A Cross-Domain Electromagnetic Compatibility Data Platform for the Digital Development of Automated Vehicles

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***Abstract* — Maintaining compliance to electromagnetic compatibility (EMC) standards becomes an increasing challenge for the automotive industry in the course of the ongoing automation of vehicles. Novel extended design procedures and test standards are required to ensure safety of automated driving functions, particularly in an adverse electromagnetic (EM) environment. In order to keep the number of tests within a reasonable and practical limit, an evaluation framework based on virtual design methods and information drawn from legacy experiments and simulations can support the automotive industry. With this digital framework appropriate technological solutions can be identified during the pre-compliance phase and efficient experimental designs can be generated to ensure EMC compliance. Furthermore, such a framework paves the way for digital EMC twins of automated vehicles (AVs) considering the complex interrelations of AV's (sub-)systems to accurately predict the behaviour of new AV functions in various EM environments. To this purpose, a cross-domain platform is being developed in this work as the backbone of such a virtual framework. It supports the handling, storage and processing of various datasets from EMC test campaigns, including (intentional) electromagnetic interference ((I)EMI) tests, as well as simulations of automotive devices-under-test (DUTs). The platform allows for the establishment of interconnections between various data sources and deeper analyses based on artificial intelligence (AI) methods to deduce EMC information for new developments, whilst maintaining traceability.**

***Keywords* — Digital twin, autonomous driving, electromagnetic compatibility, electromagnetic interference, power electronics, artificial intelligence**

I. Introduction

A digital twin of AVs with a particular emphasis on EMC requirements can greatly support the development of AVs from the design and pre-compliance phase to production. Even beyond the life cycle of a vehicle's model line it can predict the EMC-impact of redesigns, environmental changes such as new wireless communication standards or new (I)EMI sources, or a new area of application, which frequently occurs in a military context. It enables performing virtual tests on complex (sub-)systems, consisting of multiple components and devices each of which possess individual EM susceptibility and interference behaviour. These virtual tests could reduce the amount of, or ideally substitute, real laboratory tests that would be difficult to perform, among others because of the vast number of system state combinations, which would be required to be examined. Furthermore, digital twins of AVs enable model-based predictions on layout changes of such components whilst considering predictions of their impact on EMC at higher system levels. Their overall goal is to speed-up implementing and confirming EMC compliance of an automotive product, reducing the amount of lab tests by minimising test redundancy and allowing to focus on verification and validation by merely performing the most crucial component, device and system tests. Employing a digital twin should yield the same confidence and fidelity in the electromagnetic resilience (EMR) of the automotive DUT and the systems it is part of as performing real lab tests.

A digital twin is as good as the data and models it comprises, as well as the platform that enables the cross-disciplinary exchange between models and data of different types and, thus, provides a holistic EMC evaluation (Fig. 1, [1]). Hence, this paper presents a general approach to storing data of various origins, labelling them, documenting their interrelations and enriching them through their use as an input to more refined models. The presented cross-domain

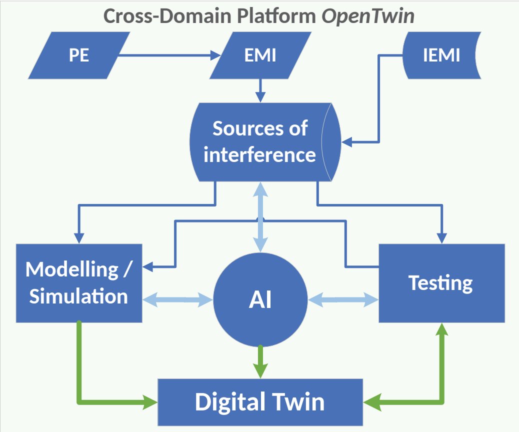


FIGURE 1: PROCESS OVERVIEW FOR THE IMPROVEMENT OF AUTOMOTIVE EM IMMUNITY AND THE AI-SUPPORTED EVALUATION OF THE SYNERGIES BETWEEN MODELLING, NUMERICAL SIMULATIONS AND LAB TESTS.

platform thus provides a general framework to render various data into EMC-relevant information by using both physics-based models and techniques from machine learning (ML). The process of data enrichment is transparently traced via metadata, which are stored with the raw and augmented datasets. The cross-domain platform provides the backbone for digital twins and may simultaneously serve as a data-lake. This includes methods for the transfer of experimental knowledge that was previously extracted from legacy data via ML to new projects, so that the gained know-how helps finding good starting points for further technical development.

