Parameter Identification In Nonlinear Systems Using Enzyme Action Optimizer

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***Abstract*—This study investigates the applicability of the enzyme action optimizer (EAO), a recent bio-inspired metaheuristic algorithm, to the problem of parameter identification in nonlinear dynamical systems. Inspired by enzymatic behavior in biological systems, EAO combines adaptive local search with stochastic diversity mechanisms to maintain a balanced exploration of complex solution spaces. Although previously shown to be effective in general optimization tasks, this work represents the first application of EAO to the specific context of nonlinear system modeling. Two well-established benchmark systems (the Rössler chaotic system and a permanent magnet synchronous motor (PMSM) model) are considered due to their nonlinear and often chaotic behavior. Simulation results demonstrate that EAO can successfully identify unknown parameters with high accuracy, minimizing the mean squared error between simulated and reference outputs. When compared to other recent metaheuristic techniques, EAO consistently exhibits superior precision and robustness, offering a promising alternative for complex system identification tasks.**

Keywords—Nonlinear system, enzyme action optimizer, parameter identification, stochastic optimization

I. Introduction

Parameter identification plays a crucial role in the modeling, control, and analysis of nonlinear dynamical systems [1]. Such systems frequently arise in various fields of science and engineering, including robotics, power systems, and biological modeling [2]. Due to their inherently nonlinear, often chaotic, and highly sensitive behavior, even minor inaccuracies in parameter estimation can result in large deviations in predicted system trajectories [3]. Therefore, accurate identification of system parameters is vital for achieving reliable simulations and effective controller design.

Traditional analytical or gradient-based techniques often struggle to address parameter identification in nonlinear systems, especially when the underlying model exhibits multimodality, strong coupling, or discontinuities. These limitations have led researchers to explore nature-inspired metaheuristic optimization algorithms [4], which provide robust, derivative-free solutions to complex and high-dimensional search problems. Over the past two decades, numerous metaheuristics (such as salp swarm algorithm, flower pollination algorithm, moth flame optimizer, and grey wolf optimizer) have been applied successfully to system identification problems, yielding promising results across diverse application domains [4].

Among the latest developments in this area, the enzyme action optimizer (EAO) stands out for its biologically motivated design and adaptive search capabilities [5]. Inspired by the catalytic behavior of enzymes interacting with substrates in biochemical reactions, EAO integrates both exploitation and exploration mechanisms in a computationally efficient manner. It does so by refining candidate solutions through sinusoidal perturbations around the current best, while simultaneously introducing diversity via stochastic interactions among other members of the population. This dual update scheme enables EAO to effectively navigate complex, multimodal landscapes without premature convergence.

Although EAO has been recently introduced and evaluated across several generic optimization benchmarks [5], its potential in solving real-world parameter estimation problems has not yet been explored. This study addresses that gap by applying EAO for the first time to the task of parameter identification in nonlinear systems. Specifically, two widely studied benchmark systems are selected: the Rössler chaotic system [6] and a permanent magnet synchronous motor (PMSM) model [7]. Both systems are known for their nonlinear dynamics, parameter sensitivity, and chaotic regimes, making them suitable testbeds for evaluating optimization algorithms. The main contributions of this study can be summarized as follows:

- The applicability of EAO is evaluated in the context of nonlinear system parameter identification, where precision and robustness are critical.
- EAO is tested on two benchmark systems, each characterized by different forms of nonlinear behavior.

- Comparative analysis is performed against other recent metaheuristics, showing that EAO offers superior convergence and identification accuracy in both cases.

The results demonstrate that EAO can identify the exact parameters with negligible or zero residual error, consistently across multiple independent trials. These findings underscore the optimizer's potential as a robust and efficient alternative for parameter estimation tasks in complex nonlinear systems.

II. Overview of Enzyme Action Optimizer

The enzyme action optimizer (EAO) is a novel bio-inspired metaheuristic that draws its conceptual foundation from the catalytic behavior of enzymes in biological systems [5]. In nature, enzymes accelerate chemical reactions by selectively binding to substrates and converting them efficiently even under dynamic or noisy environmental conditions. Inspired by this adaptive mechanism, EAO treats candidate solutions as substrates, while the best solution found so far plays the role of the enzyme that guides the search process.

At each iteration of EAO, the population of substrates is evolved using two core update strategies that work in tandem to balance exploration and exploitation.

