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Life-Time Prognostics of Dependable VLSI-SoCs using Machine-learning

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***Abstract*— Recently, the usage of on-chip embedded instruments (EIs) to ensure dependable safety-critical systems is becoming inevitable. These EIs can help to provide self-awareness, and their feedback can be used in different applications, e.g. end-of-lifetime (EOL) predictions. However, inaccuracies present in data from these EIs, due to their resolution limitations, self-aging and quantization errors during digitization, can lead to an inaccurate EOL assessment. To address this challenge, a machine learning-based system-level approach for determining the EOL of a many-processor system-on-chip (MPSoC) is discussed. It is based on the synchronous data capture of different IJTAG compatible EIs. To this end, two different data fusion techniques have been used for enhancing the accuracy of lifetime prognostics of multiple EIs; use is made of Independent Component Analysis (ICA) and the auto-encoder (AE). Different combinations of fused EIs (based on ICA and AE) along with standalone EIs for four different critical paths (CPs) have been investigated. For lifetime prediction based on different EIs/fused EIs, a data-driven degradation model was derived, and nonlinear regression has been employed for parameter estimation. Results show that data fusion of different EIs helps in obtaining better estimation of the EOL as compared to using a standalone EI.**

Keywords*— *Dependability, Reliability, MPSoC, Embedded Instruments (EIs), Data Fusion, Data-driven, Lifetime prediction, EOL, Machine Learning

I. Introduction

With the technological advancements in CMOS processes, the exploitation of MPSoC is an increasingly popular choice in safety-critical systems. This results from the increased number of transistors per square millimeter (mm^2) offering more functionality, which makes these systems more efficient in terms of area and power consumption. Unfortunately, this increased functionality comes with a cost in terms of reduced dependability. This reduced dependability is mainly because of the aging phenomena that are becoming more dominant as the channel lengths of NMOS and PMOS transistors are decreasing. These aging processes include biased temperature instability (BTI), hot carrier injection (HCI) and electromigration (EM); they result in shorter lifespans of these advance nodes, as compared to older technology nodes (90nm and above) [1].

For safety-critical applications, like the automotive and space industry, it is essential to know the end-of-lifetime (EOL). To address this challenge, and to ensure dependable safety-critical systems, an on-chip hardware architecture just like a functional architecture should be incorporated that can give self-awareness capabilities, which is the focus of this paper. Recently, the use of on-chip embedded instruments (EIs) has become a popular choice to monitor several on-chip parameters to ensure self-awareness [2]. On the other hand, the deployment of different machine learning techniques have received more attention by making failures predictable in order to take maintenance actions before these failures occur.

Despite many efforts on designing EIs [3]-[5], they have to deal with resolution limits to measure the respective quantity; and they also loose accuracy during the digital conversion, either by using time-to-digital (TDC) or analogue-to-digital (ADC) conversion circuits. These inaccuracies in the data can lead to a less accurate EOL estimation if not accounted for. In this paper, by considering EI inaccuracies we present different machine-learning techniques to investigate a *multiple* EI platform for EOL prediction. The main contributions of this paper are the following:

1. A new IJTAG compatible set of embedded instruments and processor infrastructure for EOL estimation have been proposed.
2. Machine-learning techniques like Independent Component Analysis (ICA) along with auto-encoder (AE) based data fusion for different combinations of EIs have been used with a data-driven degradation model for the EOL calculations.
3. A case study to demonstrate the different behaviour of different types of critical paths (CPs), in the presence of EI inaccuracies, has been conducted.

This paper is organized in the following manner. In section II, the complete system-level architecture that uses different types of EIs to determine the local variations in the selected CPs is discussed. Section III discusses the details on data generated from these EIs to build a database for a selected environmental condition. It also discusses a SPICE golden reference generation for the EOL that can help to evaluate the proposed machine-learning approach. In section IV, the proposed data-fusion procedures, i.e. Independent Component Analysis (ICA) and the auto-encoder (AE) algorithms, are described in detail. In the following section V, the results from the proposed methodology are presented, whereas section VI concludes the paper.

