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Digital Twin–Based Modeling and Health Management of Analog and Mixed-Signal Circuits

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Abstract— ***Modern electronic systems are based on analog and mixed-signal (AMS) circuits that interface the physical world to digital number-crunching units. The changing process variations, aged effects, environmental stress and inability of observing them when operational is increasingly becoming a challenge to guarantee their reliability and long term performance. The paper proposes a modeling and health control framework of analog and mixed-signal circuits based on digital twins, which allows providing real-time monitoring, predicting the performance of the system, and diagnosing faults proactively. The proposed digital twin combines both physics-based circuit models and data-driven learning strategies to reproduce the dynamic behavior of AMS circuits with different operating conditions accurately. Through constant alignment of simulation models with real-time measurements, the digital twin records parametric drifts, nonlinearities, and degradation by-products like bias temperature variability and electromigration. Health indicators such as gain deviation, compensating drift and bandwidth reduction, and variation in noise are reported and processed to determine a circuit state and further life expectancy. The efficacy of the suggested method in early fault detection, performance degradation monitoring, and reliability improvement is proved by a case study with analog and mixed-signal representatives blocks. Both simulation and experimental findings demonstrate that the digital twin enhances prediction accuracy and provides an opportunity to make timely maintenance-related decisions as compared to traditional methods of working with steady models. The suggested framework presents a scalable and powerful approach to smart health management of new-generation electronic systems to uphold better reliability, less down time, and long service life.***

Keywords—**:**Digital Twin; Analog and Mixed-Signal Circuits; Health Monitoring; Fault Diagnosis; Predictive Maintenance; Reliability; Degradation Modeling; Real-Time Systems.

I. Introduction

The analog and mixed signal (AMS) circuits are important in the contemporary electronic systems because they form the necessary interface between the physical world and the digital processing units. They find broad application in communication systems, sensor interfaces, and power management units, autopilot applications in vehicles, in aerospace systems, and Internet-of-Things (IoT) appliances. As compared with purely digital circuits, the AMS circuits are highly sensitive to variations in processes, environmental effects, age dependence, and nonlinearities, and as a result, conventional tools of design-time verification and static reliability analysis are no longer adequate to assure in-field performance of AMS circuits as semiconductor technology continues to be scaled up, and system complexity grows[1]. Circuit parameters may be changed over time by a variety of processes, including bias temperature instability (BTI), hot carrier injection (HCI), electromigration, and thermal stress, causing performance to drift, occasional failures, or catastrophic failures. In addition, a low observability and testability to AMS circuits under normal operation also complicates the early fault-detection and health-checking of AMS circuits[2]. New developments in the cyber-physical systems, data analytics, and real-time sensing have made it possible to introduce the concept of digital twin technology as an effective paradigm of intelligent system monitoring and lifecycle management. A digital twin is a computer image of a physical system which continuously changes by synchronizing with real-time operation data. Although digital twins have been studied widely in mechanical, aerospace, and power systems, they have not been studied as extensively on electronic circuits, especially analog and mixed-signal circuits, since it is difficult to model and the behavior is nonlinear and highly sensitive to operating conditions[3]. A digital twin can provide the opportunity to close the disconnect between in-field behavior and design-time models with a physics-based circuit model, supplemented with data-driven learning methods, in the context of electronics engineering. Using such a hybrid framework, both the basic electrical properties and the dynamic degradation properties of AMS circuits may be captured. The digital

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twin allows one to track the accurate performance, detect anomalies early, and make predictions regarding the remaining useful life (RUL) by constantly updating model parameters based on real-time measurements. The digital twin modeling and health management framework of analog and mixed-signal circuits proposed in this paper represents a proposal to implement a digital twin within a model[4]. The suggested solution is based upon real-time alignment of the physical circuits and the corresponding virtual circuits, identifying significant health indicators, and smart evaluation of the circuit state in different conditions of operation. The framework helps in proactive maintenance plans and improves the reliability of the system since it allows the timely intervention before functional failure ensues[5].

