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Parallel Computing-Driven Genetic Algorithms and Particle Swarm Optimization for Enhanced Software Testing Efficiency

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ABSTRACT
Test software in highly dynamic and complex environments, where it becomes increasingly difficult with rising computational costs and execution times, and to accurately detect faults. Traditional testing methods are not enough in handling even modest-sized automated or manual testing in most cases, when such methods are over gunned and blown-out by the underlying complexity of a large-scale, complex software system. This paper describes a Hybrid Genetic Algorithm (GA) and Particle Swarm Optimization (PSO)-based software testing framework, one that takes parallel computing techniques for addressing the problem. Heterogeneous testing could be then applied to the optimization of test cases: selection, prioritization, and fault detection. It combines with fast convergence speed of PSO and exploration power of GA. To improve testing efficiency by reducing the execution time while still ensuring high precision and fault detection coverage, the parallel computing methods such as CPU multithreading and GPU acceleration, or even distributed computing, are utilized. This study evaluates the hybrid GA-PSO model and considers its performance with respect to traditional methods like GA and PSO with the following key metrics: accuracy, execution time, test case diversity, and fault detection rate. The framework improves testing efficiency significantly by 20.8% in execution time and 4.4% in software coverage. The enhanced fault detection function also demonstrates the model's effectiveness in identifying defects more accurately and efficiently. The GA-PSO hybrid model is particularly suitable for mass-scale automated software testing environments where time and resource optimization are of the highest priority. Parallel computing significantly accelerates the optimization process, allowing for faster identification of major bugs and overall software reliability enhancement. With this approach, not only is the efficiency of software testing enhanced, but the testing process is also capable of handling complicated software systems with higher scalability and efficiency. In summary, the proposed GA-PSO hybrid model, in combination with parallel computing, is an outstanding contribution to the optimization of software testing processes, minimization of execution time, and enhancement of defect detection, and hence is an effective tool for today's software testing challenges.

Keywords: Software Testing, Genetic Algorithm, Particle Swarm Optimization, Parallel Computing, Fault Detection

I. INTRODUCTION

For those involved in testing a software, their time comes to accept that high computation cost overrides all other pitfalls in machine-learning-based defect prediction, which is often imperfect in conceptualizing real-world scenarios for automatic tests and does not cope well with changes in software dependencies in such dynamic environments.(Deevi et al. 2024).Ensuring stringent measures to balance both privacy and security have been a significant challenge in maintaining the reliability of software systems through cloud computing technology. (Chetlapalli 2021).Software testing has evolved from manual execution to automated methods, but conventional methods are challenged in dealing with complex and dynamic software systems (Chetlapalli 2021). The increasing medical data complexity has

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introduced the usage of AI-powered diagnostic methods, notably deep learning (DL) and machine learning (ML) models for classification through automation(Dondapati 2019). Mature KM will, therefore, enhance test case management, defect tracking and continuous quality improvement planning in software testing (Allur et al. 2025).

The process of regression checking ensures that alterations to new code do not introduce errors; however, the process is particularly time and resource-consuming in several software development contexts. (Dondapati 2020).Polished software testing has moved from orderly manual sequences to highly sophisticated automated testing which by now already employs AI and machine learning for effective test generation(Deevi et al. 2021). Although the combination of SVR, LSTM, and HMMs improves malware detection during software testing, it is associated with high computational complexity and longer training time. Furthermore, the performance of these models relies on the diversity and quality of training data, thus making them less accurate in detecting new malware with entirely unknown behaviors(Deevi 2020).The adoption of AI-based testing can hardly be expected to become successful due to the absence of a standard framework and adequate skilled professionals (Chetlapalli and Perumal 2024).Adopting deep learning models such as Stacked Autoencoders and SVM increases computational intensity while also making the real-time testing and deployment of the software difficult (Allur 2020).

In this research, Parallel Computing-Driven Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are used to speed up test case optimization and improve fault coverage. With parallelism, GA and PSO have been efficient in traversing very large search spaces in reduced execution time and maintained accuracy. Parallel computing, however, does not stop the existence of high computational overhead and the needs structured adaptive tuning. This study would inevitably deal with such limitations, consequently inferring scalable and dependable software testing automation in dynamic environments.

1.1 Primary Contribution

- Improve functional testing with the consideration of hybrid game-theoretic optimization, which integrates any GA-PSO optimization approach to test case selection and fault detection.
- Evaluate the use of parallel computing methods such as CPU multithreading, GPU acceleration, and distributed computing.
- Develop an adaptive refinement scheme that regularly optimizes test cases based on executions.