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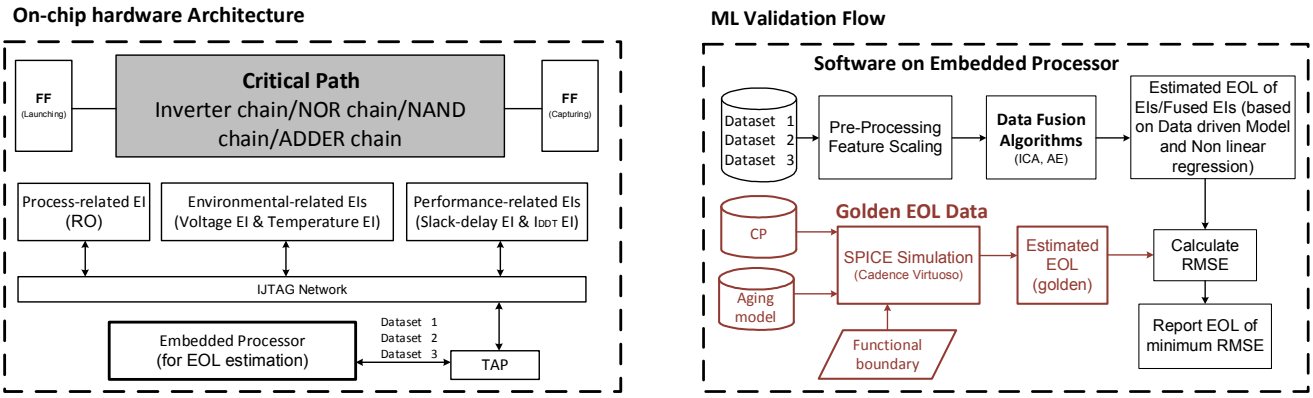

(a) (b)

Fig. 1. (a) System level hardware architecture (b) Validation flow for the proposed machine-learning based EOL prediction.

II. System Level Architecture

One of the most essential features of a dependable digital system is to ensure that critical paths meet their timing-constraints set by the operational frequency. However, due to the various aging phenomena, the propagation delays of these critical paths increases and eventually can result in a functional failure. Therefore, it is essential to monitor the slack-time of critical paths such that appropriate actions can be taken before this failure occurs. However, the slack-time can vary because of environmental conditions, like voltage droop and temperature too [2]. Therefore, to ensure correctness, a *set* of EIs have been used together to determine the aging profile of a critical path, independent of these environmental variations. Fig. 1(a) shows the system level hardware architecture of the proposed work. An embedded processor can be used to access data from these EIs (shown as Dataset 1, Dataset 2, and Dataset 3 in Fig. 1) via an IJTAG network [6], to estimate the end-of-lifetime (EOL). Details of these EIs are discussed hereafter.

A. Performance-related Embedded Instruments

Two performance-related EIs have been used in the proposed architecture, i.e. slack-delay EI and transient current (I_{DDT}) EI. These EIs can be used to determine the workload-dependent aging profile of a system [7]. In this paper, IJTAG compatible slack-delay EI and I_{DDT} EI have been used [3], [4]. The slack-delay EI has three modes of operation, being off mode, infield-calibration mode, and monitoring mode. Due to its fast calibration time it can detect slack-delay variations even in the case of fast environmental changes like voltage droop and temperature as well as for slow variations like aging. These characteristics make this design, an ideal candidate to be used for EOL calculations. However, this design has resolution limits of 13ps for 40nm technology [3], which can introduce inaccuracies in the EOL estimations.

B. Environmentally-related Embedded Instruments

It is very important to know the environmental conditions like temperature and operating supply-voltage to determine the change in slack-time because of aging. To measure these environmental quantities, IJTAG compatible temperature and voltage EIs have been presented in [4] and [5] respectively. The presented time-to-digital (TDC) based voltage EI can determine the average voltage droop over a clock-period, which is more relatable to the slack-time as compared to measuring the instantaneous voltage. It has a resolution of 10mV. The temperature EI has a resolution of 0.3°C (for a 10-bit ADC). This shows that the considered EIs can determine environmental changes with high accuracy.

C. Process-related Embedded Instruments

Ring Oscillators (ROs) have been used intensively in the literature to determine the workload-independent aging profile of a technology node. In this study, to determine the output frequency of the RO, a RO design was used together with a counter, where the latter can be controlled with a FSM.

D. The IJTAG Network

The IEEE 1687 standard (IJTAG) optimizes the access to EIs [6]. There are two parts of the IJTAG standard; one defines the hardware architecture while the other defines the software part. The IJTAG interface is serial, therefore it takes several clock cycles during shift operations to configure or read an EI. However, applications like EOL estimation require mainly fast capturing of the physical data by the EIs. Once the data is captured at the right moment (coherency) by the EIs; despite the slow interface of IJTAG, it does not affect the overall outcome as these applications do not require data at every clock cycle and they are executed only once in a while.

