

| Device Characterization Using Support Vector Machines

1. Introduction

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Traditional methods of testing wafers can be very time consuming and costly. This is due to the fact that each wafer and every die on the wafer must be thoroughly tested using a lot of hardware and man resources. It is not uncommon to take more than one working day to measure electrical test (e-test) data from a single wafer. A wafer lot usually contains up to 25 wafers. The time required to measure all wafers in a lot exceeds two weeks easily even with modern testing equipments. These individual wafers may be tested in parallel, but additional hardware is needed. Measured results may also vary depending on variations within different testing hardware. For example, testing the same die on two different wafer probe stations with identical hardware may show slightly different results. Although it is very time consuming to fully characterize wafers, it is a necessity for process flow development, model extraction, and design. In this paper, we explore the possibility of reducing the wafer testing time by using the support vector machine learning algorithm. A Support Vector Machine (SVM) can be trained on a database and later used to predict new outputs based on the training data and new inputs [1-6]. Instead of measuring all wafers using probing stations, the SVM could predict the same desired electrical data in a much reduced amount of time.

2. Wafer Yield and Electrical Test Data

Electrical test data commonly refer to characterized devices taken from wafers after completion of fabrication processes. The characteristics of a device are measured and used to determine the pass or fail of a device. The more the dices on a wafer pass the specifications and the higher the

yield the wafer has. In general, several characteristics from multiple dies are analyzed to determine the wafer yield. Device characterization refers to measuring an electrical device (transistor, capacitor, diode, resistor, etc.) to determine its current-voltage characteristics.

It is important in determining whether a fabrication process meets specifications and design rules. If requirements are not met, physical parameters can be extracted from the measured data to provide possible solutions for failure issues. If all specifications and design rules pass, then the characterized data will be used to extract device models for designers. In most cases, a device is characterized by using manual or automated probe stations in which specific voltage conditions are applied to measure the desired current.

3. Regression Support Vector Machines for Wafer Yield Prediction

A Support Vector Machine was first developed by Vladimir Vapnik and others at AT&T Bell Laboratories in the early to mid 1990s. Support Vector Machines can map the input space into a very high dimensional feature space to find an optimal solution in a high dimensional space. The major functions of SVM can be classified into two areas: classification and regression. In our application we use SVM for regression applications. In this paper measured data was taken from wafers processed by the 0.18 μm technology with the operating voltage = 1.8 Volts. Three measurement parameters such as linear threshold voltage, saturation current, and leakage current are the focus of all the experiments.

3.1 Wafer Yield in terms of Threshold Voltage, Saturation Current and Leakage Current

In general, threshold voltages, saturation currents, and leakage currents are the most important parameters in determining yield and passing/failing specification limits for transistors. The following measurement conditions are used for threshold voltages, saturation currents and leakage currents.

Linear Threshold Voltage: $V_{\text{DRAIN}} = 0.1 \text{ V}$, $V_{\text{SOURCE}} = V_{\text{WELL}} = 0.0 \text{ V}$, V_{GATE} is swept from 0 V to 1.8 V to calculate maximum slope of I_{drain} or maximum G_{mMax} . The threshold voltage is calculated using the following equation.

$$V_T = -(\text{Intercept/Slope}) - V_{\text{DRAIN}}/2 \quad (1)$$

- Saturation Current : Drain Current at $V_{\text{DRAIN}} = V_{\text{GATE}} = 1.8 \text{ V}$, $V_{\text{SOURCE}} = V_{\text{WELL}} = 0.0 \text{ V}$
- Leakage Current : Drain Current at $V_{\text{DRAIN}} = 1.8 \text{ V}$, $V_{\text{GATE}} = V_{\text{SOURCE}} = V_{\text{WELL}} = 0.0 \text{ V}$

3.2 Wafer Experiments

In our experiments, each tested wafer has 149 dies and each die has about 40 CMOS transistors with different channel widths and lengths. Tables 1a, 1b, and 1c present results obtained by SVM, SPICE simulations, and analytical calculations [7] for threshold voltages, saturation currents, and leakage currents. The radial basis function (RBF) is selected as the kernel function for the SVM. For the first experiment, the SVM is essentially used for interpolation because the training data set covers the most part of the wafer and the testing data is selected from part of the same wafer even though the testing data set is different from the training data set.

Table 1(a). Threshold Voltage Using RBF Kernel SVM, SPICE, and Calculation.

Width	Length	Measured	SVM	SPICE	Calculated	%diffSVM	%diffSPICE	%diffCALC
10	10	0.591	0.591	0.591	0.682	0.0	0.0	15.4
10	5	0.604	0.604	0.595	0.691	0.0	-1.4	14.5
10	2	0.633	0.633	0.607	0.724	0.0	-4.1	14.4
10	1	0.652	0.656	0.628	0.753	0.6	-3.8	15.4
10	0.26	0.664	0.658	0.680	0.833	-0.9	2.3	25.3
10	0.24	0.659	0.658	0.673	0.833	-0.1	2.2	26.4
10	0.18	0.598	0.657	0.630	0.773	9.9	5.3	29.3
10	0.16	0.573	0.657	0.607	0.727	14.6	6.8	26.9
2	0.18	0.633	0.633	0.623	0.768	0.0	-1.5	21.4
0.8	0.18	0.633	0.633	0.611	0.761	0.0	-3.5	20.1
0.6	0.18	0.617	0.629	0.604	0.746	2.0	-2.0	20.9
0.4	0.2	0.630	0.620	0.609	0.763	-1.6	-3.4	21.2
0.4	0.18	0.648	0.624	0.590	0.732	-3.8	-9.1	12.8
0.3	0.18	0.600	0.620	0.574	0.696	3.3	-4.3	16.0
0.24	0.2	0.587	0.614	0.578	0.671	4.6	-1.6	14.3
0.24	0.18	0.635	0.618	0.558	0.685	-2.7	-12.1	7.9
0.22	0.2	0.613	0.613	0.570	0.674	0.0	-7.0	9.9
0.22	0.18	0.562	0.617	0.551	0.605	9.8	-1.9	7.7

Table 1(b). Saturation Current Using RBF Kernel SVM, SPICE, and Calculation.

