural Grey Box Models

The combination of equivalent circuits (white box) and neural networks (black box) is chosen due to the straightforward, versatile and transparent implementation of previous knowledge. In Fig. 2, the finished grey box model structures of the SDM (Fig. 2(a)), the PKI (Fig. 2(b)) and SMN (Fig. 2(c)) are shown. Unknown component behaviour is trained and represented in different ways by the grey box model structures in Fig. 2. In SDM, the difference between the original and the white box model behaviour is represented directly by the black box model part. In PKI, the output of the known white box model part is modified until it fits the original component behaviour. It is a kind of output mapping. Furthermore, the black box part uses the input values as additional knowledge. In SMN, the input values of the white box are mapped by a black box model part so that the white box model output fits the real component behaviour. It is a kind of input mapping.

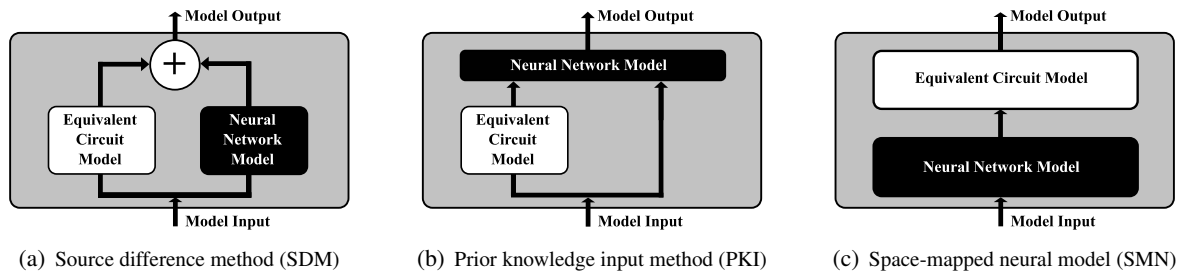


Fig. 2: Finished model structures following [13]

The basic training principle for the SDM following [13] is shown in Fig. 3. The training principles for the PKI and SMN have to be adapted to the respective model structure.

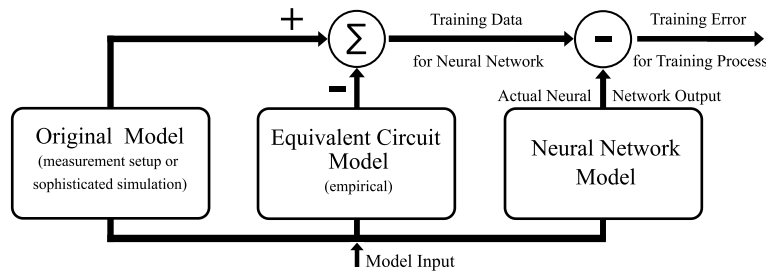


Fig. 3: Basic training principle of source difference method (SDM) following [13]

Experiments

The proposed grey box models are applied to the nonlinear filter examples of [6]. These filters are suitable and simple application examples to introduce the method of knowledge based grey box modeling. First, the application examples are briefly reintroduced and the training of the pure neural network model from [6] is summarized. After that, the training of the proposed equivalent circuit based neural grey box model is presented.

Application Examples

The used application examples (AE) from [6] are briefly reintroduced in the following. Three different nonlinear filters are used as AE. Two of them are imaginary examples (Fig. 4(a), Fig. 4(b)), which are simulated with LTspice to generate more AEs. One AE is assembled and measured at the laboratory (Fig. 4(c)), which is the preferred and intended application of the used modeling methods. These three low pass filters can reduce high-frequency (HF) noise of a signal or supply voltage. They contain nonlinear, voltage dependent capacitances and current dependent inductances.

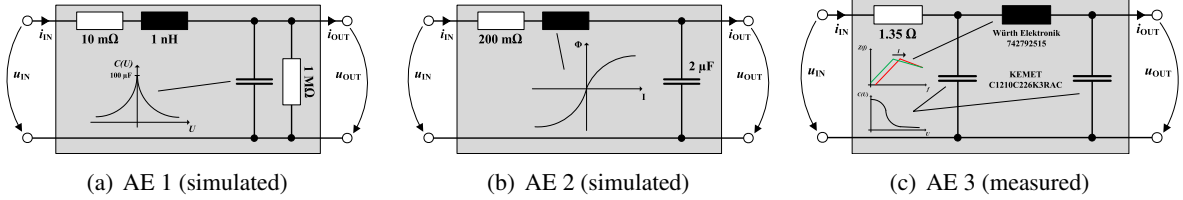


Fig. 4: Nonlinear filter application examples (AE)

