Operational Age Estimation of ICs using Gaussian Process Regression

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***Abstract*—Electronic systems life is an essential aspect of ensuring reliability and safety. An accurate age estimation could assimilate, which is helpful for any electronics system. It would also positively impact the minimisation of electronics waste and support the endeavour of green computing. In this paper, we propose a methodology for age estimation using the Gaussian Process Regression (GPR) model. Our methodology requires an RO sensor, temperature sensor, and trained GPR model for the age prediction. The Ring Oscillator (RO) output frequency relies on the trackable path, temperature, voltage and ageing. These dependencies are utilized for the training of the GPR model. We exhibit the output frequency degradation of the ring oscillator through the Synopsys PrimeSim Hspice tool with the 32nm Predictive Technology Model (PTM). We consider variations from 0 °C to 100 °C in temperature and 0.8V to 1.05V in the voltage. Our methodology predicts age precisely, showing average prediction accuracy in 85.35% cases with a deviation of one month for 13-stage RO and 90.42% cases in 21-stage RO. Our proposed methodology is more accurate than the state-of-the-art techniques in terms of prediction accuracy as well as age estimation deviation. The prediction accuracy improvement got 9.59% for 13-stage and 9.17% for 21-stage RO on our data-set than the state-of-the-art technique with a month deviation, respectively, as opposed to 2.4 months for the state-of-the-art method.**

***Index Terms*—Ring Oscillator (RO), Integrated Circuit (IC), MOS Reliability Analysis (MOSRA)**

I. Introduction

The age of ICs provides the condition of the ICs, which is essential information to know the system's reliability and also ensure the safety of the electronic systems. From the age, we can identify the ICs that have a shorter life span. We know that shorter life span ICs affect users' expectations and increase failure probability with lower performance. The poor performance makes the system less reliable, which causes negative and menacing impacts in critical areas such as security issues in defence, aerospace electronics, safety issues in health care, etc [1]. Some standards are available to detect whether the electronic parts are new or not. These Counterfeit electronic parts; detection, avoidance and prevention globally recognised standards (AS6496 [2], ARP6178 [3] and AS6081 [4]) have been recommended for detection. However, these conventional testing suffer from excessive time, cost and lower rate of the detection. These standards only provide information about whether the chip is new or old. But, we need a solution to predict the age of the ICs for reliability concerns. Many of the systems require a monitoring mechanism of the device to indicate the warning of the failure.

In [5], the authors provide a supportive solution for reducing the prediction error by correlating the internal and environmental conditions with the learned data. It only enhances the prediction accuracy of the remaining useful lifetime (RUL) of the electronic components. However, the mean time to failure (MTTF) is the average time the system runs until it fails [6], so it cannot predict the age of individual components. A methodology proposed in [7] used voltage drops across the protection diode present in IO pads to detect the recycled ICs. The voltage drop of the protection diode compared with the stored reference data and compare the voltage drop value with the stored reference value if values are the same as in NVM, which means the chip is new. Mechanical and thermal stress are damaged the soldered joints. In [8], monitoring solder joints using the RF (Radio Frequency) impedance for the early detection of the failure. The author applied the Gaussian Process (GP) model to the RF impedance obtained from the fatigue test for the estimate of the RUL. The solder joint RUL is not equivalent to IC RUL. In [9], RUL is estimated using the particle filter (PF) by monitoring the components and insulated gate bipolar transistor (IGBT) conditions. Non-linearity in the IC degradation shows a high variance which means the RUL estimation is inaccurate. In [10] has a set of tests that provide insight into the degradation due to temperature. Some other researcher has addressed path delay and frequency drift over time [10] [11].

The fore-mentioned methods [5] [6] have a limitation; they can not predict the age of the individual components. In [8], it only provided the predicted age of the solder joints, not of the ICs. A methodology presented in [9] predicts inaccurate RUL because of non-linearity in the age degradation.The state-of-the-art technique [12] have scope to improve the prediction accuracy. [12] contains the exponential sampling rate for the data-set generation that drawback for the accuracy because the exponential sampling rate provides a large gap at the higher index value. On the other hand, electronics waste has increased every year because the chip is discarded before its end of life [13]. The proposed age estimation methodology could help reduce e-waste and emphasise green computing.