Width	Length	Measured	SVM	SPICE	Calculated	%diffSVM	%diffSPICE	%diffCALC
10	10	0.017	0.017	0.018	0.018	0.2	2.2	3.0
10	5	0.034	0.034	0.035	0.035	0.1	3.0	2.5
10	2	0.080	0.080	0.086	0.083	0.0	6.3	3.7
10	1	0.153	0.152	0.162	0.160	0.0	6.2	5.1
10	0.26	0.500	0.500	0.502	0.614	0.1	0.4	22.7
10	0.24	0.542	0.539	0.544	0.665	-0.6	0.3	22.7
10	0.18	0.751	0.751	0.751	0.888	0.0	0.0	18.3
10	0.16	1.000	1.000	0.871	1.000	0.0	-12.9	0.0
2	0.18	0.164	0.164	0.155	0.185	0.0	-5.9	12.8
0.8	0.18	0.067	0.067	0.065	0.074	0.1	-3.2	11.0
0.6	0.18	0.052	0.052	0.050	0.056	0.1	-3.8	8.6
0.4	0.2	0.030	0.030	0.030	0.034	-0.1	1.5	14.1
0.4	0.18	0.035	0.035	0.035	0.038	-0.1	-2.1	6.8
0.3	0.18	0.028	0.028	0.027	0.028	-0.4	-4.3	0.7
0.24	0.2	0.021	0.021	0.020	0.021	-0.7	-7.0	-2.8
0.24	0.18	0.023	0.023	0.023	0.023	0.2	-2.1	-0.9
0.22	0.2	0.019	0.019	0.018	0.019	0.2	-4.7	-2.1
0.22	0.18	0.021	0.022	0.021	0.022	1.9	-0.2	4.0

Table 1(c). Leakage Current Using RBF Kernel SVM, SPICE, and Calculation.

Width	Length	Measured	SVM	SPICE	Calculated	%diffSVM	%diffSPICE	%diffCALC
10	10	5.48E-04	5.77E-04	2.71E-04	1.97E-03	5.3	-50.4	259.8
10	5	4.88E-04	5.07E-04	2.84E-04	3.94E-03	3.8	-41.7	708.1
10	2	5.16E-04	5.34E-04	3.08E-04	9.86E-03	3.6	-40.3	1811.8
10	1	3.88E-04	3.93E-04	3.16E-04	1.97E-02	1.4	-18.5	4984.5
10	0.9	4.81E-04	4.30E-04	3.15E-04	2.19E-02	-10.7	-34.6	4454.0
10	0.8	5.48E-04	5.03E-04	3.13E-04	2.46E-02	-8.3	-43.0	4393.3
10	0.7	5.39E-04	5.42E-04	3.09E-04	2.82E-02	0.6	-42.6	5125.8
10	0.6	5.55E-04	5.61E-04	3.05E-04	3.29E-02	1.0	-45.0	5816.5
10	0.5	5.11E-04	5.47E-04	3.01E-04	3.94E-02	7.1	-41.0	7616.4
10	0.4	5.78E-04	5.84E-04	3.02E-04	4.93E-02	0.9	-47.7	8420.9
10	0.3	4.78E-04	5.08E-04	3.37E-04	6.57E-02	6.1	-29.5	13636.1
10	0.28	5.99E-04	5.70E-04	3.64E-04	7.04E-02	-4.7	-39.2	11662.5
10	0.22	1.16E-03	1.10E-03	7.90E-04	8.96E-02	-5.2	-31.9	7615.4
10	0.2	2.57E-03	2.61E-03	1.62E-03	9.86E-02	1.4	-37.1	3729.7
10	0.19	5.06E-03	5.03E-03	2.68E-03	1.04E-01	-0.5	-47.0	1952.0
10	0.17	1.10E-01	1.10E-01	1.01E-02	1.16E-01	0.1	-90.8	5.6
10	0.16	1.00E+00	1.00E+00	2.30E-02	1.23E-01	0.0	-97.7	-87.7
2	10	3.18E-04	2.91E-04	2.60E-04	3.94E-04	-8.3	-18.4	24.0
0.8	10	3.09E-04	2.66E-04	2.58E-04	1.58E-04	-13.9	-16.6	-49.0
0.6	10	2.86E-04	2.91E-04	2.58E-04	1.18E-04	1.8	-9.8	-58.6
0.4	10	3.05E-04	3.34E-04	2.58E-04	7.89E-05	9.5	-15.5	-74.1
0.3	10	2.99E-04	2.75E-04	2.58E-04	5.91E-05	-8.2	-13.7	-80.2
0.24	10	2.88E-04	2.72E-04	2.59E-04	4.73E-05	-5.4	-9.9	-83.5
0.22	10	3.20E-04	3.00E-04	2.60E-04	4.34E-05	-6.1	-18.8	-86.4

For all three parameters, SVMs produce more accurate results than SPICE and analytical equations calculations in comparison with the measured data. The SPICE model has limitations in capturing exact accuracies across numerous widths and lengths. Classical analytical equations do not

capture the varying effects across dimensions i.e. short-channel effect, narrow-channel effect). Fig.s 1(a), 1(b), and 1(c) present device channel length versus threshold voltage with constant channel width of 10.

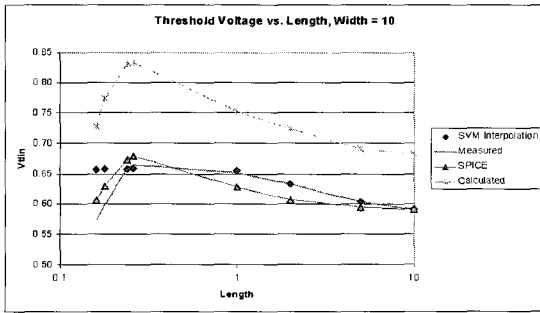


Fig. 1(a). Threshold Voltage Length Scaling (RBF SVM, SPICE, & Calculation).

