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AI-Driven Digital Twin for Health Monitoring of Wide Band Gap Power Semiconductors

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***Abstract*—A significant challenge in the implementation of health monitoring systems for estimating the health state of devices is the lack of accurate information about design details. This challenge is particularly prominent in the field of power electronics, where both IC designers and converter designers are often hesitant to share information about their designs. Addressing this issue, this paper introduces a novel AI-driven digital twin modeling methodology that enables the detection and classification of failures in power semiconductors, particularly Wide Band Gap semiconductors. By employing AI-based system identification techniques, this method offers a noninvasive approach to health monitoring of power switches with high resolution, even while operating under real conditions. The proposed method has been validated by simulating wire bond failure in a SiC power MOSFET using MATLAB SIMULINK, and the results demonstrate its accuracy.**

***Index Terms*—AI, Digital twin, Health monitoring, Kalman filter, NARX-ANN, Power converter, WBG semiconductor.**

I. Introduction

Recently, due to rapid advancements in technology and an increase in the demand for green energies, power converters are playing a significant role in transferring energy, converting electrical energy from AC to DC, from DC to DC, and from DC to AC. A power converter efficiently converts and controls energy between a source and a load. It comprises of active components, which are power semiconductor components, that regulate the power flow within the converter by turning it on and off. Additionally, it includes passive components, such as inductors and capacitors, which temporarily store energy within the converter system. Finally, there's the control unit, including signal converters and processors. However, all of these components may degrade or fail before reaching their expected useful lifetime. In [1], an industrial survey conducted by various companies, including component manufacturers, aerospace, automotive, motor drive, utility, and others, shows that power semiconductors are most prone to failure, and capacitors are the next. Therefore, to better understand and estimate the physics of failure, prevent unexpected failures in power converters, and reduce maintenance costs, the application of health monitoring systems is necessary.

A health monitoring system is a combination of several measurement devices that measure one or several parameters to detect, localize failure, and assess its intensity while the device is in service. Whereas it is possible to use different methods and measurement devices during laboratory testing, in health monitoring systems, to avoid any changes in the size and performance of the real device (e.g., load effect), the number and type of sensors are limited to prevent any alteration in the performance of the device. Therefore, selecting proper parameters that have a direct relationship with the failure mode will be challenging in many cases. To overcome this difficulty, the application of monitoring systems for model updating and estimating parameters of interest can be beneficial for increasing the accuracy of a numerical model in parallel with the physical element for further analysis. In different applications, the updated model is called a digital twin.

In the literature, a digital twin is defined as a multiphysics, multiscale, probabilistic method of modeling a real physical element [2]. However, the definition of a digital twin model also depends on the level of detail needed to describe the physical element. It can either be defined as a three dimensions or five dimensions model. The difference between these two lies in the fact that in a three-dimensional model, there are only the physical element, the virtual element, and the link between these two. However, a five-dimensional model has the additional capability of optimizing the accuracy of the virtual model [3]. Moreover, with continuous development in the field of digital twins, the application of digital twins has expanded to cover more areas every day; for instance, it now includes aerospace engineering, electronic engineering, EVs, construction, logistics, and other fields.

In the field of the electronic industry, the application of digital twins is recommended for the reliability analysis of various devices. For example, Adam Talen et al [4] created a 5D digital twin model of a Li-ion battery to predict its ideal retirement time. Similarly, in [5], it is proposed as a potent tool for diagnosing and prognosticating the health of light-emitting diodes, serving as the connection between the physical space and the virtual space to enhance the accuracy of health monitoring systems. Several studies show that in the area of power converters, using digital twin technology can be beneficial at different levels of detail, from estimating the behavior of the model to estimating the health state of each single component of the converters.