It is assumed that the AEs are inaccessible and only the rated component values without nonlinearities are known. In Fig. 4(a), a capacitance value of $100 \mu\text{F}$ without voltage dependency is assumed to be known. In Fig. 4(b), the inductance value is assumed to be $300 \mu\text{H}$ (no current dependency). In Fig. 4(c), constant values of $22 \mu\text{F}$ and $1.6 \mu\text{H}$ are chosen for the white box model part. The rest of the white box models is identical to Fig. 4(a), Fig. 4(b) and Fig. 4(c).

These AEs are only used to develop and apply a method for modeling existing and inaccessible components based on measurements and previous knowledge. These modeling methods are not intended to be used for the component design itself or for converting a physical model into a neural network model.

Neural Network Reference with LSTM

In [6], LSTM networks are trained with input and output voltage and current time series of these three AE. The time series are given an equidistant time base and they are fed to the neural network by tensors. These tensors result from the sliding window and its sequence length for modeling the dependency on the past time series. One dataset of each AE is reserved for testing the trained neural network. The other datasets (e.g. six) are used for training the neural network in an alternating procedure for many epochs (e.g. 1000). The detailed training scheme can be found in [6]. The used neural network structure and the respective inputs and outputs are shown in Fig. 5(a) and Fig. 5(b). The applied training (hyper)parameters can be found in Tab. I.

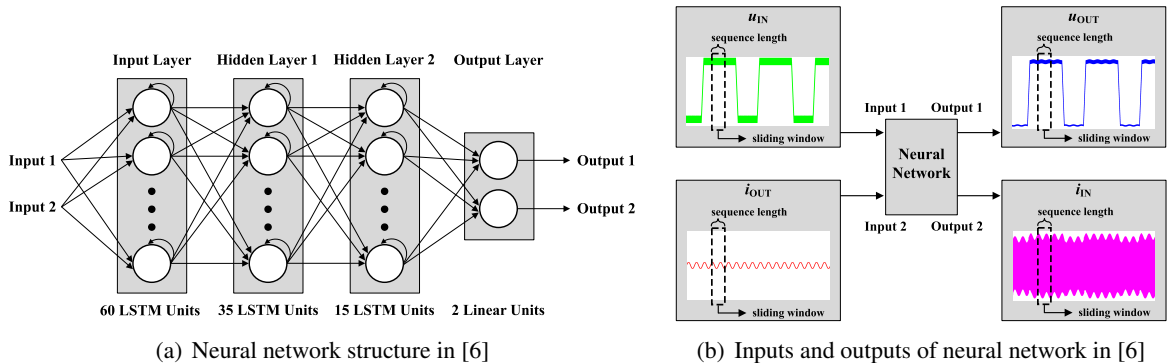


Fig. 5: Neural network in [6]

More details concerning training procedure can be found in [6]. In Tab. II, used time series characteristics examples are shown. The test results of the trained pure neural network are the reference for the comparisons to the proposed knowledge based grey box models.

TABLE I: Training (hyper)parameters in [6]

| Parameter | Value |
|-----------------|----------------------------|
| Input features | u_{IN} and i_{OUT} |
| Output features | u_{OUT} and i_{IN} |
| Optimizer | Adam |
| Loss function | MSE (sum of u- and i-loss) |
| Learning rate | 0.001 |
| Scaler | MinMaxScaler |
| Sequence length | 3 |
| Batch size | all batches |
| Epochs | 1000 |

TABLE II: Time series characteristic examples in [6]

| No. | u_{IN} | i_{OUT} |
|-----|---------------------------|-------------------------------|
| 1 | DC + LF-Sine | DC |
| 2 | DC + LF-Sine + HF-Sine | DC |
| 3 | DC + LF-Sine | LF-Sine with DC |
| 4 | DC + LF-Sine + HF-Sine | LF-Sine with DC |
| 5 | DC + LF-Sine + HF-Sine | Trapezoidal |
| 6 | DC + LF-Sine + HF-Sine | Trapezoidal + LF-Sine with DC |
| 7 | DC + Sine Sweep + HF-Sine | Trapezoidal |
| ... | ... | ... |

Training of EC based grey box models

The black box model parts in the proposed grey box models are the same in structure and size as the neural network in [6]. The training parameters and data characteristics are shown in Tab. I and Tab. II. They are chosen to be the same for a good comparability to the pure neural network model approach from [6]. Only six datasets were used for training as well. Due to the different application in form of the grey box models, an adjustment can be necessary for an optimal modeling result (future work). Only the sampling rate was increased to 100 Mpts/s to increase the frequency range. The required simulation time with a neural network (part) depends directly on the desired frequency range. The thus required sampling rate of the equidistant time series data determines the required simulation time. So it can be shorter or longer than the simulation time of the non-equidistant LTspice simulation.