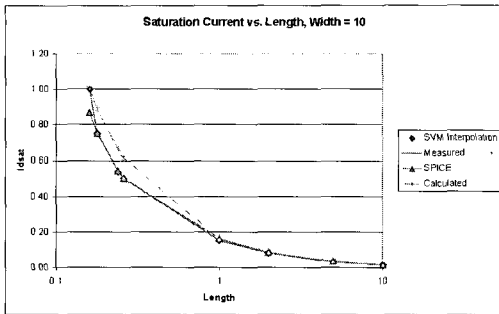


Fig. 1(b). Saturation Current Length Scaling (RBF SVM, SPICE, & Calculation).

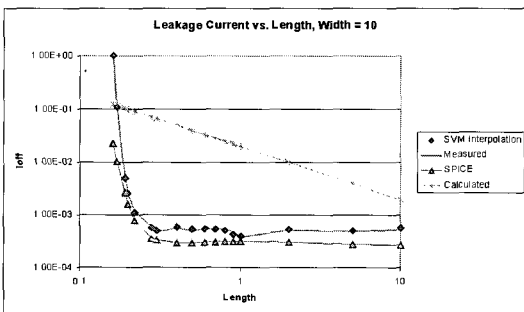


Fig. 1(c). Leakage Current Length Scaling (RBF SVM, SPICE, & Calculation).

As can be seen, SVM interpolation lines up almost exactly with the measured data in all three cases. SPICE does an acceptable job for threshold voltage and saturation current, but leakage current is slightly worse. Calculation using the analytical equations appears to have large discrepancy in comparison with the measured data.

For the initial prediction experimentation, a single die with varying channel widths and lengths containing threshold voltage, saturation current, and leakage current was used. The importance of prediction across varying widths and lengths would be useful for device model extraction. It is extremely time consuming to measure all the dimensions needed for model extraction, and even more difficult to fit them during the model development process. It would be ideal if only half the measurements were needed and use SVM to fit the other dimensions through prediction. The measured data used in this experiment was identical to that used for interpolation. Each training file was identical to what was used for interpolation, with the exception of a few dimensions that were intentionally left out. The idea behind this was to have SVM predict the correct values for those missing dimensions during test. Tables 2(a), 2(b), and 2(c) contain results for measured data vs. SVM prediction. Only several widths and lengths from each data set were used for prediction. The blue colored rows were intentionally removed from the training files. The orange colored rows are the resulting prediction and percentage difference compared to actual measurement.

Table 2(a). Threshold Voltage Prediction Using RBF Kernel SVM.

Width	Length	V _{th}	Training	Prediction	% diff
10	10	0.5915	0.5915	0.5914	0.0
10	5	0.6037	0.6037	0.6037	0.0
10	2	0.6328	0.6328	0.6328	0.0
10	1	0.6522	0.6522	0.6522	0.0
10	0.9	0.6577		0.6562	-0.2
10	0.8	0.6562	0.6562	0.6562	0.0
10	0.7	0.6565		0.6470	-1.4
10	0.6	0.6644	0.6644	0.6644	0.0
10	0.5	0.6747		0.7134	5.7
10	0.4	0.6682	0.6682	0.6682	0.0
10	0.3	0.6574	0.6574	0.6574	0.0
10	0.28	0.6635	0.6635	0.6633	0.0
10	0.26	0.6645	0.6645	0.6644	0.0
10	0.24	0.6582	0.6582	0.6582	0.0
10	0.22	0.6579		0.6441	-2.1
10	0.2	0.6235	0.6235	0.6234	0.0
10	0.19	0.6115	0.6115	0.6115	0.0
10	0.18	0.5982		0.5992	0.2
10	0.17	0.5566	0.5566	0.5869	5.4
10	0.16	0.5243	0.5243	0.5751	9.7
2	10	0.5964	0.5964	0.5964	0.0
2	0.18	0.6326	0.6326	0.6326	0.0
0.8	10	0.5848	0.5848	0.5848	0.0
0.8	0.18	0.6331	0.6331	0.6331	0.0
0.6	10	0.5731	0.5731	0.5731	0.0
0.6	0.18	0.6166	0.6166	0.6166	0.0
0.4	10	0.5497	0.5497	0.5497	0.0
0.4	0.2	0.6300	0.6300	0.6300	0.0
0.4	0.18	0.6484		0.6252	-3.6
0.3	10	0.5333	0.5333	0.5333	0.0
0.3	0.18	0.6004	0.6004	0.6004	0.0
0.24	10	0.5172	0.5172	0.5172	0.0
0.24	0.2	0.5871		0.6364	8.4
0.24	0.18	0.6352	0.6352	0.6352	0.0
0.22	10	0.5108	0.5108	0.5108	0.0
0.22	0.2	0.6134		0.6495	5.9
0.22	0.18	0.4999	0.4999	0.6490	29.8

Table 2(b). Saturation Current Prediction Using RBF Kernel SVM.

Width	Length	I _{dsat}	Training	Prediction	% diff
10	10	0.0174	0.0174	0.0174	0.2
10	5	0.0342	0.0342	0.0342	0.1
10	2	0.0805	0.0805	0.0805	0.0
10	1	0.1525	0.1525	0.1525	0.0
10	0.9	0.1664		0.1605	-3.5
10	0.8	0.1866	0.1866	0.1867	0.0
10	0.7	0.2091		0.2588	23.8
10	0.6	0.2371	0.2371	0.2369	-0.1
10	0.5	0.2804		0.0943	-66.4
10	0.4	0.3391	0.3391	0.3392	0.0
10	0.3	0.4504	0.4504	0.4507	0.1
10	0.28	0.4718	0.4718	0.4715	-0.1
10	0.26	0.5002	0.5002	0.5005	0.1
10	0.24	0.5422	0.5422	0.5419	0.0
10	0.22	0.5946		0.6042	1.6
10	0.2	0.6977	0.6977	0.6980	0.0
10	0.19	0.7415	0.7415	0.7594	2.4
10	0.18	0.8139		0.8308	2.1
10	0.17	0.9177	0.9177	0.9116	-0.7
10	0.16	1.0000	1.0000	1.0001	0.0
2	10	0.0033	0.0033	0.0035	5.3
2	0.18	0.1644	0.1644	0.1646	0.1
0.8	10	0.0013	0.0013	0.0012	-4.8
0.8	0.18	0.0668	0.0668	0.0667	-0.1
0.6	10	0.0010	0.0010	0.0010	4.4
0.6	0.18	0.0515	0.0515	0.0514	-0.2
0.4	10	0.0007	0.0007	0.0007	-1.1
0.4	0.2	0.0299	0.0299	0.0298	-0.4
0.4	0.18	0.0353		0.0321	-9.1
0.3	10	0.0005	0.0005	0.0005	-4.1
0.3	0.18	0.0282	0.0282	0.0281	-0.4
0.24	10	0.0005	0.0005	0.0004	-6.1
0.24	0.2	0.0213		0.0243	14.0
0.24	0.18	0.0230	0.0230	0.0229	-0.5
0.22	10	0.0004	0.0004	0.0004	-6.2
0.22	0.2	0.0194		0.0259	33.7
0.22	0.18	0.0243	0.0243	0.0242	-0.3