At the lowest level of detail, the converter in many cases is defined as a black box, and the digital twin is used to estimate the output of the converter due to variations in the load. At this level, different system identification techniques are used as a twin to estimate the relationship between the input and output of power converters. For instance, in [6], parametric system identification is used to understand the behavior of a synchronous buck converter under different load conditions. It links the input duty cycle to the output inductor current and output capacitor voltage, creating a state-space model of a synchronous buck converter, and then employs the recursive least squares algorithm for estimating the parameters of the model. In [7], this method is optimized by using the Kalman filtering method to estimate the parameters of the model, and their results show that this method allows for faster parameter estimation. However, defining the proper state-space model that can explain the dynamic performance of the converter is not easy in many cases. In these instances, the application of Artificial Intelligence (AI)-based methods can be helpful. In [8], Wunderlich et al. proposed the application of the Nonlinear Autoregressive with eXogenous inputs Artificial Neural Network (NARX-ANN) method to estimate the dynamic performance of converters. For training the model, they used variouse combinations of duty cycle, input voltage, and load current as input training data and inductor current and capacitor voltage of a boost converter as the output training data. They used a closed-loop NARX-ANN model for the prediction of the output. Validation of their approach in both the time domain and frequency domain shows that the model can make accurate predictions under all operating conditions.

At a higher level of detail, the concept of digital twin has been used to estimate the health state of power converters by estimating the passive components over time. For instance, in [9], the circuit schematic of a buck converter was defined as the digital twin of the converter, and the Particle Swarm Optimization (PSO) method was employed to estimate the passive components of the digital twin, making its output match as the real physical converter. This method is beneficial as it is a noninvasive method of monitoring, meaning that no additional sensors or components were added to the circuit for monitoring the converter. Similar research can be found in the literature. In [10] and [11], different methods were used to define and solve the equivalent circuit of the converter, and in [12], the Genetic Algorithm (GA) was used as the optimizer to estimate the parameters of the twin circuit.

As mentioned earlier, studies indicate that the power switch within the power converter is more prone to failure than other components. At this level, the digital twin should incorporate a higher level of detail compared to other models. This is because power switches involve multiphysics concepts at the microscale level. Moreover, without a good understanding of the behavior of the switch in different applications, the problem becomes an ill-posed problem. Addressing this challenge, many researchers have employed highly accurate Finite Element Models (FEM) of the switch to define the digital twin. For example, in [13], a FEM model was used to extract the thermal model of the MOSFET. This Reduced-Order Model (ROM) was employed as a digital twin for real-time estimation of the junction temperature of the switch in a boost converter. Additionally, in [14], a FEM was defined as the digital twin and utilized for design optimization to reduce parasitic elements inside the switch.

In many research efforts, Machine Learning (ML) techniques have been proposed as a solution to estimate the behavior of the switch or the variation of its structural parameters. For instance, in [15], a physics-informed long short-term memory (PILSTM) was utilized for plastic strain prediction in solder joints. In [16], an unsupervised learning method was proposed for the fault prognosis of SiC MOSFETs, where data from healthy devices were used to detect abnormalities through the application of Principal Component Analysis (PCA). In [17], a supervised recurrent neural network was trained to predict the sequence of the active gate driver.

Although these studies and many others demonstrate the benefits of AI for modeling the behavior of a part or the entire behavior of the switch, the emergence of new technologies in power semiconductor materials and packaging necessitates further study and application of new technologies like digital twin modeling in this area. This becomes even more critical in the application of digital twin models for health monitoring of the switching performance of power semiconductors, as any abnormality in switching performance can induce stress on the switch itself and the rest of the components in the converter.

In this regard, this paper presents a novel noninvasive digital twin model for real-time health monitoring of power semiconductors while they are operating and independent of the converter's topology. Details of the methodology are explained in the section III, and it is proved with a benchmark example in Section IV.

II. State of the Problem

Lately, due to the high demand for highly efficient power converters, there has been an increased demand for transistors made of Wide Band Gap materials (WBGs). These materials, such as Silicon Carbide (SiC) and Gallium Nitride (GaN), are capable of operating at higher temperatures, voltages, and frequencies due to their higher thermal conductivity, electron breakdown field, and electron mobility. These capabilities make them more attractive candidates for applications in harsh environments, such as traction inverters in Electric Vehicles

