## Chips Making Chips:

How Virtualization, Digital Twins and Machine Learning are Accelerating the Spiral of Innovation

David M. Fried Corporate Vice President – Semiverse<sup>™</sup> Solutions

Presented at MES & Industry 4.0 Summit, September 7, 2023





### Lam Research at a glance



#### A leader in wafer fabrication equipment and services since 1980

Global R&D, engineering, manufacturing, customer support and supply chain

~18,700 employees





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Time



### Grand Challenges: Let's Create our own Future



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#### Welcome to 2030 – The Era of Smart Tools and Smart Fabs

#### Smart tools are ubiquitous

#### Fab output has achieved unprecedented profitability

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# Equipment Intelligence ® Platform

**Transforming Production** 



### What is intelligence?



- Self-aware
- Self-maintained
  - Self-adaptive



#### What paces the development of self-awareness?



Self-aware tools *know* what parts are inside and the properties of those parts past and present

Challenges:

- All-digital supply chain
- End-to-end and point-to-point data transfers
- Standards
- IP



### Self-Aware, Self-Maintained...



#### Auto Positioning System



What Paces the Development of Self-Maintenance?

Self-maintained tools know when maintenance is required and *perform* maintenance automatically

**Self-Maintained** 

Challenges:

- Tool architectures
- Fab infrastructure
- Fab-tool co-design
- Standards



### Self-Aware, Self-Maintained, and Self-Adaptive



Machine learning on LSR-FM improved depth variability to  $\pm 1\%$ 



#### What Paces the Development of Adaptability?

Adaptive tools adjust themselves to compensate for unit process and incoming material variation to maintain consistent yield

Challenges:

- Data flow across unit modules
- Algorithms
- Standards

■ IP

Adaptive



#### Equipment Intelligence<sup>®</sup> Solutions Are More Than Just a Smart Tool

#### A new industry mindset is required

The semiconductor eco-system has to respond collaboratively

- All-digital supply chain
- End-to-end and point-to-point data transfer
- Co-design of fab and tool
- Big data and algorithms
- Standards and IP

Collaborative response must deliver equitable returns



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### Semiverse<sup>TM</sup> Solutions





#### **Digital Twin and Thread:**

Virtual representation of real asset including associated data and processes of record for all parts in the system



### Digital twin and thread enables:

#### **Virtual Build:**

Digital design for manufacturability and serviceability





### Digital twin and thread enables:

#### VR/AR-Led Training and Installation: Step-by-step instructions for system installs and post- installation service





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### Virtual Process Development

Transforming R&D



#### We develop the processes that make the chips





### How much data from a semiconductor fab?

- Example: Fleet running at high capacity
- Fleet Size 200 chambers
- Sensors 100 / chamber
- Frequency 5 Hz

Depending on the nature and complexity of the process 100 million feature data points per day

5 to 10 billion raw data points per day

For each single wafer process run, there could be as many as 5,000 features extracted





### Moore's Law and "Lam's Law"



Engineers must choose from many recipe combinations with little data available. The number of recipe combinations expected by 2030 will approach the number of silicon atoms in a computer chip

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### Yet we still do process engineering the "old" way...

#### Customer asks for Spec



#### Human process engineering

- Make hypothesis
- Choose recipes
- Run experiments

- Prep for metrology Image collection
- Data analysis



REPEAT

Spec is met





### Why can't we design a process like we design a chip?



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#### Consider memory hole etch in 3D NAND



Memory cell

#### SEM of 3D NAND Samsung 92L, 256Gb, TLC, Tech Insights

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Let's play a "game" to benchmark different AI (and human) approaches to developing an Etch Process Recipe



#### Virtual Environment for High Aspect Ratio Etch



**Cost structure:** \$1,000/recipe + \$1,000/batch of recipes **Added variability:** none

**Goal of game:** Lowest cost-to-target recipe

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#### Undirected Machines are No Match for Expert Process Engineers



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#### Human expert advantage occurs early in development

#### Expert trajectory



#### Fine-tuning stage



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Baseline from
experience

- Move rapidly towards spec
- Domain knowledge: macro trends, physics principles and models, tribal knowledge, previous trends

• Very close to spec

- Hyper-sensitive, physics seems to break down
- Smaller changes, smaller dynamic range
- Can take >50% of demo for engineer

#### Transfer point "A": Computer improves but not enough

#### **Expert Results – Without ML** Attempt 2 Attempt 1 1.0 1.0 1.0 Expert . . . . Progress tracker (A. I.) Algorithm 0.8 Transfer Point A 0.8 0.6 Progress tracker (A. I.) Transfer from here 0.4 has 42% ML trial 0.6 0.2 success rate: ML cannot consistently 0.0 50 150 200 100 50 100 n 0.4 beat expert's total Cumulative cost (\$K) Cumulative cost (\$K) 1.0 1.0 development cost Attempt 5 Attempt 4 Progress tracker (A. I.) Distance-to-target 0.2 0.0 100 120 20 60 80 0 Development Cost (\$K)

0.0<sup>⊥</sup>0

50

100

Cumulative cost (\$K)

150

200

#### Machine Learning Trials – Cost to Target (6 attempts shown)

Attempt 3

1.0

0.0<sup>⊥</sup>0

1.0

-to-target 0.0 8.0

Distance-1 5'0

0.0∔ 0

50

100

Cumulative cost (\$K)

150

200

50

100

Cumulative cost (\$K)

150

Attempt 6

200

150

0.0<sup>⊥</sup>0

50

100

Cumulative cost (\$K)

150

200

200

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#### Transfer point "C": Human First, Computer Last Lowers Cost

**Expert Results – Without ML** 



Machine Learning Trials – Cost to Target (6 attempts shown)

#### Optimal transfer point not too soon or too late (circled area)

#### **Experimental V-curve**



#### Schematic of V-curve



Amount of expert data  $\rightarrow$ 

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Embrace human machine collaboration: Humans for creative work and machines for repetition and tedious work



### Human–Machine Collaboration for Improving Semiconductor Process Development

Nature 616, 707 (2023)

Keren J. Kanarik, Wojciech T. Osowiecki, Yu (Joe) Lu, Dipongkar Talukder,

Niklas Roschewsky, Sae Na Park, Mattan Kamon, David M. Fried, Richard A. Gottscho

Scan with your phone for link to paper:





### Semiverse<sup>™</sup> Solutions for <u>10,000x lower cost</u>

Virtualization *leverages* (not replaces!) investment in physical assets and real experiments

Virtual experimentation saves time, money, and resources (per recipe)

- Real experiments \$1,000, 0.5 days
- Simulated experiments \$0.11, 8 minutes
- Emulated simulations \$3e-07, 0.0013 seconds

Virtual experimentation can be ubiquitous and an effective workforce training tool

#### **Barriers**

Business model

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- Some invention required
- Data sharing/ownership concerns



Virtual process:

fab:

#### Conclusions

The R&D little data problem requires maximum leveraging of information from real experiments

Models don't have to be accurate to be useful. They do need to be *realistic*.

The virtual environment can be used in workforce development

- Challenge problems
- Built-in analytics

The virtual environment enables speed to solution

The virtual environment reduces costs

Virtual process development – no panacea, but close!



We see ourselves in a virtuous, accelerating spiral of innovation













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