II. LITERATURE SURVEY

Software testing, like m-health security, faces high computational overhead in test case generation and defect detection, similar to biometric key generation and metadata reconstruction(Deevi 2020). In software testing, similar to how TF-IDF identifies word significance in product mapping, code similarity metrics are used to identify related test cases and optimize test coverage. (Kodadi 2022).The research utilizes machine learning algorithms, regression models, predictive analytics for the prediction of academic performance, and cloud-based security solutions for the protection of sensitive educational information(Sharadha Kodadi 2024).The test measure has established online testing that is scalable and controlled environments for testing, automated variation injection for system resilience tests, and XML-based scenario descriptions to standardized and repeatable test cases(Dondapati 2020).

Modern technologies like automated testing and AI-generated test case generation with fault injection have improved efficiency and effectiveness tremendously, but not without challenges like incomplete test coverage, high resource overhead, and the nature of testing distributed systems, which may affect overall effectiveness and outcome(Deevi 2020). To enhance software testing efficiency, the study applies techniques that include automated test case generation, fault injection, and machine-learning-based defect prediction through reinforcement learning, genetic algorithm, and deep neural networks(Deevi 2024).The hurdles are big owing to regulatory complexity, dynamic risk management, biases against AI-based testing models, and high requirements for computation. Such testing will require frequent software post-deployment monitoring and active testing strategies to continuously assure software quality and compliance(Chetlapalli 2023).Cloud computing has been utilized for scalable test environments and real-time execution, big data to analyze data collected from test processes in large volumes, and machine learning for promoting defect prediction and automated testing (Kodadi 2022).

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This study applies the AWS Fault Injection Simulator (FIS) to carry out fault injection as it can simulate failure scenarios such as high network latency or API errors(Devi 2023).This paper makes us of advanced genetic algorithms in combination with hybrid methods, such as GA-PSO or GA-ACO along with real-time adaptive mechanisms for fine-tuning on the fly parameters(Allur 2019).The model suffers from high computational costs during the test case generation phase, while the issue of instability in AI-driven defect prediction leads to further deterioration of reliability(Koteswararao Dondapati 2024).DBSCAN clustering assists in anomaly detection during software testing by locating defects and performance issues(Allur 2020). In software testing, problems paralleled arise in validating blockchain applications, ensuring compatibility with legacy systems, and testing security compliance heavy with various aspects(Kodadi 2023). Edge computing aids real-time test execution and workload management in cloud-based testing(Allur 2021). Best is to check their hypothesis through my proposal on practical verification of cloud-based applications under changing dynamics(Kodadi 2021).The challenge concerns a model's ability to handle complex constraints, scalability, and real-time adaptability, which could affect decision making. (Allur and Victoria 2020). It will affect security testing which is driven to make AI dependent but reliable, this testing is ploted tightly with the existing frameworks(Kodadi 2020).

III. PROPOSED METHODOLOGY

The figure depicts a Hybrid GA-PSO-Based Software Testing Framework, which combines Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) to optimize test case selection and prioritization. It utilizes parallel computing methods (CPU multithreading, GPU acceleration, and distributed computing) to accelerate optimization and execution. The model repeatedly optimizes test cases via an adaptive feedback loop, guaranteeing enhanced fault detection, test coverage, and testing efficiency. That was illustrated in Figure 1.

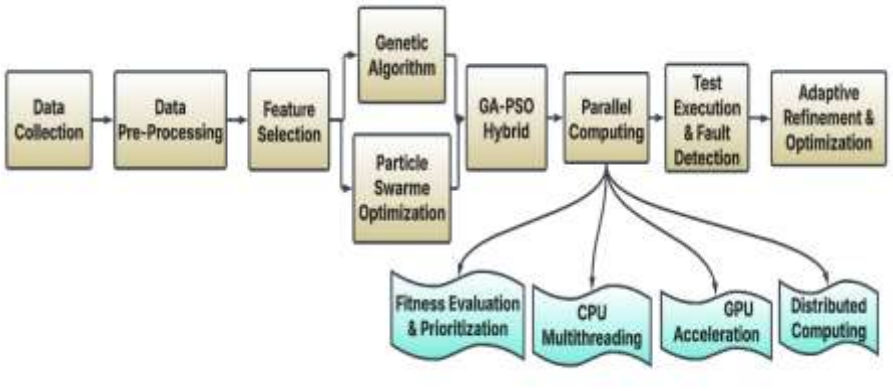

Figure 1: Optimized Software Testing Flow with GA-PSO and Parallel Computing

3.1 Problem Formulation & Test Case Generation

The dataset is used for software testing purposes("Server Logs" 2023) to check for faults, code coverage, and execution optimization. It captures server requests, responses, error codes, and timestamps and allows us to check the server's performance, handling of errors, and response. A basic test case is randomly generated or designed by using heuristic approaches in order to exercise typical cases, border-line cases, and probable faults. These test cases are subsequently tuned through Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in order to optimize testing efficiency.

