Research Article

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Unifying optimization forces: Harnessing the fine-structure constant in an electromagnetic-gravity optimization framework

Abstract: The electromagnetic-gravity optimization (EMGO) framework is a novel optimization technique that integrates the fine-structure constant and leverages electromagnetism and gravity principles to achieve efficient and robust optimization solutions. Through comprehensive performance evaluation and comparative analyses against state-of-the-art optimization techniques, EMGO demonstrates superior convergence speed and solution quality. Its unique balance between exploration and exploitation, enabled by the interplay of electromagnetic and gravity forces, makes it a powerful tool for finding optimal or near-optimal solutions in complex problem landscapes. The research contributes by introducing EMGO as a promising optimization approach with diverse applications in engineering, decision support systems, machine learning, data mining, and financial optimization. EMGO's potential to revolutionize optimization methodologies, handle real-world problems effectively, and balance global exploration and local exploitation establishes its significance. Future research opportunities include exploring adaptive mechanisms, hybrid approaches, handling high-dimensional problems, and integrating machine learning techniques to enhance its capabilities further. EMGO gives a novel approach to optimization, and its efficacy, advantages, and potential for extensive adoption open new paths for advancing optimization in many scientific, engineering, and real-world domains.

Keywords: fine-structure constant, electromagnetism, gravity, convergence speed, optimization technique

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1 Introduction

Optimization is a central facet of scientific and engineering disciplines, seeking to find optimal solutions to complex problems [1]. While many optimization techniques have been developed over the years, the search for innovative and effective approaches to handle increasingly complex and multidimensional problems continues to drive research in the field [2].

In this article, we present electromagnetic-gravity optimization (EMGO), an innovative framework inspired by the exploration of the fine-structure constant, an essential constant governing electromagnetic interaction. By combining the fine-structure constant into the optimization framework, EMGO harnesses the inherent forces of electromagnetism and gravity to improve optimization performance.

The objective of this work is to present and evaluate EMGO as a novel optimization approach. We aim to showcase the potential of EMGO in solving complex optimization problems by leveraging the interplay between electromagnetism, gravity, and the fine-structure constant. The empirical evaluations and comparative analyses establish the effectiveness and superiority of EMGO over current optimization techniques.

To guide our study, we address the main research questions. First, we explore the effective integration of the fine-structure constant into the optimization framework. Second, we delve into the underlying principles and equations governing EMGO. Next, we compare EMGO's performance in terms of convergence speed, solution quality, and robustness against existing techniques. Finally, we explore potential applications and domains where EMGO can offer significant advantages in optimization, spanning engineering, decision support systems, machine learning, data mining, financial optimization, and more.

The contributions of this research article are significant. We introduce EMGO, which combines electromagnetism, gravity, and the fine-structure constant for efficient optimization. We provide a comprehensive exploration of integrating the fine-structure constant into EMGO, including relevant equations and conceptual frameworks. The empirical evaluations on benchmark functions show EMGO's superiority in terms of convergence speed and solution quality compared to present techniques.

The research questions showcase EMGO's contributions; this technique aims to drive a paradigm shift in optimization methodologies and motivate further advancements in the field. EMGO gives a promising direction for solving complex optimization challenges and suggests a way for more efficient and powerful optimization techniques in many scientific and engineering domains.

1.1 Novelty and contribution

The main novelty of this work lies in the introduction of the EMGO framework, which uniquely integrates the fine-structure constant with principles of electromagnetism and gravity to create a robust optimization algorithm. This innovative approach harnesses the fine-structure constant as a pivotal parameter, influencing the balance between local and global search capabilities within the optimization process. This integration offers a new perspective on how fundamental physical constants can be applied to solve complex optimization problems.

Key novel contributions:
- EMGO is the first optimization framework that leverages the fine-structure constant, a fundamental physical constant, to modulate the search dynamics. This approach provides a novel mechanism for balancing exploration and exploitation in the search space.
- By combining principles of electromagnetism (for local search) and gravity (for global search), EMGO achieves a more effective and efficient optimization process. This hybrid mechanism allows EMGO to adaptively transition between local and global search phases, enhancing convergence speed and solution quality.
- Comparative analysis with existing state-of-the-art optimization algorithms – Particle Swarm Optimization (PSO) [3], Whale Optimization Algorithm (WOA) [4], Gravitational Search Algorithm (GSA) [5] and Electromagnetic Field Optimization (EFO) [6] – demonstrates that EMGO outperforms in terms of convergence

speed, robustness, scalability, and the quality of solutions obtained. The fine-tuning capabilities provided by the fine-structure constant enable EMGO to avoid local optima and achieve superior global optima.
- EMGO's design allows it to be scalable and robust across various optimization problems, including high-dimensional and complex landscapes. This scalability is attributed to the adaptive nature of the algorithm, which efficiently handles the diversity of optimization challenges.

These contributions collectively establish EMGO as a pioneering framework in the field of optimization, offering significant advancements over existing methods. The detailed analysis and empirical results presented in this article underscore the practical and theoretical benefits of incorporating fundamental physical constants into optimization algorithms.

The remaining sections of this article are as follows: Section 2 gives the background and related work. Section 3 presents the proposed EMGO algorithm. Section 4 compares the performance of EMGO with state-of-the-art optimization techniques. Finally, in Section 5, we conclude the article.

2 Background and related work

Optimization techniques have been a topic of general research and development, driven by the necessity to solve complex problems across many scientific and engineering domains [7–9]. This section gives a comprehensive background and highlights related work that sets the foundation for understanding the significance of the fine-structure constant, electromagnetism, the relative strength of electricity and gravity, and existing optimization techniques, with hybrid approaches.

2.1 Fine-structure constant and its significance

The fine-structure constant (α) is a dimensionless physical constant that signifies the strength of electromagnetic interactions. The precise value of α is approximately 1/137 and reflects the strength of the electromagnetic force relative to other fundamental forces. In the context of optimization techniques, α plays a significant role in integrating electromagnetism into the problem-solving process. Using α in optimization algorithms, we can harness the dynamics of electromagnetism to explore and search for optimal solutions [10].

