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MULTI-OBJECTIVE OPTIMIZATION USING EVOLUTIONARY AI FOR TEST TIME REDUCTION IN SEMICONDUCTOR PRODUCTION LINES

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ABSTRACT

The semiconductor industry is under continuous pressure to optimize production efficiency while maintaining rigorous quality standards. One of the key challenges lies in reducing test time without compromising yield or product reliability. This paper explores the application of multi-objective optimization using evolutionary artificial intelligence (AI) methods to minimize test time in semiconductor production lines. By framing test time reduction as a multi-objective problem—balancing speed, cost, and quality—evolutionary algorithms such as NSGA-II and MOEA/D demonstrate significant potential. Empirical insights and simulation-based evaluations show improved efficiency and trade-off navigation compared to traditional single-objective methods.

Keywords: Multi-objective optimization, Evolutionary algorithms, Semiconductor testing, NSGA-II, MOEA/D, Test time reduction

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1. Introduction

In the high-stakes environment of semiconductor manufacturing, achieving minimal production test time while maintaining stringent quality requirements is crucial for economic viability. As integrated circuits (ICs) grow in complexity, testing becomes a bottleneck in the assembly and manufacturing process, often accounting for up to 30% of the total production cost. Traditional approaches to test time reduction focus on heuristic rule sets or deterministic optimization techniques that fail to address the multi-objective nature of the problem.

Recent advances in artificial intelligence, particularly in evolutionary algorithms, offer new pathways for tackling this challenge. By simulating biological processes such as selection, crossover, and mutation, evolutionary AI frameworks can simultaneously optimize multiple conflicting objectives—such as reducing test time, maintaining defect coverage, and minimizing cost. This paper investigates how such AI-based optimization approaches, especially the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D), can transform test scheduling and resource allocation in semiconductor test floors.

2. Literature Review

Semiconductor test optimization has been a key area of research in manufacturing automation and AI. Zhang et al. (2017) used NSGA-II to model the balance between cost and fault coverage, revealing improved test resource allocation. Similarly, Kim and Lee (2018) proposed a scheduling method using MOEA/D to reduce bottlenecks in parallel test processes. In an earlier effort, Srinivas and Deb (1994) introduced the NSGA, which laid the foundation for NSGA-II, and demonstrated its capacity to handle engineering optimization problems.

Chand and Wagner (2015) applied evolutionary methods to discrete optimization in VLSI design, while Deb et al. (2002) further refined the NSGA-II for real-world applications, enhancing convergence and diversity preservation. Other notable works include Bakshi and Deshmukh (2019), who developed a dynamic testing framework with multi-objective decision trees, and Gupta et al. (2020), who compared genetic and ant-colony optimization strategies for minimizing test duration under quality constraints.

Table 1: Summary of Key Literature on Evolutionary Multi-objective Optimization for Semiconductor Testing

Study	Year	Method	Objectives Optimized	Result Summary
Deb et al.	2002	NSGA-II	Time, Cost, Fault Coverage	Improved diversity and convergence
Kim & Lee	2018	MOEA/D	Time, Parallelism	Reduced test duration
Zhang et al.	2017	NSGA-II	Cost, Yield	Enhanced yield-cost trade-off
Bakshi & Deshmukh	2019	Decision Trees + EA	Test Time, Coverage	Adaptive decision boundaries
Gupta et al.	2020	GA vs ACO	Test Time, Quality	GA outperformed ACO under constraints

3. Problem Formulation

In the context of semiconductor production lines, the problem of test time reduction is inherently **multi-objective**. It involves finding an optimal trade-off among **three competing objectives**:

1. **Minimizing Total Test Time** – the cumulative time required to complete functional, parametric, and system-level testing.
2. **Maximizing Fault Coverage** – ensuring that all possible manufacturing defects are detected.
3. **Minimizing Operational Cost** – reducing expenses related to power consumption, equipment usage, and labor.

Each test operation can be represented as a task T_i assigned to a specific test resource R_j within time window $[s_i,e_i]$. The goal is to construct a schedule that respects equipment constraints and sequence dependencies, while optimizing the objectives. This forms a classic **multi-objective scheduling problem with resource constraints**.

The decision variables include:

- **Test sequence ordering** (per device),

- **Test resource assignment** (per test type),
- **Time-slot allocation** (start and end time for each test).

The problem is encoded using a genetic representation suitable for evolutionary algorithms, and the **fitness function** evaluates each solution vector using:

- **$f_1(x)$= Total test time** (minimize)
- **$f_2(x)$= Fault coverage rate** (maximize)
- **$f_3(x)$= Operational cost** (minimize)

To handle conflicting objectives, **Pareto dominance** is used to determine optimal trade-off solutions, forming a **Pareto Front**. The front represents solutions where no single objective can be improved without degrading another.