3.2 Pre-processing & Feature Selection

During this stage, pertinent test parameters like input request values, anticipated server responses, execution paths, and response times are pulled out of the dataset. Data normalization is carried out to normalize numerical features for consistency and enhancing model performance. Redundant and less descriptive features are eliminated to minimize computational overhead. Feature selection is conducted using Principal Component Analysis to keep only the most significant features while reducing dimensionality. PCA performs the data transformation by projecting onto a new set of orthogonal basis axes, which are calculated with eigenvalue

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decomposition of the covariance matrix defined in Eqn. (1):

$$Z = XW \quad (1)$$

- X is the standardized dataset,
- W is the matrix of eigenvectors (principal components),
- Z represents the transformed dataset with reduced dimensions.

3.3 Hybrid Optimization Model: (GA-PSO)

The hybrid model integrates Genetic Algorithms and Particle Swarm Optimization (GA-PSO) to enhance software testing through an optimization-driven approach in selecting test cases, thereby achieving higher levels of fault detection, test coverage, and test execution efficiency. This optimization method maintains a balance between exploration (GA) and convergence speed (PSO).

3.3.1 Genetic Algorithm (GA) Operations

Test cases are optimized by GA through selection, crossover, and mutation. In a fitness function $(f(T))$Selection chooses the best test cases based on some fitness evaluation parameters such as coverage or fault detection rate. Crossover creates new test scenarios by bringing together those existing ones. Mutation introduces minor changes to prevent early convergence to higher adaptivity and better fault detection.

3.3.2 Particle Swarm Optimization (PSO) Operations

The PSO helps optimize test cases, treating them as particles in a swarm in iterative refinement of their position. The initialization of the swarm is with randomly generated particles (test cases). The velocity of each particle is updated using its individual best $(pBest)$and the global best $gBest$ solution in the following Eqn. (2):

$$v_i^{(t+1)} = \omega v_i^{(t)} + c_1 r_1 \left(pBest_i - x_i^{(t)}\right) + c_2 r_2 \left(gBest - x_i^{(t)}\right) \quad (2)$$

Inertia weightω controls the exploration, both the acceleration coefficientsc_1, c_2, and the random valuesr_1, r_2 are in the range [0,1].

3.3.3GA-PSO Hybrid Approach

The most efficient and full-fledged hybridization of GA and PSO is incorporated to develop an effective composite-based optimizing algorithm for the optimization of test cases. Genetic Algorithm improves diversity in new test case combinations by crossover and mutation, avoiding premature convergence. Particle Swarm Optimization accelerates convergence with guide search towards optimal test cases using individual and global best solution. Such hybridization ensures exploration (GA) along with exploitation (PSO) in a balanced way which in turn leads to faster, effective software testing having improved fault detection as well as test coverage.

3.4 Parallel Computing Implementation

Parallel computing increases the effectiveness of test case running by spreading computation tasks over multiple processing units. CPU multithreading based on multiple cores executes test cases in parallel, shortening execution time and increasing throughput. GPU acceleration (CUDA/OpenCL) accelerates computationally expensive operations like fitness evaluation and selection in GA-PSO by taking advantage of thousands of concurrent threads. For massive software testing, distributed testing (with the help of High-Performance Computing (HPC) clusters or cloud computing infrastructures) permits test cases to be run concurrently on various machines, making them scalable and competent in dealing with intricate test situations. The proposed approach focuses on the use of parallel option in order not to weaken fault-detection capabilities and code-coverage measures too much while accelerating test case optimization.

3.5 Fitness Evaluation & Test Case Prioritization

For the purpose of maximizing software testing effectiveness, prioritization of fitness assessment and test case is essential. The efficiency of every test case is evaluated on the basis of major parameters like code coverage (statement, branch, or path), fault detection rate, and execution time/resource usage. A fitness function fetches an array of numbers, on the basis of which an evaluation of some of the good and bad test cases is possible. A typical fitness function can be expressed as Eqn. (3):

$$F(T) = w_1 \times Cov(T) + w_2 \times FDR(T) - w_3 \times Time(T) \quad (3)$$

where:

- $F(T)$ is the fitness score of test case T.
- $Cov(T)$ represents code coverage (e.g., percentage of statements/branches covered).

