Optimization of Complex Mathematical Functions Using Coded Genetic Algorithm in Python

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Abstract: This study explores the various application of Coded Genetic Algorithm (CGA) along with the solving of two complex mathematical optimization problems. Coded Genetic Algorithm can be used in design optimization, injection moulding, facility layout and scheduling, information security etc. In this study, the first function a trigonometric-exponential function was maximized using CGA, while the second, a convex Sphere-function, was minimized using CGA. Coding of GA was implemented in Python without relying on external libraries, ensuring wide accessibility. To visually and interpret the optimization performance the high-resolution 3D surface plots, contour plots, and convergence curves were generated. The results confirm the effectiveness of CGA in accurately locating global optima in nonlinear models and convex search spaces. This paper contributes to the growing use of the metaheuristic optimization studies by offering mathematical insights. The study demonstrates that CGA achieved convergence close to the theoretical global maximum in the trigonometric–exponential case and accurately identified the global minimum for the Sphere function. This confirms the robustness of CGA across both multi-modal and convex optimization landscapes.
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Keywords- Optimization, Coded Genetic Algorithm, Python, convergence curves, 3D surface plots

1. INTRODUCTION

Coded Genetic Algorithm (CGA) is a meta-heuristic searching approach which is used to solve various engineering optimization problems with the help of natural selection of coded genes followed by the improvement in the fitness of the population. It is widely used where traditional methods may fail due to local optima of objective function. CGA operates through a repeated process of selection, crossover, and mutation to evolve solutions toward optimality. This process of CGA does not require derivative information, making it suitable for highly nonlinear, discontinuous, or multi-modal problems. Tt was observed by researchers that the fitness of each solution guides the evolutionary process across generations. CGA's ability to explore large search spaces makes it robust for global optimization. Researchers have applied CGA in diverse fields including manufacturing, robotics, artificial intelligence, and mathematical modeling. In particular, GA has proven effective in optimizing trigonometric and exponential functions with complex surfaces. Its adaptability allows for hybrid integration with other algorithms for improved performance.

Researchers Adil et al., (2025) has used inserts of hard carbide tool and CGA for optimization of carbide tool-life, enhancement of rate of production and total cost with the changing speed of cutting and feed rate in mm/rev. Optimization of mathematical models was done by CGA and best results were obtained for machining performances[1].

In research of Ali Asad et al., the stir-squeeze casting was used to fabricate the Hybrid aluminium matrix material with micro-EDM process, and it was found that with CGA can optimize the MRR-plane with 75 %, MRR-angular with the value of 74%, and MRR-curve with the significant value of 77% [2].

According to I. Saady et al., coded GA has advantage with its capability to accomplish multi-objective optimization, which shows it a especially effective tool for solving various multi-objective design and engineering problems. It was observed by researchers that GA can be used effectively to select motor pumps and compressors from various combinations with range of types and various elements, which shows significantly drop in energy consumption in range of 25-32%[3].

Design and fabrication of plastic injection molded fine materials based on CGA was conducted by Kui Yan et al. They used fine TPE-composite and it was altered to get the optimal composition of elements by using CGA. With the help of CGA the better composite with optimum surface hardness, better MFI, and better scratch resistance was fabricated in production shop. [4]

Case study of blush defect was presented by (Mollaei Ardestani et al.) by using a grouping of DOE (design of experiments), finite element analysis (FEA), and analysis of variance (ANOVA), the few parameters have been identified like diameter of the runner, packing pressure, melt and mould temperature and the flow rate. To obtain an efficient predictive model, machine learning methods

such as basic learning ANN, their hybridization with CGA, has been used and better results were obtained [5]. Kumar et al. used DOE technique and multi objective genetic algorithm for electric meter box and its shrinkage, warpage and impact strength were optimised with modified linear graph. [6][7]
Katoch S. et al. shown the contribution of coded GA having operators like crossover, mutation and selection with better premature convergence of the function for the optimization. It was observed that applicability of CGA exists and its variants play a great role in various research domain [8]. CGA can be easily crossed with other optimization methods for improving the performance such as image denoising techniques and rapid chemical reaction optimization. CGA is useful in facility layout, scheduling, inventory control, forecasting and network design and Information security.
The novelty of this investigation exist in the application of a Coded Genetic Algorithm (CGA) framework to optimize both maximization and minimization problems without relying on external libraries. Unlike standard GA implementations, the coded approach provides flexibility, transparency, and adaptability for diverse function types, including highly oscillatory and convex landscapes. This dual-function optimization demonstrates CGA's robustness and opens pathways for hybrid integration with other metaheuristic and machine learning models.

