San Diego State University

IC AGING PREDICTION BASED ON MACHINE LEARNING

Electrical Engineering

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2. Aging
3. Impact of threshold voltage
4. Previous work
5. Proposed method
6. Experimental results
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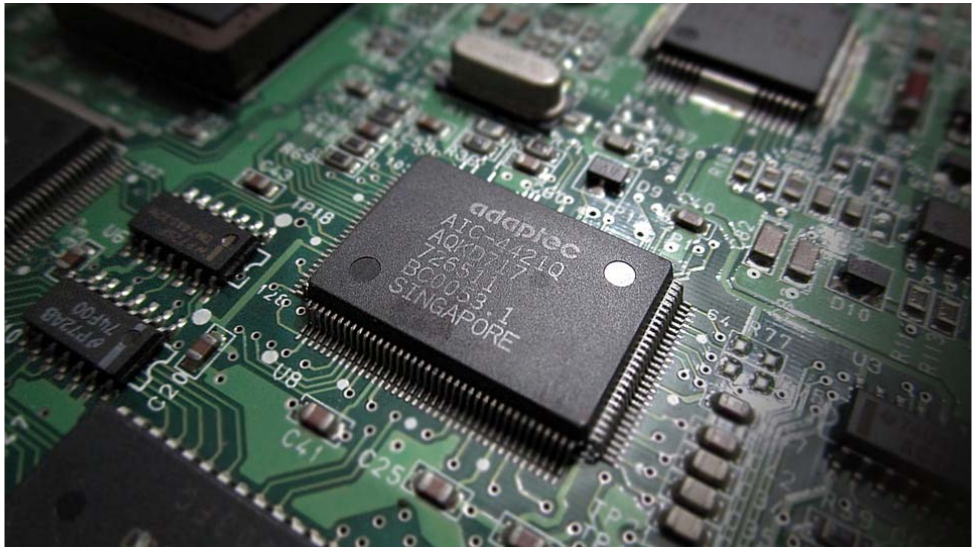
1. INTRODUCTION



Importance： robustness and reliability

https://www.army.mil/e2/c/images/2017/10/24/496445/size0.jpg

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2. Aging, and its impact on threshold voltage

NBTI

(Negative bias temperature-instability)

PBTI

(Positive bias temperature-instability)

HCI

(Hot carrier injection)

→ **Delay of critical path** → **Timing failure**

2. Aging, and its impact on threshold voltage

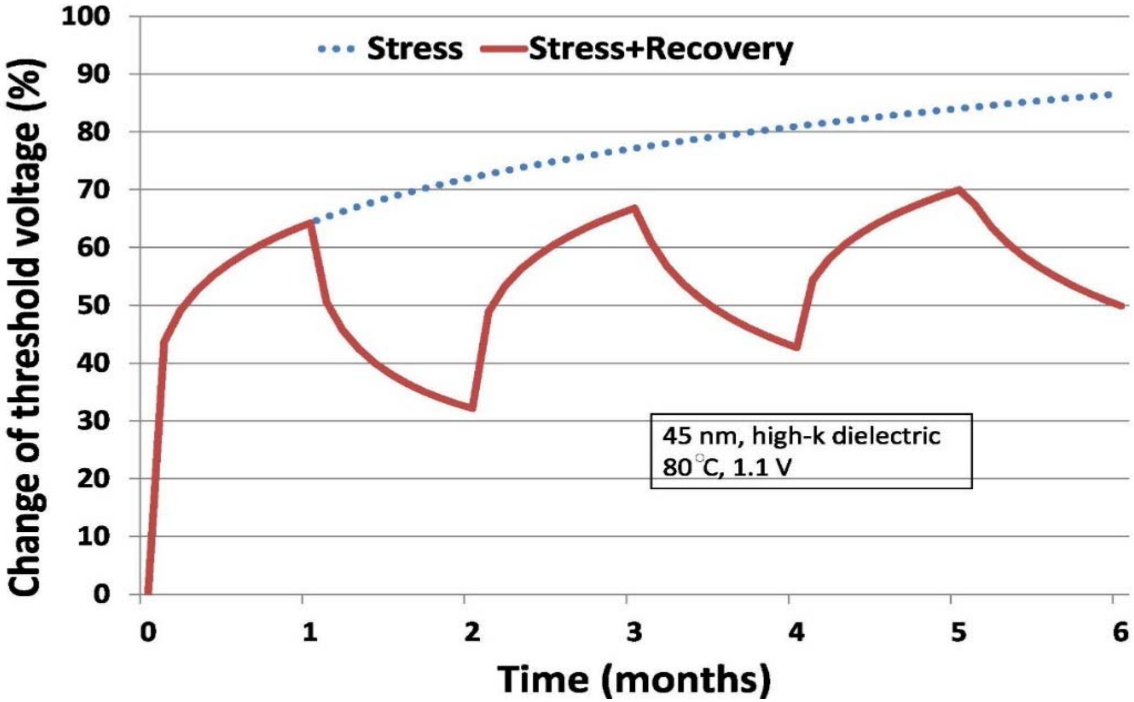
- **Aging modeling**

Threshold voltage degradation model

$$\Delta V_{th}(T,\alpha,t) = be^{-\frac{nE\alpha}{kT}}\left(\frac{\alpha}{1-\alpha}\right)^{n} t^{n}$$

- T : average temperature in Kelvin
- α : average signal duty cycle
- t : usage time
- n : time exponent
- k : Boltzmann constant
- Eα = $0.49eV$
- b : fitting constant