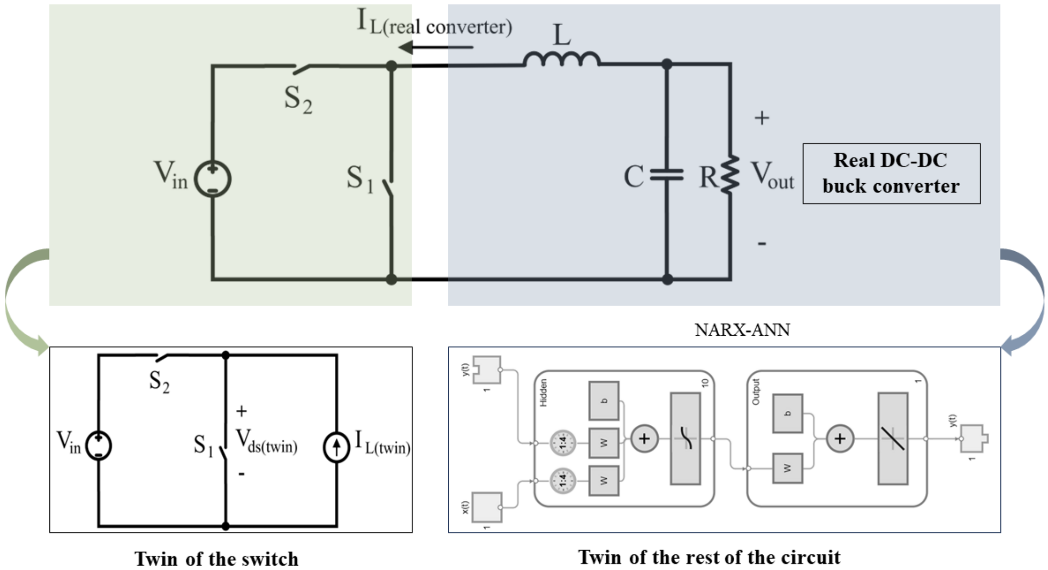


Fig. 1: Schematic of a digital twin model for a DC-DC buck converter.

(EVs). In this regard, advanced packaging technology is required to enable them to operate at their highest level of efficiency and reliability. One important consideration here is to minimize package parasitic resistance and inductance caused by the internal conduction path, as well as parasitic capacitance generated by parallel conductors separated by dielectric layers. These parasitic elements can induce overshoot voltage and ripple during switching transitions. This effect is particularly significant in WBG semiconductors due to their ability for fast switching and high di/dt and dv/dt. Despite all considerations during the design process, failures such as wire bond failure can increase the overshoot voltage and ripple during switching, leading to unwanted stress on the device itself and other connected components in a power converter, potentially affecting their reliability.

Although there are several studies in the literature about the application of different testing methods for simulating failures in real applications, there is still a need for research in the design and application of monitoring systems for real-time health state monitoring of switches. In this context, digital twin technology can assist in monitoring the switching performance of WBG semiconductors and the variation of their switching profile during device operation. This not only helps in understanding the physics behind any possible failures but also, through optimization of the switching speed with the help of feedback controller systems in converters, it is possible to enhance the switch's lifetime. However, a significant challenge in applying monitoring systems to detect the failure and the understanding Physics of the failure of the switch is that the structure of the switch's package is only known to manufacturers. On the other hand, the dynamic characteristics of the switch depend highly on the type and magnitude of the load when used in converters. Meaning, in many cases, during the design of a power switch, its application (i.e. the converter's topology) and therefore the load is unknown. Consequently, even if a converter is equipped with a monitoring system to monitor passive component degradation, lacking information about the structure of the switch's package makes the application of a monitoring system for health estimation of both active and passive components inside the converter difficult. This paper presents a novel AI-based digital twin method to overcome this problem.

III. Methodology

In this methodology, to define the digital twin, the power converter is separated into two parts: the switch and the rest of the circuit. For each of these two parts, a twin is defined separately, and their serial connection creates the digital twin that explains the power transistors's behavior (Fig 1). The twin of the switch is used for failure classification, and the twin of the rest of the circuit will be used to link the variation of the output to the failure in the switch. Moreover, the twin of the switch operates offline, with an arbitrary load and it is used to mimic the failure inside the real switch. On the other hand, the twin of the rest of the circuit will be replaced by an open-loop NARX-ANN, which is a particular type of AI that trains in real time while the converter is in service. However, many failures in power switches have small effects on the output of the converter that can be mistaken with the presence of noise. Therefore, in this research, a particular type of Extended Kalman Filter (EKF) has been used to improve the accuracy of the NARX-ANN by removing the noise from its prediction. More details and a graphical presentation about the methodology are explained in the following subsection.

