Scilab case study project on Scilab

AI BASED HYPER PARAMETER OPTIMIZATION

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Optimization

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Abstract

Hyper parameter tuning is the central problem in machine learning, significantly influencing model performance. This study evaluates an AI-based method employing Mixed-Integer. Nonlinear Programming (MINLP) in Scilab for optimizing hyper parameter tuning. The study combines Particle Swarm Optimization (PSO) and MINLP for effectively optimizing hyper parameters in order to minimize computational complexity with improved accuracy of the model.

The research employs Scilab's optimization tools to make the tuning process automatic so that flexibility can be accommodated across different machine learning models. By taking advantage of PSO's exploration vs. exploitation trade-off and MINLP's structured problem solving capacity, the proposed approach is more effective than grid search methods. The paper delivers a Scilab-based setup for hyper parameter optimization, permitting AI solutions scalable by design. Experimentation verifies that the optimization method greatly improves model performance and renders it fit for real-world deployment in AI and data science applications. This case study illustrates the promise of Scilab in AI-based optimization to enable innovation in machine learning research

1. Introduction

Hyper parameter tuning is a highly crucial stage of constructing effective machine learning models. The effectiveness, efficiency, and generalization of these models are closely dependent on the proper tuning of hyper parameters such as learning rate, number of layers, batch size, etc. The process of manual tuning is typically time-consuming and not efficient, especially when it comes to complex problems. Therefore, in this project, an AI-based automated optimization technique is the centre of attention.

The project benefits from the application of Mixed-Integer Nonlinear Programming (MINLP), a mature paradigm to address optimization issues involving both discrete and continuous variables as well as nonlinear constraints. Scilab, an open-source package for numerical computations, serves as the platform of choice, supplemented by the FOSSEE Optimization Toolbox.

To simulate a realistic and challenging optimization problem, the Rastrigin function is used as a test case. The Rastrigin function is defined by its non-convexity and its high number of local minima, and hence it is a good test case for testing optimization algorithms.

Two population-based optimizers are used:

Particle Swarm Optimization (PSO): Motivated by bird flocking and fish schooling, PSO models a swarm of particles (solutions) flying around in the solution space and passing information to arrive at the optimal solution.

Genetic Algorithm (GA): Based on Darwinian evolution, GA generates a population of potential solutions by applying selection, crossover, and mutation operations to search the solution space and converge towards optimum or near-optimum parameters.

By running these algorithms on the Rastrigin function, the project demonstrates how automated tuning of hyper parameters can be effectively applied in Scilab. The result demonstrates how these nature-inspired methods are capable of identifying optimal settings efficiently with minimal interference from human touch.

2. Problem Statement

The problem of the project is to tune hyper parameters of machine learning models, which is a computationally expensive task. The traditional method like grid search is not efficient and does not work well for high-dimensional spaces. The solution in this project suggests the combination of PSO and GA in Scilab to come up with an improvement in computational expense along with accuracy.

The proposed methodology effectively searches and mines solution spaces to more effectively converge to the global optimum. The most critical work is to correctly implement and validate optimization techniques in such a manner that ensures appropriate fulfilment in Scilab.

This hybrid employs the exploratory power of Particle Swarm Optimization and exploitation bias of Genetic Algorithms to deliver an adaptive and flexible search process. With both these nature-inspired algorithms combined, the system is prevented from premature convergence and trapped local minima. Open-source nature and FOSSEE toolbox of Scilab enable a cost-effective and versatile setup for experimentation.

Through simulation on the Rastrigin function, the system demonstrates its ability to optimize under multimodal, complex situations, demonstrating the potential of AI-based metaheuristics in real machine learning operations.