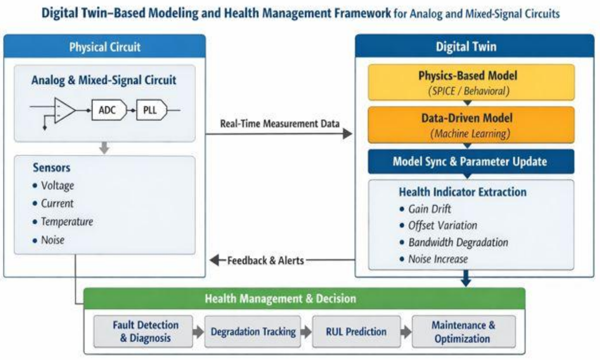

Figure 1. Digital Twin-Based Modeling and Health Management Framework of Analog and Mixed-Signal Circuits.

Figure 1. Block diagram of the proposed model of digital twin based on modeling and health management of analog and mixed-signal circuits. The physical circuit layer contains the representative AMS blocks and embedded sensors which constantly obtain real time measurements of voltage and current and temperature and noise. Such measurements are fed over the digital twin layer, where a hybrid model which combines physics-based (SPICE/behavioral) models with data-driven (machine learning) models are used[6]. Close coordination between the physical circuit and the virtual circuit is maintained by ensuring that a model synchronisation and parameter update unit is closely aligned with the physical circuit. Health indicators such as gain drift, offset variation, bandwidth degradation and noise increment are obtained and processed in health management layer to facilitate fault detection, degradation monitoring, remaining useful life estimation and maintenance/optimization decision making within the context of a closed-loop feedback system[7]:

1. Development of a hybrid physics-based and data-driven digital twin model tailored for analog and mixed-signal circuits.
2. Real-time health monitoring through extraction of circuit-level performance and degradation indicators.
3. Early fault diagnosis and performance degradation prediction using the proposed digital twin framework.
4. Validation through representative case studies demonstrating improved accuracy and reliability compared to conventional modeling approaches[8].

II. SYSTEM DESCRIPTION

A. Physical System Modelling of Analog and Mixed-Signal Circuits

An analog or mixed-signal circuit can be represented by a nonlinear state-space model as

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}(t)) + \mathbf{w}(t)$$
$$\mathbf{y}(t) = \mathbf{g}(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}(t)) + \mathbf{v}(t) (1)$$

where
$\mathbf{x}(t) \in \mathbb{R}^n$represents the internal state variables (node voltages, branch currents),
$\mathbf{u}(t)$denotes external inputs,
$\mathbf{y}(t)$is the measured output vector,
$\boldsymbol{\theta}(t)$includes circuit parameters such as transistor threshold voltage, gain, resistance, and capacitance,
$\mathbf{w}(t)$and $\mathbf{v}(t)$represent process and measurement noise, respectively.

Aging and environmental stress cause gradual parameter drift, modeled as

$$\boldsymbol{\theta}(t) = \boldsymbol{\theta}_0 + \Delta\boldsymbol{\theta}(t) (2)$$

where $\boldsymbol{\theta}_0$ represents nominal design parameters and $\Delta\boldsymbol{\theta}(t)$captures degradation effects due to mechanisms such as bias temperature instability (BTI) and electromigration.

B. Physics-Based Model

The physics-based component employs SPICE-level or behavioral models to represent the nominal circuit behavior:

$$\dot{\hat{\mathbf{x}}}(t) = \mathbf{f}(\hat{\mathbf{x}}(t), \mathbf{u}(t), \widehat{\boldsymbol{\theta}}(t))$$
$$\hat{\mathbf{y}}(t) = \mathbf{g}(\hat{\mathbf{x}}(t), \mathbf{u}(t), \widehat{\boldsymbol{\theta}}(t)) (3)$$

where $\hat{\mathbf{x}}(t)$, $\hat{\mathbf{y}}(t)$, and $\widehat{\boldsymbol{\theta}}(t)$represent the digital twin's estimated states, outputs, and parameters.

