A Robust Tolerance Optimisation Framework for Automated Optical Inspection (AOI) in Semiconductor Manufacturing

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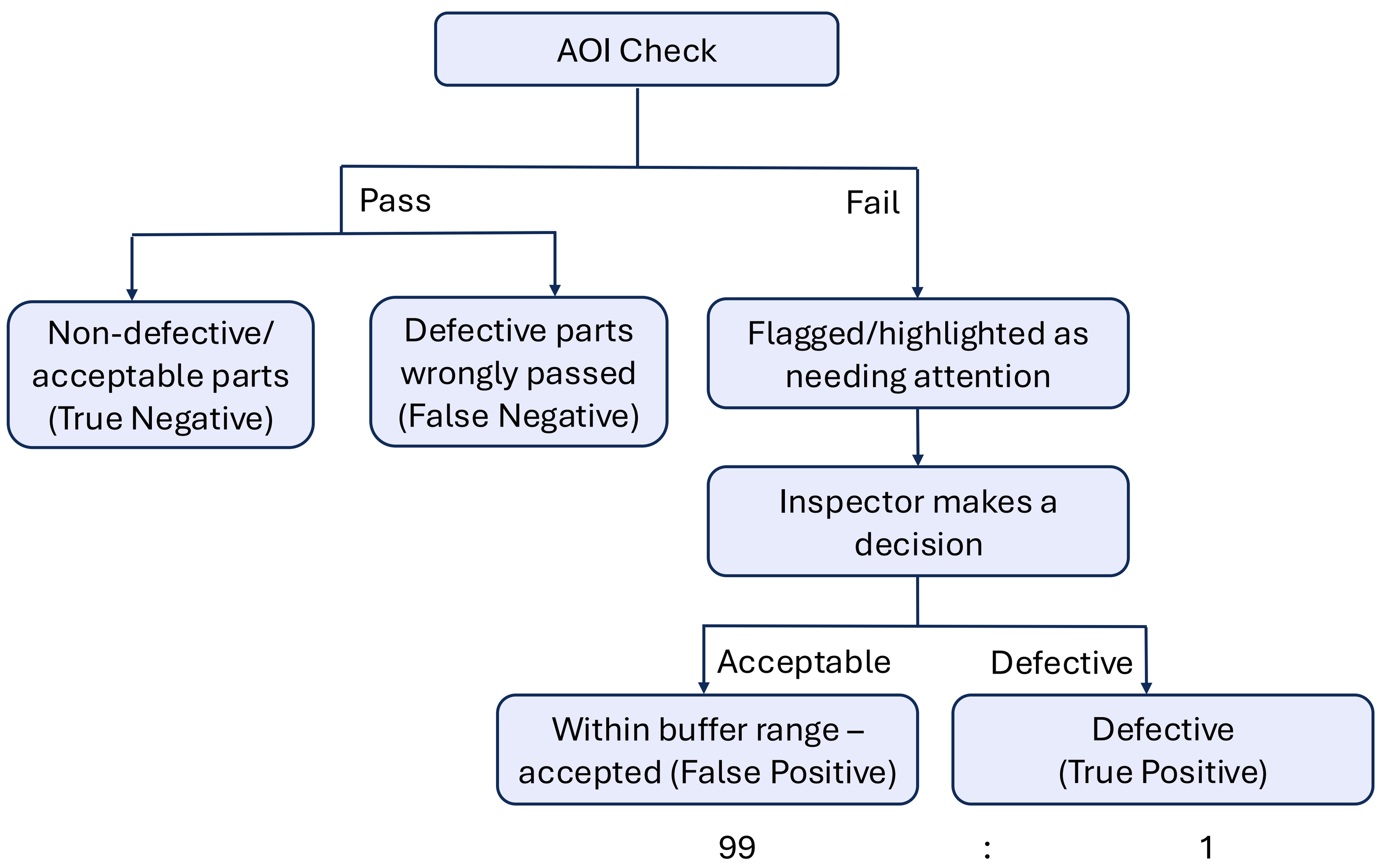
Introduction

