



Simulation based approach to calculate utilization limits in opto semiconductor frontends

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Agenda

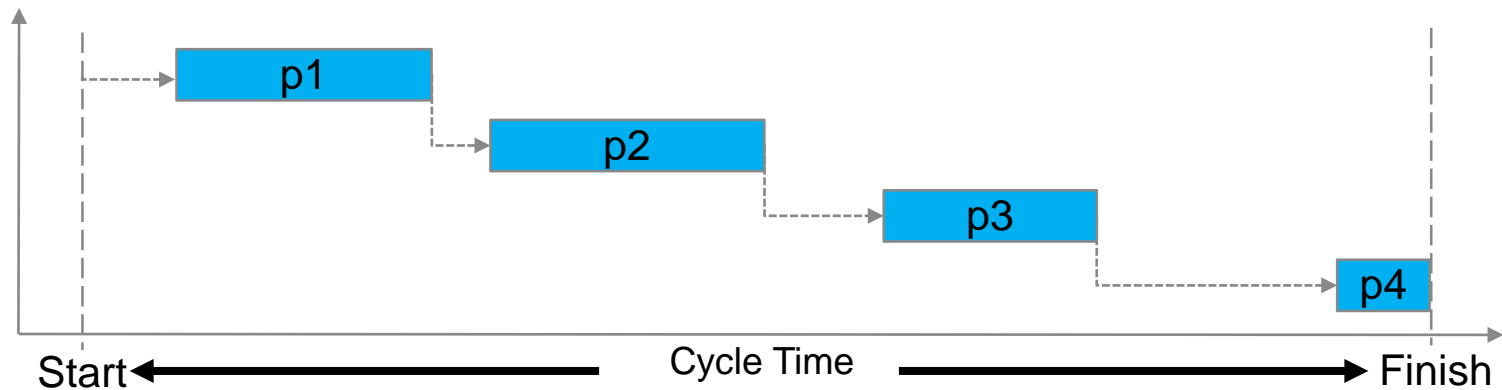
1. Project and motivation

2. Data farming based machine learning

1. System overview
2. Factors
3. Data farming
4. Training
5. Where are we today?

3. Outlook

Some introductions



$$\text{Raw Processing Time} = p1 + p2 + p3 + p4$$

$$\text{Flow Factor} = \frac{\text{Cycle Time}}{\text{Raw Processing Time}}$$

Flow factor is a performance measure which reflects how much time material is spending waiting with regard to its actual processing time.

Motivation

Equipment utilization limits



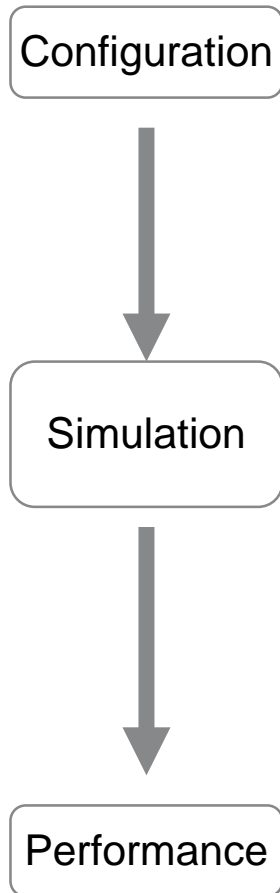
For static capacity planning it is necessary to know about maximal utilization limits for each equipment.

Estimating maximal „planned utilization limits“ to reach target flow factor.

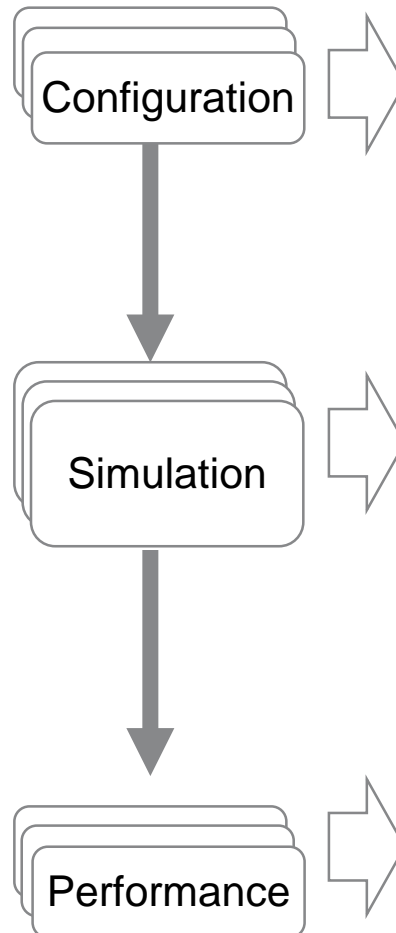
Changing approach from experience and guesswork to data based planning