In the SDM, the difference between the real and the white box model behaviour is trained to the neural network. In the PKI, the white box model outputs (prior knowledge) and the original inputs are fed to the neural network. It is trained to fit the original component behaviour. The only difference to the previous network structures is the number of input features of four instead of two caused by the additional prior knowledge input.

The training of the neural network in the SMN in Fig. 2 does not work if the equivalent circuit model is located outside the Python environment (e.g. in LTspice). It is possible to integrate LTspice in the training loop by calling it in batch mode and to pass parameters. But the gradients needed for the backpropagation in the training process are no more available after the external simulation. A possible solution can be an implementation of a kind of SPICE-simulation in Python, e.g. with a solver like [17] which allows backpropagation through ordinary differential equation for deep learning applications (future work).

Results and Discussion

The trained models are tested with time series that have been excluded from the training process. So the test data is not known by the model. First, the AE1 from Fig. 4(a) is used to compare the different modeling approaches. Additionally, one chosen modeling approach is applied to all three application examples.

In Fig. 6(a), Fig. 7(a) and Fig. 8(a), the model output time domain results for u_{OUT} and i_{IN} of the different

modeling approaches are compared to the original time series. The general shape of u_{OUT} is modeled well by all three approaches. The superimposed high frequency signal is modeled slightly to high and misshapen by the pure neural network approach. The amplitude of the high frequency signal is modeled way to low by the SDM approach. It fits a bit better by the PKI approach. The shape of i_{IN} does not fit for the pure neural network results. The results from the SDM and the PKI approach do fit better. Quantified details are discussed based on the results in the frequency domain.

In Fig. 6(b), Fig. 7(b) and Fig. 8(b), the model output frequency domain results for u_{OUT} and i_{IN} of the different modeling approaches are compared to the simulated results in the frequency domain (original data). The results are presented as magnitudes of the respective voltages and currents. EME results (e.g. quasi peak in dB) are not presented, because they can only be achieved for a whole electrical system including the EME test equipment characteristics. The modeling of an electrical component is only a small part to make a simulation of a whole system realizable (see Fig. 1).