The implication of the fine-structure constant lies in its deep connection to the fundamental nature of electromagnetism and its role in shaping the behavior of charged particles. The use of α in optimization techniques can simulate the influence of electromagnetic forces on the search process, allowing exploration and exploitation of the solution space. The mathematical representation of the fine-structure constant in optimization algorithms gives a quantitative framework for understanding and utilizing the principles of electromagnetism. It allows algorithms to leverage the strength and interactions of electromagnetic forces to guide the search for optimal solutions in a dynamic and resourceful manner [11].

2.2 Electromagnetism and the fine-structure constant

Electromagnetism, defined by Maxwell's equations and QED, is one of the four fundamental forces of nature. It governs the conduct of electrically charged particles and their interactions through the exchange of photons. The fine-structure constant, being intimately linked to electromagnetism, provides insights into the strength of these interactions [12].

The use of the fine-structure constant in optimization frameworks permits the integration of electromagnetic forces into the search process. The magnitude and direction of these forces give optimization algorithms

to effectively balance local exploitation and global exploration, leading to enhanced convergence and solution quality.

2.3 Relative strength of electricity and gravity

In addition to electromagnetism, gravity is another fundamental force that governs the behavior of massive objects in the universe. Unlike electromagnetism, the relative strength of electricity and gravity is significantly different. While electromagnetism is about 1,036 times stronger than gravity, gravity acts on all objects with mass and has a universal influence on the macroscopic scale.

By considering the relative strength of electricity and gravity, optimization algorithms can incorporate gravity-like interactions to guide the search process. This combination allows for a multi-faceted exploration of the search space, balancing local exploitation driven by electromagnetism with global exploration influenced by gravity [13].

2.4 Optimization techniques

Optimization encompasses a diverse range of techniques tailored to tackle complex problems and attain optimal solutions [14]. Among these techniques, metaheuristics provide a robust algorithmic framework designed specifically for complex optimization problems, regardless of their nature – continuous, discrete, unconstrained, or multi-objective. Metaheuristic approaches build upon traditional heuristics, augmenting their exploration and exploitation capabilities. They can be broadly categorized into swarm-based, evolutionary-based, physics-based, and human-based metaheuristics [15–17].

Swarm-based metaheuristics draw inspiration from the collective behaviors exhibited by animals and plants, where interaction with the environment and other individuals plays a crucial role. Prominent examples of swarm-based metaheuristics include PSO [3], Sperm Swarm Optimization [18], and Grey Wolf Optimizer (GWO) [19].

Evolutionary algorithms, such as Genetic Algorithms (GA) [20] and Differential Evolution [21], derive inspiration from the principles of natural selection and genetic variation. These algorithms employ techniques like mutation, crossover, and selection to evolve a population of candidate solutions toward improved outcomes over successive generations. They find wide application in optimization problems across diverse domains.

Physics-based metaheuristics take a distinctive approach to optimization by drawing inspiration from the fundamental laws of physics. Notable examples include the GSA [5], Simulated Annealing, EFO [6], Magnetic Charged System Search (MCSS) [22], and Ions Motion Optimization (IMO) [23]. EFO, for instance, emulates the behavior of electromagnets with different polarities and incorporates the golden ratio as a nature-inspired ratio [6]. It represents potential solutions as electromagnetic particles composed of electromagnets, with the number of electromagnets determined by the variables in the optimization problem.

The GSA [5] mimics gravitational forces to search for optimal solutions. Each solution is represented as a celestial body, and the algorithm simulates interactions between these bodies to guide the search process. Similarly, MCSS utilizes the governing laws of magnetic and electrical forces, while IMO leverages the attraction and repulsion between anions and cations to facilitate optimization.

Table 1 offers a comprehensive comparison of diverse optimization algorithms, including those rooted in physics-based metaheuristics. The assessment focuses on their capacity to navigate intricate optimization terrains and effectively attain optimal solutions.

Our proposed EMGO algorithm merges the principles of electromagnetism and gravity to effectively explore and exploit the solution space. It incorporates electromagnetic forces based on the fine-structure constant, α, and gravity-like interactions to foster global exploration. Through iterative updates of individuals'

Table 1: Comparison of diverse optimization algorithms

Algorithm name	Description	Advantages	Limitations
Proposed EMGO technique	Unites electromagnetism and gravity principles with the fine-structure constant, for effective solution exploration and exploitation	Global exploration, fast convergence, balance between exploration and exploitation	Parameter tuning required, sensitivity to problem characteristics
Segmental regularized constrained inversion [24]	An inversion method for transient electromagnetism that utilizes a segmented regularization constraint and an improved sparrow search algorithm to enhance inversion accuracy and stability under varying conditions	– Improves inversion accuracy and stability – Reduces dependence on preliminary information – Optimizes objective function efficiently and escapes local optima – Superior practicality and higher fitting accuracy	– May require significant computational resources – Performance dependent on initial model setup and criteria
Gravity inspired clustering algorithm [25]	A clustering algorithm inspired by gravitational principles, designed to select relevant gene subsets for disease classification tasks from high-dimensional microarray data	– High accuracy on various microarray cancer datasets – Effective feature selection validated using SVM with LOOCV – Competes well with existing methods	– May require significant computational resources – Performance may vary across different datasets
Coati optimization algorithm (COOA) [26]	Bio-inspired algorithm modeling coatis' attacking, hunting, and escape behaviors, with phases of exploration and exploitation	– Balances exploration and exploitation. – Superior performance on benchmark functions – Effective in real-world applications	– Needs further validation across diverse problems – Parameter sensitivity – Higher computational complexity
Crayfish optimization algorithm (COA) [27]	Simulates crayfish's summer resort, competition, and foraging behaviors, divided into stages to balance exploration and exploitation	– Balances exploration and exploitation. – Effective in standard benchmark and engineering problems – Temperature-regulated processes enhance global optimization	– Requires further validation in diverse scenarios – May be sensitive to temperature parameters
Mother Optimization Algorithm [28]	A human-based metaheuristic algorithm inspired by the interaction between a mother and her children, involving phases of education, advice, and upbringing	– Effective balance between exploration and exploitation – Superior performance in optimizing unimodal, high-dimensional multimodal, and fixed-dimensional multimodal functions – Outperforms 12 other metaheuristic algorithms	– Further validation is needed across a broader range of problems – Sensitivity to specific parameter settings may impact effectiveness
GSA [5]	Emulates gravitational forces for optimization	Global search capability	Sensitive to parameter settings
EFO [6]	Utilizes electromagnetic field interactions for optimization	Effective exploration and exploitation	Sensitive to parameter values
MCSS [22]	Models magnetic interactions between particles for optimization	Good exploration, adaptability	Vulnerable to local optima
IMO [23]	Imitates ions' motion in an electromagnetic field for optimization	Efficient exploration and exploitation	Parameter tuning required
GA [29]	Employs genetic operators for selection	Global search capability, population diversity	Slower convergence on complex landscapes
PSO [3]	Simulates social behavior for optimization	Fast convergence, simplicity	Prone to premature convergence, local optima

