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# Synergistic fibroblast optimization: a novel nature-inspired computing algorithm



**Key words:** Synergistic fibroblast optimization (SFO); Fitness analysis; Convergence; Benchmark suite; Monk's dataset

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# Motivations

1. Evolutionary computation techniques are developed based on the characteristics of natural phenomena, including foraging behavior, evolution, cell and molecular phenomena, cognition and neuro-systems, alignment phenomena in microscopes, non-biological systems, and geo-science based techniques.

2. The intellectual behaviour of fibroblast organism in the dermal wound healing process has inspired us to design and develop a novel synergistic fibroblast optimization (SFO) algorithm.

3. Various characteristics of fibroblast cellular organism, such as differentiation, proliferation, inflammation, migration, reorientation, alignment, ECM synthesis, collaborative, goal-oriented, interaction, regeneration, self adaptation, and evolution, have motivated us to design and develop SFO, which is a metaheuristic algorithm.

# Main ideas

1. Synergistic fibroblast optimization is a bio-inspired computing algorithm, which has been developed by the inspiration obtained from the intellectual behaviour of fibroblast cellular organism in the dermal wound healing process.

2. In the SFO algorithm, the numbers of fibroblasts and collagen particles are represented as discrete and continuous units.

3. Each cell's survival is constant for their fitness evaluation at its location, and then it determines the movement in the spatial co-ordinates, which depends on the members of the cell position towards the orientation in the evolutionary region and remodeling of collagen deposition found in the extracellular matrix (ECM) with some random perturbations.

4. This process is repeated until the pre-determined condition is met. Eventually, the swarm as a whole is collectively migrated to find an optimum solution in the problem space.

# Methods

1. The robustness, generalization, scalability, and comprehensibility of the proposed SFO algorithm are examined using the set of benchmark functions to evaluate the reliability, efficiency, robustness, and performance of the optimization algorithm in diverse and complex situations.

2. The SFO algorithm is tested with test functions, namely Sphere, Schwefel, Cosine Mixture, Alpine, Step 2, Ackley, Schumer Steiglitz, Griewank, Chung Reynolds, and Rastrigin, each of which has diverse properties, such as continuous or discontinuous, differentiable or non-differentiable, separable or non-separable, scalable or non-scalable, and unimodal or multimodal.

3. The performance of SFO is compared with those of other well-known algorithms, such as particle swarm optimization (PSO) and differential evolution (DE).