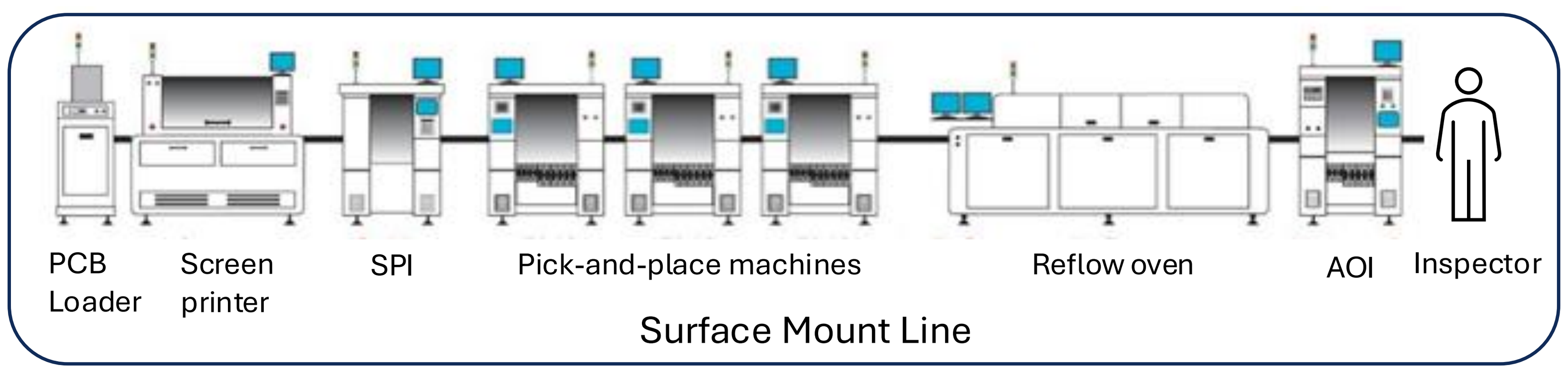
Automated Optical Inspection (AOI) systems are widely used in semiconductor manufacturing, particularly in surface mount technology (SMT) lines, to detect visual defects and ensure product quality. A critical challenge in AOI is the configuration of inspection tolerances—the thresholds that determine whether a part is classified as defective. Traditionally, these thresholds are set manually by engineers based on experience, industry standards, trial-and-error, and production context. This makes the process subjective, inconsistent, and time-consuming.

Manually tuned thresholds often result in either excessive false calls—where good parts are incorrectly flagged as defective—or missed defects that escape into downstream processes. Both outcomes lead to increased operational costs, reduced throughput, and potential quality risks.

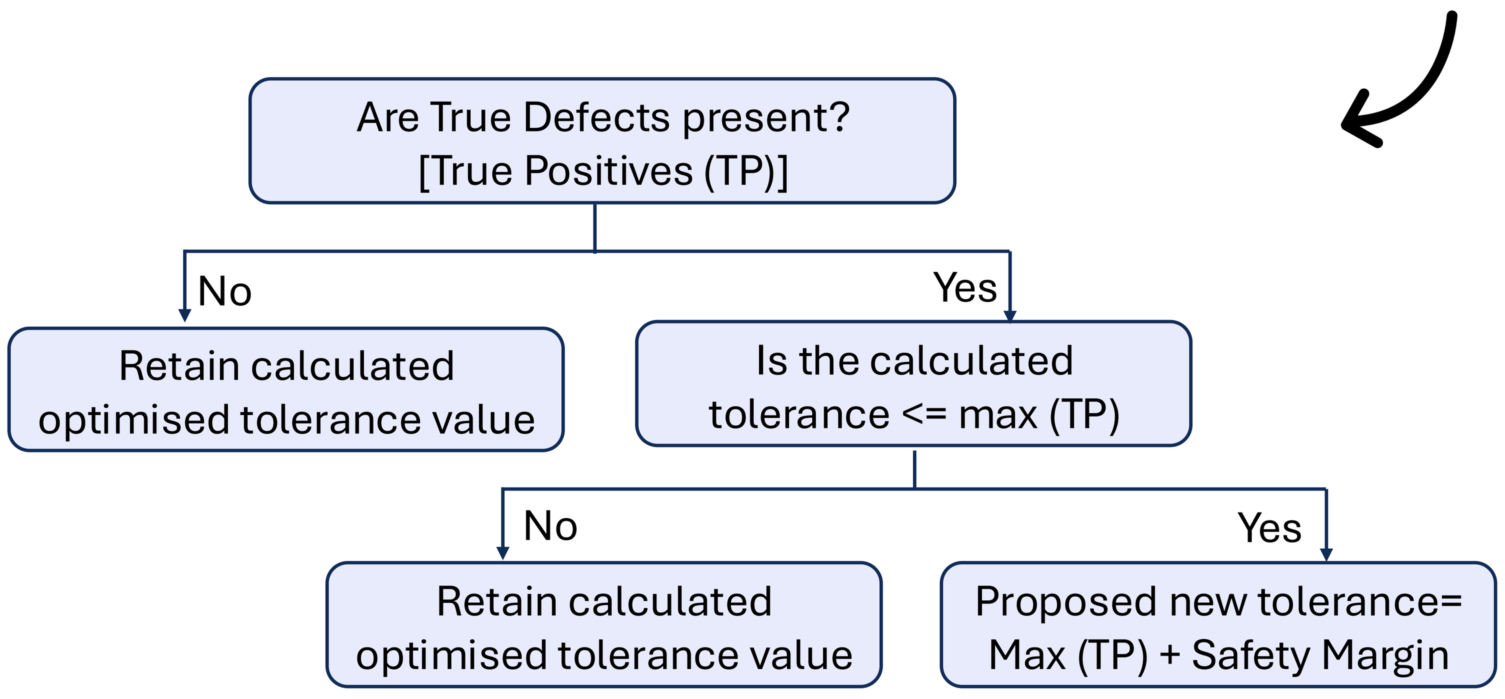
To address this, we propose an intelligent data-driven approach that leverages a digital twin of the AOI process. This virtual model enables intelligent, simulation-based optimisation of inspection thresholds. Instead of relying on intuition, thresholds are tuned using statistical and percentile-based logic, ensuring consistent performance across shifts and lines. Our goal is to eliminate manual guesswork, reduce false calls, and most importantly, maintain 100% recall of genuine defects—thereby improving the overall reliability and robustness of the inspection process.