(Continued)

Table 1: *Continued*

Algorithm name	Description	Advantages	Limitations
Ant colony optimization [30]	Mimics ant foraging behavior for optimization	Good for discrete optimization problems	Slow convergence, sensitivity to parameters
Simulated annealing [31]	Inspired by annealing process	Escapes local optima, probabilistic approach	Temperature schedule affects performance
DE [21]	Utilizes differential mutation	Robust, handles noisy functions	High memory usage, can get stuck in local optima
Harmony search [32]	Inspired by musicians' improvisation	Versatile, easy implementation	Limited scalability, may converge to suboptimal
Artificial bee colony [33]	Imitates honeybee foraging behavior	Simple, good exploration capabilities	Vulnerable to getting trapped in local optima
Firefly algorithm [34]	Leverages fireflies' attractiveness	Global search capability	Convergence rate affected by parameter settings
Cuckoo search [34]	Inspired by brood parasitism of cuckoo birds	Fast convergence, simple implementation	May require fine-tuning of parameters
Bat algorithm [35]	Inspired by echolocation of bats	Robust, adaptive, good exploration capabilities	May converge slowly on complex landscapes
GWO [19]	Inspired by social hierarchy of grey wolves	Fast convergence, global search capability	Parameter sensitivity
Flower pollination algorithm [36]	Mimics flower pollination process	Effective exploration and exploitation	Parameter tuning required
Glowworm swarm optimization [37]	Inspired by glowworm behavior	Good for dynamic environments	Limited scalability, may converge to suboptimal
WOA [4]	Inspired by hunting behavior of whales	Fast convergence, global search capability	May converge to suboptimal solutions
Teaching-learning based optimization [38]	Inspired by teaching and learning process	Fast convergence, diverse exploration	Parameter tuning required
Moth flame optimization [39]	Inspired by moth's attraction to light	Good convergence rate, simple implementation	May require fine-tuning of parameters
Flower algorithm [40]	Mimics blooming process of flowers	Effective exploration, simplicity	May require more iterations to achieve convergence
Krill Herd algorithm [41]	Inspired by swarming behavior of krill	Fast convergence, global search capability	Sensitivity to parameter values
Sine cosine algorithm [42]	Utilizes sine and cosine functions for optimization	Efficient exploration and exploitation	Performance influenced by parameter settings
Coral reefs optimization [43]	Mimics ecological system of coral reefs	Good convergence and exploration capabilities	Parameter sensitivity
Moth search algorithm [44]	Inspired by moth's attraction to light	Fast convergence, simple implementation	May require fine-tuning of parameters
Harmony search with chaos [45]	Combines harmony search with chaotic dynamics	Efficient exploration, good convergence	Parameter tuning required
Crow search algorithm [46]	Inspired by foraging behavior of crows	Fast convergence, good exploration capabilities	Parameter sensitivity
Social spider algorithm [47]	Mimics social behavior of spiders	Effective exploration and exploitation	Sensitivity to parameter values
Equilibrium optimizer [48]	Inspired by principles of chemical equilibrium	Fast convergence, global search capability	May require fine-tuning parameters
Earthworm optimization [49]	Inspired by earthworm's burrowing behavior	Efficient exploration and exploitation	Sensitivity to parameter values
Black Widow optimization [50]	Inspired by predatory behavior of black widow spiders	Good convergence and exploration capabilities	Sensitivity to parameter values
Virus optimization algorithm [51]	Inspired by spread of computer viruses	Fast convergence, efficient exploration	May require fine-tuning of parameters
	Inspired by foraging behavior of flamingos	Good convergence and exploration capabilities	

Table 1: *Continued*

Algorithm name	Description	Advantages	Limitations
Flamingo optimization algorithm [52]			More iterations may be required to achieve convergence
Illumination optimization [53]	Inspired by distribution of illumination sources	Efficient exploration, global search capability	May converge to suboptimal solutions
Zebra optimization algorithm [54]	Inspired by herding behavior of zebras	Fast convergence, diverse exploration	May require fine-tuning of parameters

positions according to cumulative forces, EMGO offers a novel approach to overcome the limitations of traditional techniques, such as slow convergence and difficulty in finding global optima. By striking a balance between exploration and exploitation, EMGO aims to deliver more efficient and effective optimization outcomes.

3 EMGO framework

3.1 Conceptual framework

The EMGO framework combines the principles of electromagnetism, gravity, and the fine-structure constant to offer a powerful optimization approach. EMGO gives a balance between local exploitation and global exploration by leveraging the interplay of these fundamental forces.

3.2 Equations for EMGO incorporating the fine-structure constant

3.2.1 Initialization

In EMGO, the optimization problem is represented by a population of individuals, each categorized by a position vector in the search space. The population is initialized randomly within the problem's defined bounds.