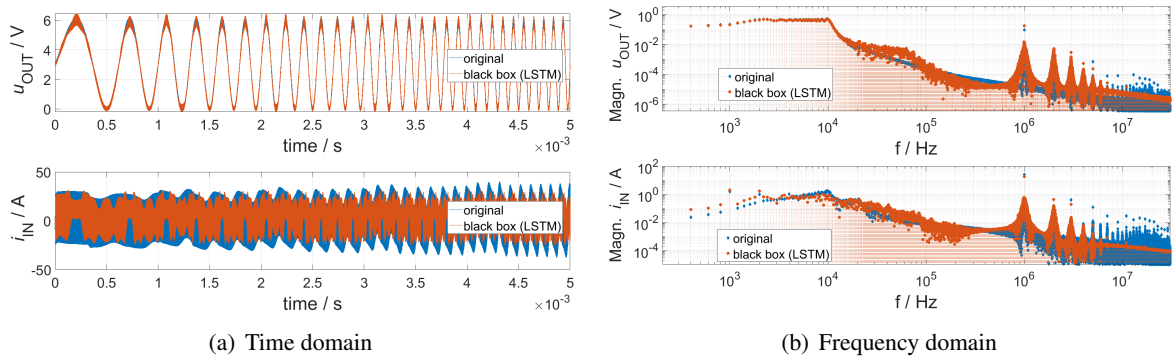


Fig. 6: Pure neural network model results for AE1

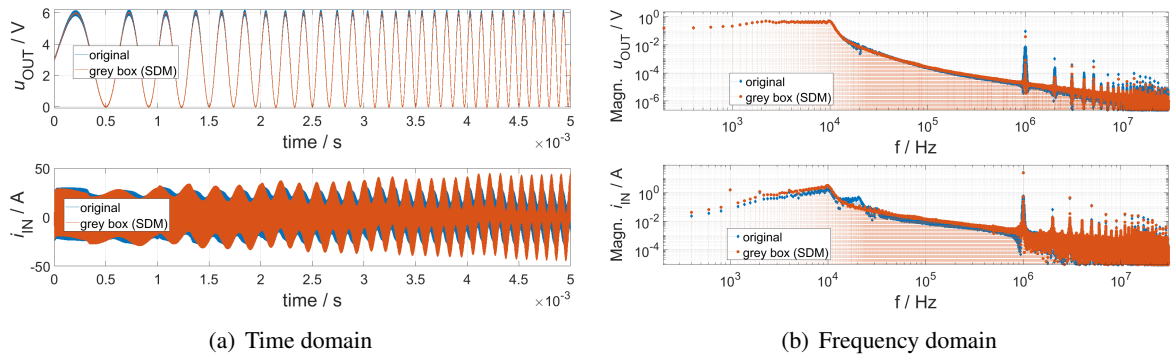


Fig. 7: Source difference method (SDM) model results for AE1

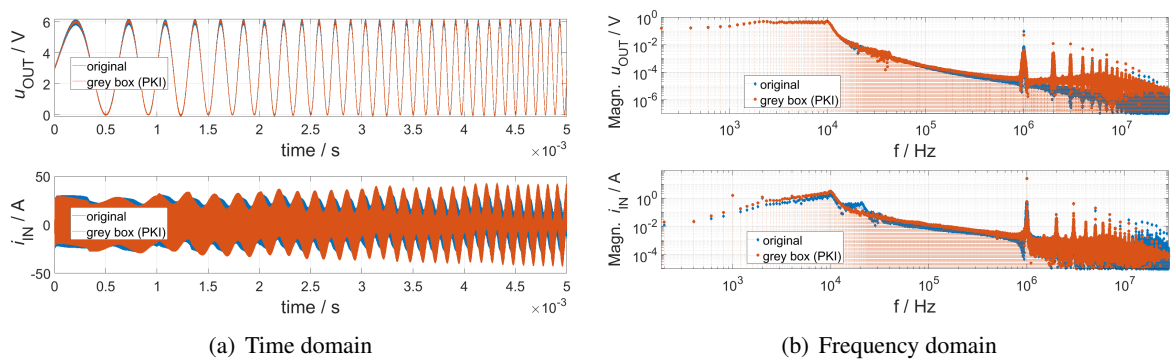


Fig. 8: Prior knowledge input (PKI) model results for AE1

The results for the pure neural network approach from [6] show a congruent fit for u_{OUT} at low frequencies (less than 1 dB deviation for most points below 10 kHz). But there are fluctuating deviations between 20 kHz and 300 kHz of up to about 15 dB. The magnitudes of the 1 MHz component and its harmonics are shown in Tab. III. They are presented in dB μ V to provide a typical scaling in the field of EMC. The respective sidebands of the model in Fig. 6(b) are much to widespread. And there is a general large deviation above 5 MHz. The ability of the used neural network to model such very small high frequency amplitudes inside a large signal can be the limit here. The results characteristic of i_{IN} is very similar. But the deviation in the low frequency range is bigger (about 10 dB below 2 kHz).

TABLE III: Magnitudes of 1 MHz component and its harmonics in dB μ V and dB μ A for AE1
(green: up to 3 dB deviation; yellow: between 3 dB and 15 dB deviation; red: more than 15 dB deviation)