A. Digital Twin Model of the Switch

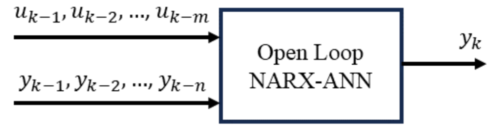
Power switches can be utilized in any power converter with almost endless various structures. The voltage and current stress of the power switches vary for the topology, load, etc.

For instance, the voltage stress across the power switch in a DC-DC boost converter is equal to the output voltage, while in a buck converter, it is input voltage values. Similarly, when the output load power changes, the energy flow in the converter changes, leading to current level variation in the elements, including the power switch. Therefore, before designing a health monitoring system for monitoring power switches while they are operating, the voltage and current ratings for all possible operational modes should be known. As it mentioned earlier, this makes defining the digital twin of the switch during the manufacturing process while the application of the switch is unknown difficult.

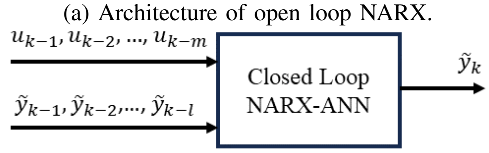
In this methodology, the twin of the switch is another switch that operates independently. It can be a real switch, a Finite Element Method (FEM) simulation of the switch, or a reduced order model of the switch capable of explaining different failures inside the switch at various levels and intensities. As mentioned earlier, this twin operates offline, without any connection to the converter, and with an arbitrary load, but with the same gate input as the real switch inside the converter. The output of this twin will be used as the input of the twin of the circuit. Then, when any abnormality is detected in the output, the cause of this abnormality will be investigated by conducting different failure scenarios through lab tests or simulations in the twin of the switch. Although using an arbitrary load in the twin of the switch makes its operational profile different from the real switch inside the converter, training the NARX-ANN with its output allows the twin model to relate the output's variation to the twin's variation, not the real switch with unknown input load. As a result, not only there is no need to add a new component to the circuit to monitor the health state of the switch, the same model can also work for different topologies and converter types. Fig 1 shows a twin of a DC-DC buck converter as an example. It can be observed that the load of the twin($I_{L(twin)}$) of the switch can be different from the load applied to the real switch($I_{L(\text{real converter})}$).

B. Digital Twin of the Rest of the Circuit

To model the rest of the circuit, artificial neural networks will be used to directly link the output of the switch to the output of the power converter. To train an ANN model, having enough data with high quality is inevitable. The number and quality of the data can vary depending on the level of complexity of the model. In more detail, an ANN model can have feedforward or feedbackward architecture. In feedforward structures, the information flows in one direction from the input to the output. These models are used in several applications in the engineering field for both regression and classification. Data for training these models are mostly static and can be generated using simulation or experimental tests. Several studies in the area of power electronics show that this method is quite powerful. But, since in this method, the output depends only on the current values of the input, and the outputs remain fixed at any instant for a fixed set of outputs, they are not suitable for modeling dynamic systems like power converters [8]. In AI models with feedbackward architecture, feedback from past outputs can be used as an extra input. This makes them suitable for training models using time series data when an AI model can capture the dynamic behavior of devices like power converters.



(a) Architecture of open loop NARX.



(b) Architecture of closed loop NARX.

Fig. 2: Architecture of NARX

There are several feedbackward AI models in the literature, but for the purpose of this paper, the application of open-loop NARX-ANN was found to be more interesting. NARX-ANN is from the family of autoregressive models with inputs using a nonlinear function that estimates the output of the next step by using a feedbacked output. In literature, there are two types of NARX-ANNs, open loop, and closed loop. While both of them have feedback from the output, in the open loop model, besides the input, the past output of the system will be used as input, while in the closed loop model, the past predicted output will be used as the input. The equation of the open loop NARX is:

$$y = F(y_{k-1}, y_{k-2}, ..., y_{k-n}, u_{k-1}, u_{k-2}, ..., u_{k-m}) \quad (1)$$