It also contributes to the energy-efficient field, improving resource utilisation and innovating eco-friendly technologies.

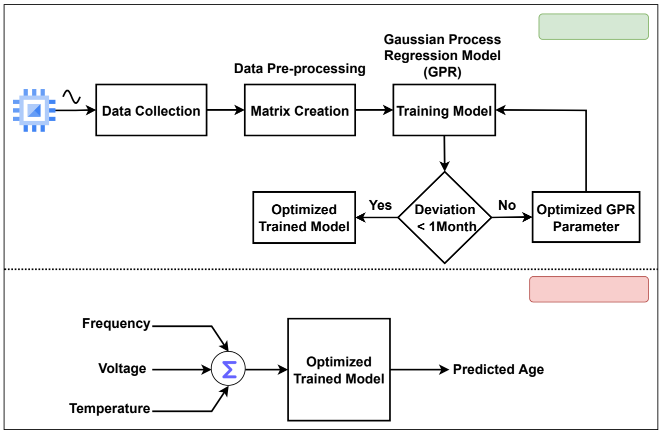

Fig. 1. Flow diagram of the proposed age prediction methodology

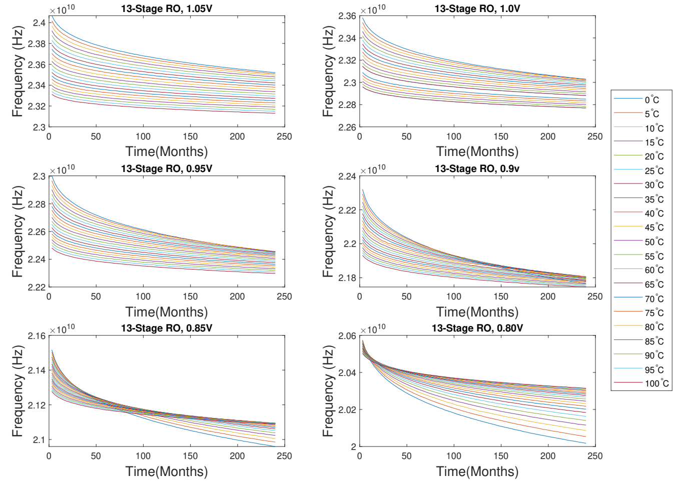

Fig. 2. Output frequency of 13-stage RO for all temperatures (0 °C to 100 °C) when voltage varies from 0.80 V to 1.05 V (with steps of 0.05 V).

Our methodology also provides the framework for detecting the recycled ICs in the global semiconductor supply chain.

Motivated by the limitations mentioned above of the existing techniques, we propose a methodology to estimate the age of ICs using the GPR model. The proposed methodology predicts the age accurately using the GPR model. A GPR model can make predictions comprising prior learning (kernels) and provide uncertainty measures over predictions. This algorithm can predict unseen data and works accurately on small datasets. Our proposed methodology has high confidence in estimating the age of the ICs, validated over 20 years of degradation. The 13-stage RO prediction accuracy is 85.35% with a deviation of one month. Respectively, 90.42% age prediction of the 21-stage RO under the same conditions. Furthermore, a detailed explanation of the results is given in Section III.

The paper is organized as follows. Section II presents the proposed methodology for age estimation, explaining the setup of the RO and variables involved in Synopsys MOSRA simulations, describes the data acquisition, pre-processing and training of GPR model. Section III shows results & analysis in various voltage and temperature conditions, exhibiting that the proposed methodology is accurate and suitable for age prediction. Finally, Section IV concludes the paper.