III. Process of Data Generation

As shown in Fig. 1(a), four different CPs are employed for simulation (using 40nm LP technology) with the aging model [8], to collect the database for EOL calculations at an operating voltage V_{DD} = 1.1V and temperature T = 125°C (accelerated case). The considered CPs are an inverter chain, NOR chain, NAND chain and a critical path from an ALU of a 16-bit OpenCore processor (openMSP430) which is an adder circuit. The total propagation delay of each CP, being the propagation delay of a signal-transition between a launching FF and capturing FF, was matched to 5ns by carefully selecting the W/L ratios of these logic gates for the above-mentioned environmental conditions. Due to the different number of

NMOS and PMOS transistors present between the supply voltage (V_{DD}) and ground (GND) in these CPs, the NBTI and PBTI have different proportions in their aging profile. For all these CPs, the functional boundary (i.e. operating frequency) is set to be 190 MHz.

Furthermore, to evaluate the end-of-lifetime (EOL) results produced by the machine learning algorithms, SPICE level EOL simulations were carried out for all CPs using our in-house aging model [8]. Fig 1(b) shows the validation flow. These SPICE simulations provided the golden reference for EOL of each critical path. This golden EOL for each CP, has been used as a benchmark to evaluate machine-learning techniques (discussed in the next sections).

IV. DIMENSIONALITY REDUCTION OF THE DIFFERENT EMPLOYED EMBEDDED INSTRUMENTS

To manage the different datasets (Dataset1,2 and 3 in Fig. 1(b)) of these different EIs (data-fusion issue) different machine-learning techniques have been used; an ICA-based and AE-based fusion techniques have been applied.

A. ICA-based EI fusion approach

For multi-sensory platforms (here including SD, RO and I_{DDT} EIs), ICA as a widely used statistical approach proven to be useful as dimensionality reduction paradigm [9]. ICA strives to create components as independent as possible via minimizing dependencies in the given data. Independent components (ICs) have been calculated using the joint approximate diagonalization of Eigen matrices. It is based on the diagonalization of cumulant matrices [10]. By choosing the number of ICs from n out of m (m number of sensors, first dimension and n number of new space in which $n \leq m$), new space will be generated. The new reduced space with the transformed variables (components) represents new fused data which covers the more relevant information from the EIs. This fused EI is known as latent variable. Here ICA has been applied to the three EIs as well as different combinations of two EIs, to capture the latent variable as new representation of data for EOL prognostics.

B. Auto-encoder based EI fusion approach

The second approach is using an AE-based fusion technique for generating a new representation [11]. An AE is an unsupervised type of machine-learning technique, used to learn efficient data coding. A typical architecture of an AE can be built using three layers (input layer, output layer and a hidden layer) very similar to the multilayer perceptron (MLP). However, the learning objectives are different in each algorithm [11], [12]. The learning procedure of an AE network consists of two parts: the encoder and the decoder part. An encoder transforms the input into more abstract feature vectors, and a decoder reconstructs the input from the feature vectors as closely as possible by minimizing a loss function. If the dimension in the hidden layer is less than the input layer, then the AE learns a compressed representation of the input, which captures the correlations and interactions between the various variables. The AE networks which are considered here, employing three EIs as well as different combinations of two EIs, result in one neuron in the hidden layer to capture the latent variable as new representation of data for EOL prognostics. After preparation of the data-fusion workflow, the calculation of the EOL will be conducted (Fig. 1(b)).

V. EOL CALCULATION FROM THE EXPERIMENTAL RESULTS

In order to perform an EOL calculation, a data-driven degradation model has been employed [13]. To this end a nonlinear poly-nominal equation proves a minimum RMSE for data points and a degradation equation. To find the parameters of the degradation model, the nonlinear regression (Levenberg-Marquardt method [14]) has been used [15]. In the next step, the EOL is calculated via extrapolating the model until it reaches the threshold. These parameters of the model have been updated for each and every EI/fused EIs [13].

As mentioned in the previous section, the threshold point (functional boundary) is defined based on the frequency limits. Table I presents the calculated EOL for different standalone and fused EIs by proposed approaches for four different CPs (CP1, CP2, CP3 and CP4) at V_{DD}= 1.1V and T = 125°C. The numbers after the ICA and AE indicate the EIs involved: SD (1), RO (2) and I_{DDT} (3). For example the EOL of CP1 based on fused EIs, ICA,2,3 (data fusion of Ro and I_{DDT} based on ICA approach) is 5.21 years while based on the standalone SD-EI, the EOL is 5.05 years. In the next step, the calculated EOLs have been validated, based on the Equation (1). In equation 1, is the golden EOL calculated for each CP. These golden EOL calculations are based on the SPICE level aging simulations, performed for a given threshold (functional boundary). These aging simulations are performed using Cadence Virtuoso tool. To validate the ML based EOL predictions, the difference of the golden EOL with respect to the EOL of an EI/fused EI has been determined first; then the root-mean-square-error (RMSE) of this difference has been calculated for each CP.