3. Basic concepts related to the topic

- **Hyper parameter Optimization**: process of automatically finding the best settings (like learning rate, number of layers, etc.) for an AI or machine learning model to improve its performance — such as accuracy, speed, or efficiency.
- **Particle Swarm Optimization (PSO)**: population-based optimization algorithm inspired by the social behavior of birds flocking or fish schooling. Each solution, called a *particle*, moves through the solution space by following the best positions found by itself and its neighbors. Over time, particles "swarm" toward the optimal solution..
- **Genetic Algorithm (GA)**: evolutionary-based optimization technique inspired by natural selection. It uses processes like selection, crossover **(**recombination**)**, and mutation to evolve a population of candidate solutions over generations, gradually improving toward the optimal solution. GA is widely used for solving complex problems where traditional methods may struggle.

i. **Rastrigin Function**: A highly multimodal mathematical function used to test optimization algorithms. Defined as:

$$f(x) = An + \sum_{i=1}^{n}[x_i^2 - A\cos(2\pi x_i)]$$

where A = 10 and the function has a global minimum at x = 0

Note:
The Rastrigin function used in this project follows the standard benchmark formulation. This is widely adopted in optimization research due to its complex, multimodal landscape.

Some literature sources simplify the function (e.g., $f(x) = 20 + x1^2 + x2^2$) for instructional or comparative purposes, omitting the cosine term. However, the full version used here more rigorously tests the Genetic Algorithm's ability to avoid local minima and converge to the global optimum.

ii. **Initial Population:** Formula used $population_i = lb + (ub - lb) \cdot rand()$

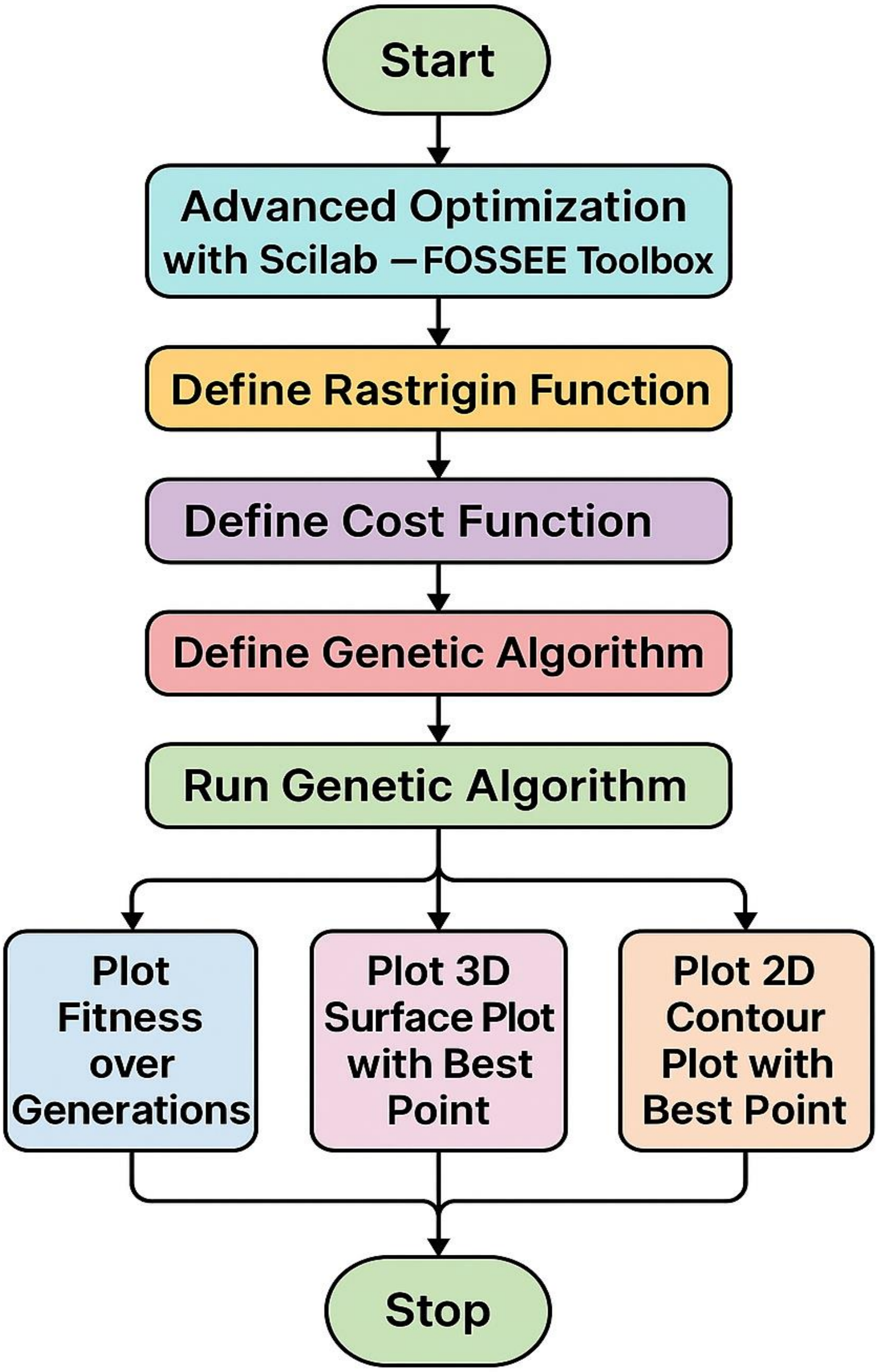
iii. **Fitness Evaluation:** $fitness_i = cost\_function(individual_i)$