Table 2(c). Leakage Current Prediction Using RBF Kernel SVM.

Width	Length	I _{off}	Training	Prediction	% diff
10	10	0.000548	0.000548	0.0006322	15.4
10	5	0.000488	0.000488	0.0005723	17.3
10	2	0.000516	0.000516	0.0004314	-16.3
10	1	0.000388		0.0693987	17799.2
10	0.9	0.000481	0.000481	0.0005654	17.5
10	0.8	0.000548		0.0693987	12554.4
10	0.7	0.000539	0.000539	0.0006116	13.5
10	0.6	0.000555		0.0693987	12396.9
10	0.5	0.000511	0.000511	0.0004205	-17.7
10	0.4	0.000578	0.000578	0.0005758	-0.4
10	0.3	0.000478	0.000478	0.0004071	-14.9
10	0.28	0.000599		0.0438514	7226.2
10	0.22	0.001161	0.001161	-0.0054695	-570.9
10	0.2	0.002574		0.0145616	465.8
10	0.19	0.005056	0.005056	0.108116	2038.3
10	0.17	0.109766	0.109766	0.80076	629.5
10	0.16	1	1	1.01599	1.6
2	10	0.000318	0.000318	0.0002467	-22.4
0.8	10	0.000309		0.0693987	22336.9
0.6	10	0.000286	0.000286	0.0002833	-0.9
0.4	10	0.000305		0.0693987	22654.7
0.3	10	0.000299	0.000299	0.000215	-28.1
0.24	10	0.000288		0.0479131	16560.9
0.22	10	0.00032	0.00032	0.0003923	22.7

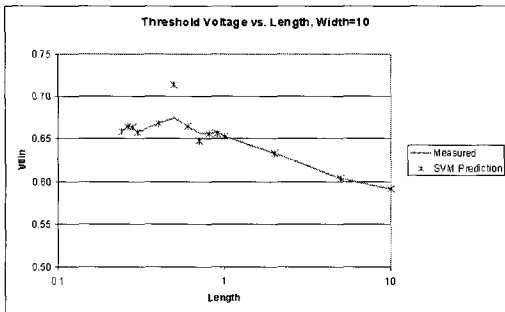


Fig. 2(a). Threshold Voltage Length Scaling (SVM Prediction vs. Measured).

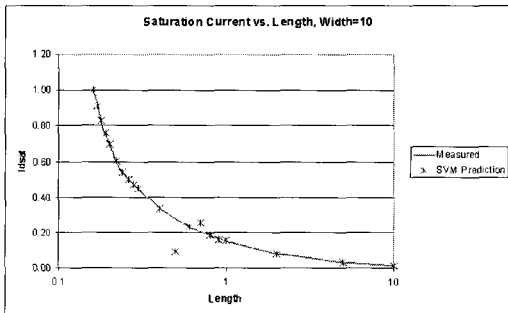


Fig. 2(b). Saturation Current Length Scaling (SVM Prediction vs. Measured).

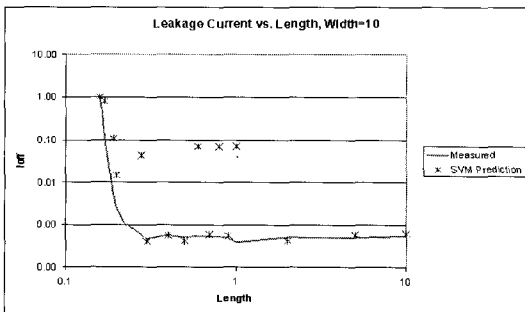


Fig. 2(c). Leakage Current Length Scaling (SVM Prediction vs. Measured).

Fig. 2(a), 2(b), and 2(c) represent length scaling curves for constant width of 10 showing the SVM prediction vs. measured values. As seen from the prediction tables and plots, SVM predicts accurately for threshold voltage and saturation current. This is

most likely due to values not having much variation across the varying dimensions. Regarding leakage current, however, SVM does not predict close to its measured counterpart. It is unusual that the SVM cannot recognize the line trends for the missing training data. Further experiments are needed for the leakage currents prediction.

The next sets of experiments focus on wafer prediction using SVM. The first wafer experiment focused on measured threshold voltage and saturation current from 149 die for a W/L = 10/10 device. The training files used rows and columns as inputs along with the corresponding parameter outputs. Since the focus is on prediction, random groups of dies were left out of the training data set. Fig. 3(a), 3(b), and 3(c) display results for measured threshold voltages, predicted threshold voltages (in yellow color) and the discrepancies between measured and predicted data (in yellow color) respectively. Similarly, Fig. 4(a), 4(b), and 4(c) display the results for saturation currents. As shown in Fig. 3(c) and Fig. 4(c), the SVM predicts threshold voltages and saturation currents with 97 % accuracy comparing to the actual measured data.