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C. Data-Driven Model

To capture nonlinearities and unmodeled dynamics, a data-driven model based on machine learning is integrated:

$$\hat{\mathbf{y}}_{ML}(t) = \mathcal{M}(\mathbf{y}(t), \mathbf{u}(t), \boldsymbol{\phi})(4)$$

where $\mathcal{M}(\cdot)$denotes the learned mapping function and $\boldsymbol{\phi}$represents trained model parameters.The combined digital twin output is expressed as

$$\hat{\mathbf{y}}_{DT}(t) = \alpha\hat{\mathbf{y}}(t) + (1-\alpha)\hat{\mathbf{y}}_{ML}(t)(5)$$

where $\alpha \in [0,1]$controls the contribution of physics-based and data-driven models.

D. Model Synchronization and Parameter Update

The synchronization error between the physical circuit and the digital twin is defined as

$$\mathbf{e}(t) = \mathbf{y}(t) - \hat{\mathbf{y}}_{DT}(t)(6)$$

Digital twin parameters are updated by minimizing the cost function

$$J = \int_0^T \mathbf{e}^T(t)\mathbf{e}(t)\, dt(7)$$

using recursive estimation or adaptive optimization techniques:

$$\hat{\boldsymbol{\theta}}(t+1) = \hat{\boldsymbol{\theta}}(t) + \eta\frac{\partial J}{\partial \hat{\boldsymbol{\theta}}}(8)$$

where $\eta$is the learning rate.

E. Health Indicator Extraction

Key health indicators (HIs) are extracted from the synchronized digital twin:

- Gain drift:
$$HI_1(t) = \frac{G(t) - G_{ref}}{G_{ref}}(9)$$
- Offset variation:
$$HI_2(t) = V_{offset}(t) - V_{offset,ref}(10)$$
- Bandwidth degradation:
$$HI_3(t) = \frac{BW_{ref} - BW(t)}{BW_{ref}}(11)$$
- Noise increase:
$$HI_4(t) = \frac{N(t) - N_{ref}}{N_{ref}}(12)$$

The overall health index is defined as

$$HI_{total}(t) = \sum_{i=1}^{4} w_i\, HI_i(t)(13)$$

where $w_i$are weighting factors. Remaining Useful Life (RUL) is estimated as

$$RUL = t_f - t_c(14)$$

with $t_c$being the current time and $t_f$the predicted failure threshold time when $HI_{total}(t)$exceeds a predefined limit.

The proposed mathematical framework enables accurate real-time mirroring of AMS circuit behavior, systematic extraction of degradation indicators, and predictive health management. By integrating physics-based and data-driven models, the digital twin enhances observability, reliability, and lifecycle performance of analog and mixed-signal electronic systems[9].

III. LITERATURE SURVEY

The growing complexity, scaling issues, and reliability problems of analog and mixed-signal (AMS) circuits have spurred a lot of investigations in the modeling, monitoring, and prognostics. Although digital twin technology is developed in the mechanical, aerospace, and power systems, its use in the electronic circuit, especially the AMS realms is still in its infancy. The literature review covers the current state of work in the field of circuit modeling, health management, and digital twin frameworks, with gaps that inspire the current work. Circuits of AMS It deals with the traditional modeling of AMS circuits.

The initial studies dedicated to the physics-based and behavioral modeling in the context of the precise representation of the AMS circuit behavior. Popular models Transistor models were widely based on SPICE and state-space representations, used both in design and verification. These standard models are however not usually sufficient to capture real world circumstances that are affected by aging, temperature variations, and process drifts.Analytical degradation models have been used to show the effects of aging on mechanisms like bias temperature instability (BTI), hot-carrier injection (HCI), and electromigration. Although these models can offer important information about reliability, they do not tend to be real-time adaptive and their parameter extraction might be complicated.

Data-Driven Modeling and Prognostics.