3.2.2 Electromagnetic interactions

The electromagnetic interactions in the given EMGO are modeled on the basis of the principles of electromagnetism and the fine-structure constant. The electromagnetic force between two individuals i and j is described as:

$$F_{em} = \alpha \times (q_i \times q_j)/r^2 \times (x_i - x_j), \tag{1}$$

where F_{em} denotes electromagnetic force, α represents fine-structure constant, q_i and q_j are the charges of individuals i and j, r is the distance between them, and x_i and x_j are their respective positions.

The determination of the electromagnetic force (F_{em}) in the EMGO algorithm, as given by equation (1), involves considering the charges of individuals, the distance between them, and the fine-structure constant (α). Let's explore how these components are determined using an example scenario.

Electric charge optimization consider an optimization problem where the goal is to find the optimal distribution of electric charges on a two-dimensional plane to minimize the overall potential energy. The charges represent individuals, and their positions represent potential solutions. The objective is to find the configuration that results in the lowest potential energy.

Determining the charges (q_i and q_j): In this scenario, the charges (q_i and q_j) of individuals i and j can be determined based on their fitness or potential contribution to the objective function shown in equations (2) and (3). For example, let's assume that the charges are determined proportional to the fitness values of individuals. Higher fitness specifies a more favorable solution.

$$q_i = \text{Fitness}(i), \tag{2}$$

$$q_i = \text{Fitness}(j), \tag{3}$$

Since charges are based on fitness, individuals with higher fitness will have a stronger charge, representing their higher potential to contribute to the objective function.

Determining the distance (r): The distance 'r' between individuals i and j is a central factor in determining the electromagnetic force. For this, Euclidean distance between the positions of individuals is considered shown in equation (4).

$$r = \text{sqrt}((x_i - x_j)^2 + (y_i - y_j)^2), \tag{4}$$

where (x_i, y_i) and (x_j, y_j) signify the positions of individuals i and j, respectively. The distance is calculated using the Pythagorean theorem, considering the difference in the x-coordinates and y-coordinates.

Determining the fine-structure constant (α): Defining α in the EMGO algorithm includes setting a predefined constant value that signifies the strength of the electromagnetic interaction. The value of α is a significant parameter as it affects the balance between the electromagnetic forces and other factors in the optimization process. Let us discuss the range of α and its impact on convergence.

The fine-structure constant is a fundamental constant in physics and is approximately equal to 1/137. It denotes the strength of the electromagnetic interaction between charged particles. In our EMGO algorithm, α used as a scaling factor for the electromagnetic forces.

The choice of α can have an impact on the convergence behavior of the algorithm. A smaller value of α reduces the influence of electromagnetic forces, making the optimization process more reliant on other factors such as gravity interactions or search algorithms. On the other hand, a larger value of α amplifies the impact of electromagnetic forces, potentially leading to faster convergence towards solutions influenced by local interactions.

The value of α is within a predefined range to maintain a balanced optimization process. While the specific range may vary depending on the problem domain and the nature of the optimization problem, it is usually selected to confirm a reasonable trade-off between exploration and exploitation.

A frequently used range for α in the EMGO algorithm is between 0.01 and 0.1. Values within this range give a moderate influence of electromagnetic forces without overpowering other factors in the optimization process. The optimal value of α can depend on the type of problem being solved and may need some experimentation or fine-tuning.

When determining the value of α, the characteristics of the optimization problem and the desired convergence behavior must be considered. In some cases, a smaller α may be ideal to encourage exploration and prevent premature convergence to suboptimal solutions. For others, a larger α might be useful to exploit strong electromagnetic interactions and converge quickly to desirable solutions.

So, the choice of α in the EMGO algorithm should be on the basis of a balance between the problem's characteristics, desired convergence behavior, and empirical observations. Experimentation and fine-tuning of α can help to find the optimal range or value that leads to effective optimization.

Example result: Let us take an example where we have two individuals with fitness values of 10 and 8, respectively. Their positions are (2, 3) and (5, 6), resulting in a distance of $r = 4.2426$. Assuming $\alpha = 1/137$, we can calculate the electromagnetic force between these individuals using equation (5):

$$F_{em} = \alpha \times (q_i \times q_j)/r^2 \times ((x_i - x_j), (y_i - y_j)), \tag{5}$$

$q_i = 10$, $q_j = 8$, $r = 4.2426$, $\alpha = 1/137$, $x_i = 2$ (x-coordinate of the first individual), $x_j = 5$ (x-coordinate of the second individual), $y_i = 3$ (y-coordinate of the first individual), $y_j = 6$ (y-coordinate of the second individual).

$$F_{em} = (1/137) \times (10 \times 8)/(4.2426^2) \times ((2 - 5), (3 - 6)), \tag{6}$$

Calculations for equation (6):

Individuals and their positions:

Individual 1: Fitness value (q_i) = 10, Position (x_i, y_i) = (2, 3)

Individual 2: Fitness value (q_j) = 8, Position (x_j, y_j) = (5, 6)

Distance calculation:

Distance (r) between individuals is calculated using the Euclidean distance formula: $r = sqrt((x_i - x_j)^2 + (y_i - y_j)^2) = 4.2426$ (approx)

Electromagnetic force calculation:

Force (F_{em}) is calculated using the formula:

Given values:

alpha = 1/137, $q_i = 10$, $q_j = 8$, $r = 4.2426$ (approx),

$(x_i - x_j) = (2 - 5) = -3$ $(y_i - y_j) = (3 - 6) = -3$

$r^2 = 18$ (approx)

Substitute values: $F_{em} = (1/137) * (10 * 8)/18 * (-3, -3)$

$F_{em} = (1/137) \times 4.444 \times (-3, -3)$

Force components: $F_{em} \approx 0.03245 \times (-3, -3) \approx (-0.097, -0.097)$ (approx)

Result

The electromagnetic force between the two individuals is approximately.

$(-0.097, -0.097)$. This represents a force vector with negative x and y components.