Methodology



1. Collect only false calls such that $X = x_1, x_2, x_3, \ldots, x_n$ where 'n' is the total number of measurements
2. $X = \text{sort}(X) = \{x_i \in X \mid x_i \leq x_{i+1}, \forall i \in [1, n-1]\}$
3. $\text{Rank} = [p(n-1)/100] + 1$, where 'p' is the percentile
4. $i = \lfloor \text{Rank} \rfloor$, $d = \text{Rank} - i$,
   $\text{Percentile Value} = x_i + d\,(x_{i+1} - x_i)$
5. Check for robustness against true negatives



Results

- Proof of concept was obtained through preliminary research, using data from the solder inspections of **917 different parts.**
- Collectively, these parts exhibited **54,019 false flags** and **544 true defects**.
- Considering a percentile rank of 80, new tolerances for each part were generated, resulting in a reduction of false flags to **44,209** while retaining the **544** true defects. This corresponds to an **18%** decrease in false flags, a notable yet reliable improvement.
- **Recall** = TP/[T P + F N] **= 100%**

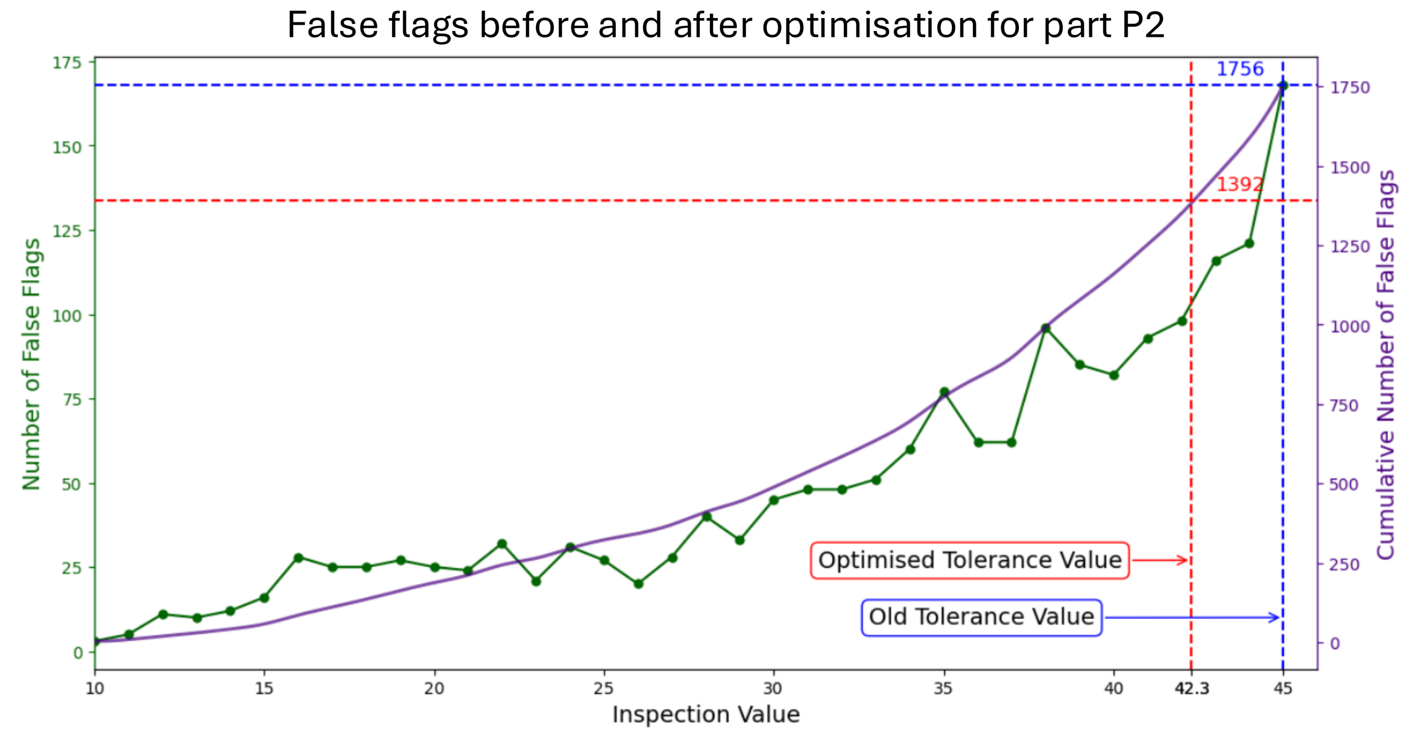
Sample Set Of Data

Model	Part Number	Current Tolerance	False Call Count	True Defect Count	Optimised Tolerance	New False call count	New True Defect Count
A	P1	42.62	2264	5	40.50	1885	5
B	P2	45.00	1756	0	42.30	1392	0
C	P3	40.00	1231	2	35.00	984	2
D	P4	30.00	1100	3	27.60	879	3
E	P5	45.00	25	27	44.20	19	27
F	P6	45.00	605	5	43.30	478	5
G	P7	25.00	13	5	23.68	10	5

Output of the Validation Process

Model	Part Number	Training True Defect Count	Validation True Defect Count	True Defects Flagged	True Defects Escaped	Validation Status
A	V1	28	13	13	0	Pass
B	V2	81	35	35	0	Pass
C	V3	18	9	9	0	Pass
D	V4	22	10	10	0	Pass
E	V5	23	11	11	0	Pass

False flags before and after optimisation for part P2



Benefits and Discussion