The following wafer experiment was based on the idea of using one wafer as training data to predict data for another wafer. Because it is unrealistic to completely predict electrical data for an unknown wafer, training data was taken from one entire wafer and 30 % of the second wafer. The goal now is to predict the other 70 % of the second wafer. Again, threshold voltage and saturation current were used as the key test parameters, while leakage current data were limited. The input values for the training files now contain a column for wafer number as well as channel width and channel length. In this experiment, it was decided to use dimensions of W/L = 10/10, 10/0.18, 0.22/10, and

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13
1					0.5354	0.5886	0.5847	0.5742	0.5368				
2				0.5712	0.5877	0.5993	0.6058	0.5878	0.5846	0.5542			
3			0.5689	0.5913	0.5958	0.6062	0.6181	0.6122	0.5986	0.5967	0.5734		
4		0.5594	0.5890	0.5927	0.6021	0.6112	0.6020	0.6104	0.6039	0.5994	0.5880	0.5731	
5		0.5709	0.5974	0.6030	0.5998	0.6089	0.6012	0.6081	0.5940	0.6112	0.6043	0.5850	
6	0.5359	0.5745	0.5994	0.6017	0.6060	0.6077	0.6132	0.6060	0.6014	0.6085	0.6065	0.6033	
7	0.5548	0.5865	0.5987	0.6015	0.6091	0.6078	0.6084	0.5992	0.6011	0.6085	0.6116	0.5941	0.5789
8	0.5652	0.5965	0.6030	0.6064	0.6157	0.6173	0.6141	0.6082	0.6137	0.6110	0.6130	0.5990	0.5846
9	0.5712	0.5972	0.6041	0.6110	0.6106	0.6148	0.6261	0.6164	0.6097	0.6113	0.6070	0.6079	0.5904
10	0.5520	0.5861	0.5961	0.6026	0.6199	0.6110	0.6107	0.6127	0.6090	0.6071	0.6026	0.5961	
11		0.5908	0.6072	0.6097	0.6076	0.6168	0.6043	0.6030	0.6033	0.6059	0.6065	0.6003	
12		0.5810	0.5991	0.6078	0.6088	0.6060	0.6087	0.6219	0.6104	0.6034	0.6077	0.5895	
13			0.5897	0.6046	0.6082	0.5977	0.6136	0.6027	0.6015	0.6014	0.5988		
14				0.5880	0.5867	0.6022	0.5958	0.5966	0.5979	0.5963			
15					0.5840	0.5775	0.5877	0.5949	0.5824				

Fig. 3(a). Measured Threshold Voltage for 149 Dies, W/L = 10/10.

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13
1					0.5354	0.5886	0.5847	0.5742	0.5368				
2				0.5712	0.5877	0.5993	0.6058	0.5878	0.5846	0.5542			
3			0.5689	0.5913	0.5958	0.6062	0.6181	0.6122	0.5986	0.5967	0.5734		
4		0.5594	0.5890	0.5927	0.6021	0.6112	0.6020	0.6104	0.6000	0.6008	0.5880	0.5731	
5		0.5709	0.5974	0.6030	0.5998	0.6089	0.6012	0.6081	0.6006	0.6015	0.6043	0.5850	
6	0.5359	0.5745	0.5994	0.6017	0.6060	0.6077	0.6132	0.6060	0.6013	0.6022	0.6065	0.6033	
7	0.5548	0.5865	0.5987	0.5976	0.5985	0.5078	0.6094	0.5992	0.6011	0.6085	0.6116	0.5941	0.5789
8	0.5652	0.5965	0.6030	0.5983	0.5992	0.6173	0.6141	0.6082	0.6137	0.6110	0.6130	0.5990	0.5846
9	0.5712	0.5972	0.6041	0.5980	0.5998	0.6148	0.6261	0.6164	0.6097	0.6113	0.6070	0.6079	0.5904
10	0.5520	0.5861	0.5961	0.6026	0.6188	0.6110	0.6107	0.6127	0.6090	0.6071	0.6026	0.5961	
11		0.5908	0.6072	0.6097	0.6076	0.6168	0.6043	0.6030	0.6033	0.6059	0.6065	0.6003	
12		0.5810	0.5991	0.6078	0.6088	0.6060	0.6087	0.6045	0.6054	0.6034	0.6077	0.5895	
13			0.5897	0.6046	0.6082	0.5977	0.6136	0.6052	0.6061	0.6014	0.5988		
14				0.5880	0.5867	0.6022	0.5958	0.6059	0.6068	0.5963			
15					0.5840	0.5775	0.5877	0.5949	0.5824				

Fig. 3(b). Measured Threshold Voltage for 131 Dies, SVM predicted shown in yellow color. W/L = 10/10.

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13
1					0.0	0.0	0.0	0.0	0.0				
2				0.0	0.0	0.0	0.0	0.0	0.0	0.0			
3			0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
4		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.7	0.2	0.0	0.0
5		0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.1	-1.6	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-1.0	0.0	0.0	0.0
7	0.0	0.0	0.0	-0.6	-1.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	-1.3	-2.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	-2.0	-1.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.0	0.0	0.0
11		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
12		0.0	0.0	0.0	0.0	0.0	0.0	-2.8	-0.8	0.0	0.0	0.0	0.0
13			0.0	0.0	0.0	0.0	0.0	0.4	0.8	0.0	0.0		
14				0.0	0.0	0.0	0.0	1.5	1.5	0.0			
15					0.0	0.0	0.0	0.0	0.0				

Fig. 3(c) Percentage Difference for Threshold Voltage: Predicted SVM vs. Measured, W/L = 10/10.