Both the development and implementation of the cross-domain platform are jointly achieved by academic and industrial partners. Whereas the former contribute with state-of-the-art methodologies and their theoretical foundations, they benefit from the vast experience of the latter partners. This includes the exchange of information about EMC requirements, standards and best practice, the definition and scaling of relevant EMC scenarios, as well as insights into existing digital processes involving a large number and variation of use cases. In this work, special emphasis is given to the generation of example data from various sources, which will be processed by the cross-domain platform to demonstrate the deduction of EMC-relevant information. These data include both studies on conducted and radiated (I)EMI and comprises both measured and simulated data, with the underlying setups motivated by industrial use cases.

Similarly, both industry and academic researchers benefit from the cross-domain platform, which is based on an open access framework. In an industrial context, the platform allows for fusing data from various business units, for further processing and reordering them and for their storage together with metadata for full traceability, such that a company's know-how is manifested and made accessible and usable for new developments. An academic use of the platform comprises a systematic bookkeeping of research results, combined with full access of subsequent researcher generations.

This paper starts with a brief summary of the cross-domain platform *OpenTwin* to be developed (Section II). In the following Section III and Section IV the generation of exemplary experimental data on conducted and radiated electromagnetic interference (EMI) and intentional electromagnetic interference (IEMI) is presented, respectively. Examples of ML-based processing and refining of data that have been computed from different physics-based models are then provided in Section V and Section VI.

II. THE OPENTWIN CROSS-DOMAIN PLATFORM

The *OpenTwin* cross-domain platform developed in this work will, in its final state, be used to generate digital twins for the EMC behaviour of new concepts of AVs. It thus provides a general framework for the systematic construction of digital twins based on annotated legacy data with various levels of refinement, stemming from different sources.

Although the term *digital twin* has no unique definition, it is generally agreed that it consists of a physical asset, a virtual representation (model) and a data transfer between them [2], [3]. A digital twin has the potential to cover the entire physical asset's life cycle represented by its digital models, which can be data-driven, physics-driven or a hybrid. The physics-driven models are either analytical or realised by numerical simulation and may be capable of handling multi-scale or multi-physics behaviour of the physical asset.

At its root, the digital twin contains data about the various employed models as well as additional data describing the asset, ideally in a machine-readable format. From a data management perspective, this collection of data is diverse, large in volume and requires fast access to support high-throughput data-processing methods, e.g. based on AI. Most of the data for a digital twin originate from measurements, simulations or data post-processing methods. The models and data defining a digital twin and emerging from the information gathered on *OpenTwin* will be used for the EMC assessment of the current state of systems in various EM environments as well as that of future redesigns. Already before the platform has been supplied with sufficient data that have been transformed on an adequate level of refinement, the implemented data and services will be used for the development of EMC concepts for novel AVs.

Fig. 2 shows the data model, that is proposed in this work, for handling any kind of data stemming from the sources mentioned above, to enable the core aspects of a digital twin. Essentially, the metadata of a data generation process are separated from the collected data, which are stored in the *Quantity Container*. This allows for optimising this entity for storing large heterogeneous data. Unidirectional references from the *Quantity Container* to the corresponding metadata via abstract unique identifiers guarantee a highly efficient editing ability. The referenced *Series Metadata* entity contains metadata about the data acquisition process, which could be, e.g. a measurement series, and all information about the acquired