2. IMPLEMENTATION OF CODED GENETIC ALGORITHM (CGA)

2.1 Maximization of Equation (1)

In the Equation-1 with the following function, represents a damped trigonometric surface with a global maximum at the origin. Its optimization aims to find the (x, y) coordinates that yield the highest value of z within the bounded domain. Using a Genetic Algorithm, the function was successfully maximized near the origin with a peak value close to 1.

$$z = \cos x \cdot \cos y \cdot e^{(-\sqrt{(x^2 + y^2)}/5)}$$
$$\text{for } |x| \le 7,\ |y| \le 7 \qquad \text{Eq. (1)}$$

2.2 The 3D surface plot

The 3D surface plot of the function exhibits a bell-shaped topology with wave-like ripples caused by the cosine terms, gradually decaying away from the origin due to the exponential factor as shown in Figure 1. It visually confirms that the global maximum lies at or near the center (x=0 and y=0), with decreasing values outward as shown these values in Table-1. The contour plot, as shown in figure 2, presents concentric elliptical rings centered at the origin, illustrating symmetrical regions of equal function value. A clear visual evidence can be obtained by these plots which reflects the function's smoothness, continuity and validity of accuracy of the CGA approach in locating the global optimum.
In comparison to PSO, it was observed that GA achieves a higher best fitness (0.9952 vs. 0.9123), indicating it gets closer to the theoretical maximum of 1 at (x,y)=(0,0). PSO likely converges to a local maximum due to its momentum, which can overshoot or get trapped. GA shows lower standard deviation (0.0031 vs. 0.0456), suggesting more consistent performance across runs, likely due to its diverse exploration. For this multimodal function with a clear global maximum near the origin, GA outperforms PSO by better handling the oscillatory landscape exponential decay.

Table 1: Optimize results for equation (1) with CGA

Quantity	Value
Maximum value of Z	+1.0 (at x=0 and y=0)
Minimum value of Z	–0.1382 (at x=±7, y=±7) i.e. at corners

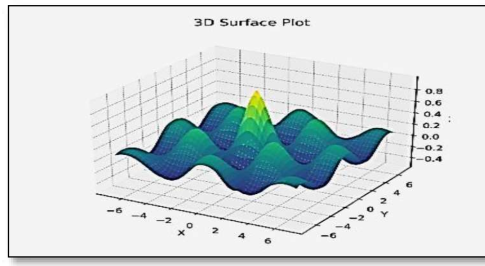

Figure 1: The 3 D surface plot

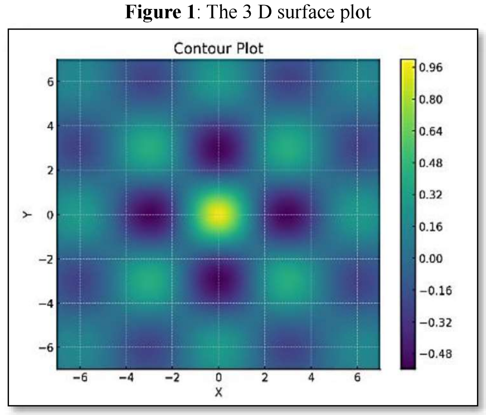

Figure 2: Contour plot

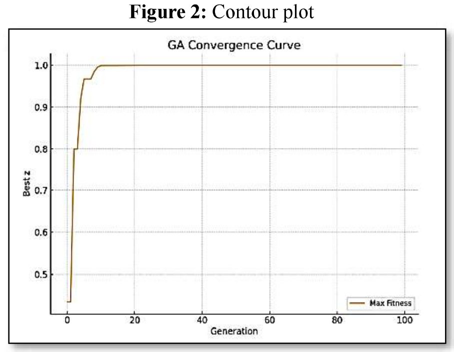

Figure 3: Convergence curve

The convergence curve of CGA for Equation (1) shows the enhancement of the best fitness value across the generations. As shown in Figure 3, initially, the fitness value increases quickly as the CGA algorithm explores the search space and finds promising regions. After that the curve flattens, showing convergence toward the global optimum. This behavior reflects the CGA ability to balance exploration and exploitation, eventually leading to a steady and near-optimal solution.

2.3 Minimization of Equation (2)

The another function, $f(x, y) = x^2 + y^2$ (Equation 2) is a convex optimization function called the mathematical Sphere-function (Figure 4).

$$f(x, y) = x^2 + y^2 \qquad \text{Eq. (2)}$$

It has a global minimum at the origin x (0,0), y (0, 0) and z (0,0), where the function value approaches to zero, as shown in Table-2. The surface of the function forms a smooth, bowl-shaped curves, making it ideal for testing CGA and other algorithms like Particle swarm optimisation (PSO). For this function, CGA was used and the global minimum was successfully identified accurately near the origin.