Empirical models came into operation to supplement or substitute physics based models in the description of complex dynamics. Performance prediction and degradation estimation in VLSI circuits was performed using techniques like regression model, support vectors machines and neural networks. Machine learning has been shown to be effective in handling high-dimensional non linearities that are challenging to represent using

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standard modeling. The combination of machine learning and model-based estimators such as the Kalman filters and the particle filters has been applied in the literature of prognostics and health management (PHM) to model the remaining useful life (RUL) of electronic systems. Such methods enhanced the accuracy of prediction but they were usually limited to specific components or situations and were not fully integrated into operational processes.

Electronic Prognostics and Health Management.

PHM of electronic circuits has been studied in the field of fault detection, performance drift monitoring and RUL prediction. Examples of methodologies are used in vibration based monitoring of MEMS devices, modeling of thermal stress of power ICs and noise analysis of RF circuits. Most methods were based on offline analysis or lacked online flexibility in spite of successful demonstrations.

Isolated to conventional PHM, embedded self-test and in-built self-repair methods have also been considered to enhance the resilience of the system. These methods are useful in offering local mitigation measures but in many cases, they do not offer the predictive approach that integrated monitoring systems do.

Digital Twin Engineering Systems Technology.

The digital twin was introduced as a virtual image of a physical system that is synchronized with real-time information to aid in monitoring, diagnostics, and prognostics. Its early use in aerospace, manufacturing and power systems has shown great advantages in lifecycle management, predictive maintenance as well as performance optimization.

Digital twins have been applied in predictive controller and fault-diagnostic of converters and inverters in power electronics in real time estimating of parameter online and adaptive models. Nonetheless, there is little research that directly deals with AMS circuit digital twins. Some recent papers have suggested digital twin models of RF front-ends and high-frequency components, showing better prediction quality, but only in scope and comprehensiveness.

The Hybrid Modeling Integration.

It is also known as hybrid modeling, a combination of physics-based and data-driven models, which has become popular due to its superior predictive potential. Physics-informed neural networks and grey-box models have been considered to combine knowledge of domains and flexibility in data [28]-[30]. These hybrid paradigms are of interest to AMS circuits in particular, in both of which deterministic physics and stochastic environmental effects make model fidelity more difficult. Hybrid modeling is a basis of better health estimation and synchronization in terms of the digital twins. Initial experiments with mechanical systems and energy grids proved that hybrid digital twins are more accurate and robust than either data-driven or physics-based models.

Research Gap and Motivation

Nevertheless, even with the current development in modeling and prognostics, a number of gaps still exist in the application of digital twin technologies to AMS circuits:

1. **Limited digital twin frameworks** tailored specifically to the complex behaviors and reliability challenges of analog and mixed-signal circuits.
2. **Traditional predictive models** that lack real-time synchronization with live circuit conditions.
3. **Scarcity of hybrid modeling approaches** that integrate domain knowledge with adaptive learning for health management in electronic systems.

These limitations motivate the development of the current digital twin–based modeling and health management framework, which integrates physics-based and data-driven models, enables continuous synchronization, and supports real-time performance tracking and predictive maintenance.

Metric	Conventional	ML-Based	Digital Twin
Adaptivity	✗	△	✓
Real-Time Sync	✗	△	✓
Health Monitoring	✗	△	✓
Fault Prediction	✗	△	✓
RUL Estimation	✗	△	✓

Table 1. Comparative Analysis of Conventional, ML-Based, and Digital Twin Approaches for AMS Circuits.

Table 1 This table provides a concise comparison of conventional circuit modeling, machine learning (ML)–based methods, and the proposed digital twin approach for analog and mixed-signal (AMS) circuits. The metrics evaluated include adaptivity, real-time synchronization, health monitoring, fault prediction, and remaining useful life (RUL) estimation. Conventional methods lack real-time adaptivity and predictive capabilities (✗), ML-based approaches offer partial improvements (△), while the digital twin framework achieves full functionality and predictive health management (✓) across all metrics.