II. Proposed Methodology

The 13-stage and 21-stage RO have been designed using the 32nm Predictive Technology Model [14] and we kept 21 temperature levels from 0 °C to 100 °C with step 5 °C and voltage variation from 0.8V to 1.05V with step 0.05V for the data collection. Fig. 1 shows the flow of the proposed age estimation methodology. In the training phase, the first block of the flow diagram is the CMOS model that allows collecting the raw data in the data acquisition process. As mentioned in Section II(C), the linear sampling rate has been set during the data acquisition process. This concept provides uniform distribution of the data points, which is beneficial in predicting the age of ICs. This raw data is formatted in a specific manner for the training of the GPR model.We have constructed a matrix in a stairs fashion through the raw data as described in Section II(C). Next is the algorithm for training which is the GPR model. After that, we optimized the GPR model by changing the GPR parameters for less than a month deviation. The training and testing process has been explained in Section II(E). In the prediction phase, eventually, we get the optimized model from the training phase. We deployed this model for the age estimation of the ICs with fed new frequency, voltage and temperature.

A. *Effect of ageing on the ring oscillator*

Fig. 2 illustrates degradation of the output frequency of the 13-stage. A similar output obtains for 21-stage RO, which is not shown due to the paucity of pages.

Bias Temperature Instability (BTI) and Hot Carrier Injection (HCI) ageing mechanisms affect the RO during its operational mode and degrade the output frequency of RO. The trapped charge increases over time in the oxide-semiconductor boundary underneath the MOSFET gate because of the BTI effect.

BTI mechanism has two phases one is stress, and the other is relaxation. The trapped charge increase due to the breaking of the Si-H bond in the stress phase and the annealing process reduces this charge during the relaxation phase. The interface trapped charge increases the threshold voltage, consequently increasing the gate delay. In [15], the gate delay dependency is illustrated in term of the threshold voltage. The charge injected in the gate dielectric is known as HCI and occurs due to the high electric field, which affects the device parameter, including switching activity and threshold voltage.

B. *Data Acquisition Assessing Voltage and Temperature Variations*

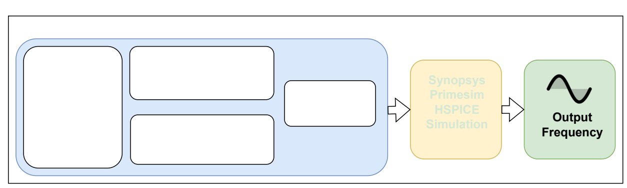

Fig. 3. Data collection flow diagram of the ring oscillator

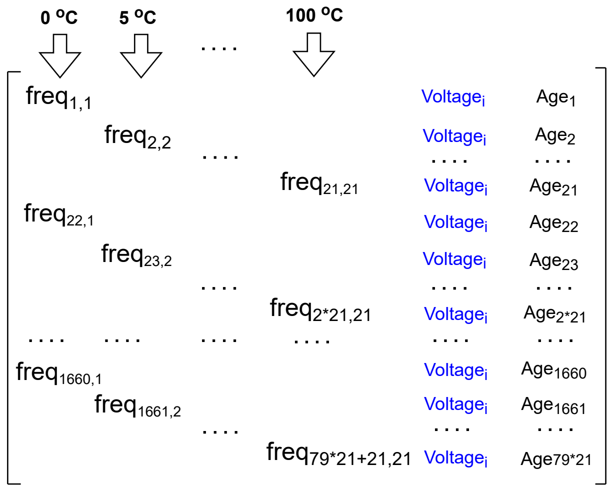

Fig. 4. Data matrix created with series of ring oscillator output frequency (freq) for each temperature per column, associated voltage and age.

We collected raw data from the CMOS model using the Synopsys PrimeSim HSPICE tool in this phase. Fig. 3 demonstrates the data collection flow of the CMOS circuit. Data generation is undertaken through Synopsys software using MOS reliability analysis (MOSRA) tool with advised parameters of CMOS circuit model and ageing model card; which provide a realistic ageing scenario of the circuit. The RO output frequency is generated under various stress conditions, i.e. voltage and temperature for the 20 years of ageing. Here, we consider 20 years of ageing degradation because it is the lifetime of aerospace, automotive and industrial applications.