A. Sinusoidal Refinement Around the Best Solution

The first strategy perturbs each substrate using a sinusoidal transformation relative to the best-known solution:

$$x_{i,1}^{(t)} = \left(x_{best}^{(t-1)} - x_i^{(t-1)}\right) + q_i \cdot sin\left(AF_t \cdot x_i^{(t-1)}\right) \quad (1)$$

where $x_i^{(t-1)}$ is the position of the ith substrate at the previous iteration, $x_{best}^{(t-1)}$ is the best substrate found so far, q_i is a randomly generated vector with values uniformly distributed in $[0,1]^D$, where D is the problem dimension, AF_t is an adaptive factor that increases over time, defined as $AF_t = \sqrt{t/t_{max}}$, where t is the current iteration and t_{max} is the maximum number of iterations and $sin(\cdot)$ is an element-wise sine function applied to each component of the vector.

This sinusoidal mechanism allows the algorithm to explore regions around the best solution in a smooth and adaptive manner, encouraging fine-grained local search.

B. Diversity-Driven Substrate Interaction

The second update introduces stochastic diversity by leveraging differences between other randomly selected substrates:

$$x_{i,2}^{(t)} = x_i^{(t-1)} + sc_1 \cdot \left(x_p^{(t-1)} - x_q^{(t-1)}\right) + AF_t \cdot sc_2\left(x_{best}^{(t-1)} - x_i^{(t-1)}\right) \quad (2)$$

where $x_p^{(t-1)}, x_q^{(t-1)}$ are two randomly selected substrate positions from the population such that $p \neq q \neq i$. sc_1 and sc_2 are random scalar coefficients drawn from the interval $[EC, 1]$, where EC is the enzyme concentration. These control the magnitude of perturbation and the influence of the best solution. The first term introduces directionality through the difference vector, while the second term biases the movement toward the best-known solution.

C. Selection and Replacement Mechanism

After generating both candidate positions $x_{i,1}^{(t)}$ and $x_{i,2}^{(t)}$, their objective function values are evaluated. The better one replaces the current solution if it provides an improvement. Additionally, the global best is updated if a new minimum is found. This ensures steady progress without sacrificing diversity.

In essence, EAO mimics the natural balance enzymes maintain between broad catalytic capability and selective substrate targeting. The adaptive factor AF_t increases gradually over time, shifting the algorithm's behavior from exploration (early iterations) to exploitation (later iterations). Simultaneously, the enzyme concentration parameter EC controls the level of convergence intensity, ensuring a smooth and effective search trajectory. Thanks to its elegant balance of biological realism and computational simplicity, EAO has demonstrated superior performance across diverse optimization scenarios, particularly in high-dimensional and multimodal landscapes.

III. Problem Statement for Parameter Identification of Nonlinear Systems

In the realm of system modeling, nonlinear dynamic systems pose significant challenges due to their inherent complexity, sensitivity to initial conditions, and parameter uncertainties [8]. Accurate parameter identification is essential not only for system understanding but also for the development of robust control and prediction mechanisms. Due to the intricate behavior of such systems (especially those exhibiting chaos or strong nonlinear coupling) even small deviations in parameter values can lead to significant changes in system response. Therefore, robust optimization-based identification methods are essential to ensure accurate model reconstruction and reliable simulation outcomes. In this regard, this section focuses on the problem of identifying unknown parameters in two well-known nonlinear systems: the Rössler chaotic system [6] and the permanent magnet synchronous motor (PMSM) system [9], both of which have been frequently studied in the literature for their rich dynamical behavior. The goal is to estimate unknown parameters by minimizing the deviation between the system output generated using candidate parameters and the reference output obtained using true parameters. The mathematical models, parameter search ranges, and actual values are summarized in Table 1.

TABLE I. Adopted nonlinear systems and parameter ranges along with actual model parameters

Nonlinear system	Model	Parameter range	Actual model parameters
Rössler chaotic system [6]	$\dot{x} = -y - z$	$0 \leq a \leq 1$	$a = 0.2$
	$\dot{y} = x + ay$	$0 \leq b \leq 1$	$b = 0.2$
	$\dot{z} = b + z(x - c)$	$0 \leq c \leq 10$	$c = 5.7$
PMSM system [9]	$\dot{x} = -x + yz$	$10 \leq a \leq 30$	$a = 20$
	$\dot{y} = -y - xz + az$	$1 \leq b \leq 10$	$b = 5.46$
	$\dot{z} = z + b(y - z)$		

The Rössler system [6] is widely used in the study of nonlinear dynamics and chaos due to its compact structure and rich behavior. It is governed by the set of differential equations provided in Table 1. Here, x, y, and z represent the system states, while a, b, and c are unknown parameters to be identified. The settings given in Table 1 ensure a sufficiently rich and challenging identification landscape, especially due to the system's sensitivity to parameter perturbations.

The second system under consideration is a PMSM system [9]. This formulation given in Table 1 captures the core electromechanical interactions while preserving nonlinear characteristics and the potential for chaotic behavior. In this context, x, y, and z again denote the system states, while a and b are the unknown parameters to be estimated. The optimizer explores the parameter space defined by the ranges given in Table 1, providing a meaningful challenge due to the system's nonlinear and coupled structure. For both systems, mean squared error (MSE) [10] between the true and estimated trajectories was used as the performance metric.