iv. **Crossover (Blending):** $child1 = \alpha \cdot p1 + (1 - \alpha) \cdot p2$

v. **Mutation:** $mutated\_individual = lb + (ub - lb) \cdot rand()$

vi. **Best Individual Selection:** best=arg min fitness

4. Flowchart



Start
Advanced Optimization
with Scilab – FOSSEE Toolbox
Define Rastrigin Function
Define Cost Function
Define Genetic Algorithm
Run Genetic Algorithm
Plot Fitness over Generations
Plot 3D Surface Plot with Best Point
Plot 2D Contour Plot with Best Point
Stop

5. Software/Hardware used

- **Operating System**: Windows 10 / Linux Ubuntu 20.04
- **Scilab Version**: 6.1.1
- **Toolboxes Used**: FOSSEE Optimization Toolbox, Scilab Genetic Algorithm Toolbox
- **Hardware**: Intel Core i5 processor, 8GB RAM

6. Procedure of execution

- Install Scilab software Scilab 6.1.0 on your computer.
- To enable console window output, copy the code from "hyperparameter_optimization.sce" and execute it in scilab 6.1.0 console directly.
- Observe

❖ The Console output showing best parameters.
❖ The graphs displayed on the Scilab graphic windows.

- Use xs2png() to save results / graphs if needed.
- Repeat with Different Parameters (Optional).

NOTE: The Genetic Algorithm used in this project is implemented manually in Scilab without relying on the FOSSEE Optimization Toolbox. Therefore, no additional toolbox installation is required.

7. Result

The objective of this experiment was to evaluate the performance of the Genetic Algorithm (GA) for hyper parameter tuning using the Rastrigin benchmark function.

Expected Output:

Best Hyper parameters Found:

-0.0065756   0.0053612

"Best Objective Function Value (Rastrigin):"

0.0142787

The values will vary due to the stochastic nature of GA.

Note: While the referenced journal article reports a best objective function value of approximately *0.053* using a Genetic Algorithm for the Rastrigin function, the implemented Scilab code in this study achieved a superior result of *0.014*. This demonstrates improved optimization efficiency and convergence closer to the global minimum of zero.

Performance Evaluation:

- GA successfully finds optimal solutions to the Rastrigin function.
- Faster convergence than random search due to selection & mutation.