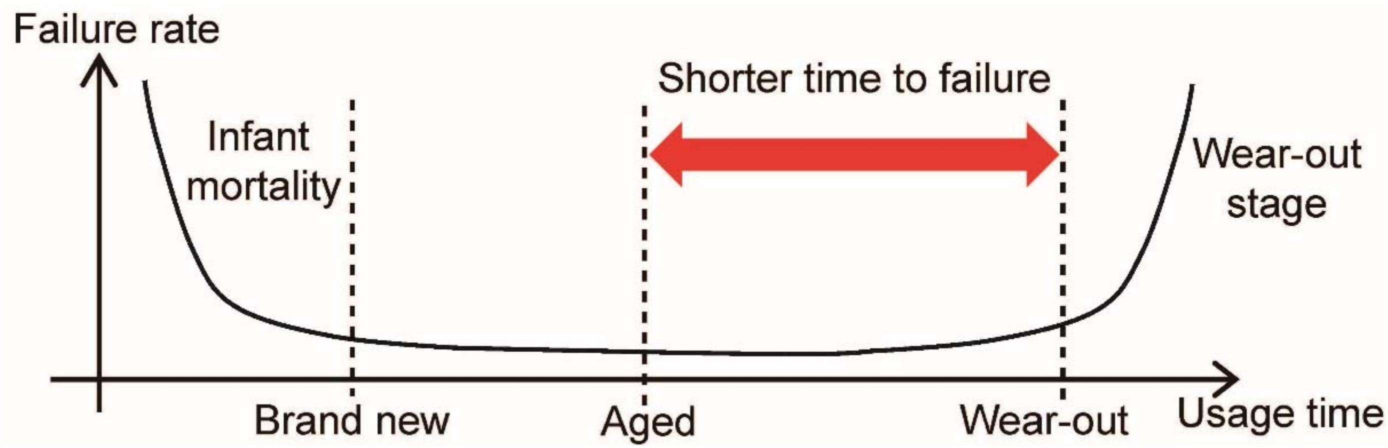
3. Impact of threshold voltage on digital circuit propagation delay



Under two conditions, the threshold voltage in a MOSFET changes over time.

3. Impact of threshold voltage on digital circuit propagation delay

Bathtub curve showing device failure characteristics*



*D. Pantic, "Benefits of integrated-circuit burn-in to obtain high reliability parts," IEEE Transactions on Reliability, 1986.

4. Previous work

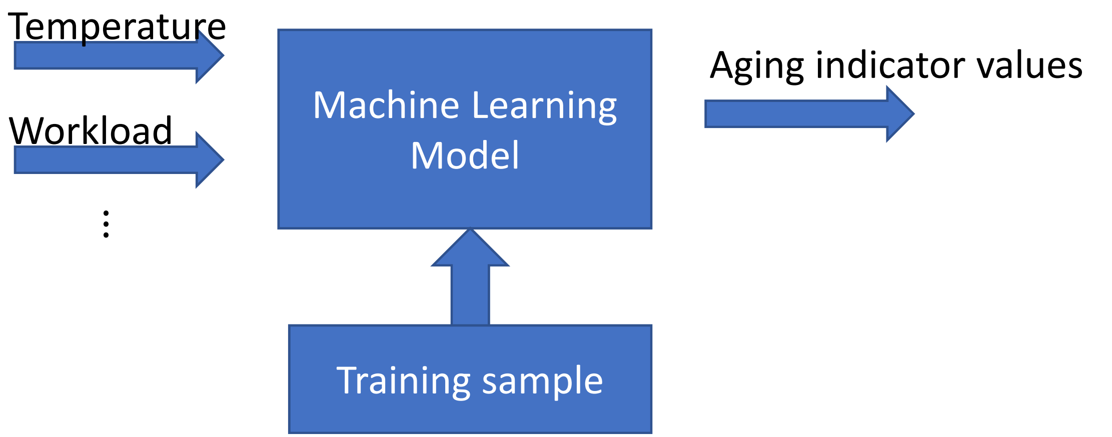
Classic approaches:

- **Look-up table*---Not suitable for large scale device**
- **Aging sensors** ---Extra overhead introduced**
- **Electromagnetic signature***--- Hard to measure (reflection coefficient measured)**

* Z. Yang et al., "Workload-aware failure prediction method for VLSI devices using an LUT based approach," in Int'l Instrum. and Meas. Technology Conf., 2018.
**M. Agarwal et al., "Circuit failure prediction and its application to transistor aging," in IEEE VLSI Test Symp., 2007.
***S. Shinde, et al., "Wideband microwave reflectometry for rapid detection of dissimilar and aged ICs," IEEE Trans. Instrum. Meas., 2017.

4. Previous work

Machine learning Model

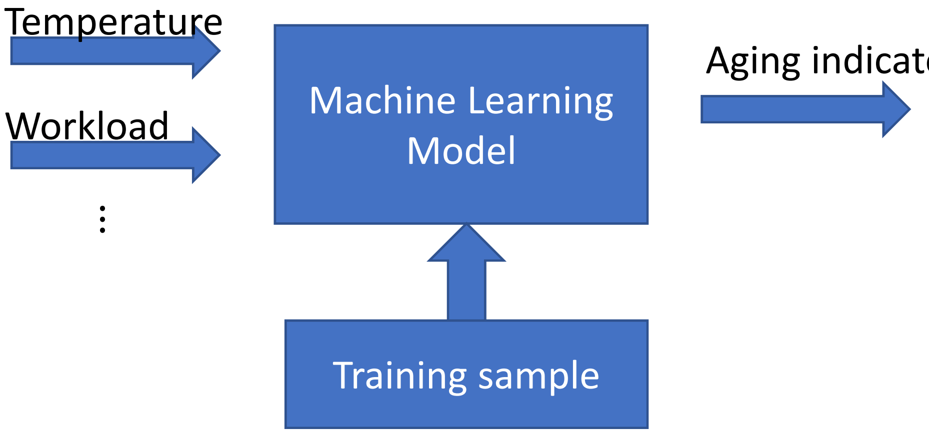


* N. Karimi and K. Huang, “Prognosis of ic aging based on machine learning,” in Int’l Symp. on Defect and Fault Tolerance in VLSI and Nanotechnology Systems, 2016.
** A. Vijayan, et al, “Fine-grained aging-induced delay prediction based on the monitoring of run-time stress,” IEEE Trans. Comput.- Aided Design Integr. Circuits Sy, 2018.

