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INFORMATION, COMMUNICATION & COMPUTING

Fields of Expertise TU Graz

Kay Uwe Römer, Information, Communication & Computing
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AI-based tools for translation, content summarization and generation such as DeepL or ChatGPT play an increasing role in education and research. TU Graz recently published a very open guideline (perhaps too open) for use of these tools in education, and the German Science Foundation DFG recently published a first set of guidelines on the use of these tools in research, specifically for writing scientific articles and proposals and their review, see https://www.dfg.de/service/presse/pressemitteilungen/2023/pressemitteilung_nr_39/. While the guidelines do not preclude the use of such AI tools, their use is seen as "neither negative nor positive". Since tools cannot appear as authors, instead human authors take full responsibility for scientific integrity when using such AI tools. An interesting aspect is that human authors "must ensure that the use of generative models does not infringe on the intellectual property of others and that no scientific misconduct occurs, for example in the form of plagiarism." This raises intricate questions as the tools are usually trained on content produced by other human authors found on the internet or provided as input to the tools by their human users. Therefore, these AI tools may easily reproduce such human input when later used by other users. That leads DFG also to the conclusion that "the use of generative models is inadmissible in the preparation of reviews in view of the confidentiality of the review process." For now, this spares us from a world where AI-generated papers and proposals are reviewed by AI-tools. But the prospect of humans having to review AI-generated content does not sound any better as it will inevitably lead to a severe bottleneck in a qualified human reviewer workforce.

In this edition of TU Graz research, Jan Hansen, assistant professor at the Institute of Electronics, gives us some insights into his research. Enjoy your read!

Jan Carsten Hansen

Using Machine Learning to Improve the EMC of Electric Vehicles

When designing electronic systems, many – often conflicting – design parameters need to be traded against each other. Classical multi-objective optimization (MOO) problems can be formulated. In Electromagnetic Compatibility (EMC), computer models are complex, have long computation times, and are often inaccurate. Machine learning could possibly enable MOO for EMC, which could ease the optimization of the electromagnetic design of various types of electronic systems.

Electric and electronic devices are used to solve many – if not most – of the challenges of modern society, be it mobility, communication, computation or medicine. Devices are constantly evolving towards greater functionality, higher integration density, higher frequencies and lower cost. For example, in the automotive industry, there is the transition from combustion to electric vehicles, and a significant increase in the used number of electronic control units (ECUs). Today's vehicles have up to 150 ECUs including numerous processors to monitor the various functions such as engine management, transmission control, interior maintenance, as well as safety measures such as e.g. brake and airbag control. Figure 1 shows an example of the various electronic systems in modern vehicles. The electromagnetic compatibility (EMC) of all components ensures that within such a complex system, all components operate reliably and safe, and no component is disturbed by the electromagnetic emissions of any other.

In an electric vehicle (EV), the major source of electromagnetic emission is the powertrain, which consists of the traction inverter with switching power semiconductors and the electrical machine (Figure 2, courtesy of BMW). The application of silicon carbide (SiC) and gallium nitride (GaN) power semiconductors in high-voltage power electronics significantly reduces the volume of the traction inverter (more than 200% is reported [1]) while even increasing the power density (300%), which reduces the weight of EVs and increases their range. >