System overview

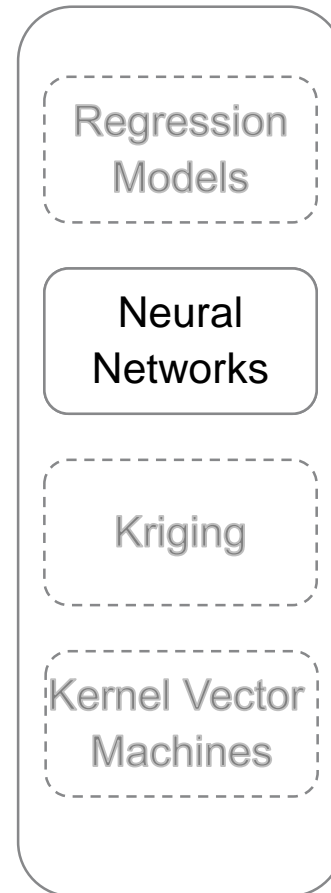
Challenge



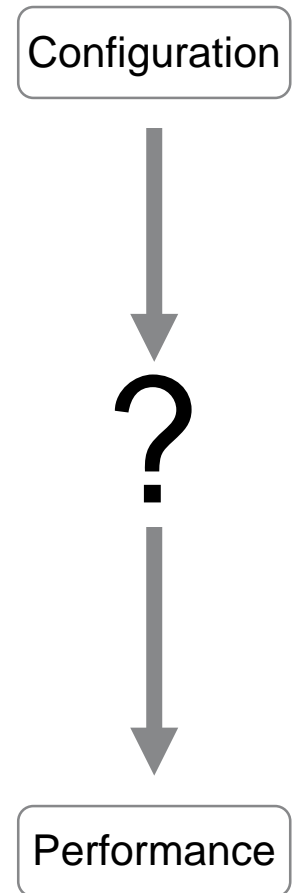
Data Farming



Machine Learning



Application



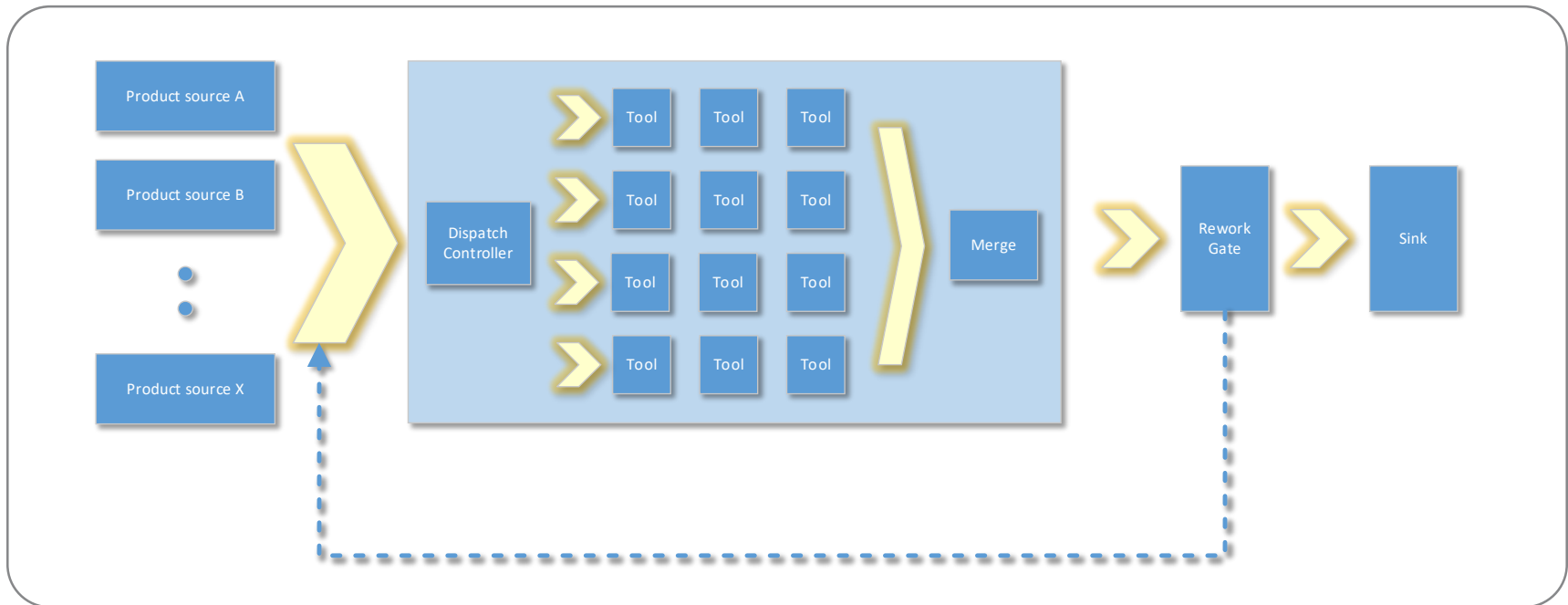
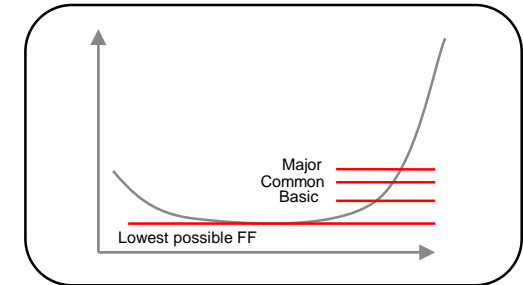
Data Farming: Configuration