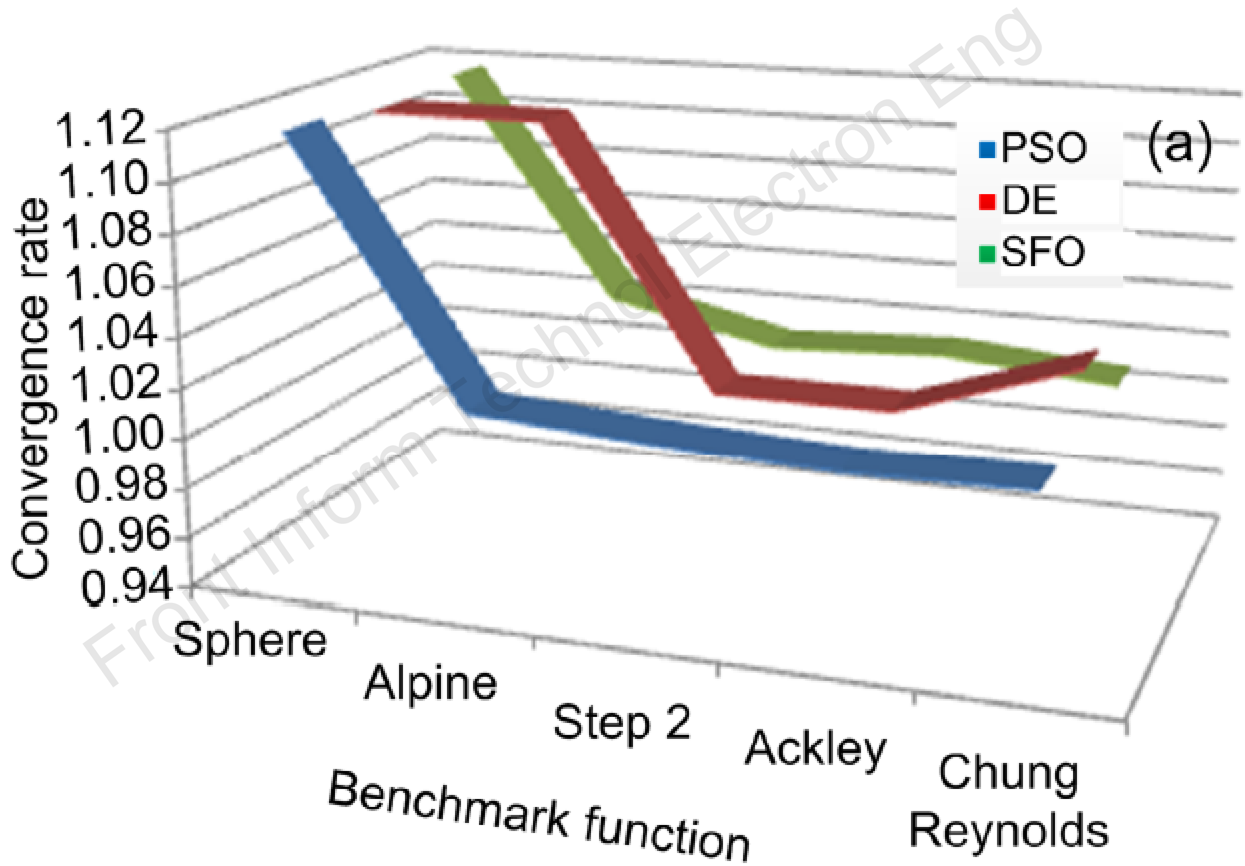
# Major results

**Table 2 Mean-squared error (MSE) comparison of the synergistic fibroblast optimization (SFO) algorithm**

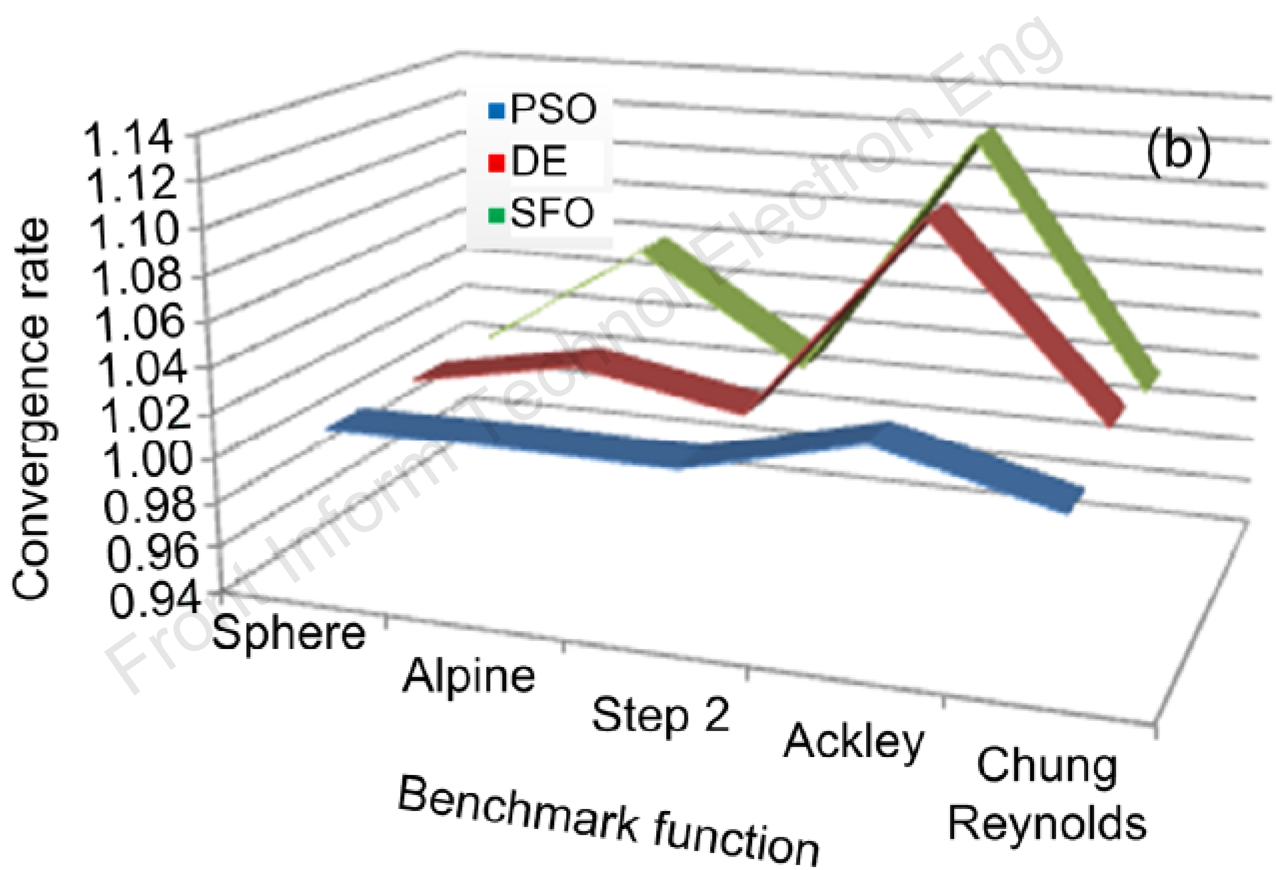
| Benchmark function | Problem size | MSE | | |
|---|---|---|---|---|
| | | 1000 iterations | 5000 iterations | 10 000 iterations |
| Sphere | $[0, 10]^D$ | 0.0064 | 0.0289 | 0.0729 |
| Schwefel | $[-10, 10]^D$ | 0.2500 | 0.6400 | 9.6100 |
| Cosine Mixture | $[-1, 1]^D$ | 0.9801 | 0.9216 | 0.8100 |
| Alpine | $[-10, 10]^D$ | 53.2900 | 0.0400 | 0.0100 |
| Step 2 | $[-100, 100]^D$ | 0.0900 | 0 | 0 |
| Ackley | $[-35, 35]^D$ | 0 | 0.6400 | 0.0400 |
| Schumer Steiglitz | $[-100, 100]^D$ | 174.2400 | 222.0100 | 81.0000 |
| Griewank | $[-100, 100]^D$ | 16.8100 | 32.4900 | 68.8900 |
| Chung Reynolds | $[-100, 100]^D$ | 0.6400 | 0 | 0 |
| Rastrigin's | $[-5.12, 5.12]^D$ | 0 | 0.01 | 1.5129 |

Grey-shaded areas indicate the multi-modal functions with the best results. White areas indicate the uni-modal functions