C. Data Pre-processing

RO output frequencies fetched with the associated age for various stress conditions, i.e. voltage and temperature. In this stage, using fetched data, built a matrix for the training of the GPR model. Fig. 4 shows constructed data matrix that contains frequency for all temperatures, voltage and associated age. In the matrix, stairs fashion frequency is allocated for grouping all temperatures taken at the same age. Matrix dimension is 23x1680, columns containing 21 temperature levels, one voltage and another for associated age; the number of rows is equivalent to 80 frequency samples per operating temperature multiplied by 21 operating temperatures. The sampling rate is given in equation 1 for the construction of the matrix.

$$s = l_z \times \frac{T}{N} \tag{1}$$

Where s is sampling rate, l_z is index, $z = \{1, 2, ..., N\}$, T is total time to do estimation and N is the total number of sample. The first 21 columns represent the output frequencies assigned for the different temperatures of 0 to 100°C (with step size 5°C), 22^{nd} column represents the corresponding operating voltage, and the 23^{rd} column is the associated age of RO.

We consider training dataset $\mathbf{D_{tr}} = \{\{X_{j,k}, Age_k\}, k = 1, 2, ..., t\}$, where $X_{j,k} \epsilon \{freq_{j,j'}, Voltage_i\}$ is the frequency values of RO at given temperature $j, j' = 0, 5, ..., 100$ till k timestamp with corresponding voltage, $Age_k \epsilon \mathbb{R}$ is the corresponding age of ro after k timestamp and $freq_{j,j'} \epsilon \mathbb{R}$.

D. Gaussian Process Regression

A Gaussian process is a collection of random variables. The property of GP is that any finite collection of these random variables follows a gaussian distribution. The gaussian process written in equation 2.

$$f(t) \sim GP(\mu, \sigma^2) \tag{2}$$

Where *f(t)* is the estimated probability density of the process t, μ is the mean and σ^2 is covariance.

Gaussian process regression [16] is a non-parametric bayesian approach for regression and we choose this method because it works well on small dataset and provides predictions based on prior knowledge (kernel). We consider GPR with Matern 5/2 kernel [17] for age estimation.The Matern 5/2 covariance function is defined in the equation 3.

$$k(\ t_i, t_j\ ) = \sigma_f^2 \left(1 + \frac{\sqrt{5}\ d}{\sigma_l} + \frac{5\ d^2}{3\ \sigma_l^2}\right) exp\left(-\frac{\sqrt{5}\ d}{\sigma_l}\right) \tag{3}$$

Where d is Euclidean distance between t_i and t_j data points, σ_f is standard deviation and σ_l is the characteristic length scale.

E. Training and Testing of GPR Model

We have a data matrix for training and testing, and it randomly splits into 70% and 30% ratios. The GPR model is trained through the data matrix that is shown in Fig. 4. GPR implementation is done on MATLAB, and once it has been trained, it is ready for age prediction. We used Matern 5/2 kernel and optimized the model using Bayesian optimization with a maximum number of 30 evaluations. For 13-stage RO, beta 441.16, sigma 0.69 and LogLikelihood -5.42e+03 is optimized parameter for GPR model and similarly, beta 420.39, sigma 0.69 and LogLikelihood -5.26e+03 for 21-stage RO.

III. Results And Analysis

We used 32nm Predictive Technology Model [14] to implement the ring oscillator circuits. Ageing simulation performed at 0.80V to 1.05V supply and 0°C to 100°C temperature with the help of Synopsys PrimeSim HSPICE tool. We used the 32nm PTM CMOS model with the Synopsys built-in Level 1 MOSRA Model for the MOS Reliability Analysis.

A. Age Estimation on Voltage and Temperature Variations

We stress RO over the 20 years with various temperature and voltage levels. The goal of our methodology is to predict age accurately. We apply temperature and voltage levels differently because stress conditions are not always the same, so we consider temperature from 0 °C to 100 °C and voltage from 0.8V to 1.05V. The deviation of predicted age from the actual age of 13-stage RO and 21-stage RO is shown in Fig. 5 and Fig. 6 for five temperature levels (0°C, 25°C, 50°C, 75°C,