and the equation of the closed loop NARX is

$$\hat{y} = G(\hat{y}_{k-1}, \hat{y}_{k-2}, ..., \hat{y}_{k-l}, u_{k-1}, u_{k-2}, ..., u_{k-m}) \quad (2)$$

where u is the input of the system, y is the output of the system, $\hat{y}$ is the predicted output, n, l, and m are the feedback delay of the output, predicted output, and the input respectively, and F and G are nonlinear functions [18]. While for training closed-loop NARX, enough data is needed to explain the dynamic performance of the model, open-loop NARX can be trained in real-time when the device is working. Fig 2 shows the architecture of both closed-loop NARX and open-loop NARX.

Therefore, as this paper assumes the target application of the switch is unknown during the design of the digital twin, the open-loop NARX will be a good choice as the twin of the rest of the circuit. As it mentioned earlier, the NARX-ANN will be trained by using the feedback of the converter's output as input and the output of the twin of the switch as the input. Using output feedback both during the training and prediction will not only make the training procedure fast and selecting hyperparameters (number of neurons, number of hidden layers, etc.) easier, but it will also increase the prediction accuracy. However, this accuracy will be affected by the presence of noise in the data; As because of the noise, understanding the sequence between data will be difficult for the AI model. To overcome this problem, a method based on the application of the EKF has been used in this paper to improve the accuracy of the NARX-ANN to predict the real output of the converter, even if the data is noisy.

Moreover, as mentioned earlier, NARX-ANN utilizes the output of the previous time steps to predict the output of the circuit at the current time step. This implies that failures inside the switch can be detected faster than in real-time. With this method, to protect the switch, the input can be adjusted one time step before the overshoot voltage surpasses the threshold voltage. It should be noted that the size of each time instance defines how much faster than real-time the model can estimate the output. The larger the difference between each time instance, the faster the model. However, when selecting the width of each time step, the resolution of failure detection should also be taken into consideration.

C. EKF-NARX

While the converter is operating in real condition, several sources of the noise can effects the accuray of the measured output. As mentioned earlier, the prediction accuracy of the NARX-ANN will be effected by this noise. To overcome this problem, the EKF technique will be used in this paper to estimate the true output from the noisy measurement. Generally, the Kalman Filter (KF) process is designed to estimate the state of a linear model. For nonlinear systems, like power converters, before applying the filtering equation, a linearization procedure will be applied. This linearization will be done by linear Taylor approximation of the system function at the previous state estimate and that of the observation function at the corresponding predicted position. The Kalman filter obtained through this process will be called the EKF [19]. The EKF estimates the true state in two stages. First, using the state-space equation of the system, it will predict the true state of the system. Then, based on the measured value, it will adjust the estimated state of the system at each time instant. In an EKF algorithm for the prediction stage:

$$\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}) + w_k \tag{3}$$

This means slightly before the time instant k, the state of the model ($\hat{x}_k^-$) depends on the past state of the model ($\hat{x}_{k-1}$) and past input of the model (u_{k-1}) plus noise in the measurement (w_k) . Moreover, the covariance of the prediction error in the same time instant (P_k^-) is calculated as:

$$P_k^- = F_k P_{k-1} F_k^T + Q_k \tag{4}$$

where F_k is the Jacobian of the state transition function and Q_k is the process noise. In the updating stage:

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \tag{5}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - h(\hat{x}_k^-)) \tag{6}$$

$$P_k = (I - K_k H_k) P_k^- \tag{7}$$

where K_k is the Kalman gain, H_k is the Jacobian of the measurement fucntion (h) and z_k is the measured value at time instant k.

The goal of applying the EKF in this work is to estimate the true state, which is the true output of the converter, from noisy measured data at each time instant. By comparison between the equation of the NARX ("1") and the equation used as a state-space equation in EKF ("3") it can be seen that they are similar to each other. Therefore, NARX-ANN is used in EKF as the space-state equation of the power converter. However, using a neural network as the state-space function of the model makes the calculation of the Jacobian of the transformation function (F_k) and the Jacobian of the measurement function (H_k) difficult. As mentioned earlier, since the output of the digital twin of the switch is used as the input of the digital twin of the circuit, the variation in the output does not depend on the variation of the real switch's output. Therefore, in the first step during the calculation of F_k, only the variation of the output during the delayed time should be taken into account. In addition to this, while the sampling frequency is high, it can be assumed that the system is linear within the delayed time instants plus one time instant. In this case, F_k can be considered as equal to one. This assumption needs to hold true only in the very first time instants. Because if we assume that in the first iteration, the delay in the output from time instant 1 to n is used to predict the output at time $n+1$, at the second iteration, the delay from time instant 2 to $n+1$ will be used for predicting $n+2$, and then after n iterations, true values will used as delayed time to predict the next true value from the noisy data.