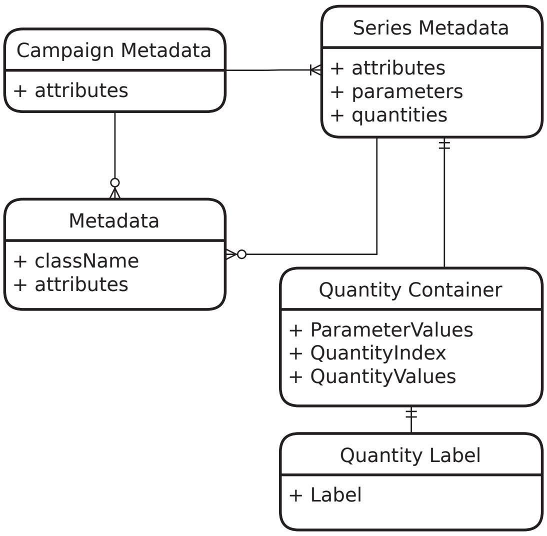


FIGURE 2: CONCEPTUAL DATA MODEL FOR DIGITAL TWINS.

quantities and the parameters that were varied during the acquisition process. A top-level entity, *Campaign Metadata*, acts as an instance to describe the entire dataset. Generically constructed *Metadata* entities allow nested metadata to be added. Finally, a *Quantity Label* entity enables the annotation of individual data points.

The concentration of all metadata in particular entities allows changes to be made without having to access the large data point collections. Here, this data model is implemented and tested in *OpenTwin* [4]. Its features include the ability to handle numerical simulations of multiple physics domains, the visualisation of results, a pipeline editor for highly customised Python-based data processing and a distributed version control of models. The metadata entities are also included in the version control, providing implicit version control of the stored data points, but with reduced storage overhead. Combining modelling with data handling of simulated, measured and post-processed data in a single version-controlled software enables traceability of model modifications and corresponding data changes. This forms the basis for approval and certification processes in a product's life cycle.

With respect to hardware resources, *OpenTwin*'s microservice architecture allows for distributed deployment. This functionality permits the deployment of modules which require high computational power, such as simulation solvers, on specialised computing nodes, whereas large storage functionality can be deployed on other nodes. In cases in which the distribution of computational tasks conflicts with security requirements, methods of secure distributed computation can be considered [5].

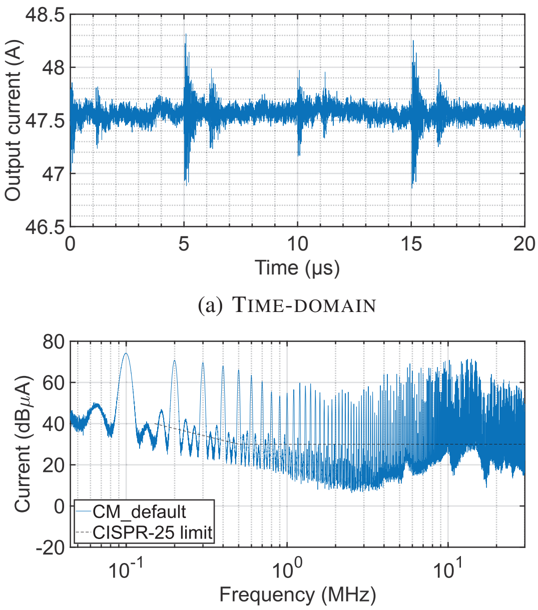
III. CONDUCTED EMI FROM AUTOMOTIVE DC-DC-CONVERTERS

Automotive power electronics (PE) components have been identified as important sources of potential EMI in a diversified board net of electric vehicles (EVs) [1]. Hence, laboratory adaptations of modern DC-DC-converters based on wide-bandgap semiconductors interfacing the ≈450 V EV battery and the 12 V side with an intermediate stage of 48 V have been evaluated in detail in this project [6], [7]. The collected data is exemplary considered as a first data source for *OpenTwin*.