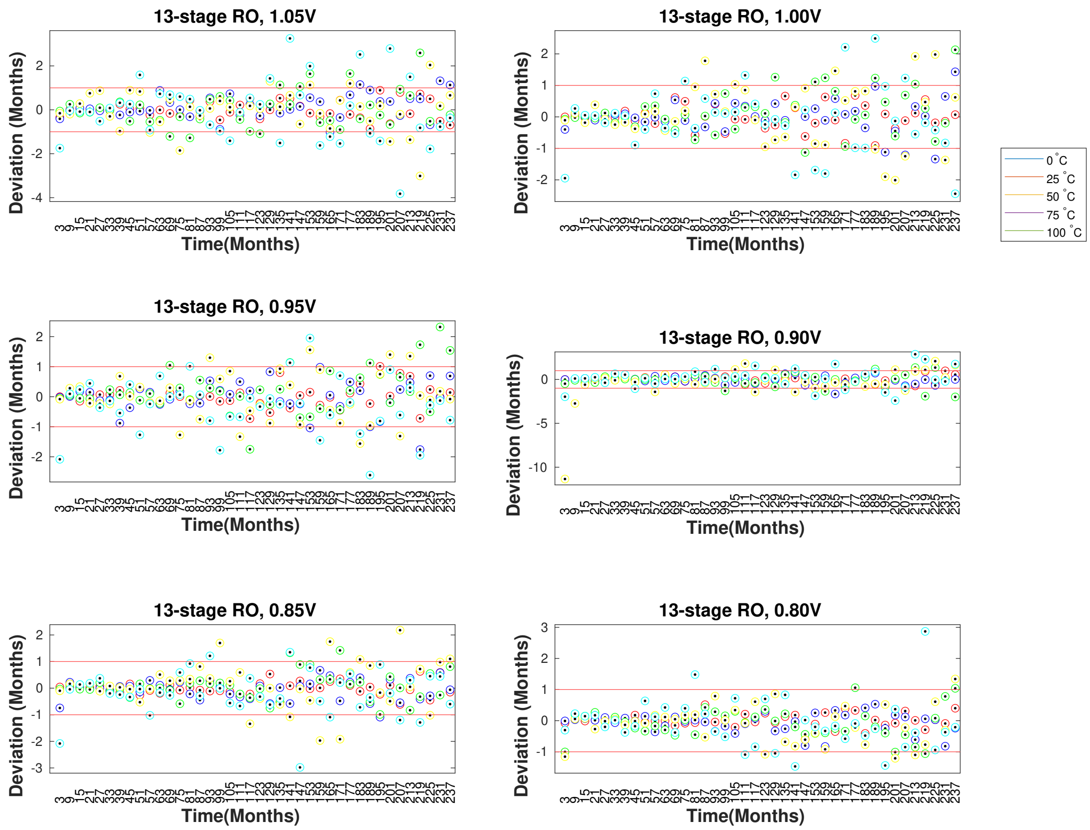

Fig. 5. Deviation of 13-stage RO using GPR for five representative temperatures (0°C, 25°C, 50°C, 75°C and 100°C) .

TABLE I
COMPARISON WITH STATE-OF-THE-ART TECHNIQUE

Voltage Level	Prediction Accuracy					
	13-Stage RO			21-Stage RO		
	Proposed Methodology	State-of-the-art [12]	Improvement	Proposed Methodology	State-of-the-art [12]	Improvement
1.05V	**80.36%**	73.04%	9.10%	**87.20%**	78.51%	9.96%
1.0V	**84.46%**	75.77%	10.28%	**90.35%**	81.43%	9.87%
0.95V	**83.21%**	74.76%	10.15%	**90.29%**	80.06%	11.33%
0.90V	**81.31%**	74.17%	8.78%	**88.39%**	79.82%	9.69%
0.85V	**88.93%**	80.95%	8.97%	**89.34%**	85.54%	4.25%
0.80V	**93.86%**	84.23%	10.25%	**96.96%**	87.32%	9.94%

100°C). Maximum number of deviation points exist between the red lines, and these red lines represent the deviation range of less than a month. Hence, the predicted age is near to the actual age. The Table I shows the comparison with the State-of-the-art technique [12] results of the age prediction for both RO. The results show prediction accuracy for temperatures 0 °C to 100 °C with different voltage levels. State-of-the-art techniques [12] and proposed methodology models have been trained with the same data, but the average accuracy improvement is 9.59% for the 13-stage and 9.17% for the 21-stage RO. The reason for accuracy improvement is the data set and the model. We have taken the linear sampling rate instead of the exponential sampling rate. This concept provides uniform distribution of data points that are beneficial in predicting the age of ICs. The exponential sampling rate has a big gap between two data points at high index value, affecting prediction accuracy.