4. Previous work

Machine learning Model

For each given training sample, *ALL* input features should be constant w.r.t. time



* N. Karimi and K. Huang, "Prognosis of ic aging based on machine learning," in Int'l Symp. on Defect and Fault Tolerance in VLSI and Nanotechnology Systems, 2016.
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5. Proposed method

Multivariate Adaptive Regression Splines (MARS)

- For solving regression-type problems
- Handle continues and categorical data[1]
- No assumption relationship (linear, logistic)
- “Divide and conquer” (High dimensional)[2]
- Determine most important variables
- Determine most significant interactions

$$\mathrm{d}_j = f_j(O,t) = a_0 + \sum_{i=1}^{M} a_i \cdot B_i(O,t)$$

[1] J. Friedman, “Estimating functions of mixed ordinal and categorical variables using adaptive splines,” Stanford University Department of Statistics, Technical Report 108, pp. 1–42, 1991.
[2]http://www.statsoft.com/textbook/multivariate-adaptive-regression-splines

5. Proposed method

- **Multivariate Adaptive Regression Splines (MARS)**
- **Model calibration**
- **Equivalent aging time**

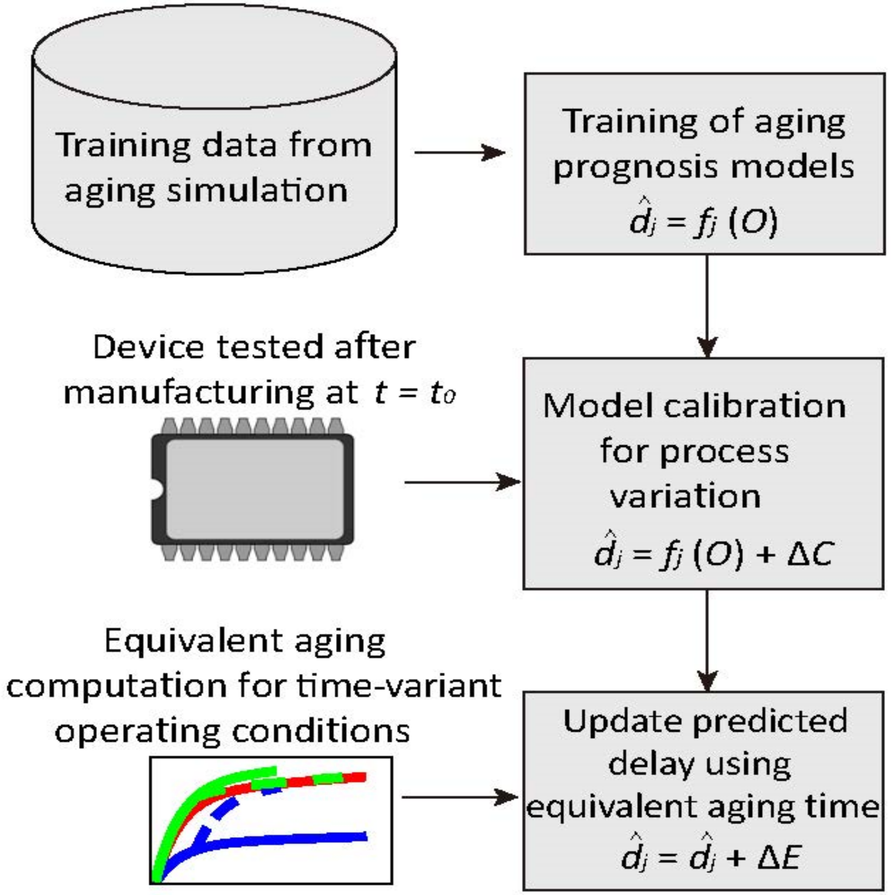


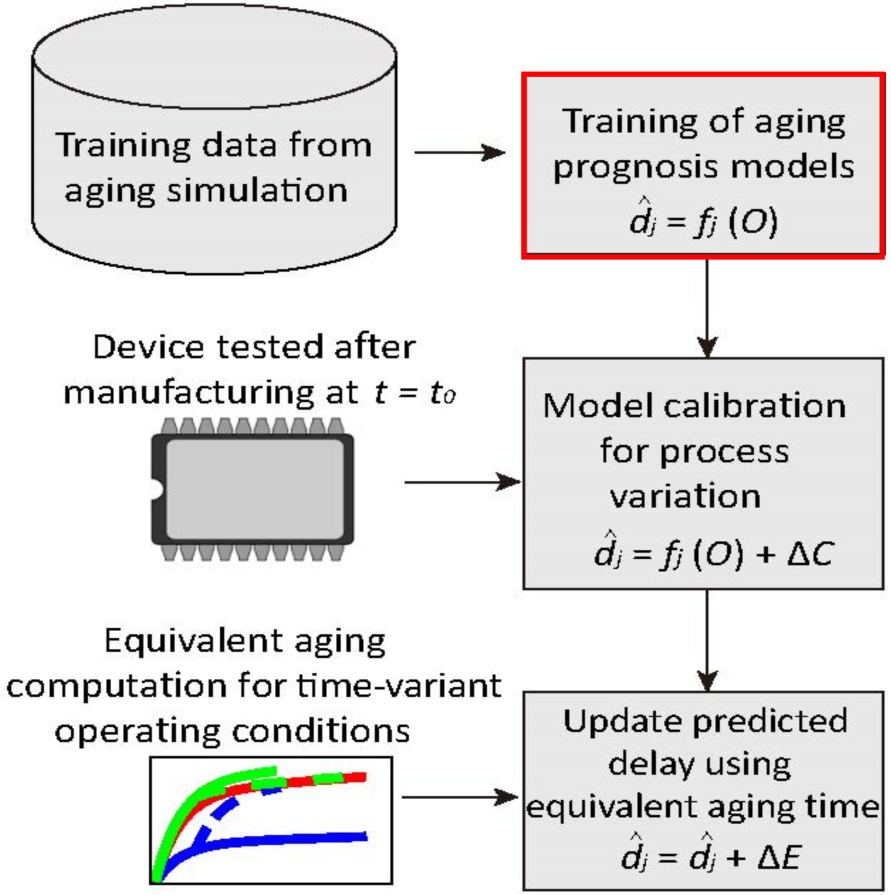
Figure. Overview of the proposed approach.