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13
1					0.9834	0.8987	0.8715	0.8974	1.0000				
2				0.8843	0.8643	0.8485	0.8236	0.8552	0.8986	0.9260			
3			0.9019	0.8444	0.8387	0.8284	0.8162	0.8223	0.8415	0.8399	0.8861		
4		0.8287	0.8512	0.8452	0.8244	0.8245	0.8351	0.8295	0.8159	0.8360	0.8645	0.8957	
5		0.8925	0.8493	0.8250	0.8322	0.8204	0.8239	0.8225	0.8263	0.8183	0.8223	0.8650	
6	0.9687	0.8714	0.8316	0.8329	0.8261	0.8151	0.8198	0.8217	0.8316	0.8132	0.8105	0.8341	
7	0.9193	0.8456	0.8341	0.8362	0.8231	0.8143	0.8105	0.8073	0.8318	0.8110	0.8057	0.8428	0.8953
8	0.9003	0.8397	0.8311	0.8162	0.8177	0.8169	0.8260	0.8092	0.8159	0.8138	0.8084	0.8397	0.8661
9	0.8878	0.8482	0.8306	0.8237	0.8205	0.8145	0.7940	0.8086	0.8284	0.8186	0.8138	0.8089	0.8512
10	0.9348	0.8709	0.8416	0.8300	0.8213	0.8094	0.8038	0.8110	0.8098	0.8092	0.8122	0.8300	
11		0.8482	0.8244	0.8221	0.8193	0.8158	0.8527	0.8225	0.8193	0.8046	0.8129	0.8166	
12		0.8798	0.8498	0.8217	0.8244	0.8210	0.8153	0.8022	0.8125	0.8177	0.8126	0.8552	
13			0.8471	0.8439	0.8384	0.8405	0.8188	0.8098	0.8301	0.8185	0.8189		
14				0.8469	0.8324	0.8287	0.8404	0.8308	0.8108	0.8185			
15					0.8896	0.8645	0.8279	0.8305	0.8536				

Fig. 4(a). Measured Saturation Current for 149 Dies, W/L = 10/10.

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13
1					0.9834	0.9887	0.8715	0.8974	1.0000				
2				0.8843	0.8643	0.8485	0.8236	0.8552	0.8698	0.9280			
3			0.9019	0.8444	0.8387	0.8284	0.8162	0.8223	0.8415	0.8399	0.8861		
4		0.9287	0.8512	0.8452	0.8244	0.8245	0.8351	0.8265	0.8288	0.8258	0.8545	0.8957	
5		0.8925	0.8493	0.8250	0.8322	0.8204	0.8239	0.8225	0.8277	0.8246	0.8223	0.8650	
6	0.9687	0.8714	0.8316	0.8329	0.8261	0.8151	0.8198	0.8217	0.8264	0.8233	0.8105	0.8341	
7	0.8193	0.8456	0.8341	0.8406	0.8375	0.8143	0.8105	0.8073	0.8219	0.8110	0.8057	0.8428	0.8853
8	0.8003	0.8367	0.8311	0.8393	0.8363	0.8169	0.8260	0.8092	0.8159	0.8138	0.8084	0.8397	0.8881
9	0.8876	0.8482	0.8306	0.8381	0.8350	0.8145	0.7940	0.8086	0.8284	0.8196	0.8138	0.8089	0.8512
10	0.9348	0.8708	0.8416	0.8300	0.8213	0.8094	0.8038	0.8110	0.8098	0.8092	0.8122	0.8300	
11		0.8482	0.8244	0.8221	0.8193	0.8158	0.8527	0.8225	0.8193	0.8046	0.8129	0.8166	
12		0.8798	0.8498	0.8217	0.8244	0.8210	0.8153	0.8220	0.8189	0.8177	0.8126	0.8552	
13			0.8471	0.8439	0.8394	0.8405	0.8198	0.8207	0.8176	0.8185	0.8169		
14				0.8469	0.8324	0.8287	0.8404	0.8195	0.8164	0.8185			
15					0.8596	0.8645	0.8279	0.8305	0.8536				

Fig. 4(b). Measured Saturation Current for 131 Die, SVM predicted shown in yellow color, W/L = 10/10.

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13
1					0.0	0.0	0.0	0.0	0.0				
2					0.0	0.0	0.0	0.0	0.0	0.0			
3			0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0		
4		0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.8	-1.2	0.0	0.0	
5		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.8	0.0	0.0	
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.6	1.2	0.0	0.0	
7	0.0	0.0	0.0	0.5	1.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	2.8	2.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	1.7	1.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
12		0.0	0.0	0.0	0.0	0.0	0.0	2.9	0.8	0.0	0.0	0.0	0.0
13			0.0	0.0	0.0	0.0	0.0	1.3	-1.5	0.0	0.0	0.0	0.0
14				0.0	0.0	0.0	0.0	-1.4	0.7	0.0			
15					0.0	0.0	0.0	0.0	0.0				

Fig. 4(c). Percentage Difference for Saturation Current: Predicted SVM vs. Measured, W/L = 10/10.

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13
1					0.4270	0.5962	0.5972	0.5966	0.5951				
2				0.5912	0.5945	0.5971	0.5966	0.5967	0.5985	0.5958			
3			0.5885	0.5895	0.5897	0.5909	0.5920	0.5949	0.5951	0.5949	0.5958		
4		0.5895	0.5875	0.5896	0.5875	0.5909	0.5915	0.5906	0.5921	0.5951	0.5969	0.5981	
5		0.5869	0.5892	0.5889	0.5896	0.5925	0.5911	0.5909	0.5895	0.5945	0.5945	0.5968	
6	0.5928	0.5896	0.5880	0.5920	0.5891	0.5909	0.5905	0.5922	0.5916	0.5932	0.5928	0.5953	
7	0.5924	0.5926	0.5927	0.5932	0.5940	0.5932	0.5926	0.5912	0.5899	0.5908	0.5907	0.5947	0.5980
8	0.5922	0.5915	0.5976	0.5936	0.5927	0.5844	0.5933	0.5917	0.5895	0.5911	0.5912	0.5916	0.5981
9	0.5940	0.5945	0.5937	0.5965	0.5938	0.5938	0.5953	0.5957	0.5925	0.5912	0.5938	0.5924	0.5976
10	0.5968	0.5940	0.5952	0.5952	0.5934	0.5878	0.5959	0.5949	0.5922	0.5929	0.5899	0.5933	
11		0.5961	0.5948	0.5869	0.5958	0.5966	0.5951	0.5925	0.5933	0.5912	0.5933	0.5958	
12		0.5984	0.5963	0.5962	0.5967	0.5958	0.5946	0.5929	0.5910	0.5939	0.5940	0.5964	
13			0.5983	0.5961	0.5967	0.5859	0.5942	0.5950	0.5948	0.5937	0.5951		
14				0.5979	0.5967	0.5944	0.5953	0.5953	0.5950	0.5941			
15					0.5964	0.5964	0.5956	0.5956	0.5965				

Fig. 5(a). Measured Threshold Voltage for 149 Die, W/L = 10/10.