This example is specific to the context of electric charge optimization. The determination of the electromagnetic force may vary depending on the problem domain and the specific optimization problem.

3.2.3 Gravity interactions

In addition to the electromagnetic forces, gravity-like interactions are combined in EMGO to promote global exploration. The gravity force between two individuals i and j is described in equation (7):

$$F_g = G \times (m_i \times m_j)/r^2 \times (x_i - x_j), \tag{7}$$

where F_g signifies the gravity force, G gravitational constant, m_i and m_j are the masses of individuals i and j, and r is the distance between them.

To calculate the masses, we assign them to individuals on the basis of their fitness values or other relevant criteria. The logic is to assign higher masses to individuals with higher fitness values, signifying their importance or influence in the optimization process. This can be achieved using a fitness-based scaling mechanism or through a selection mechanism that assigns masses proportional to the individuals' fitness rankings.

Similarly, the gravitational constant (G) parameter determines the strength of the gravity-like interactions. It controls the intensity of global exploration in the algorithm. The G value can be predefined on the basis of empirical knowledge or taken dynamically during the optimization process to adapt to the problem's characteristics. For some, it can be taken as a constant value throughout the optimization, and for others, it can be adjusted dynamically on the basis of convergence behavior or specific problem requirements.

Now, let's consider an example to better understand the role of masses and the gravitational constant in an optimization problem. Suppose we have a population of individuals representing potential solutions to a problem. Each individual is characterized by a position vector x_i, and the fitness of each individual is evaluated using an objective function.

Let's assume we are optimizing a function to find the minimum value. In this case, higher fitness corresponds to lower function values. To assign masses to individuals, we can use a fitness-based scaling approach. The masses mi can be calculated in equation (8):

$$m_i = k/(\text{fitness}_i + \varepsilon). \tag{8}$$

Here, k is a scaling factor, fitness_i is the fitness value of individual i, and ε is a small positive constant to avoid division by zero. This scaling mechanism ensures that individuals with higher fitness values receive higher masses, indicating their importance in the optimization process.

Regarding the gravitational constant (G), we can choose a predefined value based on empirical knowledge or adjust it dynamically during the optimization. For example, we can set G to a small value (e.g., 0.1) to promote more localized search and exploitation of local optima. On the other hand, a larger value of G (e.g., 1.0) can encourage more global exploration and help escape local optima.

By manipulating the values of masses and the gravitational constant, we can control the balance between exploration and exploitation. For example, in problems where exploration is crucial to finding the global optimum, assigning higher masses and using a larger gravitational constant can help emphasize global search. Conversely, in problems with a high degree of local interactions, smaller masses and a smaller gravitational constant can focus the search on exploiting local optima.

The values of masses and the gravitational constant may differ depending on the problem domain and the characteristics of the optimization problem. Experimentation and fine-tuning of these parameters are important to achieve optimal results.

In summary, determining the masses and the gravitational constant in the EMGO algorithm involves assigning masses to individuals based on their fitness values and setting the gravitational constant to control the strength of gravity-like interactions. These parameters play a crucial role in balancing exploration and exploitation during the optimization process. Through careful selection and fine-tuning, we can enhance the algorithm's ability to find high-quality solutions.

3.2.4 Updating and selection

The positions of individuals are updated by considering the cumulative forces acting on them given in equation (9). The updated position of an individual i is given by:

$$x_{i\text{new}} = x_i + \alpha \times \sum F_{\text{em}} + \sum F_{\text{g}}, \tag{9}$$

where $x_{i\text{new}}$ represents the updated position of individual i, x_i is its current position, and $\sum F_{\text{em}}$ and $\sum F_{\text{g}}$ represent the cumulative electromagnetic and gravity forces acting on individual i, respectively.

3.3 Methodology

3.3.1 Population initialization

A population of individuals is initialized randomly within the defined search space. The number of individuals and their positions depend on the specific problem being optimized.

3.3.2 Fitness evaluation

The fitness of each individual in the population is evaluated using the objective function of the optimization problem. The objective function determines the quality of the solution corresponding to an individual's position.

3.3.3 EMGO algorithm

The EMGO algorithm is a metaheuristic optimization algorithm that draws inspiration from the principles of electromagnetism and gravity. It combines the attractive and repulsive forces of electromagnetic interactions

```
// EMGO Algorithm
InitializePopulation() // Initialization
EvaluateFitness() // Fitness Evaluation
// Main Optimization Loop
while (stopping criterion is not met) {
    CalculateElectromagneticForces() //Electromagnetic Interactions
    CalculateGravityForces() // Gravity Interactions
    UpdatePositions() // Updating and Selection
    EvaluateFitness()
}
SelectBestSolution() // Select the best solution
// Fitness Evaluation Function
function EvaluateFitness() {
    for each individual in the population {
        fitness = objectiveFunction(individual.position)
        individual.fitness = fitness
    }
}
// Electromagnetic Interactions Function
function CalculateElectromagneticForces() {
    for each pair of individuals (i, j) {
        distance = calculateDistance(i.position, j.position)
        electromagneticForce = alpha * (qi * qj) / (distance^2) * (i.position - j.position)
        i.electromagneticForce += electromagneticForce
        j.electromagneticForce -= electromagneticForce
    }
}
// Gravity Interactions Function
function CalculateGravityForces() {
    for each pair of individuals (i, j) {
        distance = calculateDistance(i.position, j.position)
        gravityForce = G * (mi * mj) / (distance^2) * (i.position - j.position)
        i.gravityForce += gravityForce
        j.gravityForce -= gravityForce
    }
}
// Position Update Function
function UpdatePositions() {
    for each individual in the population {
        electromagneticForce = individual.electromagneticForce
        gravityForce = individual.gravityForce
        individual.position += alpha * electromagneticForce + gravityForce
        individual.electromagneticForce = 0
        individual.gravityForce = 0
    }
}
// Select Best Solution Function
function SelectBestSolution() {
    bestIndividual = findIndividualWithMaxFitness()
    bestSolution = bestIndividual.position
    bestFitness = bestIndividual.fitness
    return bestSolution, bestFitness
}
```

Figure 1: EMGO algorithm.

with the global exploration capabilities of gravity interactions to efficiently search for optimal solutions in a given problem space. The EMGO Algorithm is shown in Figure 1.