5. Proposed method

Multivariate Adaptive Regression Splines (MARS)

$$\mathrm{d}_j = f_j(O,t) = a_0 + \sum_{i=1}^{M} a_i \cdot B_i(O,t)$$

a_0 : intercept
a_i : the slope parameter,
t : the usage time
O : operating condition vector
$B_i(O,t)$: the i-th basis function



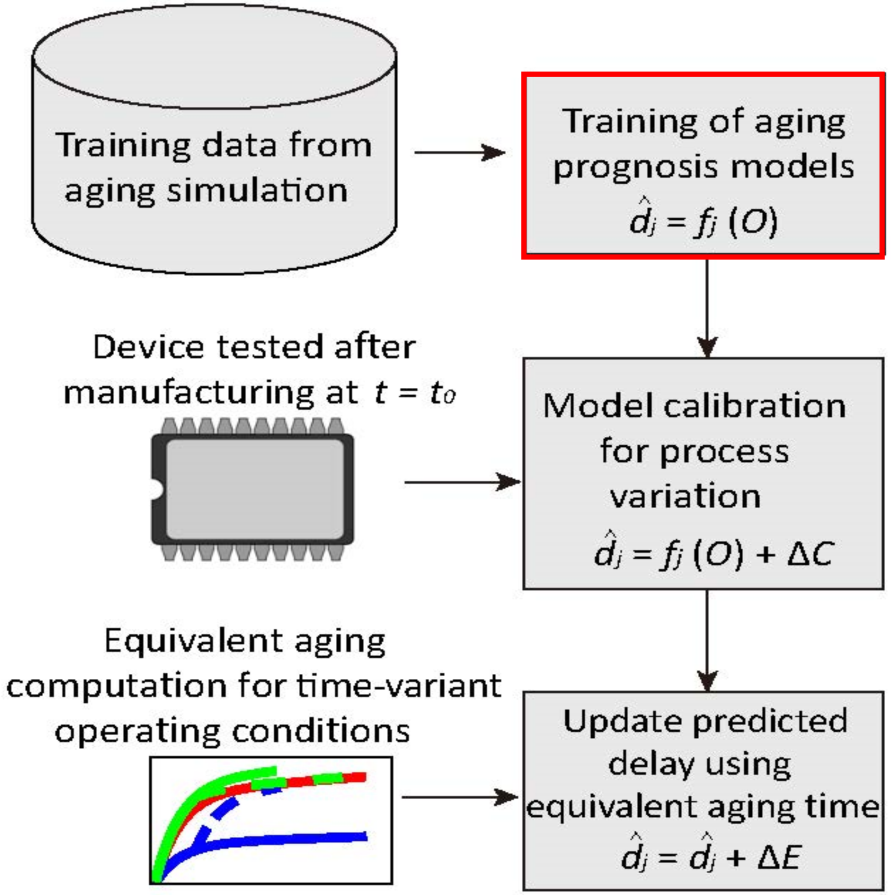
5. Proposed method

Multivariate Adaptive Regression Splines (MARS)

$$d_j = f_j(O,t) = a_0 + \sum_{i=1}^{M} a_i \cdot B_i(O,t)$$

Training method

- Starts with an empty model
- Repeated add basis functions that minimize sum-of-squared error
- Search all possible basis functions until convergence is reached
- Pruning technique to solve overfitting problems by removing the least effective basis function



5. Proposed method

Model calibration

1) Get best/worse cases of performances

2) Compute compensation factors for new device

3) Process calibration using compensation factor

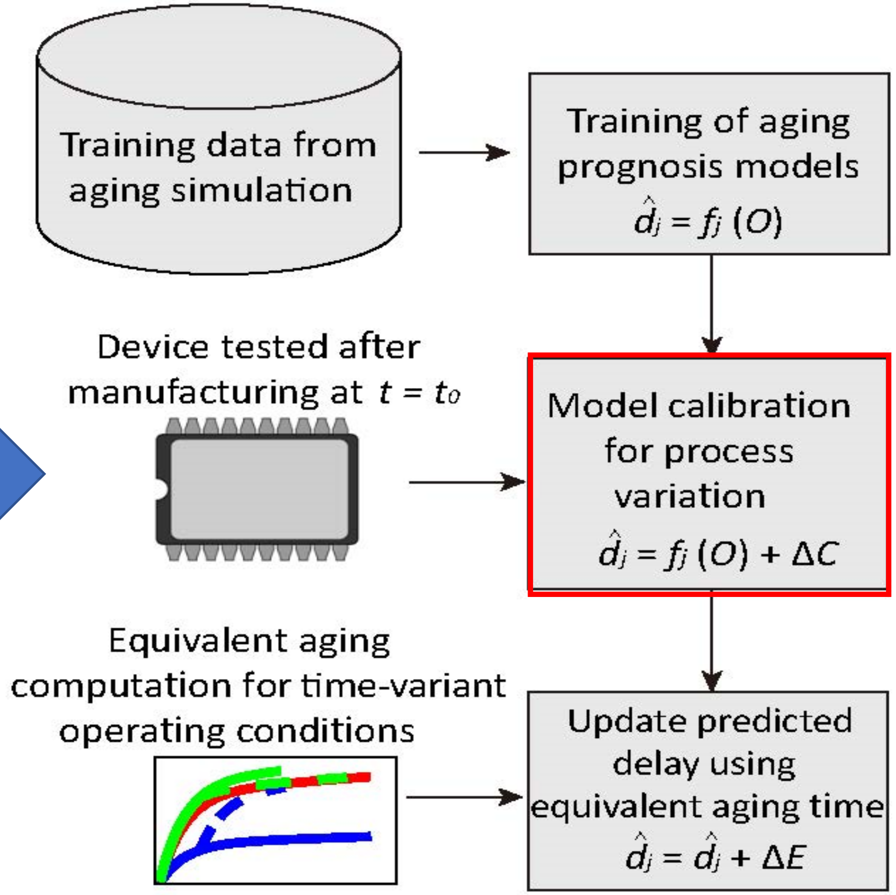
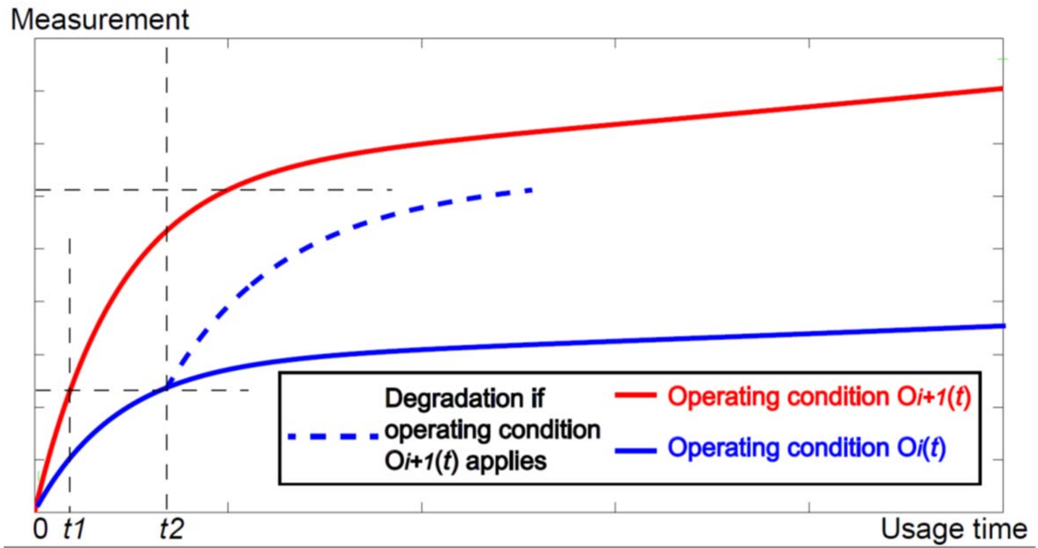


Figure. Overview of the proposed approach.