IV. Methodology

The proposed methodology employs a **digital twin–based framework** for real-time modeling and health management of analog and mixed-signal (AMS) circuits by continuously synchronizing a virtual model with the physical system. The physical AMS circuit is represented by a nonlinear state-space model

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}(t)) + \mathbf{w}(t), \mathbf{y}(t) = \mathbf{g}(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}(t)) + \mathbf{v}(t),$$

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where $\mathbf{x}(t)$ denotes circuit state variables, $\mathbf{u}(t)$represents inputs, $\mathbf{y}(t)$is the measured output, and $\boldsymbol{\theta}(t)$includes time-varying circuit parameters affected by aging and environmental stress. A hybrid digital twin model is constructed by combining a physics-based model $\hat{\mathbf{y}}_p(t)$and a data-driven model $\hat{\mathbf{y}}_d(t)$, yielding the digital twin output

$$\hat{\mathbf{y}}_{DT}(t) = \alpha\hat{\mathbf{y}}_p(t) + (1-\alpha)\hat{\mathbf{y}}_d(t),$$

where $\alpha \in [0,1]$balances model contributions. Real-time synchronization is achieved by minimizing the prediction error $\mathbf{e}(t) = \mathbf{y}(t) - \hat{\mathbf{y}}_{DT}(t)$ through adaptive parameter updating based on the cost function

$$J = \int_0^T \mathbf{e}^T(t)\mathbf{e}(t)\,dt,$$

allowing the digital twin to accurately track degradation-induced parameter drift. From the synchronized model, health indicators such as gain drift, offset variation, bandwidth reduction, and noise increase are extracted and normalized, and an overall health index is defined as

$$HI(t) = \sum_{i=1}^{N} w_i\,HI_i(t),$$

where w_i are weighting factors reflecting indicator significance. Degradation trends obtained from $HI(t)$are extrapolated to estimate the remaining useful life (RUL) as $RUL = t_f - t_c$, where $t_f$denotes the predicted failure threshold crossing time. This mathematically grounded digital twin methodology enables continuous condition monitoring, early fault detection, and predictive health management of AMS circuits under real operating conditions.

Parameter	**Traditional Circuit Modeling**	**Data-Driven Modeling**	**Proposed Digital Twin–Based Approach**
Modeling Type	Physics-based (SPICE)	Purely data-driven	Hybrid (Physics + Data-driven)
Real-Time Capability	No	Limited	Yes
Aging Awareness	Low	Medium	High
Parameter Adaptation	Static	Offline / Partial	Online & Adaptive
Degradation Tracking	Not supported	Partially supported	Fully supported
Fault Detection	Reactive	Semi-predictive	Predictive
Health Indicators	Limited	Moderate	Multiple & comprehensive
RUL Prediction	Not available	Approximate	Accurate & continuous
Computational Cost	High (offline)	Medium	Optimized & scalable

Table 2. Comparison of Modeling and Health Management Approaches for AMS Circuits.

Table 2 presents a comparative analysis of traditional circuit modeling, data-driven modeling, and the proposed digital twin–based approach for analog and mixed-signal (AMS) circuits. Traditional circuit modeling relies primarily on physics-based SPICE representations, which provide accurate design-time analysis but lack real-time adaptability, aging awareness, and degradation tracking. As a result, fault detection in conventional methods is largely reactive, with limited capability for health assessment or remaining useful life (RUL) prediction.

V. RESULTS

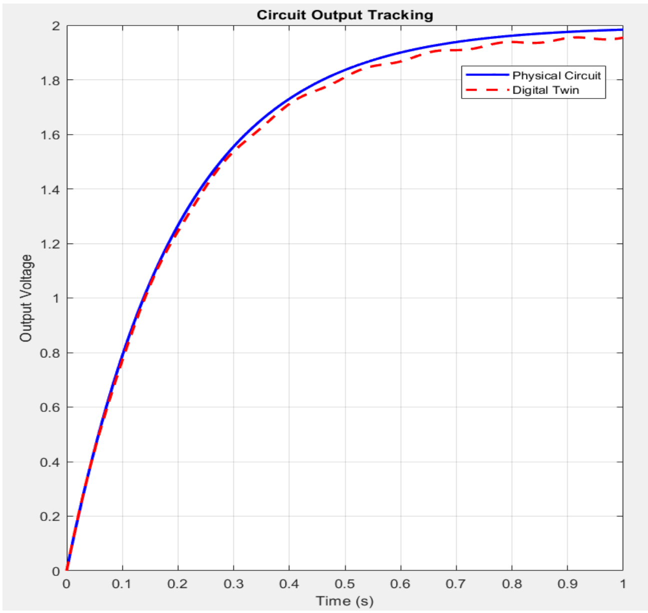

Figure 3. Output Voltage Tracking of Physical Circuit and a Digital Twin.