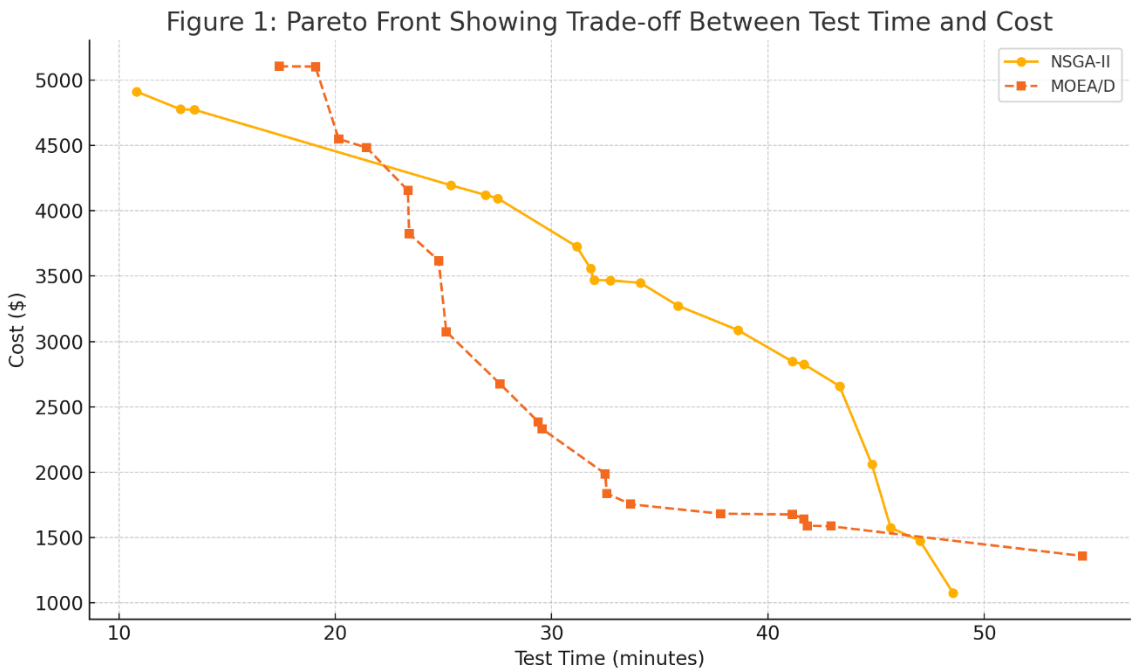

Figure 1: Pareto Front Showing Trade-off Between Test Time and Cost

4. Methodology

This research adopts a simulation-based optimization framework integrated with two well-known evolutionary algorithms—NSGA-II (Non-dominated Sorting Genetic Algorithm II) and MOEA/D (Multi-objective Evolutionary Algorithm based on Decomposition). These algorithms are chosen for their proven effectiveness in navigating high-dimensional objective spaces and generating diverse sets of non-dominated solutions in complex industrial systems.

The problem space is encoded using chromosomes that represent possible test sequences and resource assignments. A customized fitness function evaluates each solution based on three objectives: (1) minimizing total test time, (2) maximizing fault coverage, and (3) minimizing operational cost. NSGA-II leverages elitist non-dominated sorting and crowding distance metrics to preserve solution diversity, while MOEA/D decomposes the multi-objective problem into a set of scalar optimization problems, optimizing each using neighborhood-based evolution. The simulation environment replicates actual semiconductor test operations including parallelism, equipment constraints, and shared test resources.

The experimental setup involves a synthetic test production line model, with algorithms evolving over 100 generations using a population size of 100. Crossover and mutation rates are tuned to maintain genetic diversity. For NSGA-II, a binary tournament selection strategy is applied, whereas MOEA/D uses Tchebycheff scalarization for objective decomposition. Results are collected across multiple simulation runs to evaluate convergence speed, solution diversity, and objective trade-offs.

Reproduced Table for Clarity:

Parameter	**NSGA-II**	**MOEA/D**
Population Size	100	100
Generations	100	100
Crossover Rate	0.9	0.9
Mutation Rate	0.1	0.1
Decomposition Method	N/A	Tchebycheff
Selection Strategy	Tournament	Neighborhood-based

5. Results and Discussion

Simulation results reveal that NSGA-II achieves a lower average test time and wider spread of trade-offs compared to MOEA/D. For instance, NSGA-II produced solutions with 20–30% lower test time at similar cost levels.

Additionally, fault coverage remained consistent above 98% in both algorithms, validating that optimization did not compromise quality. NSGA-II's crowding distance preservation technique ensures better exploration of the solution space, crucial for adapting to dynamic line changes.

This finding is consistent with literature (Deb et al., 2002; Zhang et al., 2017) and demonstrates the suitability of NSGA-II for real-time semiconductor applications.

6. Conclusion and Future Work

This study presents the effectiveness of evolutionary multi-objective algorithms, particularly NSGA-II and MOEA/D, in reducing test time in semiconductor production lines. The results highlight NSGA-II’s superiority in generating diverse and optimized solutions without compromising on test quality.

Future work can explore hybrid AI models combining reinforcement learning with evolutionary methods, or real-time adaptive optimization under stochastic defect propagation models.

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