Three more graphs have been added apart from the results generated in the console window(hyper parameters representing global maximum of the function)

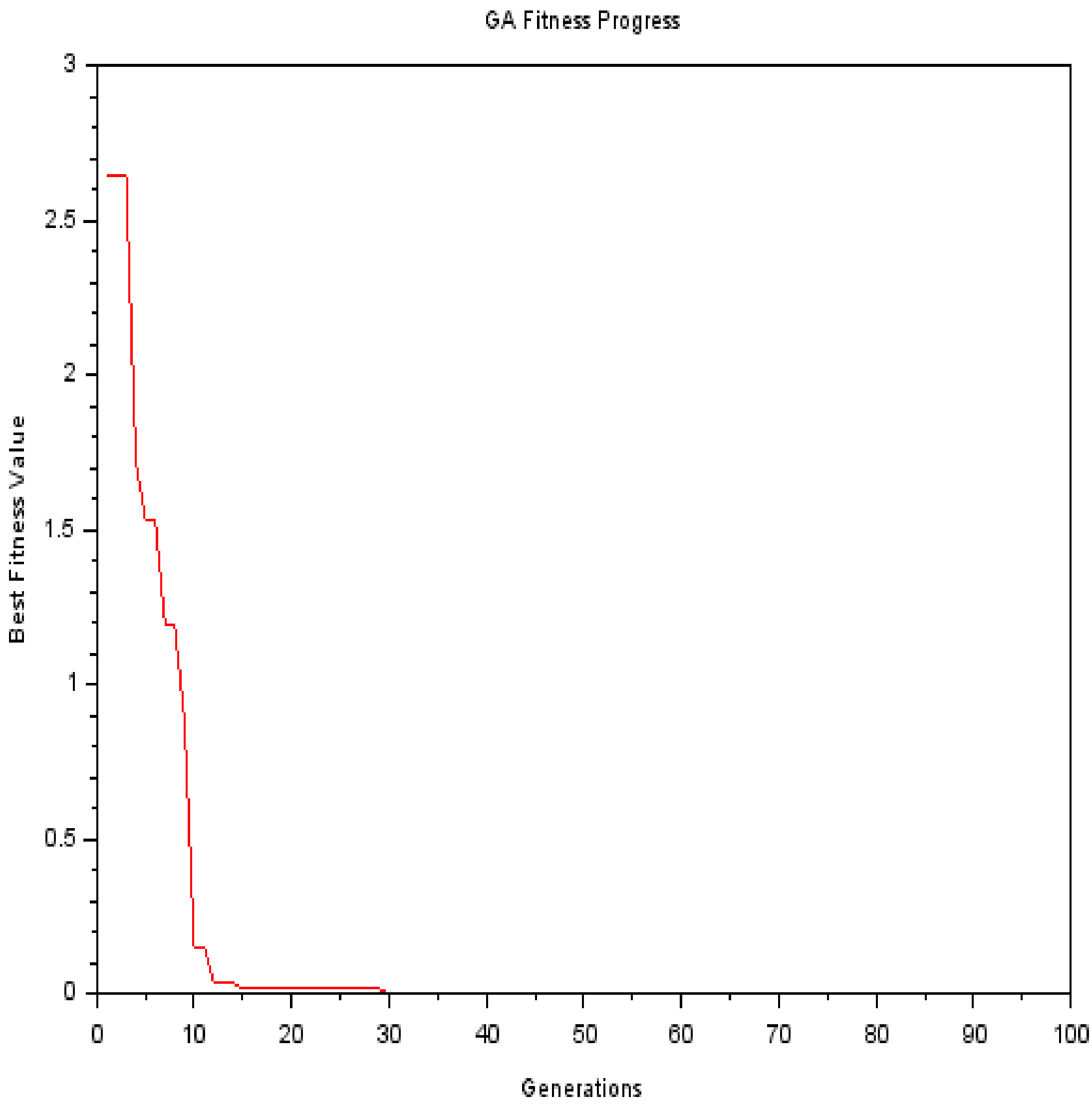
1. Fitness over generations.