IV. CONCLUSION

In this paper, we presented a methodology to predict the age of ICs using the GPR model. The output frequency of the RO is appropriate for training the GPR model. The Output frequency of RO is a reliable proxy for age estimation. Our work's main aim is to improve the electronic systems' reliability awareness. It also helps to reduce the e-waste and unlawful approaches to reusing ICs. This paper shows age prediction results of 13-stage and 21-stage RO. The voltage variation from 0.8V to 1.05V and the temperature variation from 0 °C to 100 °C. The average prediction accuracy of 13-stage RO has 85.35%; respectively, 90.42% for 21-stage RO with deviation of one month.

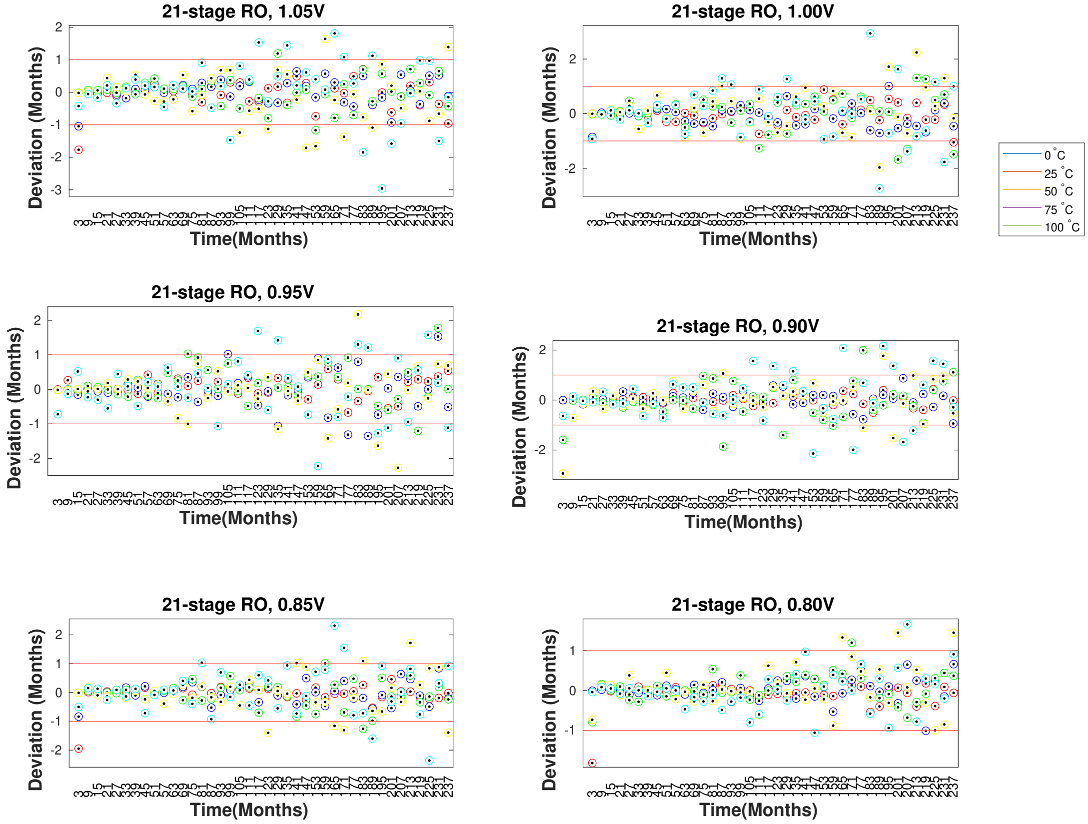

Fig. 6. Deviation of 21-stage RO using GPR for five representative temperatures (0°C, 25°C, 50°C, 75°C and 100°C) .

ACKNOWLEDGMENT

We would like to acknowledge the funding support received from Ministry of Electronics and Information Technology (MeitY), Govt. of India and the ODA Research Seed Funding, University of Liverpool, UK under the Global Challenge Research fund.

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