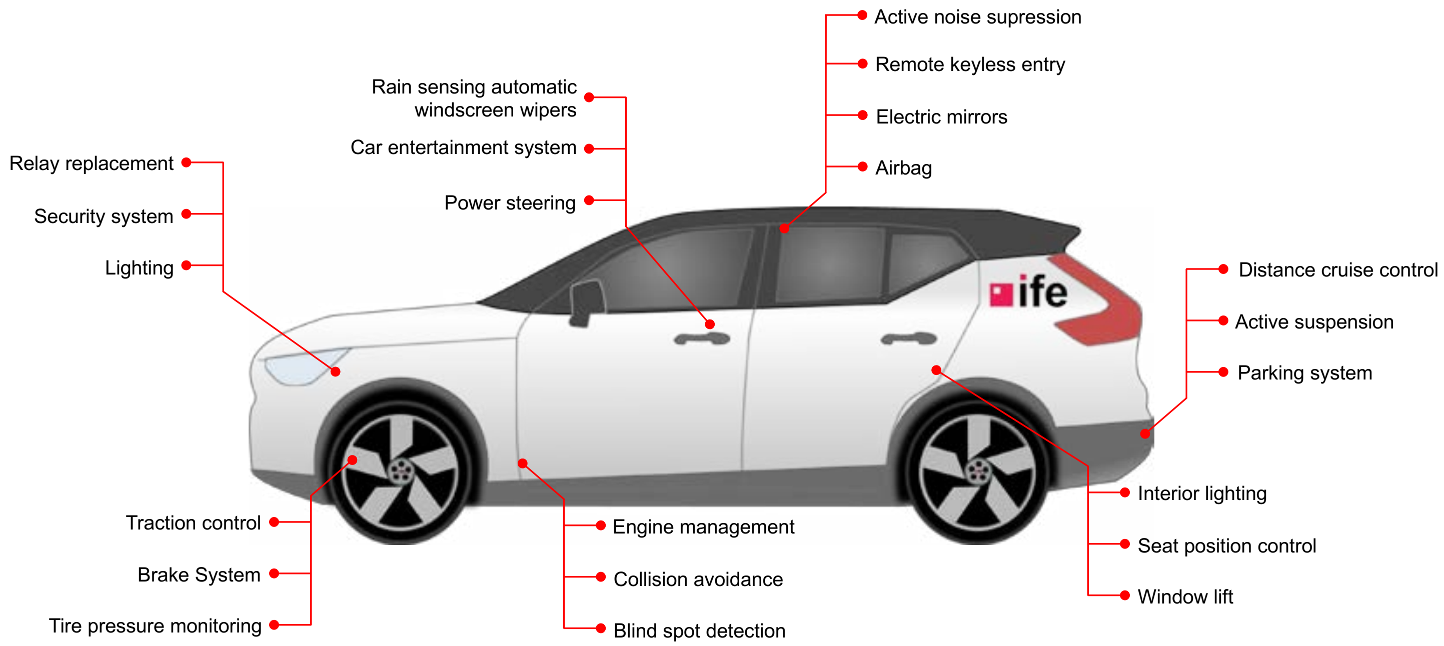

Figure 1: A modern vehicle contains a large variety of electronic components, which form a complex electronic system.
Source: Jakob Schmidt

Computational methods have contributed significantly to this success. But SiC and GaN semiconductors generate much higher emissions in particular at high frequencies, more than 20 dB above 30 MHz. Cost, size, and weight of emission filters become a major concern. Reduced to the essential ones, between 10 to 30 design parameters must be traded against each other to find the sweet spots with respect to given design requirements, such as performance, efficiency, volume, cost, and ease-of-design.

Computer models to analyze and predict the unwanted electromagnetic emissions and their subtle propagation paths are complex. They suffer from long computation times and inaccuracy in particular at frequencies above 30 MHz. Machine-learned models may prove to be the way out. So-called surrogate models are trained by repeatedly evaluating the established deterministic computer models (alternatively, measurements can be used). The surrogate approximates the behavior of the physical model and has a computation time of milli-seconds. This allows for several millions of computations within a single day, potentially offering a completely different approach to virtual EMC design as seen today. A surrogate model offers novel paths in design, be it multi-objective optimization, the improvement of the model quality by model calibration [2], or risk analysis.

But which obstacles do we need to remove when generating a surrogate? There is a trade-off between the model's accuracy, its richness in features, the number of its parameters and their ranges, and the number of samples required to train it. Several studies of electronic components and systems have been carried out [3,4,5]. Between 30 and 500 training samples are needed to achieve an accuracy of the surrogate better than 15% root-mean-square error for numbers of design variables between four and fifteen, with realistic parameter ranges and complexity of the model response surface. These results indicate that the generation of surrogate models for EMC design is in reach with moderate computational effort.

The surrogate serves as a container of all possible designs. Feasible designs can be drawn from this container as a function of given design requirements. For a competitive design, the assembly elements

Figure 2: The electric powertrain is the heart of an electric vehicle and its major source of emission. (courtesy of BMW Group Steyr Plant).
Source: Jakob Schmidt

needed e.g. for emission filters or gaskets should be as low-cost as possible. Changing from Si- to SiC / GaN power semiconductors increases this cost (schematically drawn in Figure 3) because of the higher emission levels. The evaluation of a surrogate model of a simple power converter is shown in Figure 4. The investigated design elements are the common mode choke and the so-called Cy-capacitors and their parasitic inductance. Among all possible designs, those using Si are red, and those using novel SiC power semiconductors are green. The green samples are admissible only for larger values of the design elements, which is equivalent to higher cost. The evaluation of the surrogate takes a couple of minutes, so that these important cost-design relations are conveniently studied.