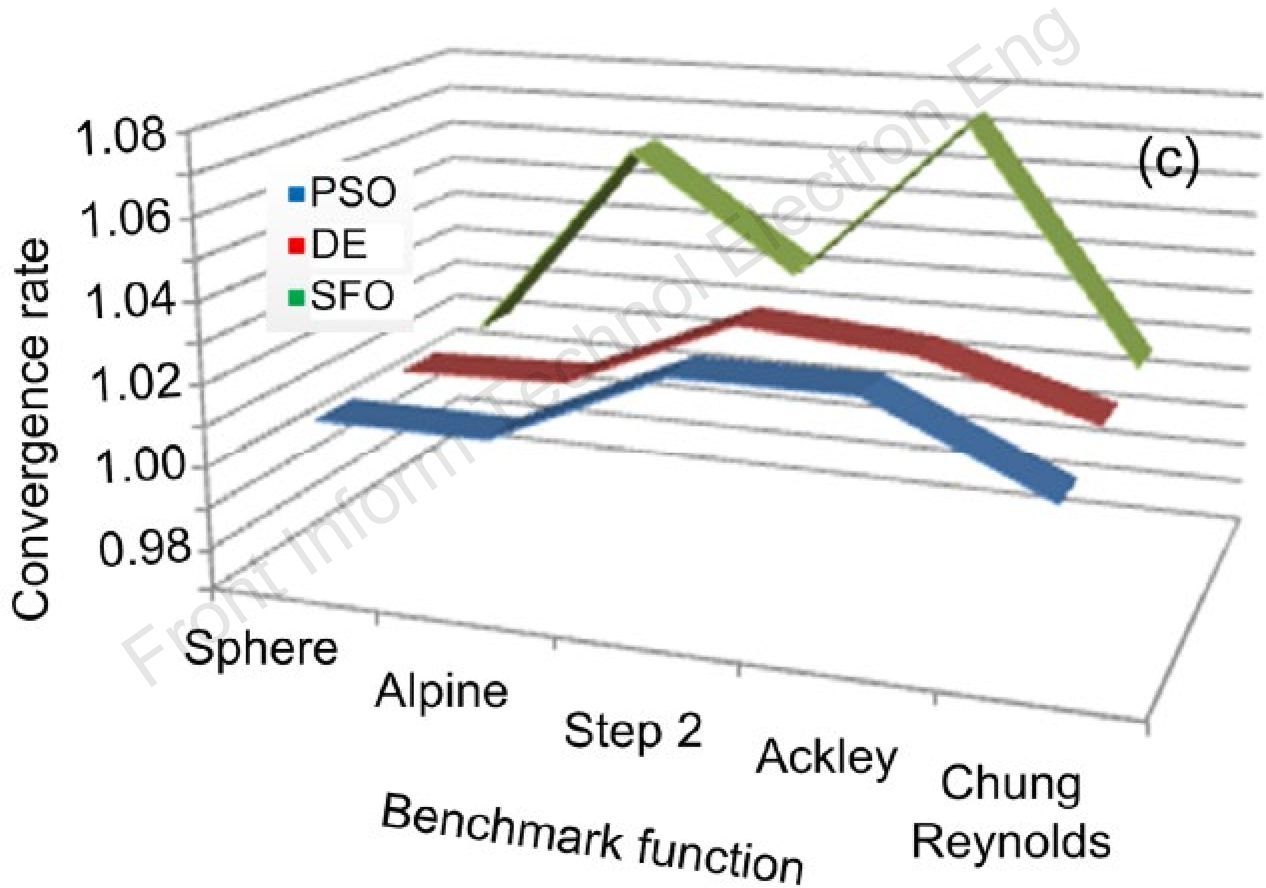
# Average convergence rate of SFO with PSO and DE in 1000 iterations