5. Proposed method

Equivalent aging time



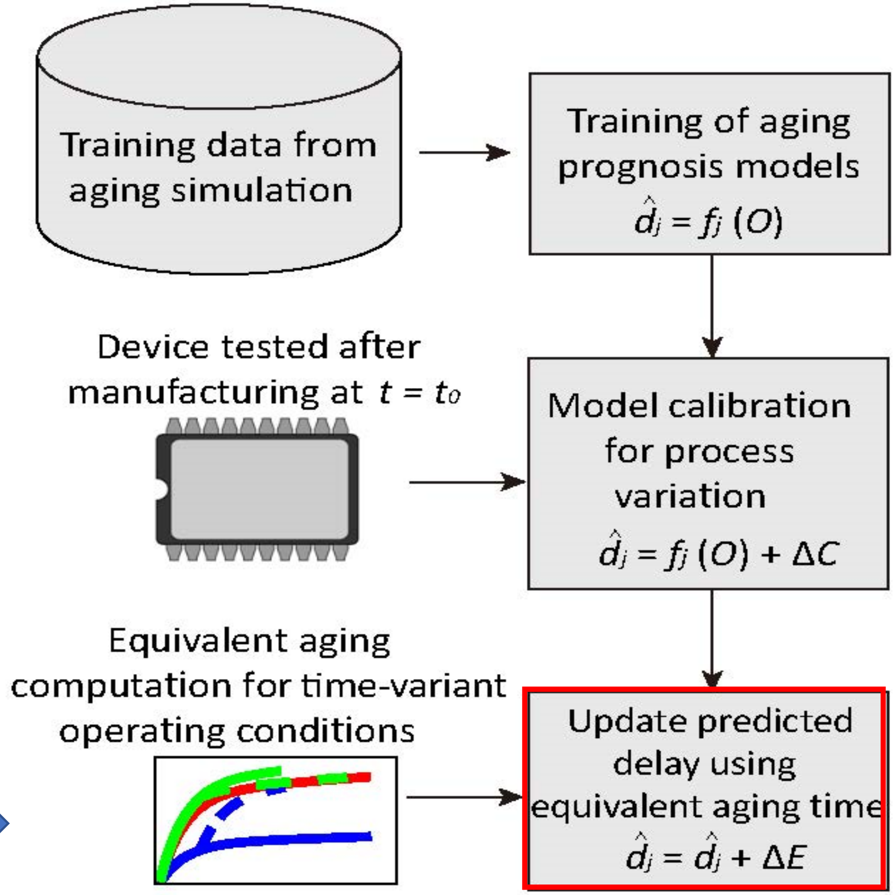
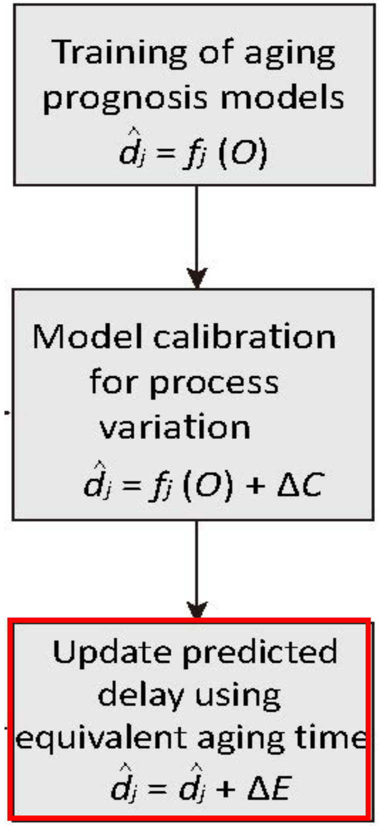


Figure. Overview of the proposed approach.

5. Proposed method

Algorithm 1 Time-Variant Aging Prediction

1: **procedure** TIME VARIANT PREDICTION
2: Train the function $d_j = f_j(O, t)$ using simulation samples, calibrate the model for process variations
3: Select the total number of intervals N
4: Set inputs $\tilde{O}(t) = [O_1(t_1^*), O_2(t_2^*), \cdots, O_N(t_N^*)]$
5: Set $i = 1, j = 1, t_{i,equ} = 0, t_{N+1}^* = t_{end}$
6: Select desired prediction time t in the i-th time interval
7: Compute equivalent prediction time $t_p = t_{i,equ} + (t_{i+1}^* - t_i^*)$
8: Aging prediction of the j-th performance at the end of the i-th interval: $d_{j,i} = f_j(O_i, t_p)$
9: **If** $i < N$
10: Equivalent aging time computation: $t_{i+1,equ} = g(d_{j,i}, O_{i+1})$
11: **End**
12: $i = i + 1$
13: **While** $i < N$, repeat steps 6-12
14: $j = j + 1$
15: **While** $j < M$, repeat steps 2-14
end procedure