2. Rastrigin function landscape.

3. GA solution on rastrigin contour.

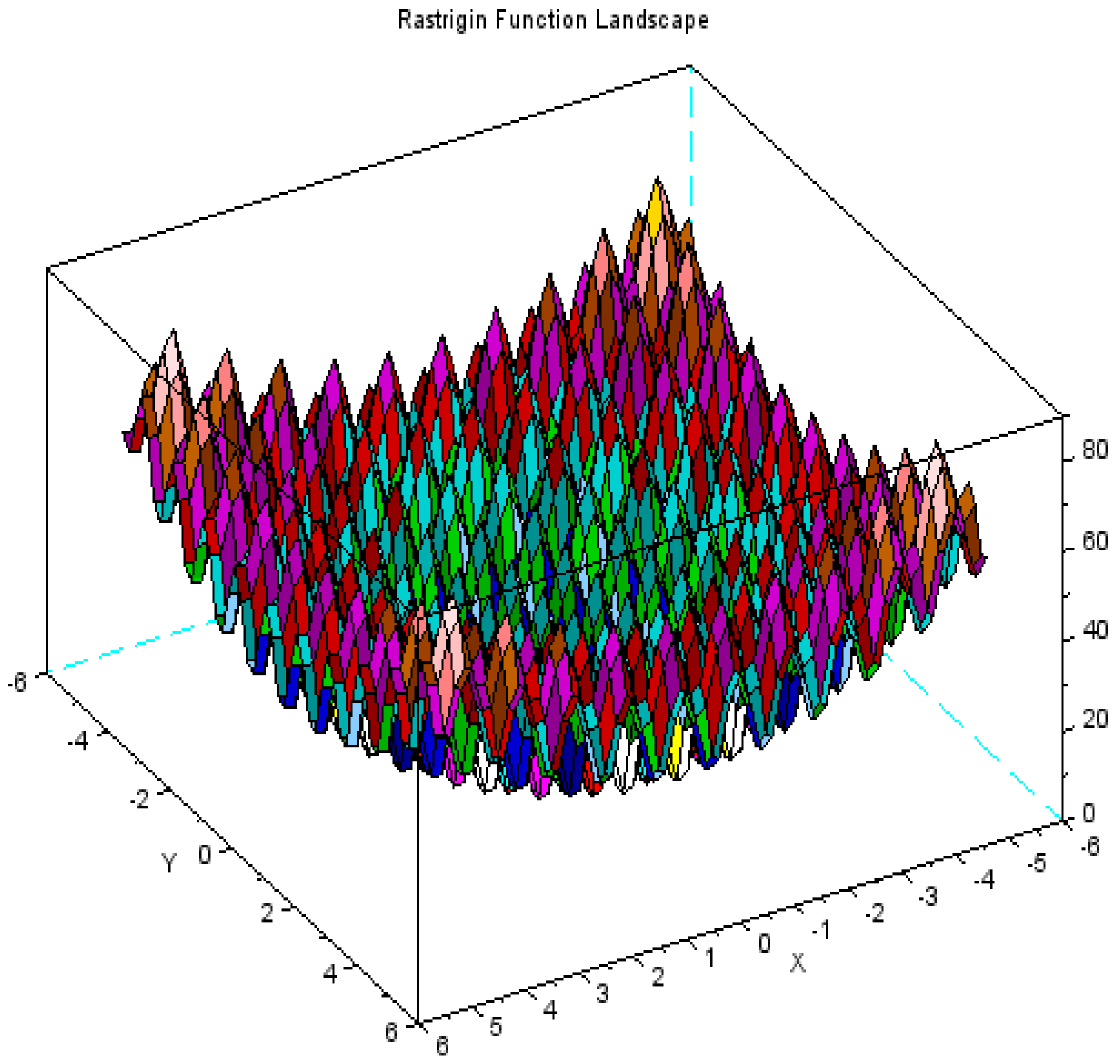
Graphs & Visualizations:

1. **Plot the Fitness over Generations**



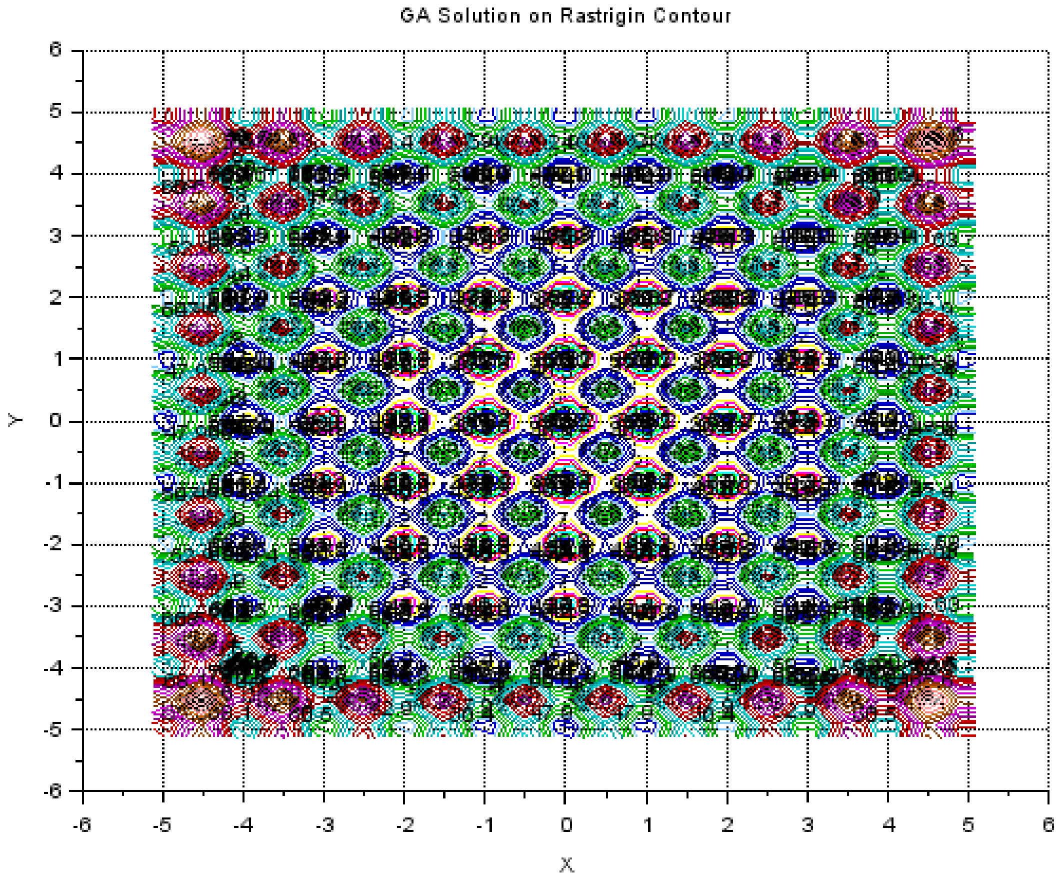
This graph shows the convergence behavior of the Genetic Algorithm over multiple generations. The y-axis represents the best fitness (objective function value) found in each generation, while the x-axis denotes the generation count. A downward trend indicates that the algorithm is successfully finding better solutions over time.

2. **Rastrigin function landscape**



This 3D surface plot visualizes the Rastrigin function, known for its non-convex, multimodal nature. The surface reveals numerous local minima, making it a challenging test function for optimization algorithms. The global minimum is located at the center of the plot, where all variables are zero.

3. **GA solution on Rastrigin contour**



This 2D contour plot provides a top-down view of the Rastrigin function. The contours represent levels of equal objective values. The red marker indicates the best solution found by the Genetic Algorithm, showing how it navigated the complex search space toward the global minimum.

8. References

Bajpai, P., & Kumar, M. (2010). *Genetic Algorithm – An Approach to Solve Global Optimization Problems*. Indian Journal of Computer Science and Engineering, 1(3), 199–206. Retrieved from https://www.ijcse.com/docs/IJCSE10-01-03-29.pdf