The implementation of our inspection tolerance optimisation method has demonstrated measurable improvements across multiple dimensions of AOI performance. In initial testing on solder inspection data, we observed an 18% reduction in false flags at the 80th percentile rank, while maintaining a 100% recall rate. This directly translates to fewer unnecessary re-inspections, reduced machine downtime, and more streamlined production lines.

By moving away from trial-and-error methods and relying instead on statistically guided thresholds, inspection processes become significantly more consistent and repeatable. This leads to faster inspection times, improved utilisation of inspection hardware, and greater confidence in results. Engineers no longer need to rely on guesswork to set tolerance values—optimal parameters are automatically surfaced through simulation, making them readily available for direct implementation.

The ability to virtually test and tune threshold values also minimises the risk associated with live adjustments on production equipment. Overall, this approach supports data-driven decision making, improves operational efficiency, and significantly reduces the time and cost involved in manual AOI tuning—benefiting both quality assurance teams and production engineers.

Conclusion

This intelligent approach to AOI tolerance optimisation uses simulation and percentile logic to reduce false calls by 18% while maintaining 100% recall. It offers a reliable, transparent alternative to manual tuning and provides a foundation for future integration into a real-time adaptive digital twin system.

This work belongs to a knowledge transfer partnership between Ulster University and Elite Electronic Systems Ltd is funded by Innovate UK Knowledge Transfer Network (KTN) and Invest Northern Ireland (Invest NI) [Project Number:10078007].

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