Factor	# Levels	Level Type
Number of Equipment	7	quantitative
Dedication	3	categorical
Batching	7	categorical
Product Mix	3	categorical
Breakdown	3	quantitative
Maintenance	3	quantitative
Processing Times	6	quantitative
Rework	3	quantitative
Setup	3	quantitative

All factors total in
214326 supporting points

Data Farming: Simulation

- Parameterized workcenters at different utilization levels
- Models for all scenarios automatically generated
- Determined 4 flow factor targets each
- Single run between few ms and a few hours
- 4 weeks of simulation time on high performance cluster



Data Farming: Validation

Queuing model with 5 servers: M/M/5

Service: $\mu = 80$ wafer/day
Arrivals: $\lambda = 368$ wafer/day } UUM = 92%

Results:

9.28 wafers in queue

0.0125 days service time

0.0377 days average time spent in system

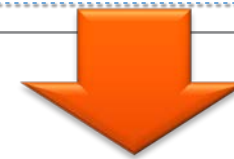
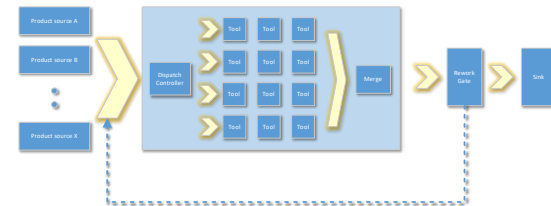
0.0252 days waiting time / wafer



$$FF_{Theory} = \frac{0.0252}{0.0125} = 2.01$$

Simulation

Tool count = 5
No breakdowns, ...
UUM = 92%



$$UUM = 92\% \Rightarrow FF_{NN} = 2.0(*)$$

For all tested M/M/k models with $k = \{1, 2, 3, 5, 15\}$, the simulation returns nearly identical results compared to the multi server formula (Accuracy +/-1%)

Machine Learning: Neural network



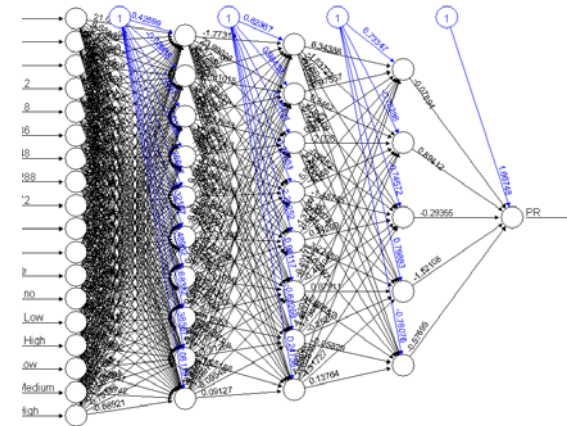
PROS

- ✓ Easy to implement
- ✓ Applicable for interpolation
- ✓ Measurable error during training