6. Experimental setup

ISCAS'89 Benchmark

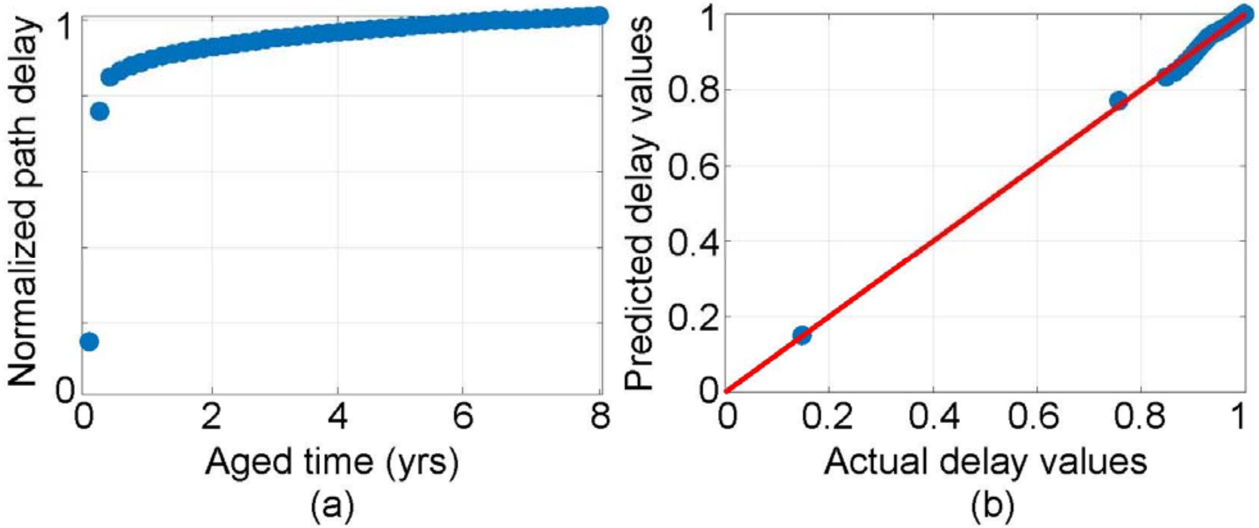
Circuit Name	Number of Primary Inputs	Number of primary Outputs	Number of Latches	Number of AND/OR/NOT Gates
s510	19	7	6	211
s1494	8	19	6	647
s5378	35	49	179	2779
s9234	19	22	228	5597
s15850	14	87	597	9772

Critical paths are selected such that if degraded by **20%**, a circuit timing failure occurs

6. Experimental setup

	Scenario 1		Scenario 2			Scenario 3			
temperature	**25℃**	**50℃**	**25℃**	**50℃**	**75℃**	**25℃**	**10℃**	**75℃**	**50℃**
time intervals	**[0, 4 years]**	**[4, 8 years]**	**[0, 2 years]**	**[2, 6 years]**	**[6, 8 years]**	**[0, 2 years]**	**[2, 4 years]**	**[4, 6 years]**	**[6, 8 years]**

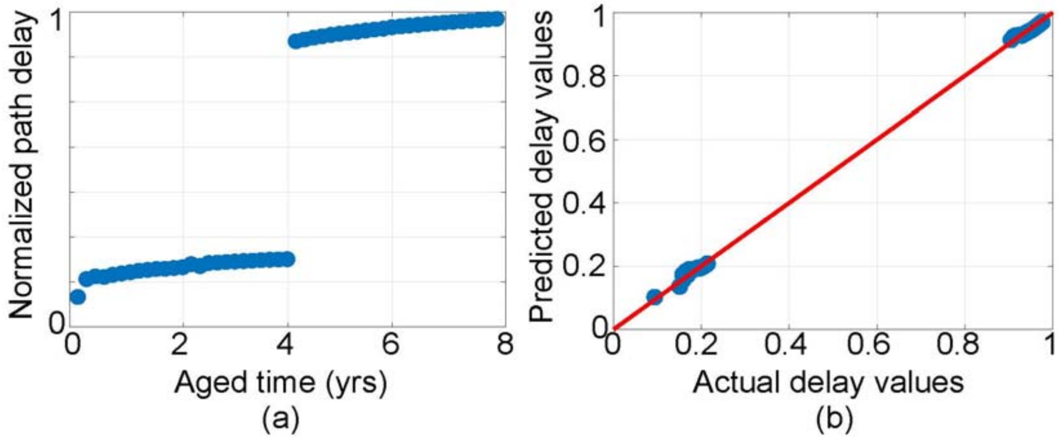
6. Experimental setup



Example of a path delay prediction under constant operating condition: α= 50%; T = 25℃ from benchmark s5378, (a) normalized aging degradation plotted as a function of usage time, (b) prediction scatter plot using the proposed model.

6. Experimental results--Scenario 1

Scenario 1	
25℃	50℃
[0, 4 years]	[4, 8 years]



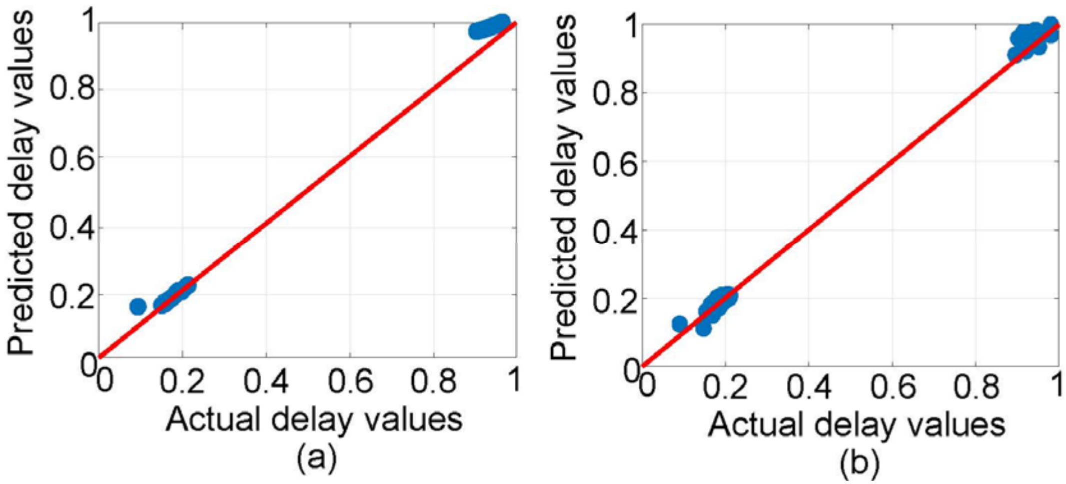
Aging prediction plot for a path delay in s5378 under scenario 1: (a) normalize aging degradation and (b) prediction plot for this path.