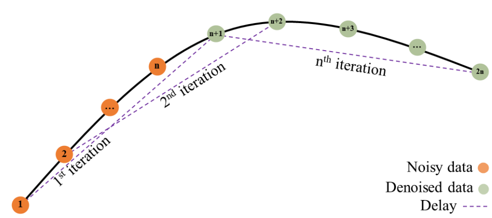


Fig. 3: Feedback output at first iterations of the EKF-NARX.

On the other hand, as the noise is assumed to be Gaussian with a zero mean value:

$$x_k^{measured} = x_k^{true} + \epsilon \tag{8}$$

where $\epsilon \sim N(0, \sigma)$ and σ is standard deviation of the noise. Therefore, similar to the F_k, the H_k can also be considered as equal to one. Although this makes the concept of the EKF close to the definition of the KF, still, as the system is nonlinear, the EKF is selected for the purpose of this paper. These estimated true values will be used in the next step to estimate the properties of the failure in the switch.

D. Failure detection and assessment

As mentioned earlier, the estimation of the variation in the parameters of the rest of the circuit has been excluded from this method, as they are unknown for the IC manufacturers.

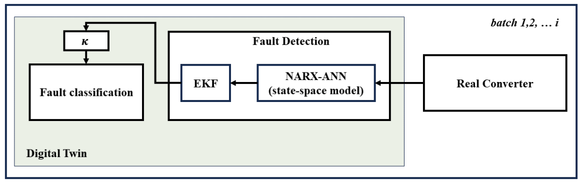


Fig. 4: Schematic of a digital twin model for a DC-DC buck converter.

With this assumption, and using NARX-ANN as a black box system identification method, the relationship between the output of the converter and the output of the twin of the switch under steady-state conditions can be defined as:

$$\kappa = |\text{Output of the converter}| + |\text{Output of the twin of the switch}| \tag{9}$$

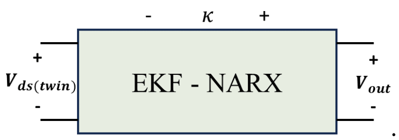


Fig. 5: Black box schematic of the rest of the circuit.

where κ is defined as the gain of the black box, and it is calculated easily using Kirchhoff's voltage law (see Fig 5). This expression should hold true both before and after the failure. The κ should be calculated when the switch is intact, then it assists in estimating the output of the twin of the switch after failure is detected. Once the output of the switch is detected, it can be used for failure classification, which involves failure localization and assessment. The type of the algorithm for failure classification and therefore the type of model of the switch depend on the possible failure mechanism. Returning to subsection A, the twin of the switch can be modeled using different methods.

One method is the application of the large-signal model of the switch. Owing to the fact that ideal power switches do not exist in real-world applications, to model the exact behavior of the switch in all possible operations modes, a model by including all the parasitic elements is used in this paper. Fig 6 shows the associated circuit schematic of this model. Moreover, this model can be used for predicting the behaviour of Si-based and WBG devices. However, one should note the fact that regular power devices like the Si and SiC power switches conduct when the V_{GS} is more than V_{th} whether the applied voltage to their drain-source is positive or negative. Unlike these devices, GaN semiconductors conductivity is controlled by V_{GS} and V_{GD} when the applied voltage to their drain-source is positive and negative, respectively [20]. In this paper, this schematic model is used for estimating the properties of the failure.