In particular, the fast-switching processes of Silicon Carbide (SiC) and Gallium Nitride (GaN) transistors result in transients that cause EMI at the fundamental frequency and its harmonics at a few hundred kilohertz and higher frequencies at several megahertz. Although substantial radiated emissions might arise from harmonics beyond 30 MHz, affecting nearby components and devices susceptible to radiative coupling, the focus of this work is on conducted emissions, as automotive PE are a main source of conducted EMI in automated EVs. As detailed in previous work, common mode (CM) and differential mode (DM) interferences have been measured both at the input and output lines of high- and low-stage DC-DC-converters [7]. Their expected impact on automotive DUTs is highest at the 48 V intermediate stage, as well as at the legacy user 12 V board net.

EMI data collected with laboratory test setups within this project include oscilloscope time series of input and output voltage, voltage over individual transistors [6], individual power line or CM/DM voltages at the line impedance stabilisation networks (LISNs) of the standards-compliant setup, as well as induced radio frequency (RF) currents in the converter's input and output lines. The latter voltages and currents have also been recorded with spectrum analysers, providing more accurate average and peak emission amplitudes and a higher frequency resolution, but lacking insights into the individual transient processes and their periodicity, which the time series contribute. As an example, results for the evaluation of a SiC-based DC-DC-converter with an input voltage of 450 V, an output voltage of 48 V, an output current of 48 A, a switching frequency of 100 kHz and for a SiC-chip temperature of 90 °C are presented in Fig. 3. The variation of transient currents with time is highlighted in Fig. 3a, which are averaged out in the recorded spectra in Fig. 3b for the same parameter.

Such time- and frequency-domain datasets have been collected for various operating conditions of the DC-DC-converters, including the variation of parameters such as input and output voltage (SiC: 300 V–450 V to 48 V, GaN: 48 V to 12 V–14 V), output current (SiC: 12 A–48 A, GaN: 24 A–220 A), switching frequency (SiC: 50 kHz–100 kHz, GaN: 250 kHz and 500 kHz), transistor chip temperature (SiC: 90 °C–150 °C) etc. A controlled automated evaluation of this vast number of datasets could uncover the underlying relationships between specific transients, their impact on the resulting EMI spectra and their dependence on the varied parameters. Additionally, the availability of corresponding time- and frequency-domain datasets on *OpenTwin* enables testing analysis methodologies that can relate both datasets to each other, for a large number of parameter variations [8]. For those cases in which the results can be made equivalent, EMC testing could be considerably accelerated by



(a) TIME-DOMAIN

(b) CM FREQUENCY-DOMAIN

FIGURE 3: SELECTED TIME SERIES AND SPECTRUM OF CONDUCTED EMI BY AN AUTOMOTIVE SIC-BASED DC-DC-CONVERTER, WITH $V_{\text{in}} = 450\,\text{V}$, $V_{\text{out}} = 48\,\text{V}$, $I_{\text{out}} = 48\,\text{A}$, $f_{\text{sw}} = 100\,\text{kHz}$ AND $T_{\text{chip}} = 90\,°\text{C}$.

performing time-domain measurements only.

IV. SUSCEPTIBILITY OF AUTOMOTIVE DUTS TOWARDS RADIATED IEMI

Another subset of information required for the development of an AV digital twin includes data related to the electromagnetic susceptibility (EMS) of automotive components and (sub-)systems. Beyond tests with EMI signals following automotive standards for both measurements and specific threshold levels, this work also includes radiated IEMI tests involving RF sources and testing areas with restricted availability and access, such as the Bundeswehr Research Institute for Protective Technologies and CBRN Protection (WIS[1]). Work is ongoing to reproduce selected IEMI tests with commercially available laboratory equipment, but these will likely remain limited in the available peak EM field strength for a working volume that can accommodate the typical size of an automotive (sub-)system [9].