IV. Simulation Results

To assess the performance of the proposed EAO, extensive simulations were carried out on both nonlinear systems described earlier: the Rössler chaotic system and the PMSM system. The optimizer was configured with a population size of 30 and a maximum of 200 iterations. Each experiment was repeated independently for 20 trials to evaluate statistical consistency and robustness.

A. Statistical Evaluation

As reported in Table 2, EAO achieved a remarkably low average mean squared error (MSE) of 9.7721E−33 across the 20 runs on the Rössler system. The standard deviation is on the same order of magnitude, suggesting a stable optimization performance. More impressively, the algorithm found the global optimum (i.e., MSE = 0) in several runs, with the best result being zero error and the worst being only 6.2226E−32, which still represents an extremely close approximation to the true system dynamics.

The results for the PMSM system are even more striking. As shown in Table 2, EAO consistently achieved perfect parameter identification across all 20 runs, with zero mean, zero standard deviation, and both minimum and maximum MSEs recorded as 0. This indicates not only exceptional accuracy but also complete robustness in this particular application.

TABLE II. Statistical Performance of EAO

Nonlinear system	Mean	Standard Deviation	Minimum	Maximum
Rössler chaotic system	9.7721E−33	1.8540E−32	0	6.2226E−32
PMSM system	0	0	0	0

B. Performance on the Rössler Chaotic System

The evolution of the MSE in the best-performing trial is depicted in Fig. 1. As seen, EAO quickly reduces the error within the first few dozen iterations, demonstrating fast convergence. Fig. 2 shows the real-time parameter estimation curves for parameters a, b, and c during this best run. The convergence of these estimates exactly to their true values further confirms the optimizer's accuracy and stability.

C. Performance on the PMSM System

Fig. 3 illustrates the MSE evolution for the best trial, which reaches zero in fewer than 100 iterations. Fig. 4 complements this by showing the estimation trajectories of parameters a and b. Both parameters rapidly converge to their true values, highlighting EAO's ability to precisely capture the underlying dynamics of the system, even under nonlinear coupling and chaotic behavior.

D. Comparison with Reported Approaches

To further contextualize the effectiveness of EAO, comparative results with recent metaheuristic-based studies are summarized in Tables 3 and 4. For the Rössler system, Table 3 compares the EAO with WOA-L9 and SINECOS-L13 algorithms reported in [11]. EAO not only achieves exact identification for all three parameters but also eliminates all residual error (MSE = 0), outperforming its counterparts that suffer from small but non-negligible deviations. For instance, SINECOS-L13 identified parameter b as 0.20413 (vs. the true value of 0.2), and c as 5.70375 (vs. 5.7), which, while close, introduce minor modeling inaccuracies that EAO avoids entirely. Similarly, in the PMSM case (Table 4), EAO was compared with ILCOA and ABC algorithms as reported in [8]. While both alternatives demonstrated respectable results (particularly ILCOA with an MSE of 9.8380E−30) EAO once again delivered exact values for both a and b, with an MSE of zero.

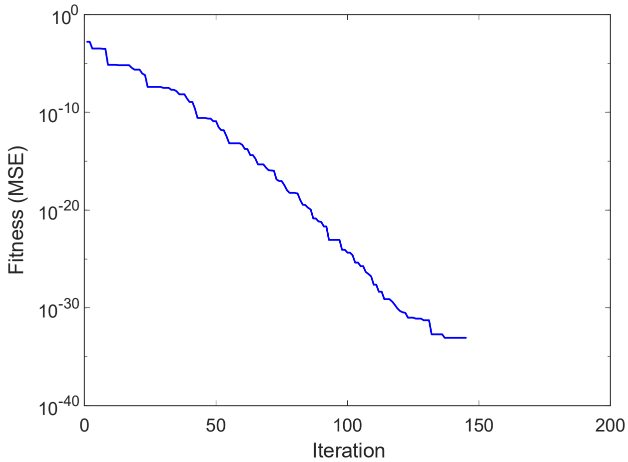

Fig. 1. MSE evolution in the best performing trial (Rössler chaotic system)