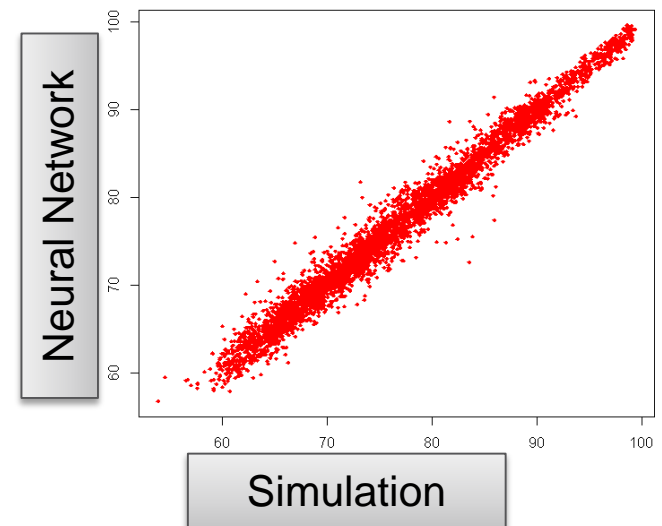


CONS

- ✗ Black box
- ✗ Long training phase

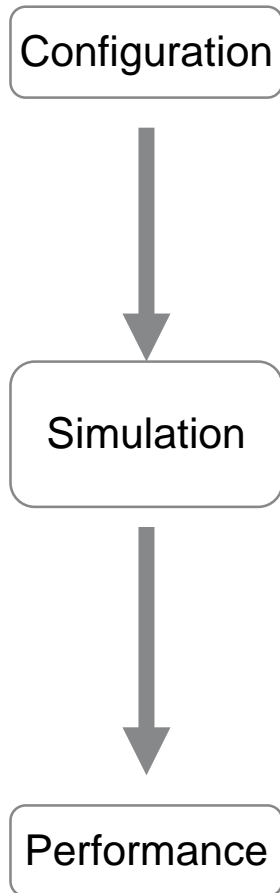


Real vs predicted NN

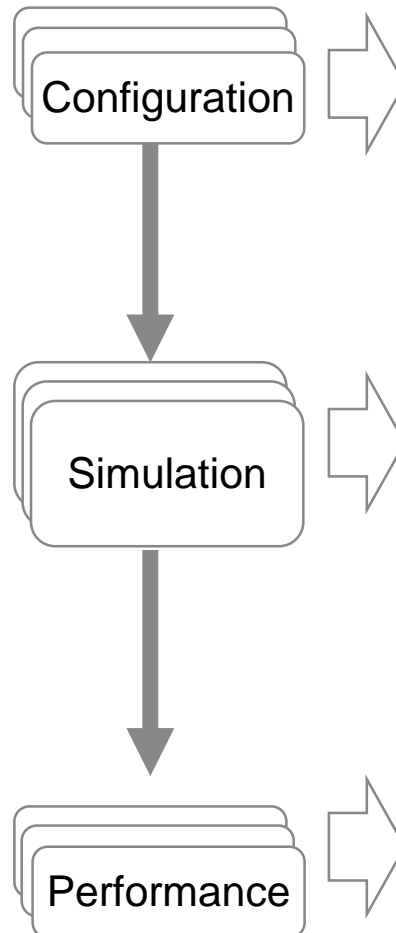


Where do we stand now?

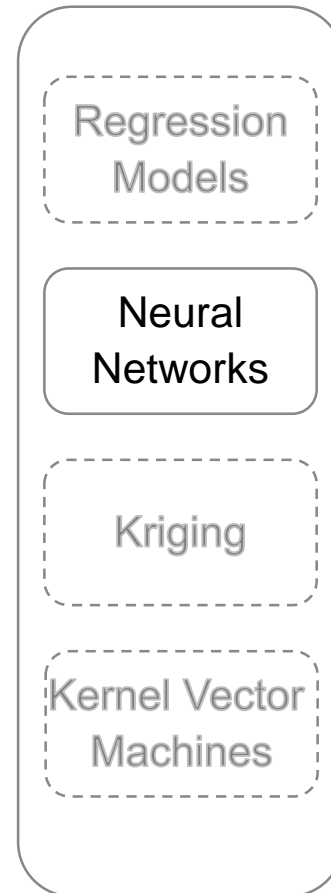
Challenge



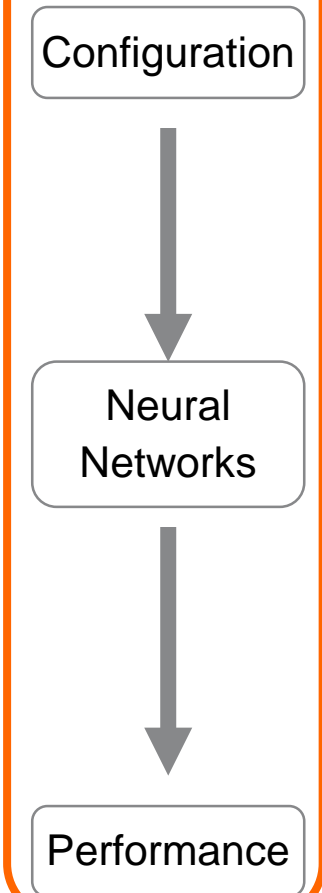
Data Farming



Machine Learning



Application



Where do we stand now?