$$RMSE = \sqrt{\left(EOL_{golden\ EOL\ \text{for each CP}} - EOL_{EI/fused\ EIs\ for\ each\ CP} \right)^2} \quad (1)$$

For appropriate countermeasures, the minimum values of the RMSE and their corresponding EOL were calculated for all CPs. Table II depicts the calculated RMSE value of reported EOLs for different CPs and different EIs/fused EIs. The minimum RMSE value highlighted in red (Table II). Corresponding to these minimum RMSE values, EOL predictions from table I are selected for countermeasures. For instance, for CP1, the minimum RMSE value depicted in red is achieved by the AE 1,2 fused EI (RMSE=0.086 year); the corresponding EOL of this RMSE is 4.72 year (Table I). Similarly, the summary of EOL selection for all the CPs is listed in table III. For the EOL selection for countermeasures based on the minimum achieved RMSE, as Table III depicts, different CPs as well as different data-fusion approaches have been investigated to see the different behaviour of standalone/fused EIs. In terms of minimum RMSE, the fused EIs, including AE 1,2 for the CP1, ICA1,2,3 for the CP2, ICA1,3 for the CP3, and the AE 1,2, for the CP4 proved to be superior for EOL predictions with regard to standalone EIs.

Table I. Calculated EOL (in years) of different single and fused EIs based at V_{DD} = 1.1V and T = 125°C.

EI/Fused EIs	SD EI	RO EI	I_{DDT} EI	ICA 1,2,3	ICA 1,2	ICA 1,3	ICA 2,3	AE 1,2,3	AE 1,2	AE 1,3	AE 2,3
CP1-NOT	5.05	5.41	8.50	6.07	5.21	6.44	6.70	6.07	4.72	5.84	6.65
CP2 -NOR	0.94	1.21	1.30	1.12	1.06	1.08	1.22	1.08	1.02	1.03	1.19
CP3 -NAND	5.28	8.51	11.91	8.23	6.65	8.02	10.54	8.06	5.92	7.28	10.47
CP4- ADDER	3.03	3.16	3.83	3.32	3.09	3.40	3.46	3.29	2.87	3.13	3.44

Table II. Calculated RMSE of different single and fused EIs at V_{DD} = 1.1V and T = 125°C.

EI/Fused EIs	SD EI	RO EI	I_{DDT} EI	ICA 1,2,3	ICA 1,2	ICA 1,3	ICA 2,3	AE 1,2,3	AE 1,2	AE 1,3	AE 2,3
CP1-NOT	0.241	0.59	3.68	1.25	0.40	1.633	1.89	1.25	0.086	1.031	1.84
CP2 -NOR	0.180	0.080	0.18	0.001	0.057	0.044	0.103	0.038	0.100	0.087	0.06
CP3 -NAND	2.6	0.620	4.02	0.341	1.23	0.139	2.651	0.170	1.96	0.608	2.58
CP4- ADDER	0.082	0.2	0.87	0.374	0.140	0.447	0.508	0.335	0.078	0.181	0.493

Table III. Defined EOLs for countermeasures at V_{DD} = 1.1V, T = 125°C.

EI/Fused EIs	ML-Approach	EOL (years)	RMSE (years)
CP1-NOT	AE 1,2	4.72	0.086
CP2 -NOR	ICA 1,2,3	1.12	0.001
CP3 -NAND	ICA 1,3	8.02	0.139
CP4- ADDER	AE 1,2	2.87	0.078

VI. Conclusions

In this paper, the aging profile of a functional core has been provided by employing different IJTAG compatible EIs. To this end, four different critical paths (CPs) of functional cores have been used for monitoring. Moreover, data fusion has been used to investigate the behaviour of standalone/fused EIs for the data-driven EOL prediction. The corresponding EOL for appropriate counter measures must have the minimum RMSE with respect to the golden EOL for each CP. Two machine learning algorithms with different context have been employed to achieve the most efficient data fusion (in terms of obtaining minimum RMSE) for each CP; since each CP have different behaviour/ complexity, they show different level of correlation between different EIs. Hence, the data fusion algorithms show different results for each CP and each fused combination of EIs; in which, AE 1,2, ICA1,2,3, ICA1,3, and the AE 1,2, fused EIs, provide the minimum RMSE for CP1, CP2, CP3 and CP4, respectively. All in all, data fusion of EIs based on ICA/AE show a minimum RMSE for EOL calculations over the usage of standalone EIs.

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