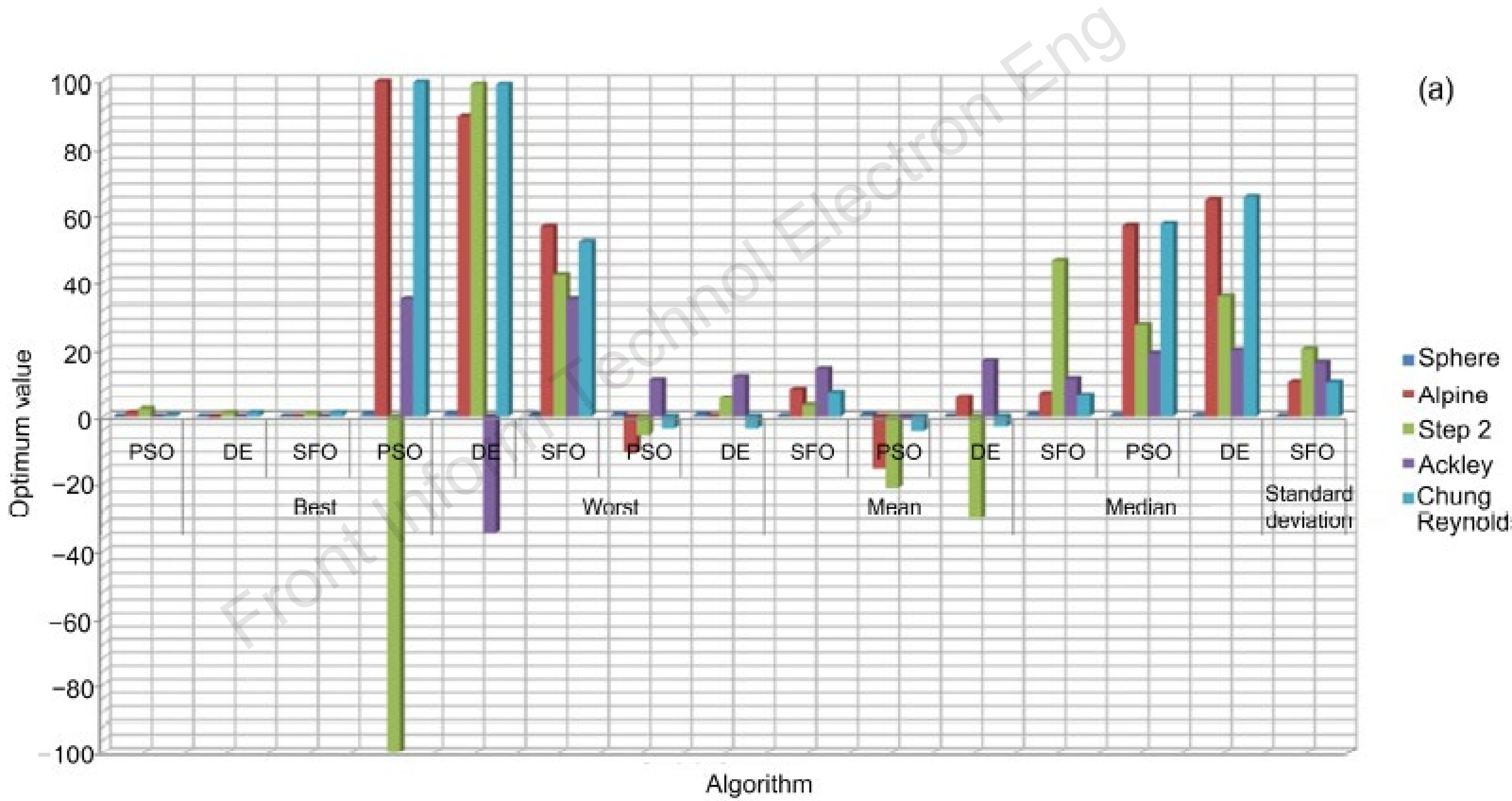
# Average convergence rate of SFO with PSO and DE in 5000 iterations