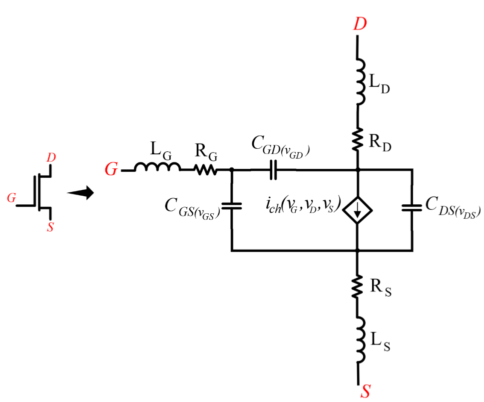


Fig. 6: Circuit schematic of a switch.

IV. Benchmark Example

The method explained in Section III was tested here by simulating the DC-DC Buck converter shown in Fig 1 using MATLAB SIMULINK. The details of the converter's design are explained in Table I.

TABLE I: Design details of the DC-DC buck converter.

Items	Value	Unit
L	200	μH
C	470	μF
R	45	Ω
V_{DC}	100	V
R_D	64.94	$\mu\Omega$
R_S	6.436	mΩ
L_D	3.648	nH
L_S	4.3	nH
$I_{L(twin)}$	1	A
Switching frequency	25	MHz

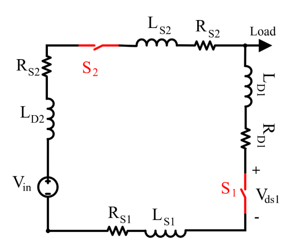
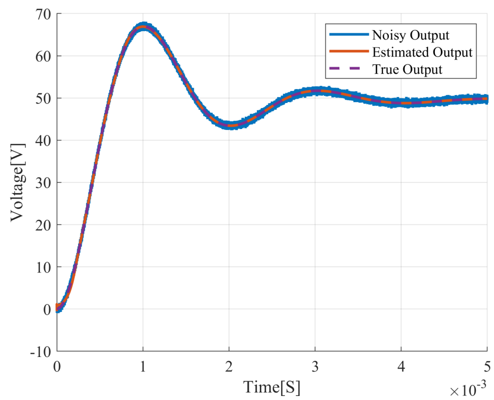
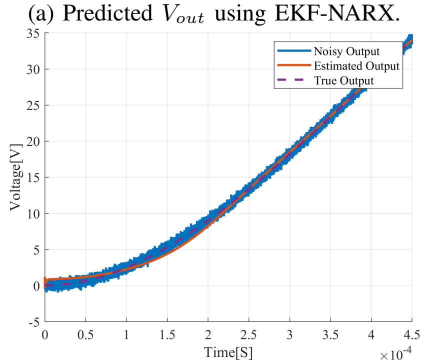


Fig. 7: Circuit schematic of the switch.

A SiC Power MOSFET with the TO-247 package has been used as the both switches in the half-bridge configuration. The package of the switch is considered to have a wire-bonded structure with six wire bonds made of copper. For simulating the failure, a simplified static circuit schematic of the switch is used as both the real switch and the twin of the switch, wherein each switch the parasitic resistances and inductances are lumped as R_D, R_S, L_D, and L_S, representing the parasitic resistances and parasitic inductances of the drain and source, respectively. The sampling time is considered as 5 [ms]. The failure in the switch is defined as the failure in one of bond wires of the S1 and simulated with a 0.2 [nH] increase in the parasitic inductance of the source after 0.8 [ms] (L_{Snew} = 4.5 [nH]). To resemble the real application, white Gaussian noise was added to the output voltage of each batch. The Signal to Noise Ratio (SNR) is assumed to be 10 [dB], and this noise is added to each batch without any correlation. For modeling



(a) Predicted V_{out} using EKF-NARX.



(b) Zoomed Predicted V_{out} for the first 0.45 [ms].