In previous work, IEMI tests with broadband and mesoband pulses on an acceleration sensor indicated that such a sensor is resistant to field strengths up to 180 kV/m for the former and 40 kV/m for the latter pulse type, respectively [10]. Here, results of radiated IEMI tests on the electronic control unit (ECU) for the acceleration sensors previously tested, using a high-power pulsed S-band source (3 GHz, continuous wave, 0.7 µs RF pulse width, 2 MW peak output power), are presented as an example. On an open area test site (OATS), the peak electric field for a distance of 30 m between the DUT and the RF source is ≈8 kV/m. The DUT includes a cable tree, load boxes and periphery that represent the ECU's network and connections when embedded within a vehicle. The main coupling path of the S-band IEMI signal is known to be through the ECU's cable tree.

In addition to detailed information about the (I)EMI signals in the time- and frequency domain obtained from calibration measurements, e.g. with D-dot sensors, the behaviour of a DUT during EM exposure needs to be captured. Ideally this is realised with a similar high time-resolution to be able to synchronise the DUT's behaviour with the (I)EMI source. Data that can be obtained from a DUT strongly depend on its functionality, hence they likely require a custom solution per DUT to be embedded in *OpenTwin* for the development of an AV digital twin.

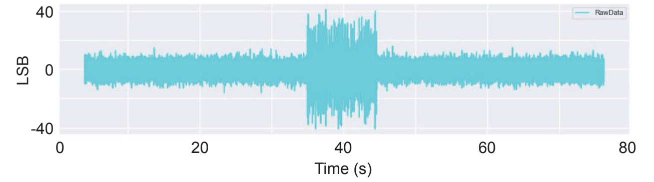
The typical analysis of the impact of (I)EMI signals on an airbag ECU involves the monitoring of the least significant bit (LSB). The LSB represents the smallest increment of the digital representation of a quantised analogue input signal and determines the resolution of the converted digital signal. In Fig. 4 the LSB of the ECU's data stream is monitored during the exposure to a pulsed S-band signal. In Fig. 4a it can observed, that the raw LSB data is strongly affected by the IEMI exposure in the time range central in the plot. Upon evaluating the obtained LSB values and comparing them with a threshold defined by standards, Fig. 4b displays that the limits are exceeded for this IEMI exposure. On *OpenTwin* the full datasets including multiple repetitions of the IEMI exposure can be automatically analysed in more depth, including examining the variation of the LSB during a single IEMI pulse, as highlighted in Fig. 4c.

V. SIMULATION-BASED ANALYSIS OF THE SUSCEPTIBILITY OF AUTOMOTIVE CABLES TO (I)EMI

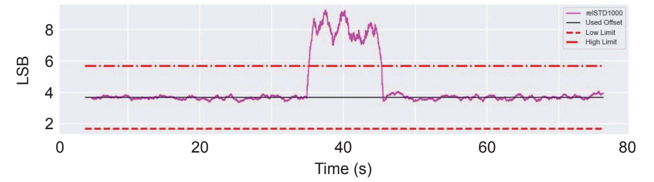
An important source of information to predict an AV's EMC behaviour in various EM environments are numerical simulations. These can comprise electric circuit simulations with, e.g. LTspice [11] or computational electromagnetics (CEM)-simulations based on well-known numerical methods including finite-differences time-domain (FDTD), finite element method (FEM), and method of moments (MoM). The latter forms the basis of FEKO [12], the EM simulation software used to obtain the results presented in this section.

The automotive wire harness is known to be a key coupling path for RF signals received from both the vehicle's internal and external environment [13]. An (I)EMI signal coupling into it can affect both the ECUs and other controllers that process signals from their peripherals as well as the functional safety of connected sensors and the integrity of the transmitted signals. Whereas the coupling into such a harness can be analytically determined for relatively simple cable layouts, more complex, realistic configurations require either extensive experimental efforts or CEM based simulations [14]. Recently, in order