| Frequency | u_{OUT} (simulated) | u_{OUT} (LSTM) | u_{OUT} (SDM) | u_{OUT} (PKI) | i_{IN} (simulated) | i_{IN} (LSTM) | i_{IN} (SDM) | i_{IN} (PKI) |
|-----------|-----------------------|-------------------|------------------|------------------|----------------------|-------------------|-------------------|-------------------|
| 1 MHz | 99.57 dB μ V | 105.00 dB μ V | 91.59 dB μ V | 93.84 dB μ V | 148.03 dB μ A | 145.33 dB μ A | 147.70 dB μ A | 147.69 dB μ A |
| 2 MHz | 60.26 dB μ V | 69.74 dB μ V | 32.26 dB μ V | 81.58 dB μ V | 96.12 dB μ A | 112.46 dB μ A | 82.47 dB μ A | 96.61 dB μ A |
| 3 MHz | 51.59 dB μ V | 69.40 dB μ V | 49.40 dB μ V | 81.02 dB μ V | 111.82 dB μ A | 105.85 dB μ A | 112.93 dB μ A | 112.34 dB μ A |
| 4 MHz | 40.00 dB μ V | 54.65 dB μ V | 28.94 dB μ V | 74.15 dB μ V | 77.70 dB μ A | 133.73 dB μ A | 79.31 dB μ A | 80.00 dB μ A |
| 5 MHz | 56.90 dB μ V | 47.23 dB μ V | 48.30 dB μ V | 72.81 dB μ V | 101.87 dB μ A | 75.96 dB μ A | 101.36 dB μ A | 105.71 dB μ A |
| 6 MHz | 16.65 dB μ V | 30.88 dB μ V | 14.57 dB μ V | 56.83 dB μ V | 75.82 dB μ A | 55.86 dB μ A | 73.50 dB μ A | 83.52 dB μ A |
| 7 MHz | 37.50 dB μ V | 28.30 dB μ V | 25.32 dB μ V | 65.25 dB μ V | 89.25 dB μ A | 57.91 dB μ A | 89.25 dB μ A | 96.52 dB μ A |

The outputs of the SDM model in Fig. 7(b) show better results than the pure neural network approach. The components of u_{OUT} in general do fit better across the whole frequency range. The magnitudes of the 1 MHz component and its harmonics are shown in Tab. III. The respective spreading is fitting better than in Fig. 6(b). The general fitting above 5 MHz is better. The results characteristic of u_{OUT} and i_{IN} are very similar. The deviation in the low frequency range is lower, only about a third as in Fig. 6(b).

For u_{OUT} , the PKI model in Fig. 8(b) shows a very good fit up to about 20 kHz. There seems to be a local modeling problem around 20 kHz. The general fit is good, but becomes worse in the MHz range. In general, the magnitudes above 2 MHz are too high. The magnitudes of the 1 MHz component and its harmonics are shown in Tab. III. The results characteristic of i_{IN} is very similar to the characteristic of u_{OUT} . Across all approaches, there is a modeling problem for i_{IN} around 20 kHz.

The SDM is chosen for AE2 and AE3, because it shows the best results for AE1 compared to the other approaches. The time domain results for AE2 are shown in Fig. 9. There are large deviations for u_{OUT} and i_{IN} between the original and modeled results. The modeling for AE2 is as difficult as in [6]. A possible reason can be the complexity of the example or the used training parameters. But the comparison to all other results suggests that the used training data is insufficient. A presentation of the frequency domain results is omitted.

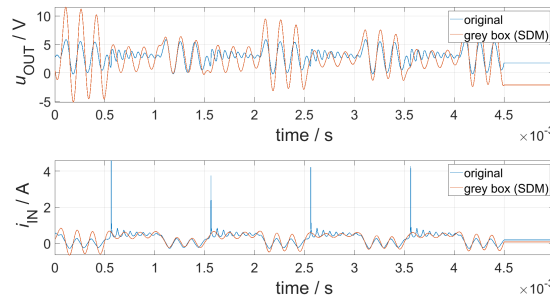


Fig. 9: Source difference method (SDM) model time domain results for AE2

In Fig. 10(a), the model output time domain results for u_{OUT} and i_{IN} are shown for AE3. The general shape of u_{OUT} is quite similar compared to the original time series and distinctive details are recognisable. But the general amplitude is about 13% smaller and there is an offset of about 10%. The general shape and the details of i_{IN} is also similar compared to the original time series. The general amplitude is about 15% smaller but there is no visible offset.

The respective frequency domain results for u_{OUT} and i_{IN} of AE3 are compared and shown in Fig. 10(b). A separate consideration of noise floor and dominant amplitudes is made for analysing the results systematically. The components of u_{OUT} show a generally increasing deviation with rising frequency. In contrast to that, the noise floor of i_{IN} is modeled constantly too high.