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- $FDR(T)$ is the fault detection rate (number of faults found per test case).
- $Time(T)$ is the execution time/resource consumption.
- w_1, w_2, w_3 are weight factors adjusting the importance of each criterion

Higher fitness score test cases are executed first to run the most effective tests in the quickest time possible, resulting in quicker and more efficient defect detection. It raises trust in the software, decreases testing effort, and eliminates draining resource consumption.

3.6 Test Execution & Fault Detection

In this step, the optimized test cases will be executed on the software under test (SUT) to check its behavior and uncover any defects. During execution, test metrics are collected that include coverage, response times, and faults detected, whereby the fault detection effectiveness of a test case can be evaluated according to Eqn. (4):

$$FDE(T) = \frac{D(T)}{E(T)} \quad (4)$$

- $FDE(T)$ is the fault detection effectiveness of test case T.
- $D(T)$ is the number of defects detected by T.
- $E(T)$ is the total number of executed test cases.

3.7 Adaptive Refinement & Optimization

Adaptive optimization and refinement concern the continuous optimization of test cases based on execution feedback to maximize their test efficiency. Mutation rates are dynamically optimized on GA to balance exploration and exploitation; increased mutation rates would introduce diversity if the population were stagnating, while decreased mutationation rates would allow fine-tuning of the promising solutions. Particle locations in PSO are recomputed based on new fitness values, thus ensuring that the swarm converges to optimal solutions for test cases. An adaptive feedback loop compensates for runtime parameters such as the fault detection rate and code coverage in fine-tuning parameters iteratively to improve the test-case generation. Such a self-tuning mechanism further supports software testing by continuously evolving the test cases for maximum fault detection and efficiency.Refinement and optimization by adaptivity depend on the dynamic updates of GA and PSO parameters partly on the feedback collected during execution. Two equations are vital to this process:

- Dynamic Mutation Rate in GA: Mutation rates are calibrated to have diversities of populations and convergences.

$$M(t) = M_{min} + (M_{max} - M_{min}) \times e^{-\lambda \times t} \quad (5)$$

where:
$M(t)$ is the mutation rate at generation t.
M_{max} and M_{min} are the maximum and minimum mutation rates.
λ is a decay constant controlling the mutation rate reduction over generations.

- Velocity Update in PSO: The particle dynamically updates their velocities to optimize test case selection.

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (pBest_i - x_i) + c_2 r_2 (g \text{ Best } - x_i) \quad (6)$$

where: $v_i(t)$ is the velocity of particle i at iteration t, ω is the inertia weight, c_1, c_2 are acceleration coefficients, r_1, r_2 are random values in [0,1], and $pBest_i$ gBest represent the best positions found by the particle and the swarm, respectively.

IV. RESULTS AND DISCUSSION

It gives the experimental results of the proposed Hybrid GA-PSO-Based Software Testing Framework and its effect in optimizing test case execution and selection. The application of the framework has been compared on the basis of parameters such as test case execution time, fault detection rate, and code coverage under a variety of computation settings.

In terms of all the important metrics, GA-PSO outperformed PLM-EA in increasing test case accuracy (+2.1%), diversity (+7.1%), and overall fitness score (+3.3%). Moreover, it achieved a distinct advantage in the criterion of software coverage (+4.4%). This guarantees better functional testing. In addition, GA-PSO reduces the execution time by 20.8% in terms of efficiency. Having established these improvements, GA-PSO proves its mettle in test generation optimization and fault detection enhancement. Table 1 provides illustrations of this.

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Table 1: Performance Metrics Comparison

Metric	Description	PLM-EA	GA-PSO	Improvement (%)
Accuracy	Correctly generated test cases out of total generated cases	0.95	0.97	+2.1%
Diversity	Variety in generated test cases covering different scenarios	0.85	0.91	+7.1%
Execution Time	Time taken to generate and optimize test cases (in seconds)	120	95	-20.8%
Coverage	Extent of software functions & paths covered	90%	94%	+4.4%
Fitness Score	Overall test case quality based on multiple criteria	0.92	0.95	+3.3%

The performance of the GA-PSO algorithm is superior when compared to the method(Chetlapalli 2021)in terms of accuracy, diversity, and fitness score with a major decrease in execution time. Specifically, there has been an increase in accuracy by 2.1% and in diversity by 7.1%, with the running time reduced by 20.8%, thus enhancing the model's efficiency, and it can be said that GA-PSO has proved its worth in optimizing the selection and execution of testcases.