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13
1					0.4270	0.5962	0.5972	0.5966	0.5951				
2				0.5912	0.5945	0.5971	0.5966	0.5967	0.5985	0.5958			
3			0.5885	0.5895	0.5897	0.5909	0.5920	0.5949	0.5951	0.5949	0.5958		
4		0.5895	0.5875	0.5896	0.5875	0.5909	0.5915	0.5906	0.5921	0.5951	0.5969	0.5981	
5		0.5869	0.5892	0.5889	0.5896	0.5925	0.5911	0.5909	0.5895	0.5945	0.5945	0.5968	
6	0.5918	0.5920	0.5921	0.5923	0.5925	0.5926	0.5928	0.5929	0.5931	0.5932	0.5934	0.5935	
7	0.5920	0.5921	0.5923	0.5925	0.5926	0.5928	0.5929	0.5931	0.5932	0.5934	0.5935	0.5937	0.5938
8	0.5921	0.5923	0.5925	0.5926	0.5928	0.5929	0.5931	0.5932	0.5934	0.5935	0.5937	0.5938	0.5940
9	0.5923	0.5924	0.5926	0.5928	0.5929	0.5931	0.5932	0.5934	0.5935	0.5937	0.5938	0.5940	0.5941
10	0.5924	0.5926	0.5928	0.5929	0.5931	0.5932	0.5934	0.5935	0.5937	0.5938	0.5940	0.5941	
11		0.5928	0.5929	0.5931	0.5932	0.5934	0.5935	0.5937	0.5938	0.5940	0.5941	0.5943	
12		0.5929	0.5931	0.5932	0.5934	0.5935	0.5937	0.5938	0.5940	0.5941	0.5943	0.5944	
13			0.5932	0.5934	0.5935	0.5937	0.5938	0.5940	0.5941	0.5943	0.5944		
14				0.5935	0.5937	0.5938	0.5940	0.5941	0.5943	0.5944			
15					0.5938	0.5940	0.5941	0.5943	0.5944				

Fig. 5(b). One wafer and 43 Dies used as Training Data, 106 Dies used for SVM Prediction (in yellow color), W/L = 10/10.

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13
1					0.0	0.0	0.0	0.0	0.0				
2					0.0	0.0	0.0	0.0	0.0				
3			0.0		0.0	0.0	0.0	0.0	0.0	0.0			
4		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
5		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
6	-0.2	0.4	0.7	0.1	0.6	0.3	0.4	0.1	0.3	0.0	0.1	-0.3	
7	-0.1	-0.1	-0.1	-0.1	-0.2	-0.1	0.0	0.3	0.6	0.4	0.5	-0.2	-0.7
8	0.0	0.1	-0.9	-0.2	0.0	-0.2	0.0	0.2	0.7	0.4	0.4	0.4	-0.7
9	-0.3	-0.4	-0.2	-0.6	-0.2	-0.1	-0.4	-0.4	0.2	0.4	0.0	0.3	-0.6
10	-0.7	-0.2	-0.4	-0.4	0.0	-0.8	-0.4	-0.2	0.3	0.2	0.7	0.1	
11		-0.6	-0.3	-0.6	-0.4	-0.5	-0.4	0.2	0.1	0.5	0.1	-0.3	
12		-0.9	-0.5	-0.5	-0.6	-0.4	-0.1	0.2	0.5	0.0	0.1	-0.3	
13			-0.8	-0.8	-0.5	-0.4	-0.1	-0.2	-0.1	0.1	-0.1		
14				-0.7	-0.5	-0.1	-0.2	-0.2	-0.1	0.1			
15					-0.4	-0.4	-0.2	-0.2	-0.3				

Fig. 5(c). Percentage Difference for Threshold Voltage: Predicted SVM vs. Measured, W/L = 10/10.

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13				
1					2.97E+15	1.33E-02	1.32E-02	1.33E-02	1.32E-02								
2					1.36E-02	1.37E-02	1.36E-02	1.36E-02	1.35E-02	1.34E-02	1.31E-02						
3					1.38E-02	1.40E-02	1.40E-02	1.40E-02	1.38E-02	1.37E-02	1.32E-02	1.31E-02					
4					1.34E-02	1.38E-02	1.42E-02	1.44E-02	1.44E-02	1.43E-02	1.41E-02	1.37E-02	1.29E-02				
5					1.38E-02	1.40E-02	1.43E-02	1.46E-02	1.49E-02	1.48E-02	1.45E-02	1.41E-02	1.36E-02	1.32E-02			
6					1.34E-02	1.37E-02	1.42E-02	1.46E-02	1.50E-02	1.52E-02	1.52E-02	1.51E-02	1.49E-02	1.44E-02	1.39E-02	1.32E-02	
7					1.34E-02	1.39E-02	1.42E-02	1.47E-02	1.51E-02	1.52E-02	1.52E-02	1.51E-02	1.48E-02	1.40E-02	1.35E-02	1.29E-02	
8					1.36E-02	1.39E-02	1.42E-02	1.48E-02	1.52E-02	1.51E-02	1.52E-02	1.51E-02	1.51E-02	1.47E-02	1.41E-02	1.36E-02	1.30E-02
9					1.35E-02	1.38E-02	1.42E-02	1.47E-02	1.52E-02	1.51E-02	1.51E-02	1.51E-02	1.51E-02	1.47E-02	1.41E-02	1.35E-02	1.31E-02
10					1.32E-02	1.35E-02	1.41E-02	1.48E-02	1.50E-02	1.51E-02	1.51E-02	1.51E-02	1.50E-02	1.45E-02	1.40E-02	1.33E-02	
11					1.36E-02	1.39E-02	1.43E-02	1.47E-02	1.50E-02	1.51E-02	1.50E-02	1.47E-02	1.43E-02	1.38E-02	1.33E-02		
12					1.34E-02	1.37E-02	1.40E-02	1.43E-02	1.46E-02	1.47E-02	1.46E-02	1.43E-02	1.40E-02	1.36E-02	1.32E-02		
13						1.33E-02	1.37E-02	1.38E-02	1.41E-02	1.42E-02	1.42E-02	1.40E-02	1.37E-02	1.33E-02			
14							1.34E-02	1.36E-02	1.38E-02	1.39E-02	1.38E-02	1.36E-02	1.34E-02				
15								1.33E-02	1.34E-02	1.35E-02	1.34E-02	1.34E-02					

Fig. 6(a). Measured Saturation Current for 149 Die, W/L = 10/10.