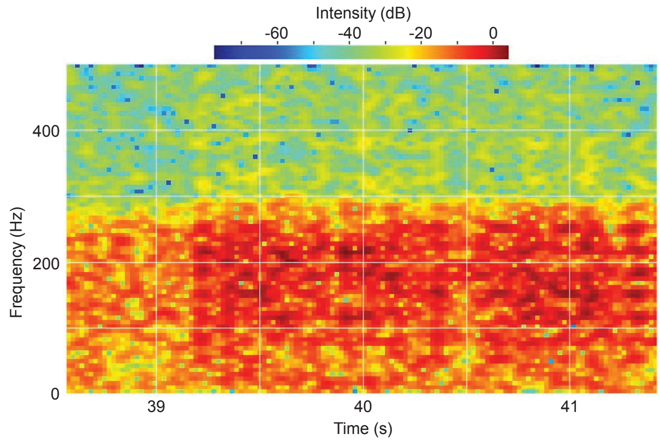
[1]WIS is a departmental research institute of the German Federal Government and is subordinate to the Federal Office of Bundeswehr Equipment, Information Technology and In-Service Support (BAAINBw).



(a) RAW



(b) EVALUATION

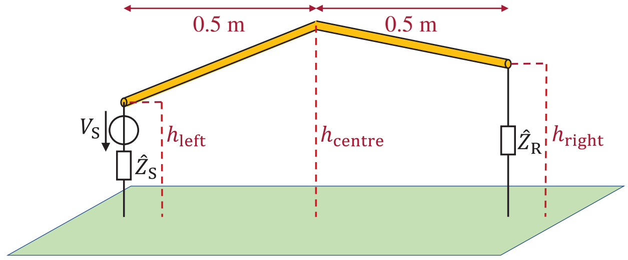


(c) FREQUENCY-DOMAIN ANALYSIS

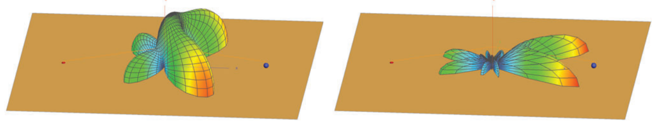
FIGURE 4: RAW AND EVALUATED LSB DATA FROM AN AIRBAG ECU EXPOSED TO AN S-BAND IEMI SIGNAL.

to accelerate the evaluation of cable layouts with regard to EM susceptibility, a method based on the reciprocity of an object's RF signal receiving and transmitting properties has been proposed [15]. Instead of simulating an incoupling signal, the reciprocal and simpler determination of an excited cable's radiation pattern via CEM is carried out. The cable layout to be assessed is excited by a known continuous wave (CW) signal from a voltage source, as schematically shown in Fig. 5a. The resulting three-dimensional EM field can be determined from the simulation at numerous positions around the layout, as shown in Fig. 5b. Through reciprocity such patterns also represent the EMS of the cable layout to a specific RF signal arriving from a certain direction.

When combining the results for various RF frequencies, the susceptibility of a given layout to broadband pulses, e.g. from IEMI sources, can be evaluated. *OpenTwin* is ideally suited to store these simulation data and to enable the automatic superposition of the results for CW signals into more complex, broadband signals. In a subsequent step, *OpenTwin* hosts ML algorithms that can identify hidden patterns in the relation between radiation profiles and cable layout properties. These can be provided by a trained ML model, e.g. a regression



(a) KINKED CABLE LAYOUT OVER A GROUND PLANE



(b) RADIATION PATTERNS AT 300 MHz AND 1 GHz

FIGURE 5: MOM SIMULATION TO EVALUATE THE EMS OF AN AUTOMOTIVE WIRE HARNESS.

neural network of moderate size, which in turn can serve to generate further data for *OpenTwin*. Instead of performing a computationally intensive CEM simulation of a complex wire harness layout, a trained ML model can then be used to predict the susceptibility of such a harness to any (I)EMI signal of interest.