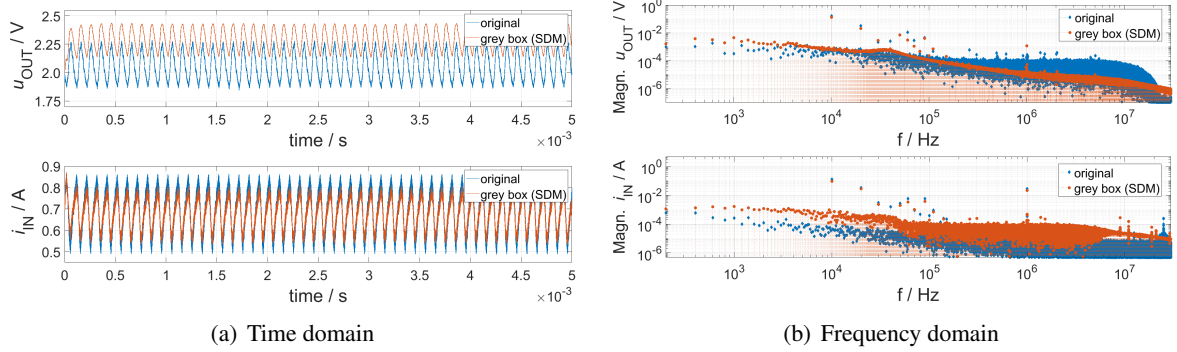


Fig. 10: Source difference method (SDM) model results for AE3

The magnitudes of selected, dominant frequency components are shown in Tab. IV. As an overall result, half of the compared magnitudes are inside a 3 dB deviation range. The rest shows more or less larger deviations.

TABLE IV: Magnitudes of selected, dominant frequency components in dB μ V and dB μ A for AE3
(green: up to 3 dB deviation; yellow: between 3 dB and 15 dB deviation; red: more than 15 dB deviation)

| Frequency | u_{OUT} (measured) | u_{OUT} (SDM) | i_{IN} (measured) | i_{IN} (SDM) |
|-----------|----------------------|-------------------|---------------------|------------------|
| 10 kHz | 104.61 dB μ V | 102.59 dB μ V | 102.53 dB μ A | 99.54 dB μ A |
| 20 kHz | 90.51 dB μ V | 86.36 dB μ V | 90.47 dB μ A | 88.94 dB μ A |
| 30 kHz | 66.67 dB μ V | 69.04 dB μ V | 69.75 dB μ A | 67.38 dB μ A |
| 40 kHz | 68.09 dB μ V | 57.00 dB μ V | 63.97 dB μ A | 38.59 dB μ A |
| 50 kHz | 77.20 dB μ V | 77.08 dB μ V | 68.63 dB μ A | 66.01 dB μ A |
| 60 kHz | 80.81 dB μ V | 69.43 dB μ V | 75.37 dB μ A | 70.65 dB μ A |
| 70 kHz | 68.97 dB μ V | 60.87 dB μ V | 59.40 dB μ A | 40.86 dB μ A |
| 80 kHz | 49.95 dB μ V | 53.38 dB μ V | 53.80 dB μ A | 42.28 dB μ A |
| 90 kHz | 73.12 dB μ V | 71.86 dB μ V | 75.40 dB μ A | 71.55 dB μ A |
| 100 kHz | 45.93 dB μ V | 47.23 dB μ V | 51.57 dB μ A | 45.51 dB μ A |
| 110 kHz | 53.66 dB μ V | 56.81 dB μ V | 59.50 dB μ A | 57.11 dB μ A |
| 1000 kHz | 31.27 dB μ V | 61.41 dB μ V | 89.22 dB μ A | 86.97 dB μ A |

Conclusion and Future Work

Knowledge based grey box models are generally suitable to model partly known and internally inaccessible circuits for time domain simulations of EME-relevant voltage and current spectra (RQ1). They lead to better modeling results than pure neural network models from just as little training data (RQ2). In this work, only six datasets have been used for the training of every model. The requested amount of training data is an important aspect in industrial applications. A simulation speed advantage of knowledge based grey box models is not existing in general (RQ3).

For future work, it is advised to apply such knowledge based grey box modeling approaches to more complex components with also unknown model parts. The advantages of knowledge based grey box models are assumed to be determined more clearly. So e.g. an integrated DC-to-DC-converter can be integrated into a whole system EMC simulation which would not have been possible before. The used nonlinear filters served as simple and well known examples for comparing the applied methods. For that, they are assumed to be inaccessible. Potential for future improvements is offered by hyperparameter optimizing for every application example, by usage of more training data, by using a higher order filter model with heavy parasitics and by a combination of input and output mapping [14]. The space-mapped neural network approach and state-space neural network should be implemented to examine their potential.

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