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13		
1					2.97E+15	1.33E-02	1.32E-02	1.33E-02	1.32E-02						
2					1.36E-02	1.37E-02	1.36E-02	1.36E-02	1.35E-02	1.34E-02	1.31E-02				
3					1.38E-02	1.40E-02	1.40E-02	1.40E-02	1.38E-02	1.37E-02	1.32E-02	1.31E-02			
4					1.34E-02	1.38E-02	1.42E-02	1.44E-02	1.44E-02	1.43E-02	1.41E-02	1.37E-02	1.29E-02		
5					1.38E-02	1.40E-02	1.43E-02	1.46E-02	1.49E-02	1.48E-02	1.45E-02	1.41E-02	1.36E-02	1.32E-02	
6					1.39E-02	1.39E-02	1.39E-02	1.39E-02	1.38E-02	1.38E-02	1.38E-02	1.37E-02	1.37E-02	1.37E-02	
7					1.40E-02	1.39E-02	1.39E-02	1.39E-02	1.38E-02	1.38E-02	1.38E-02	1.38E-02	1.37E-02	1.37E-02	1.37E-02
8					1.40E-02	1.40E-02	1.39E-02	1.39E-02	1.38E-02	1.38E-02	1.38E-02	1.38E-02	1.37E-02	1.37E-02	1.37E-02
9					1.40E-02	1.40E-02	1.40E-02	1.39E-02	1.39E-02	1.38E-02	1.38E-02	1.38E-02	1.38E-02	1.37E-02	1.37E-02
10					1.40E-02	1.40E-02	1.40E-02	1.40E-02	1.39E-02	1.39E-02	1.38E-02	1.38E-02	1.38E-02	1.38E-02	1.38E-02
11					1.40E-02	1.40E-02	1.40E-02	1.40E-02	1.39E-02	1.39E-02	1.39E-02	1.38E-02	1.38E-02	1.38E-02	1.38E-02
12					1.40E-02	1.40E-02	1.40E-02	1.40E-02	1.39E-02	1.39E-02	1.39E-02	1.38E-02	1.38E-02	1.38E-02	1.38E-02
13					1.40E-02	1.40E-02	1.40E-02	1.40E-02	1.39E-02	1.39E-02	1.39E-02	1.39E-02	1.38E-02	1.38E-02	1.38E-02
14					1.40E-02	1.40E-02	1.40E-02	1.40E-02	1.39E-02	1.39E-02	1.39E-02	1.39E-02	1.38E-02	1.38E-02	1.38E-02
15					1.40E-02	1.40E-02	1.40E-02	1.40E-02	1.39E-02	1.39E-02	1.39E-02	1.39E-02	1.38E-02	1.38E-02	1.38E-02

Fig. 6(b). One wafer and 43 Die used as Training Data, 106 Dies used for SVM Prediction, W/L = 10/10.

Row/Column	1	2	3	4	5	6	7	8	9	10	11	12	13
1					0.0	0.0	0.0	0.0	0.0				
2					0.0	0.0	0.0	0.0	0.0	0.0			
3			0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0		
4			0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
5			0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	4.3	1.4	-2.1	-4.7	-7.6	-9.2	-9.4	-9.0	-7.5	-4.5	-1.3	3.6	
7	4.3	0.5	-2.0	-5.5	-8.2	-9.1	-9.0	-9.1	-8.8	-5.5	-2.2	1.6	5.8
8	3.0	0.6	-2.1	-5.9	-8.6	-8.4	-8.8	-8.7	-8.6	-6.5	-2.4	0.7	5.7
9	4.2	1.1	-2.0	-5.4	-8.4	-8.3	-8.3	-8.3	-8.5	-6.3	-2.7	1.6	4.6
10	5.9	3.4	-1.0	-4.1	-7.2	-8.0	-8.2	-8.3	-7.9	-5.0	-1.6	3.5	
11		2.8	0.4	-2.2	-5.3	-7.3	-7.8	-7.4	-5.9	-3.2	0.0	3.3	
12		4.9	2.6	0.3	-2.5	-4.2	-5.3	-4.9	-3.3	-0.8	1.6	4.7	
13			5.3	2.6	0.4	-1.2	-2.0	-1.7	-0.5	1.5	4.1		
14				4.7	2.7	1.2	0.5	0.7	2.0	3.7			
15					5.4	4.2	3.5	4.1	4.2				

Fig. 6(c). Percentage Difference for Saturation Current: Predicted SVM vs. Measured, W/L = 10/10.

0.22/0.18 to understand how SVM would handle prediction across different dimensions. Multiple training data files were needed for each dimension to produce the results in Fig. 5(a), 5(b), 5(c), 6(a), 6(b), 6(c). In all cases, the SVM predicts values within 10 % of the actual measured data.

4. Discussions

From all experiments in this work, it has been observed that the SVM can predict electrical data very accurately within a single die. Within a wafer, the SVM can produce electrical data with 90 % accuracy. Using all data from the first wafer and 30 % data of the second wafer, the SVM can predict the electrical data, i.e., threshold voltages and saturation currents of the remaining 70 % of the second wafer with 90 % accuracy. This means that there is a potential to reduce the wafer testing time by 35 %.

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