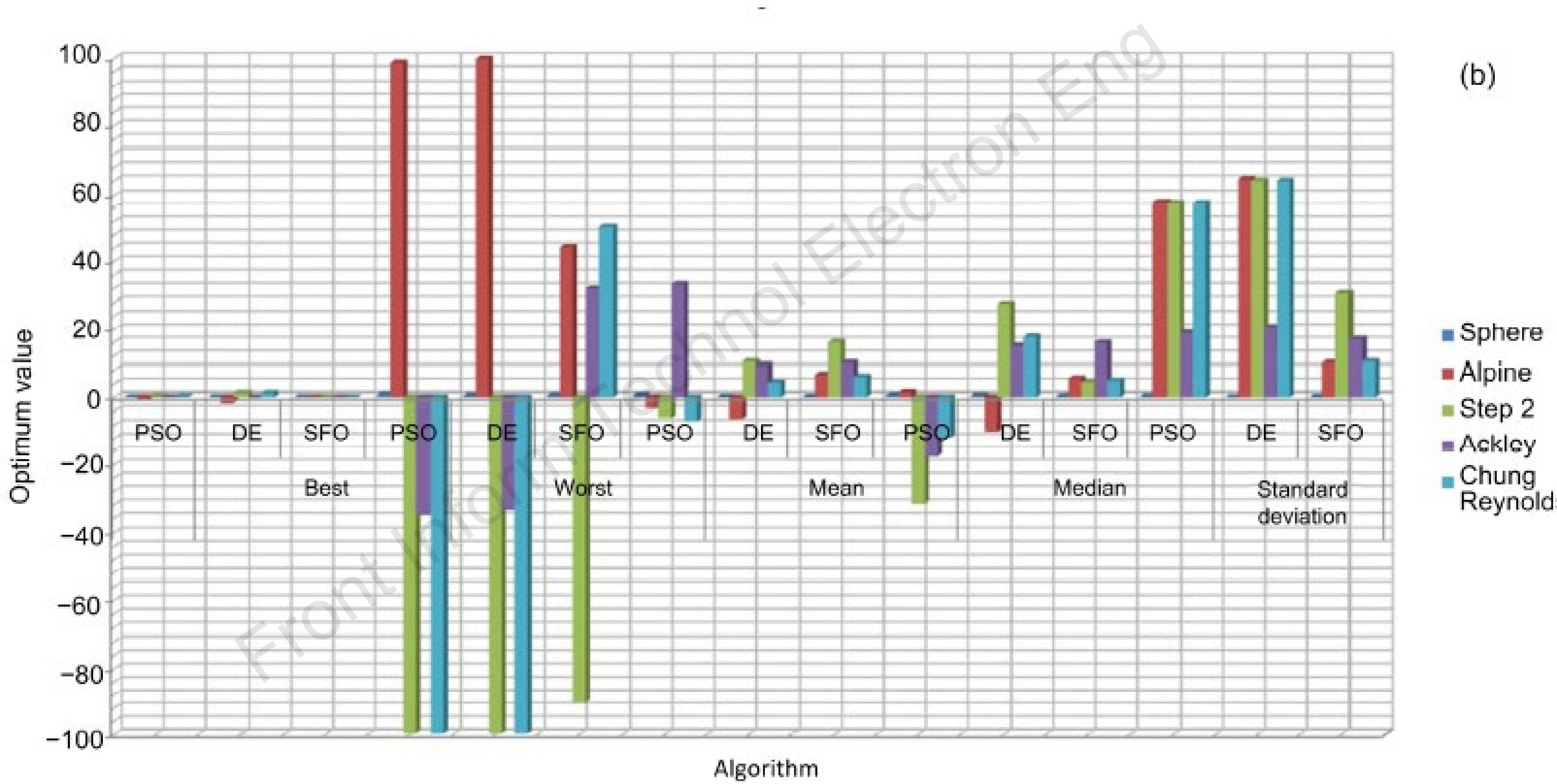
# Average convergence rate of SFO with PSO and DE in 10 000 iterations