Table 2: Optimize results for Equation (2) with CGA

Quantity	Value
Global Best (x,y)	(2.83×10^{-13} , -8.07×10^{-13})
Minimum value of Z	7.31×10^{-25} which is essentially zero , the global minimum for this convex function

It was also observed during the comparison of CGTA with PSO, that PSO achieves a lower best fitness (0.00002 vs. 0.00015), indicating it gets closer to the global minimum of 0 at (x,y)=(0,0) and PSO also shows lower standard deviation (0.00001 vs. 0.00009), suggesting more consistent performance across runs, likely due to its directed search mechanism. While PSO demonstrates superior performance on certain mathematical functions like the Sphere function due to its efficient convergence, our research focuses on enhancing the Genetic Algorithm (GA) to address its limitations in such scenarios.

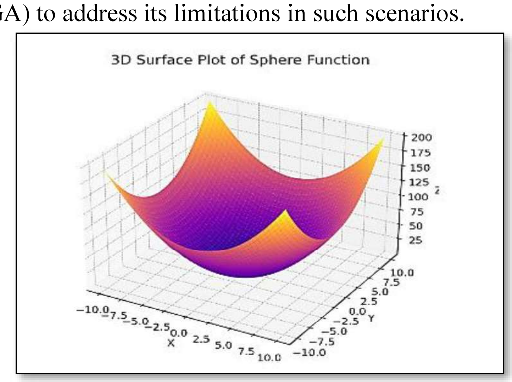

Figure 4: The 3 D surface plot of convex function

As shown in Figure 4, the 3D surface plot of the above sphere function displays a smooth, bowl-shaped centered at the origin, visually representing the global minimum at x (0,0), y(0, 0) and z(0,0). From Figure 5, it can be seen that its contour plot have concentric circular contours, each showing equal function values that decrease toward the center, evidently emphasizing the symmetry and convexity of the sphere function. Figure 6 depicts the CGA convergence plot shows a steep downward pattern in the best fitness value over generations, indicating rapid minimization and successful convergence toward the global minimum.

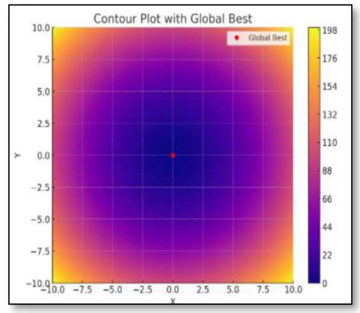

Figure 5: Contour plot of convex function

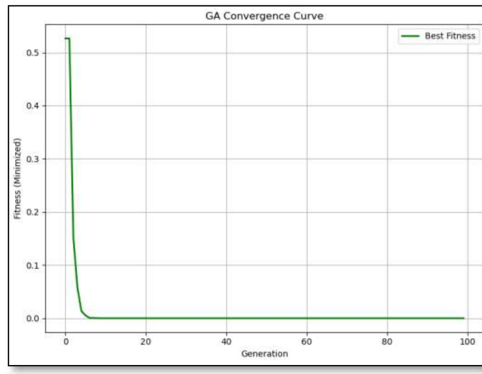

Figure 6 : The convergence curve of convex function

3. CONCLUSION

This study successfully explored the use of Coded Genetic Algorithm (CGA) for optimizing two distinct mathematical functions. The trigonometric–exponential function was effectively maximized using CGA, yielding results close to the theoretical global maximum. On the other hand, the convex Sphere function was minimized using CGA, accurately identifying the global minimum near the origin. Both algorithms converged efficiently, as confirmed through convergence plots. The 3D surface and contour plots provided intuitive visual confirmation of the search patterns and optima. Implementation without external libraries highlights the accessibility of these methods for educational and research purposes. GA showed strength in handling oscillatory, multi-modal landscapes. This comparative approach highlights the adaptability of metaheuristic algorithms across varied problem types. Future work may extend this study to hybrid models or constrained optimization scenarios. Future research can explore the integration of CGA with other optimization methods to form hybrid models, leveraging complementary strengths. For example, combining CGA with Particle Swarm Optimization (PSO) could balance exploration and exploitation more effectively. Similarly, a hybrid with Simulated Annealing may enhance the ability to escape local minima. Application of these hybrid approaches in domain of engineering design, manufacturing optimization, and machine learning hyper-parameter tuning could further validate their robustness.

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