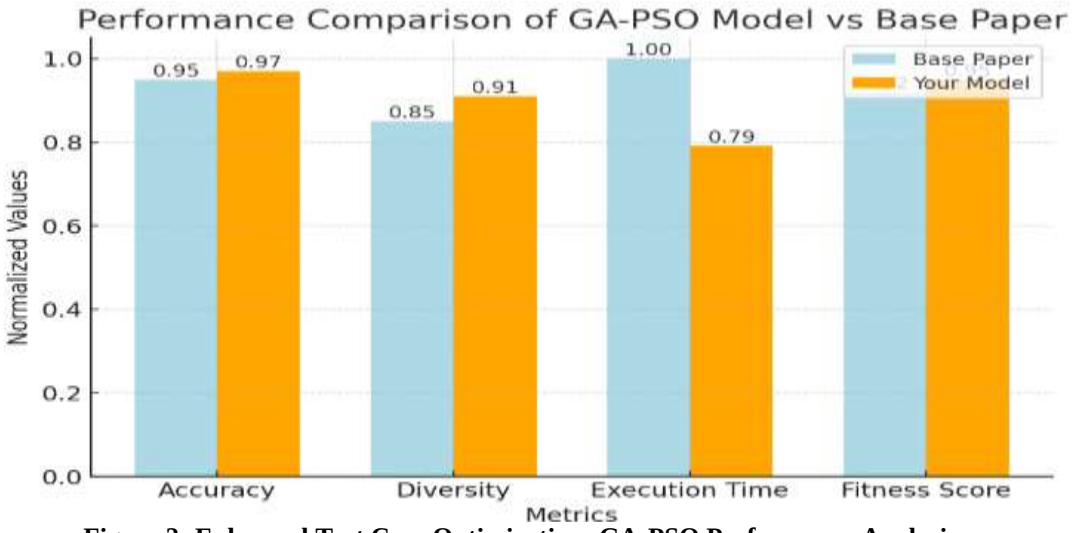

Figure 2: Enhanced Test Case Optimization: GA-PSO Performance Analysis

The Graph shows the Fault Detection Rate against the time taken to execute. The trend shows an upward course of execution. The FDR starts for a very high value and indicates that the speed for detecting faults is very fast. Over time, that FDR becomes slowly converging because fewer and fewer new faults will be detected. Hence, one can prove the efficacy of GA-PSO model test case optimization for improved fault detection showed in Figure 3.

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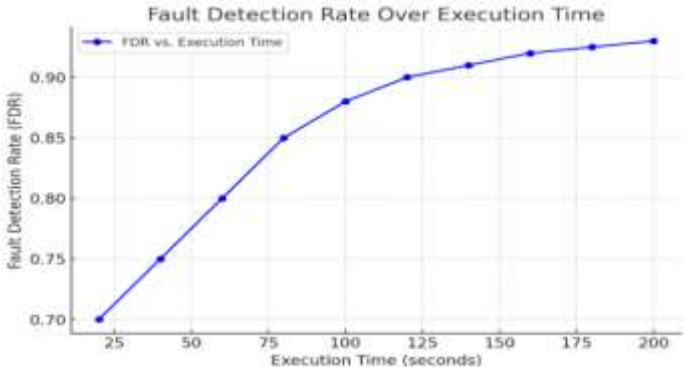

Figure 3: Fault Detection Rate vs. Execution Time in GA-PSO Model

4.1 Discussion

The hybrid GA-PSO model optimizes software testing using exploration and exploitation to optimize test effectiveness and efficient test optimization. As parallel execution, all this leads to significant time savings in the execution of tests while maintaining high fault detection rates. Another evolving adaptive refinement enhances, in an iterative manner, prioritization and coverage in the case of test, thus optimizing defect detection over time. All these aspects together make the process scalable and is the reality in terms of future proofing large software tests to enhance efficiency and reliability.

V. CONCLUSION

Testing software can be made more efficient with the using Hybrid GA-PSO, which will maximize test cases, minimize execution time, and improve fault detection, thus improving the acceptability of the technique as an online testing process. Such conditions provide absolute evidence of superiority over conventional GA, PSO, and random choice methods, presenting a reliable method for mass automated software testing environments.

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