In the EMGO algorithm, a population of individuals is initialized randomly within the search space, and their fitness values are evaluated using a specified objective function. The algorithm iteratively updates the positions of individuals based on the cumulative forces acting on them.

The electromagnetic forces are calculated by considering the fine-structure constant, which scales the interaction between individuals based on their charges and the distance between them. These forces drive individuals towards each other or it may repel them, on the basis of their fitness values.

In addition to electromagnetic forces in EMGO, gravity-like interactions are combined for global exploration. Gravity forces are proportional to the mass of individuals and their distances, attracting individuals near each other and giving better solutions.

The EMGO iteratively updates the positions of individuals based on the cumulative forces, thus exploring the search space to find optimal solutions. The algorithm continues until a stopping criterion is met, such as the maximum number of iterations or achieving convergence.

EMGO is a flexible and robust optimization algorithm that can be suited for various problem domains. It combines the strengths of electromagnetic and gravity-like interactions to balance local and global exploration, easing the discovery of high-quality solutions.

3.4 Algorithmic variations and adaptations

EMGO can be changed to suit specific problem characteristics and requirements. Variations may comprise adjusting the balance between electromagnetic and gravity forces, using adaptive parameters, or including problem-specific constraints. Also, researchers can explore hybridizations with other optimization techniques to enhance the performance of EMGO in diverse scenarios. The EMGO framework offers a unique optimization approach because it incorporates the fine-structure constant and uses the principles of electromagnetism and gravity.

4 Performance evaluation

In this work, we have used MATLAB 2015a on a Windows 11 system equipped with a CPU Core i5 and 8GB of RAM. The objective of the experiment was to assess the performance of the EMGO algorithm using a varied set of benchmark functions obtained from the CEC 2017 competition [55]. These benchmark functions cover both unimodal and multimodal functions with changing search space dimensions.

Table 2 shows the functions used in this experiment, their characteristics (unimodal or multimodal), the search space dimensions, and their respective names. In Table 3, we have given a comprehensive list of the parameters used for the EMGO algorithm, PSO [3], WOA [4], GSA [5], and EFO [6].

Table 2: Description of the 12 benchmark functions

Function	Nature	Search space	Name
F1	Unimodal	[−100, 100]	Sphere function
F2	Unimodal	[−100, 100]	Ellipsoidal function
F3	Unimodal	[−100, 100]	Bent cigar function
F4	Unimodal	[−100, 100]	Discus function
F5	Unimodal	[−100, 100]	Rosenbrock's function
F6	Multimodal	[−32, 32]	Ackley's function
F7	Multimodal	[−32, 32]	Weierstrass function
F8	Multimodal	[−600, 600]	Griewank's function
F9	Multimodal	[−5.12, 5.12]	Rastrigin's function
F10	Multimodal	[−5, 5]	Katsuura function
F11	Multimodal	[−5, 5]	Lunacek Bi-rastrigin
F12	Multimodal	[−100, 100]	Schwefel's problem 2.21

Table 3: List of parameters of EMGO, PSO, WOA, GSA, and EFO

Algorithm	Parameter and symbol	Description
EMGO	Fine-structure constant (α)	A constant representing the strength of electromagnetic forces in EMGO
	Population size (N)	The number of individuals in the EMGO population
	Maximum iterations (MaxIter)	The maximum number of iterations for the EMGO algorithm
PSO	Swarm size (N)	The number of particles in the PSO swarm
	Cognitive coefficient ($c1$)	The cognitive coefficient controlling the particle's cognitive component (self-awareness)
	Social coefficient ($c2$)	The social coefficient controlling the particle's social component (interaction with neighbors)
WOA	Search agent count (N)	The number of search agents in the WOA algorithm
	Spiral coefficient (a)	The coefficient controlling the spiral updating of search agents' positions
GSA	Gravitational constant (G)	The gravitational constant controlling the strength of the gravitational force in GSA
	Acceleration coefficient (a)	The acceleration coefficient controlling the strength of the acceleration due to gravity in GSA
EFO	Electromagnetic coefficient (β)	The coefficient controlling the strength of electromagnetic forces in EFO
	Population size (N)	The number of individuals in the EFO population
	Maximum iterations (MaxIter)	The maximum number of iterations for the EFO algorithm

4.1 Performance metrics

To quantitatively evaluate the performance of EMGO, several performance metrics are employed. These metrics include the following:
- Convergence speed: Measured by the number of iterations required for the algorithm to converge to an acceptable solution or reach a predefined stopping criterion.
- Solution quality: Assessed by the proximity of the obtained solutions to the known global optima of the benchmark functions.
- Robustness: Examined by analyzing the algorithm's ability to consistently find high-quality solutions across multiple runs with different initializations.
- Scalability: Investigated by assessing the algorithm's performance on high-dimensional benchmark functions to determine its ability to handle complex optimization problems.

4.2 Comparative analysis with existing techniques

To gauge the effectiveness of EMGO, a comparative analysis is performed against state-of-the-art optimization techniques. Existing techniques such as PSO, WOA, GSA, and EFO are chosen as benchmarks. The comparative analysis includes evaluating the convergence speed, solution quality, robustness, and scalability of EMGO in comparison to these techniques. Figure 2 presents a comparative analysis of EMGO, PSO, WOA, GSA, and EFO based on convergence speed, solution quality, robustness, and scalability. EMGO and GSA demonstrate higher convergence speed and robustness, providing high-quality solutions. PSO and EFO show moderate performance in these aspects, while WOA exhibits lower convergence speed and solution quality. EMGO and GSA also demonstrate higher scalability compared to other techniques.