6. Experimental setup

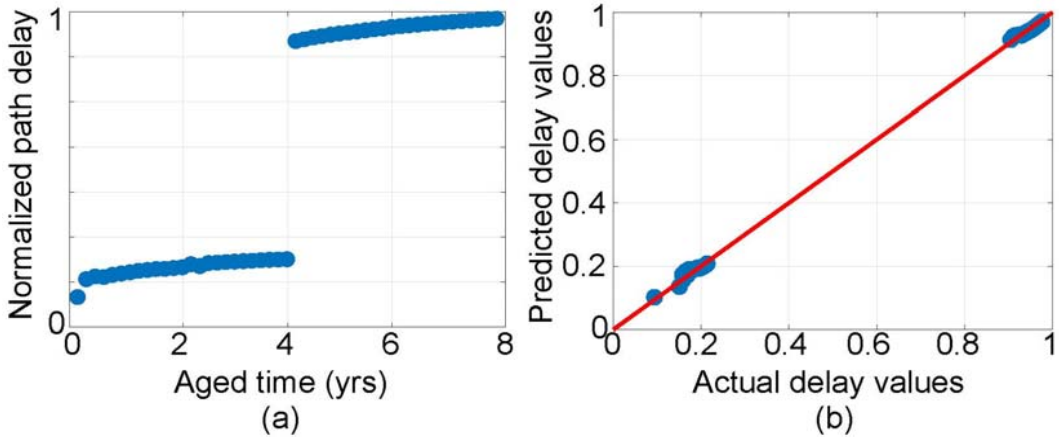
Two state-of-the-art models:
SVM (support vector machine)*: Good at unbalanced date
RNN (Recurrent neural network)** : Good at solving time series problems

*A. Vijayan, et al"Fine-grained aging-induced delay prediction based on the monitoring of run-time stress," IEEE Trans. Comput.-Aided Design Integr. Circuits Syst., 2018.
**R.Williams and D. Zipser, "A learning algorithm for continually running fully recurrent neural networks," Neural Computation, 1989.

6. Experimental results--Scenario 1



Prediction scatters plots for the same path delay shown in (b) using: (a) SVM regression and (b) RNN models.



Aging prediction plot for a path delay in s5378 under scenario 1: (a) normalized aging degradation and (b) prediction plot for this path.

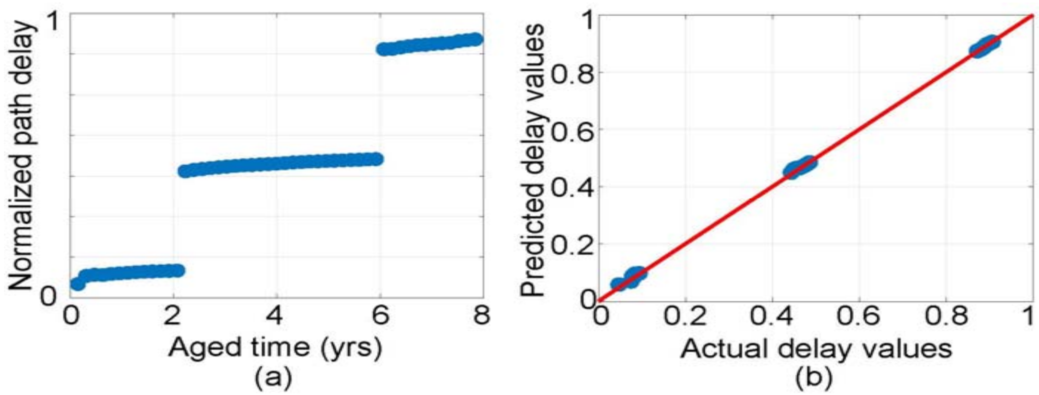
6. Experimental results--Scenario 1

TABLE 1
AGING PREDICTION RESULTS UNDER TIME-VARIANT OPERATION CONDITION IN SCENARIO 1.

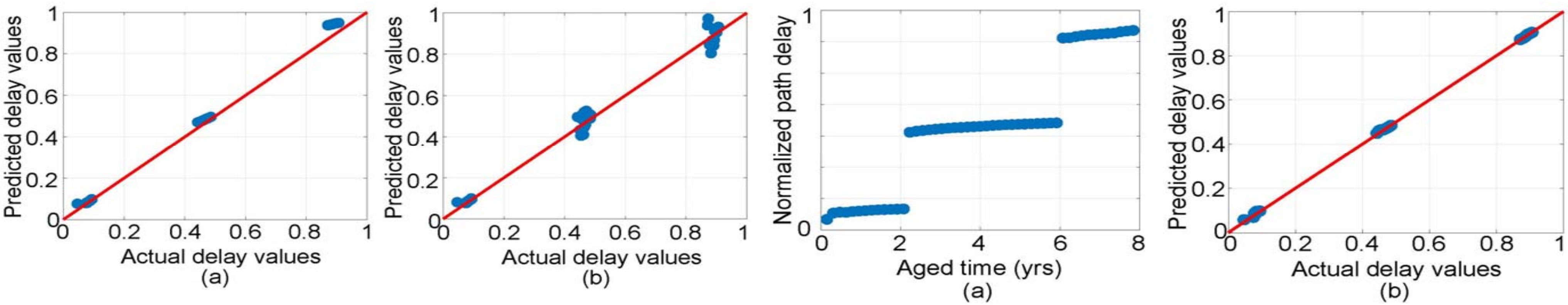
Benchmark (# of critical paths)	RMSE Proposed model	RMSE SVM	RMSE RNN
s510 (21)	1.35%	2.49%	2.78%
s1494 (57)	1.29%	2.31%	2.63%
s5378 (392)	1.45%	2.61%	2.91%
s9234 (179)	1.42%	2.64%	2.85%
s15850 (180)	1.53%	2.67%	2.92%

6. Experimental results--Scenario 2

Scenario 2		
25℃	**50℃**	**75℃**
[0, 2 years]	**[2, 6 years]**	**[6, 8 years]**



6. Experimental results--Scenario 2



Prediction scatter plots for the same path delay using: (a) SVM regression and (b) RNN models.