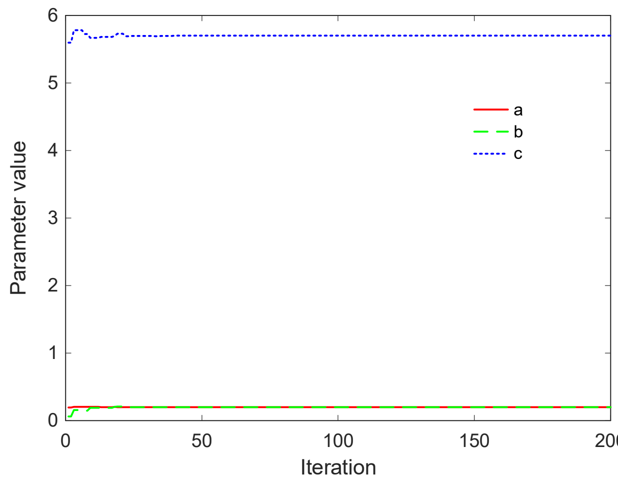

Fig. 2. EAO optimization process for estimations of a, b and c parameters (Rössler chaotic system)

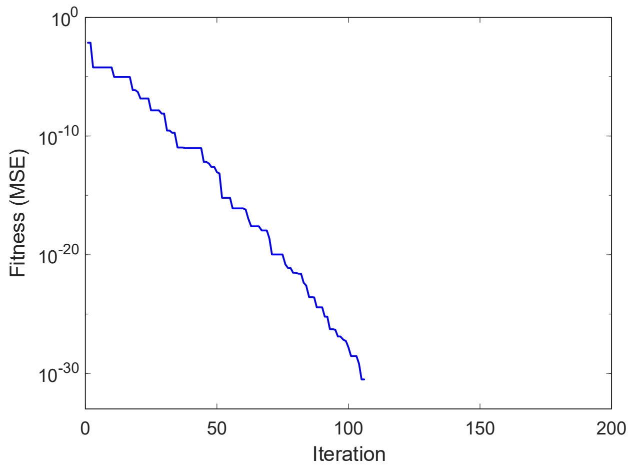

Fig. 3. MSE evolution in the best performing trial (permanent magnet synchronous motor system)

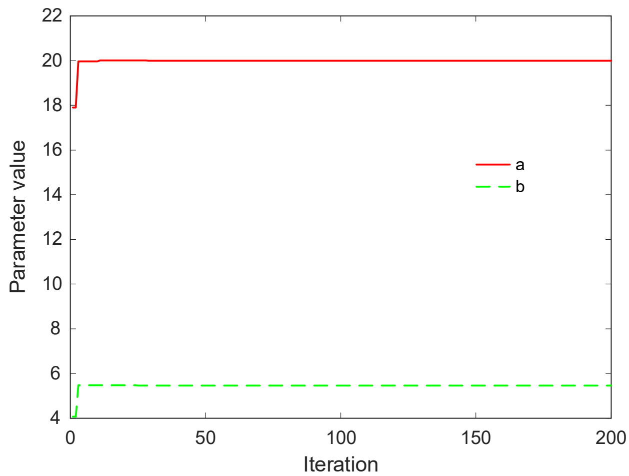

Fig. 4. EAO optimization process for estimations of a and b parameters (permanent magnet synchronous motor system)

TABLE III. EVALUATION OF PARAMETER IDENTIFICATION ACCURACY IN PRIOR STUDIES OF THE RÖSSLER CHAOTIC SYSTEM

Parameter	WHALE-L9	SINECOS-L13	EAO (Proposed)
a	0.20003	0.20025	**0.20000**
b	0.19982	0.20413	**0.20000**
c	5.69982	5.70375	**5.70000**
MSE	1.14241E−06	3.32594E−06	**0**

TABLE IV. EVALUATION OF PARAMETER IDENTIFICATION ACCURACY IN PRIOR STUDIES OF THE PERMANENT MAGNET SYNCHRONOUS MOTOR SYSTEM

Parameter	ILCOA	ABC	EAO (Proposed)
a	20.0000	19.9984	**20.0000**
b	5.4600	5.4606	**5.4600**
MSE	9.8380E−30	2.8018E−05	**0**

V. CONCLUSION

This study explored the potential of the EAO in addressing the challenging task of parameter identification in nonlinear systems. While EAO has been previously introduced in the optimization literature, its application to system modeling, particularly chaotic and highly nonlinear dynamics, has not been explored until now. Two benchmark systems, the Rössler chaotic system and a PMSM model, were selected for evaluation. In both cases, EAO demonstrated outstanding performance, consistently achieving zero or near-zero mean squared error in repeated trials. The algorithm proved capable of accurately identifying all unknown parameters with minimal variation, confirming its effectiveness in capturing nonlinear system behavior. Furthermore, comparative results against several recently proposed metaheuristic approaches (such as WOA-L9, SINECOS-L13, ILCOA, and ABC) highlighted EAO's competitive edge in terms of convergence speed, precision, and stability. Unlike its counterparts, EAO achieved exact matches with the true parameter values across all runs, further emphasizing its robustness and practical reliability.

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