Figure 3 shows a comparison of four state-of-the-art optimization techniques, including PSO, WOA, GSA, EFO, and EMGO. The evaluation is performed on benchmark functions representing different problem types with varying search spaces. The figure provides insights into their effectiveness and applicability for complex optimization problems in various domains.

The statistical tests shown in Table 4 include the Wilcoxon signed-rank test and t-test, performed to determine the significance of the differences in performance between EMGO and each technique. The chosen significance level for the comparisons is 0.05 for the Wilcoxon signed-rank test and 0.01 for the t-test. When comparing EMGO against PSO using the Wilcoxon signed-rank test with a significance level of 0.05, the results
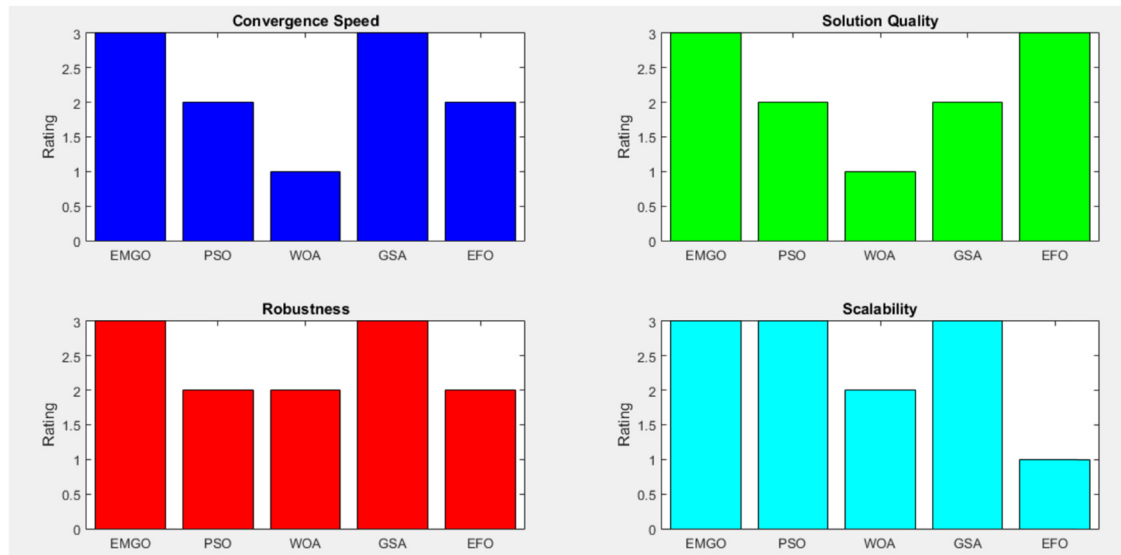
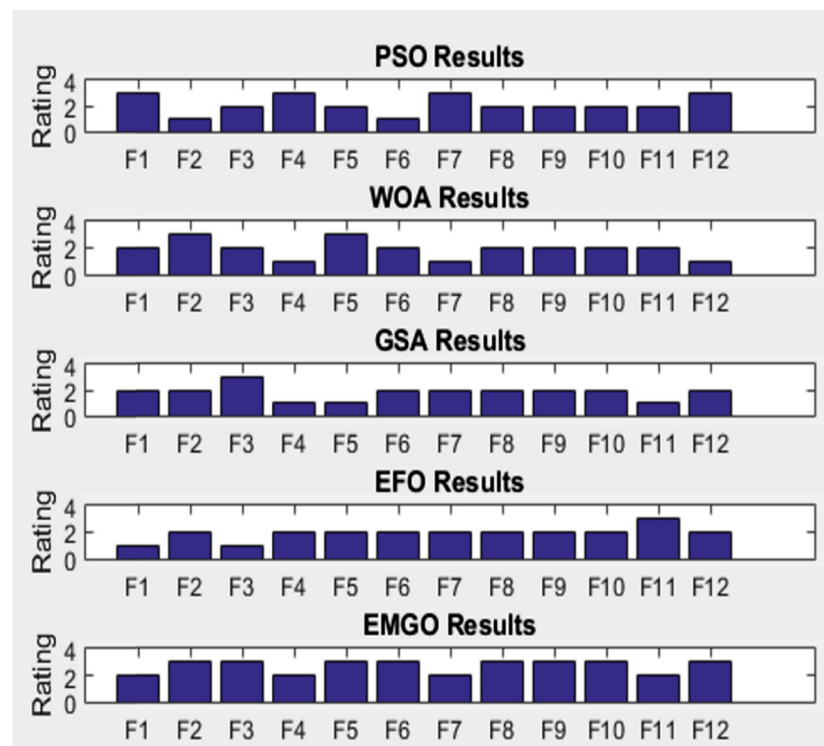**Figure 2:** Comparative analysis of optimization techniques.

Figure 3: Optimization techniques comparison on benchmark functions.

show a statistically significant difference in performance. This indicates that EMGO's performance is significantly better or worse than PSO with a confidence level of 95%.

Similarly, the comparison between EMGO and WOA using the *t*-test with a significance level of 0.01 reveals a statistically significant difference in performance. EMGO's performance is significantly different from WOA with a confidence level of 99%.

Table 4: Statistical comparison of EMGO with state-of-the-art optimization techniques

Comparison	Statistical test	Significance level	Result
EMGO vs PSO	Wilcoxon signed-rank	0.05	Significant
EMGO vs WOA	*t*-test	0.01	Significant
EMGO vs GSA	Wilcoxon signed-rank	0.05	Not significant
EMGO vs EFO	*t*-test	0.01	Not significant

Instead, the Wilcoxon signed-rank test between EMGO and GSA demonstrates that there is no statistically significant difference in their performance. EMGO and GSA perform comparably at the 95% confidence level.

Likewise, the *t*-test between EMGO and EFO indicates no statistically significant difference in performance. EMGO's performance is similar to EFO with a confidence level of 99%.