With the expected start of the Christian Doppler Laboratory "EMC-aware robust electronic systems" in January 2024, we have the possibility to conduct in-depth research on the application of machine-learning in EMC. Besides electric vehicles, we are going to study the applicability of machine-learning techniques to assess optimization, improvement of model accuracy, and risk assessment for various electronic systems.

Jan Carsten Hansen

Jan Hansen received his B.Sc. in mathematics/physics from Trent University, Peterborough, ON, Canada, in 1995, his Diploma in physics from Freiburg University, Freiburg in Breisgau, Germany, in 1998, and his Ph.D. in wireless communications from ETH Zurich, Zurich, Switzerland, in 2003. After completing his Ph.D., he was with the Information Systems Laboratory, Stanford University, Stanford, CA, USA, working in digital communication theory, channel modeling, and wave propagation. He then joined Robert Bosch GmbH, Stuttgart, Germany, to work in electromagnetic compatibility (EMC) simulation, eventually serving as head of the simulation team in Bosch's Automotive Electronics' EMC Department. Since 2022, he has been assistant professor at the Institute of Electronics at Graz University of Technology and part-time staff scientist at Silicon Austria Labs. His primary research interests are the development of EMC simulation methods, electronics and electronics modeling, and the application of machine-learning techniques.

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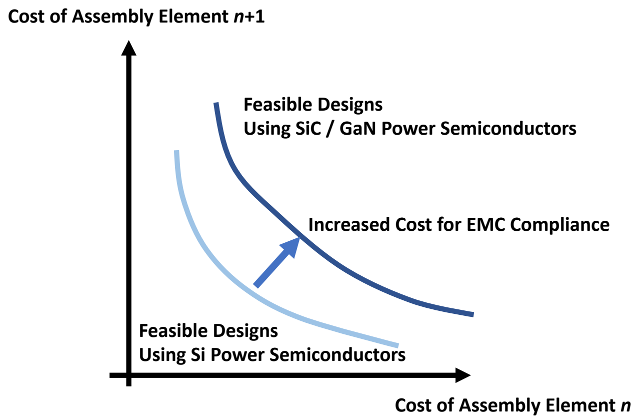

Figure 3: Multi-objective optimization results in the Pareto fronts of best-possible feasible designs. Using SiC/GaN instead of Silicon power semiconductors, the cost for required EMC measures increases. Examining surrogate models helps to quantify this cost.

Source: Stefan Schoder

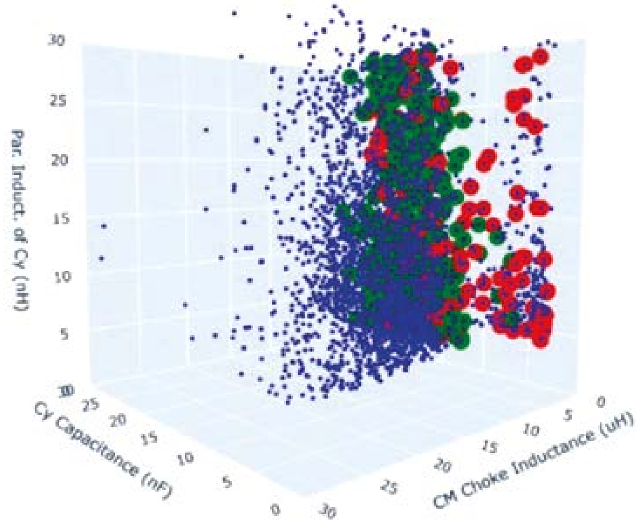

Figure 4: Simulation results (blue dots: all EMC compliant samples) of a practical example and typical EMC design elements. Red: using Si-, green: using SiC power semiconductors. Red samples are EMC compliant with smaller design elements, which means lower cost, than green samples.

Source: Stefan Schoder

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