new	old
85.00%	84.00%
85.00%	84.00%
85.00%	75.00%
91.00%	80.00%
89.00%	82.00%
91.00%	82.00%
86.00%	80.00%
90.00%	85.00%
70.00%	85.00%
77.00%	80.00%
84.00%	81.00%
78.00%	78.00%
75.00%	70.00%
83.00%	84.00%
80.00%	78.00%
85.00%	84.00%

Is there actually this much capacity unused?

How could equipment perform much better than estimated?

Outlook

Current state and short term goals

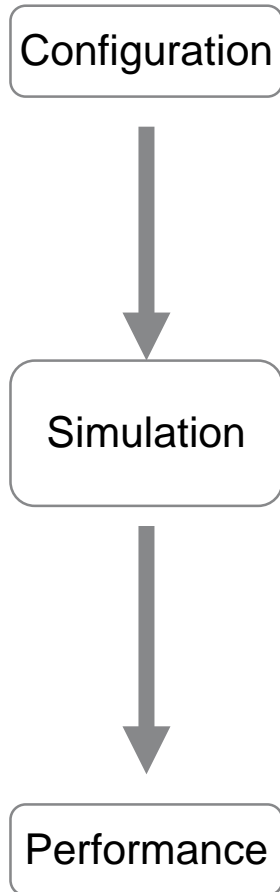
- Planned max for equipment utilization
- Systematic basis for equipment evaluation
- Where are differences between model and real equipment coming from?
- Analyzing the effect of operators
- Analysis of potentials

Mid to long term goals

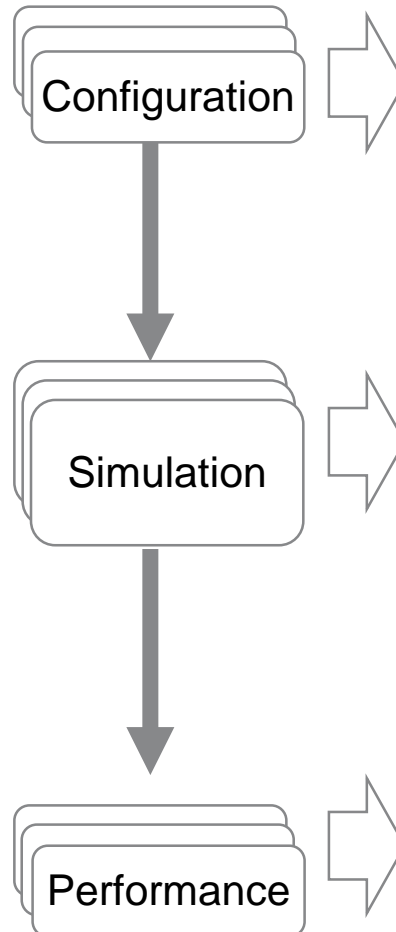
- Relevant worst case configurations
- Additional factors
- Ideal workcenter type assignment with regard to financial KPIs
- Fab wide flow factor planning based on flow factor limits

Questions?

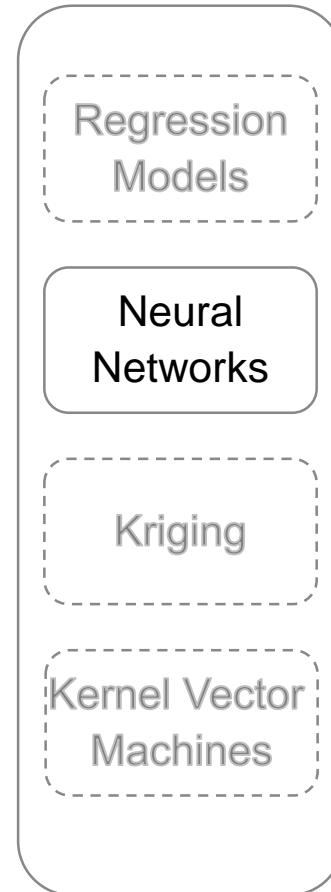
Challenge



Data Farming



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