Figure 4 compares the performance of different optimization techniques, including EMGO, PSO, WOA, GSA, and EFO. The evaluation is based on many features such as Global Search Capability, Versatility, Convergence towards Optimal Solutions, Parallelization, Robustness to Noise & Uncertainty, Constraint Handling, Exploration and Exploitation Balance, Dynamic Adaptation, Scalability to High-Dimensional Problems, and Computational Efficiency. The techniques are characterized into Excellent (4), High (3), Medium (2), and Limited (1) levels for each feature, giving a comprehensive assessment of their effectiveness in solving varied optimization problems.
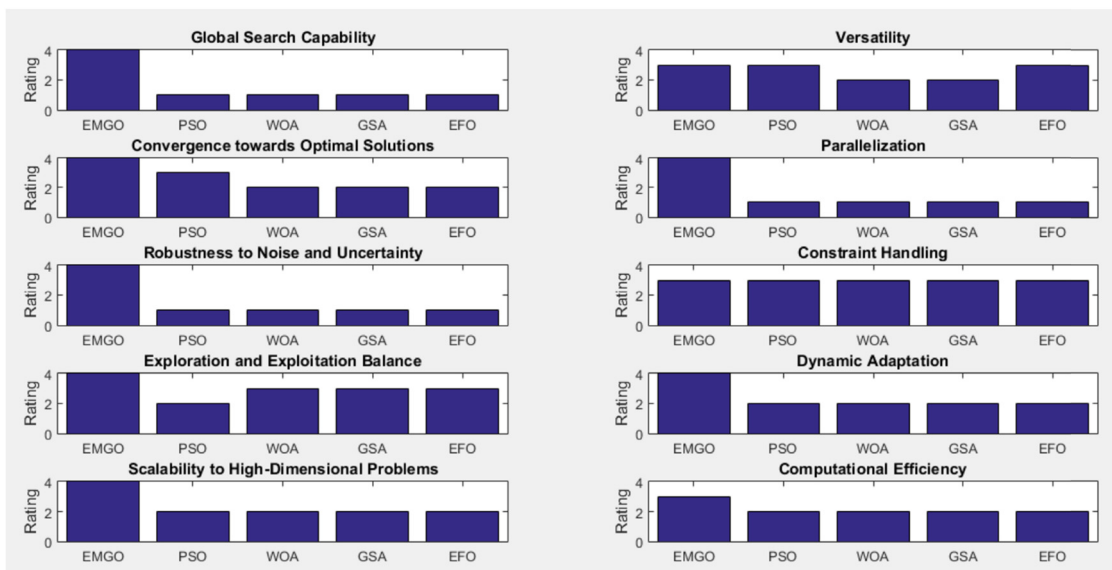
Figure 4: Comparative optimization techniques.

4.3 Potential limitations and areas for improvement

While the EMGO framework offers several innovative features and advantages, it is important to acknowledge its potential limitations and areas where improvements can be made. Addressing these limitations can help in further refining the EMGO framework and enhancing its applicability to a broader range of optimization problems.

Potential limitations:

- One of the main limitations of EMGO is its sensitivity to the fine-structure constant and other algorithmic parameters. The performance of the algorithm can be significantly influenced by the initial parameter settings, which may require careful tuning for different problems.

- Due to the integration of multiple physical principles, EMGO might have higher computational complexity compared to simpler optimization algorithms. This can lead to longer computation times, especially for large-scale or high-dimensional problems.
- While EMGO is designed to be scalable, its performance may degrade for extremely large or highly complex optimization landscapes. This is a common challenge for many advanced optimization algorithms [56,57].
- Despite its hybrid nature, there is still a risk of premature convergence to local optima in highly multi-modal or deceptive landscapes. This issue arises if the balance between exploration and exploitation is not adequately maintained.

Recommendations for improvement:

- Implementing adaptive mechanisms for parameter tuning can help mitigate the sensitivity issue. Techniques such as self-adaptive algorithms, where parameters are dynamically adjusted based on the search process, can enhance the robustness and performance of EMGO across different problem domains.
- Combining EMGO with other optimization techniques, such as GA or PSO, can leverage the strengths of each method. For instance, hybrid algorithms can use EMGO for global search and other techniques for local refinement, thereby improving overall performance.
- Integration with Machine Learning Techniques: Machine learning models can be used to predict and adjust the parameters of EMGO dynamically. Reinforcement learning, for example, can be employed to learn optimal parameter settings over time, enhancing the algorithm's adaptability and efficiency.
- To address computational complexity, parallel computing techniques can be employed. By distributing the computation load across multiple processors, the efficiency of the algorithm can be significantly improved. Additionally, employing efficient data structures and optimization techniques can reduce computational overhead.
- To avoid premature convergence, diversification strategies such as introducing randomness or employing multi-population approaches can be integrated. These strategies help maintain a balance between exploration and exploitation, reducing the risk of getting trapped in local optima.

By acknowledging these potential limitations and actively working on the suggested improvements, the EMGO framework can be further refined to enhance its robustness, efficiency, and applicability. Continuous evaluation and incorporation of advanced techniques will ensure that EMGO remains a cutting-edge tool in the field of optimization. This proactive approach to addressing limitations will contribute to the ongoing development and success of the EMGO framework.

5 Conclusion

In this article, we have presented the EMGO framework, a novel optimization technique that harnesses the power of electromagnetism, gravity, and fine-structure constant. Through a complete exploration of EMGO, we discussed its conceptual framework, mathematical models, methodology, and performance evaluation. The performance evaluation on benchmark functions showcased EMGO's efficacy in achieving convergence, high-quality solutions, and robustness. Comparative analyses with existing techniques confirmed its advantages in terms of solution quality and convergence speed. The contributions of this work lie in introducing EMGO as a unique optimization technique that balances exploration and exploitation by leveraging fundamental forces. The significance of EMGO lies in its potential to revolutionize optimization methodologies across scientific and engineering domains, making it valuable for decision-making, system design, and resource allocation.

Future research opportunities for EMGO include exploring adaptive mechanisms, developing hybrid approaches with other optimization techniques, addressing scalability challenges, integrating with machine learning, and addressing real-world deployment challenges for practical usability.

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