VI. ML TO DETECT (I)EMI IN VEHICLES

As previously explained, AVs will challenge EMC standards and industrial procedures to make them functionally safe. (I)EMI-related challenges for autonomous systems in an unfriendly EM environment have been examined before [1]. The interactions of efficient PE for electrical drives and advanced signal processing for autonomous operations require new concepts of EMC processes during the design of AVs. It is worthwhile to investigate methodologies that potentially protect an AV against (I)EMI by a permanent online analysis of its inherent data traffic. Such a task is ideally suited for ML that can analyse a large dataset and its underlying patterns in real-time. But even without an onboard implementation on fast hardware it is beneficial to assess the EMC of certain design variants by such a method to harden an AV against (I)EMI. In the latter case, online data are replaced by data gained via circuit simulation and *OpenTwin* provides an ideal framework for data management and processing.

In this project, autoencoders (AEs), which are usually employed for intelligent dimensional reduction of high-dimensional input data, are implemented via neural networks [16], [17]. In addition to mapping data on a low-dimensional so-called *latent space* before further data analysis, as depicted in Fig. 6, AEs are here also used as adaptive filters to detect anomalies on AV system communication signals.

Normal patterns of the internal data transfer are learned during operation and disturbed signals are quickly identified. They can also be classified after mapping on the *latent space*. Depending on the result of an online analysis, an

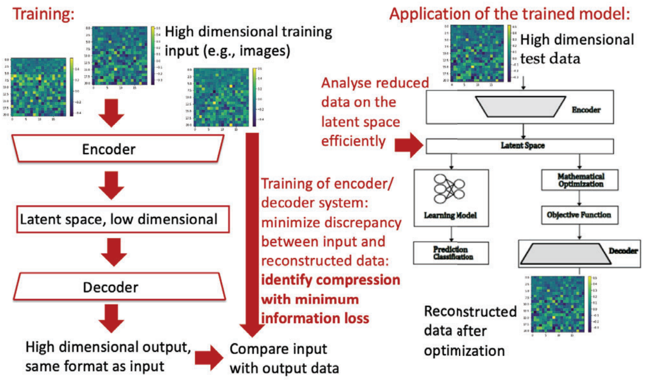


FIGURE 6: AE FOR DATA COMPRESSION.

AV's (sub-)system can be switched into a fail-safe mode or can employ built-in redundancies. Such methods can also be applied to detect changes of the system due to sudden failure of components, caused by aging or by (I)EMI.

An AE consists of an encoder with the shape of the incoming data, e.g. time series of simulated or measured currents, as the input format and a low-dimensional output shape, configuring the *latent space* [18]. Its second part is a downstream decoder with interchanged input and output shapes. The goal of training AEs is to obtain a minimum information loss when compressing data. This is achieved by processing the data through the encoder and decoder and comparing the resulting reconstructed data to the original data with respect to an adequate metric, as shown in Fig. 6. The AE adapts its internal weights to the incoming data and *learns* to compress them with a minimum information loss. Hence, the resulting *latent space* is an ideal feature space for high-dimensional data. For anomaly detection, the sequence consisting of an encoder and a downstream decoder is only trained by *normal* data and learns to reproduce the underlying pattern in high accuracy. Data from specimens deviating from the pattern will typically be mapped onto an output that differs significantly from the input and can thus be identified by a high information loss.

VII. CONCLUSIONS

This paper presents the cross-domain platform *OpenTwin* supporting digital twin development for AVs with a focus on EMC. The data stored, labelled and interconnected on the platform stem from (I)EMI measurements on automotive PE and sensor components, as well as from simulations on automotive wire harness layouts presented in this work. Furthermore, an AE-based data analysis is detailed, which enriches the *OpenTwin* data. Next steps involve the AI-supported extraction of hidden patterns in the available data and predictions on the EMS and EMI of automotive DUTs.

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REFERENCES

[1] U. Aizpurua, T. Brandt, M. Hagel, E. Kampert, M. Wendt, S. Dickmann, K. F. Hoffmann, and M. Stiemer, "Avoiding electromagnetic interference induced risks for autonomous driving," in *dtec.bw-Beiträge der Helmut-Schmidt-Universität*, Band 1, 2022, pp. 174–180.

[2] AIAA, "Digital twin: Definition & value—an AIAA and AIA position paper," AIAA Digital Engineering Integration Committee and others, Reston, VA, USA, White paper, Dec. 2020.