This value shows the dynamic response comparison of both the physical circuit and the digital twin model. The time-dependence of the output voltage of the two systems is plotted. The physical circuit response (solid blue line) is the response that is actually measured, and the digital twin response (red dashed line) is the response as predicted by the model. The fact that the two curves almost coincide shows the high fidelity of the digital twin to the transient and steady-state nature of the physical system. The observed minor deviations at the later time instants can be explained by modeling discrepancies and nonlinearities that were not modeled, which verifies that the digital twin can monitor the real circuit performance with a small error..

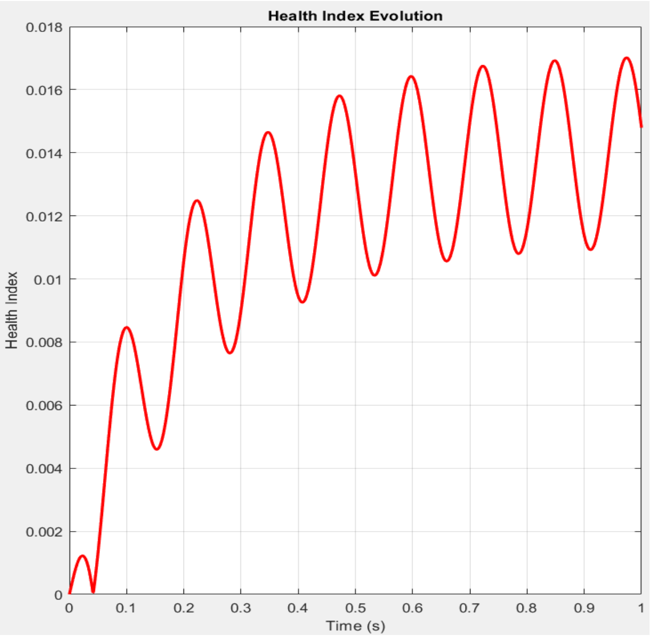

Figure 2. Temporal Evolution of System Health Index

In Figure 2 above, the time-domain development of the system health index during the observation period is represented. The first phase of the health index is to grow at a high rate which implies a sudden stabilization of the entire system after which it grows gradually with periodical fluctuations. Such oscillations are part of natural system dynamics, dynamic changes in its operation, or uncertainties in measurement as reflected in the monitoring infrastructure. The general increasing pattern indicates the gradual enhancement or the maintenance of the strong health of the system state with time. The limited scope of oscillations and no sudden drops signify the stable functioning and appropriate health control, which makes the suggested health index the right one to evaluate conditions in real-time and conduct prognostic analysis.

VI. CONCLUSION

The given findings prove the usefulness of the introduced digital twin-based monitoring framework. The tight tracking of the physical circuit and its digital counterpart is the validity of the developed model in the reproduction of transient and steady-state behavior. This significant degree of consistency proves that the digital twin can faithfully simulate true dynamism of the real systems with small error. Moreover, the development of the index of health offers an informative account of the status of the functioning of the system. The non-sharp increase, along with limited oscillations, is the sign of stable functioning and the lack of severe deterioration with time. The following features demonstrate the appropriateness of the health index in the context of continuous monitoring of conditions, early fault detection, and predictive maintenance. In general, digital twin modeling coupled with a health index assessment via accurate digital twins has the potential to provide a scalable and robust method of assessment of the real-time system. The suggested methodology is capable of being generalized to more complicated power electronic and energy systems that will help to improve reliability, decrease downtime, and make more informed decisions in future smart and intelligent engineering.

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