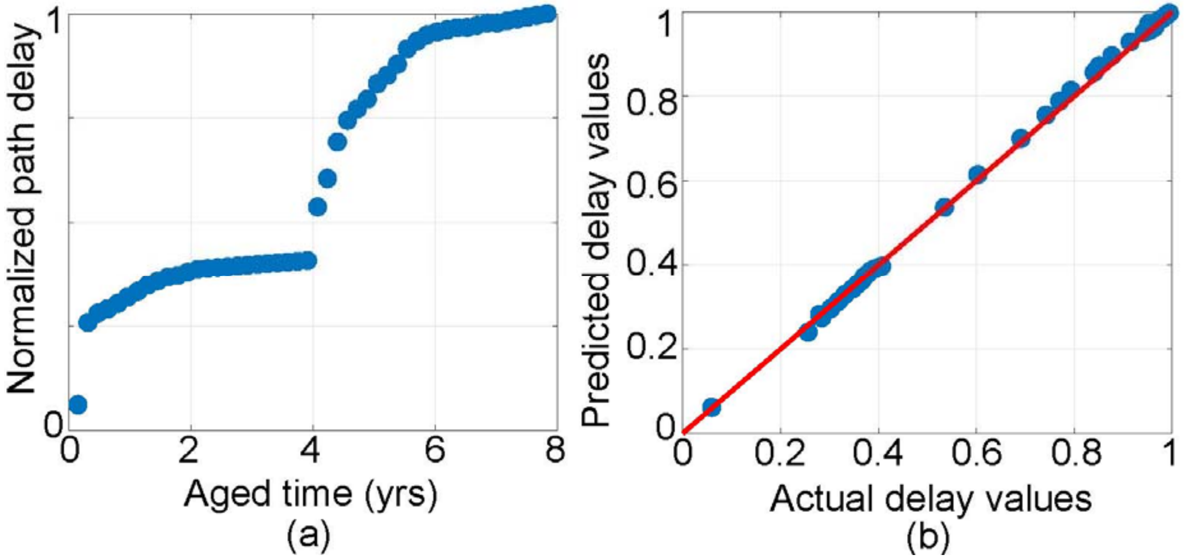
6. Experimental results--Scenario 2

TABLE 2
AGING PREDICTION RESULTS UNDER TIME-VARIANT OPERATION CONDITION IN SCENARIO 2.

Benchmark (# of critical paths)	RMSE Proposed model	RMSE SVM	RMSE RNN
s510 (21)	1.29%	3.90%	4.80%
s1494 (57)	1.25%	3.85%	4.63%
s5378 (392)	1.39%	3.98%	4.86%
s9234 (179)	1.43%	5.26%	5.46%
s15850 (180)	1.55%	5.30%	5.54%

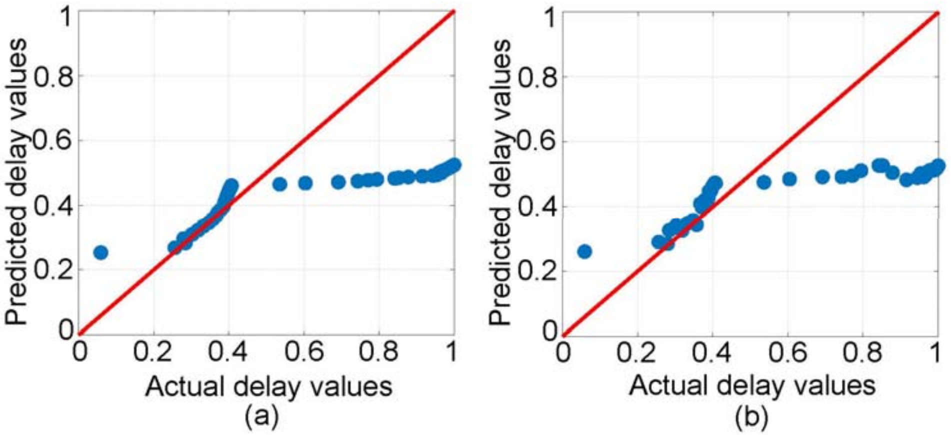
6. Experimental results--Scenario 3

Scenario 3			
25℃	10℃	75℃	50℃
[0, 2 years]	[2, 4 years]	[4, 6 years]	[6, 8 years]

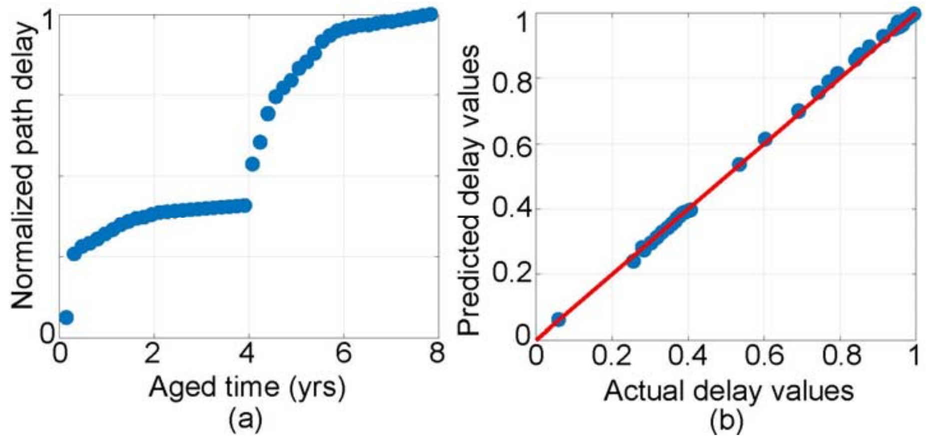


Aging prediction plot for a path delay in s5378 under scenario 3: (a) normalized aging degradation and (b) prediction plot for this path

6. Experimental results--Scenario 3



Prediction scatter plots for the same path delay using: (a) SVM regression and (b) RNN models.



Aging prediction plot for a path delay in s5378 under scenario 3: (a) normalized aging degradation and (b) prediction plot for this path

6. Experimental results--Scenario 3

TABLE 3
AGING PREDICTION RESULTS UNDER TIME-VARIANT OPERATION CONDITION IN SCENARIO 3.

Benchmark (# of critical paths)	RMSE Proposed model	RMSE SVM	RMSE RNN
s510 (21)	1.18%	4.56%	4.51%
s1494 (57)	1.21%	4.49%	4.43%
s5378 (392)	1.15%	4.62%	4.55%
s9234 (179)	1.26%	4.89%	4.86%
s15850 (180)	1.31%	4.86%	4.72%

8. Conclusions

- **Proposed** a general-purpose model
- **Extended** the existing prediction scheme (arbitrary time-variant dynamic operation conditions)
- **Outperformed** existing method (accuracy)

Future Work

a) **Getting access to working condition directly on-chip.**

b) **Finding a way to improve prediction robustness.**

c) **Explore the impact of interaction among working conditions.**

d) **Explore more efficient ways of improving prediction model for complicated IC device.**

Thank your for listening