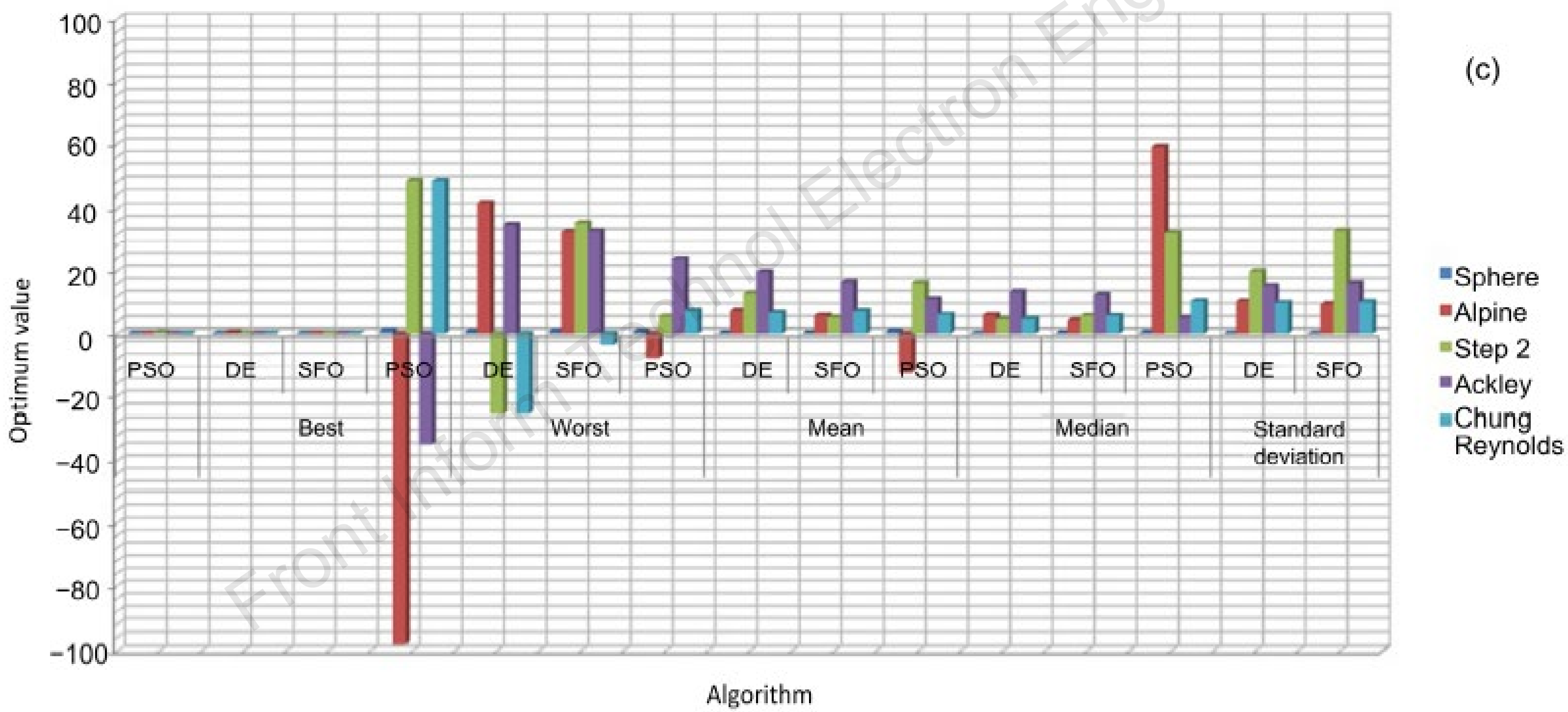
# Statistical measures of SFO, DE, and PSO in 1000 iterations



# Statistical measures of SFO, DE, and PSO in 5000 iterations



# Statistical measures of SFO, DE, and PSO in 10 000 iterations



# Conclusions and future work

1. Benchmark functions were used to validate the reliability and efficiency of SFO from various perspectives.

2. Experiments proved that SFO delivers better results than competitive algorithms in fitness function evaluation and convergence analysis, in finding an optimum solution to the minimization problem. It also offers an enhanced outcome for most of the test functions, specifically, Sphere, Cosine Mixture, Rastrigin's, Step 2, Ackley, and Chung Reynolds.

3. Future work may focus on investigating the performance of the SFO algorithm in real-time applications like the traveling salesman, graph coloring, optimized routing, combinatorial and assignment problem, and scheduling and resource constraint problems.