Fig. 8: Removing noise from measured V_{out} using EKF-NARX.

the rest of the circuit, the intact S1's drain-source voltage is utilized as the input of the NARX-ANN. Then, the NARX-ANN was trained with three hidden layers, each containing 10 neurons. The input delay and feedback delay are both set to 6-time instants, and the Levenberg-Marquardt algorithm is employed as the training function. Moreover, the performance of the model has been evaluated by calculating the Mean Square Error as:

$$MSE = 1/N \sum_{k=1}^{N} (y_k - \hat{y_k})^2 \tag{10}$$

where N is the number of time steps. This model is used to detect the failure one time step before it occurs. Initially, the model is trained with $V_{ds(twin)}$ and V_{out} while the switch is intact. Then, this model predicts the output voltage using $V_{ds(twin)}$ as the input and the feedback voltage output of the converter in the failure scenario. Fig 8 shows the predicted output using the proposed algorithm. From Fig 8b it can be seen that in the first steps of denoising, the error between the calculated and estimated values was high. However, by using more data in subsequent time steps, the predicted value converged to the true value of the signal. Moreover, the calculated error between the predicted values in the two mentioned states, used as the indication of the failure and presented in the Fig 9. It can be observed that although the estimated error was noisy

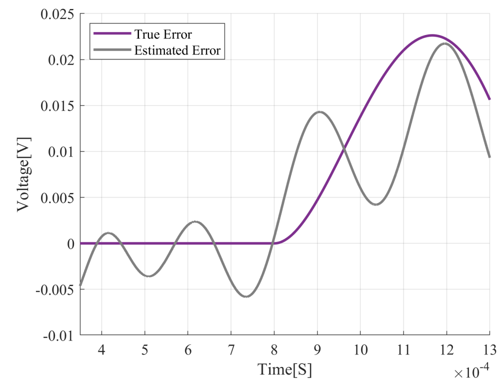


Fig. 9: Fault detection.

even before the moment of failure, its trend increased after the failure and followed the true error's pattern. This is because, in this example, to challenge the proposed method, the failure is assumed to be a very small change in L_S, occurring shortly after the start. Moreover, assuming SNR = 10 [dB] means that the measured value is near the acceptable range.

For the failure classification, the first step is to calculate the κ to understand the gain of the rest of the circuit or the black box.

$$\kappa = V_{out} + V_{ds(twin)} = 150.246[V] \tag{11}$$

Using this κ, the $V_{ds(twin)}$ after the failure calculates as 100.422[V]. This is the peak overshoot voltage of the switch after it experiences the failure. To esitmate the value of the L_S Kirchhoff's law used when the switch is off as:

$$V_{ds} = (R_D + R_S) \times I_{ds} - (L_S + L_D) \times \frac{dI_{ds}}{d_t} + V_{in} \tag{12}$$

The I_{ds} is assumed to be the same as before, while the failure in the switch changes only the V_{ds}. Therefore, by using 12 the L_S calculated as 4.64 [nH] means the relative error is equal to 3%. Considering the high level of noise in this benchmark example, this value can be regarded as an acceptable estimation.

This example demonstrates the accuracy of the model in detecting and estimating the intensity of the failure while the measured data is noisy. The definition of the twin of the switch provides the possibility to measure the output of the switch in a controlled environment. Therefore, the measurement noise and environmental effects can be minimized to an acceptable range.

V. Conclusion and Discussion

This work presents a digital twin modeling method for health monitoring, fault detection, and classification of power switches in power converter applications, and it proved by simulating wire bond failure in a TO247 SiC MOSFET as a case study.

Since this method is independent of the converter's topology and does not require additional sensors or components, it can be applied to converters already in service. Furthermore, through this method, IC designers can assist converter designers in developing precise monitoring systems capable of estimating the health status of all elements inside the converter, including the switch, without sharing sensitive design information about IC packages.

Using this methodology provides the possibility to understand the physics behind the failure in WBG-based power switches while they are operating in different applications and under different environmental conditions. This insight can help IC designers with design improvements for the next generation of the package of switches. Additionally, as this algorithm operates in real-time and in parallel with the real device, it provides valuable information that can help mitigate failures inside the switch and increase the switch's reliability. For instance, in the example of wire bond failure, a smart PID controller can optimize the switching speed (or optimize the di/dt or dv/dt) to reduce the switching overshoot voltage to an acceptable range. Therefore, it can also help the converter designer to improve the remaining useful lifetime of a switch, even after a minor failure in its structure. Along with these benefits, as this method is a noninvasive monitoring technique, not only it can be used in algorithms for estimating their Remaining Useful Lifetime (RUL) by estimating the degradation of the performance of the switch over time, but the extracted data can also be used further to develop different ML models for reliability analysis and AI-based package design techniques.

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