[3] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital twin: Enabling technologies, challenges and open research," *IEEE Access*, vol. 8, pp. 108 952–108 971, 2020.

[4] OpenTwin Organization, "OT-OpenTwin," [Online], Last accessed: 2024-10-25. [Online]. Available: https://github.com/OT-OpenTwin

[5] J. Wagner and P. Thoma, "Secure cloud-based simulation," in *2022 Kleinheubach Conference*, 2022, pp. 1–4.

[6] S. S. Kulkarni, M. Wendt, S. Brandt, K. F. Hoffmann, E. Kampert, and S. Dickmann, "Conducted emissions of an upto 2 3kW SiC interleaved buck converter under varied operative conditions," in *2024 International Symposium on Electromagnetic Compatibility – EMC Europe*, 2024, pp. 1–6.

[7] M. Wendt, E. Kampert, J. Wendt, K. F. Hoffmann, and S. Dickmann, "Conducted EMI from GaN-based 48V to 12V DC-DC converters for automotive applications," in *PCIM Europe 2024; International Exhibition and Conference for Power Electronics, Intelligent Motion, Renewable Energy and Energy Management*, 2024, pp. 2337–2344.

[8] C. Keller and K. Feser, "Fast emission measurement in time domain," *IEEE Transactions on Electromagnetic Compatibility*, vol. 49, no. 4, pp. 816–824, 2007.

[9] U. Aizpurua, E. Kampert, and S. Dickmann, "Improved determination of the electric field in radiated IEMI tests with EMP and UWB signals," in *2024 International Symposium on Electromagnetic Compatibility – EMC Europe*, 2024, pp. 1–6.

[10] T. Brandt, S. Fisahn, M. Schaarschmidt, U. Aizpurua, E. Kampert, and S. Dickmann, "Investigating electromagnetic interference induced risks for autonomous driving," *Advances in Radio Science*, vol. 22, pp. 1–8, 2024, Last accessed: 2024-10-25. [Online]. Available: https://ars.copernicus.org/articles/22/index.html

[11] Analog Devices, Inc., "LTspice," Last accessed: 2024-10-25. [Online]. Available: https://www.analog.com/en/resources/design-tools-and-calculators/ltspice-simulator.html

[12] Altair Engineering Inc., "FEKO," Last accessed: 2024-10-25. [Online]. Available: https://www.altair.de/feko/

[13] A. R. Ruddle and A. J. M. Martin, "Adapting automotive EMC to meet the needs of the 21st century," *IEEE Electromagnetic Compatibility Magazine*, vol. 8, no. 3, pp. 75–85, 2019.

[14] U. Aizpurua, E. Kampert, and S. Dickmann, "EMC study of automotive wire harness configurations in a GTEM cell," in *2023 International Symposium on Electromagnetic Compatibility – EMC Europe*, 2023, pp. 1–6.

[15] T. Liang, G. Spadacini, F. Grassi, and S. A. Pignari, "Worst-case wideband radiated IEMI for unshielded and shielded cables: A statistical analysis of the main influencing parameters," *IEEE Transactions on Electromagnetic Compatibility*, vol. 61, no. 4, pp. 1244–1252, 2019.

[16] M. Stiemer, M. Hagel, U. Aizpurua, M. ElSayed, and I. Cahani, "Machine learning based data analysis for electromagnetic reverberation chambers*," in *2023 Kleinheubach Conference*, 2023, pp. 1–4.

[17] M. Stiemer, "Machine learning based classification and prediction of electromagnetic absorption in electrical reverberation chambers," in *2023 XXXVth General Assembly and Scientific Symposium of the International Union of Radio Science (URSI GASS)*, 2023, pp. 1–4.

[18] M. Sakurada and T. Yairi, "Anomaly detection using autoencoders with nonlinear dimensionality reduction," in *Proceedings of the MLSDA 2014 2nd Workshop on Machine Learning for Sensory Data Analysis*, 2014, pp. 4—11.