Journal of Innovative Technology, Vol. 7, No. 2, pp. 37-43, September 2025
http://doi.org/10.29424/JIT.202509_7(2).0004

Artificial gorilla troops optimization algorithm for key term separated input non-linear output error system identification

Muhammad Aown Ali [1], Naveed Ishtiaq Chaudhary [2*], Maria Malik [3], Muhammad Qanat Abbas [4]

ABSTRACT

This research study gives an overview of the identification of an input non-linear output error system (IN-OES) leveraging an artificial gorilla troops optimization algorithm (AGTOA). The key term, separated identification auxiliary-based model IN-OES, with the heuristic optimization algorithm AGTOA, is implemented to predict the parameters of the system. The efficiency of the swarm-inspired algorithm AGTOA is exploited for the parameter prediction of the IN-OES system, and promising outcomes were observed through the evaluation of fast convergence, prediction of real parameters of the system, and high fitness values, such as best fitness values, average fitness values, worst fitness values, and standard deviation values in no-noise and multiple-noise sce-narios, i.e., .0, 0.00021, 0.0022, 0.023.

Keywords: Non-linear systems; input non-linear output error system; optimization algorithm; artificial gorilla troops optimization algorithm; heuristic technique.

1. INTRODUCTION

Nonlinear systems [1-3] are intricately interconnected because of their impulsive behavior, sensitivity to primary conditions, and that the response does not follow a simple linear pattern; that is to say, the fact that their operation is not predictable [4-5]. It is this complexity that makes non-linear systems the most realistic models of many natural [6] and engineered processes [7-8]. These systems are typically applicable in various aspects such as artificial intelligence [9-10], artificial neural networks [11-12], machine learning [13-15], recommender systems [16-17], cloud computing [18-19], intelligent computing algorithms [20-22], and many more.

One commonly studied class of nonlinear systems is the input non-linear output error system (IN-OES) [23]. These models are particularly important in system identification and control [24-25], where precisely predicting system performance is crucial for optimization and performance improvement.

The Input Nonlinear Output Error System (IN-OES) model combines both static and dynamic mechanisms to capture the non-linear characteristics of a system. To accurately identify the parameters of IN-OES models, optimization techniques [31-32] are often required. These techniques can be generally characterized into local [33-34] and global search algorithms [35-37]. Local search algorithms such as the least mean square algorithm [38-39], fractional gradient algorithm [40-41], and local beam search algorithm [42], focus on releasing a single solution through iterative improvement. While they offer faster convergence, they are likely to get stuck in local optima. On the other hand, global search algorithms [43] are designed to explore the entire solution space, thereby mitigating the risk of local optima entrapment. Popular global optimization techniques include the particle swarm optimization algorithm [44-45], the genetic algorithm [46-47], the cuckoo-search algorithm [48-49], and the improved shuffled frog leaping algorithm [50].

A recently developed global optimization algorithm, the Artificial Gorilla Troops Optimization Algorithm (AGTOA) [51], draws motivation from the collective intelligence and social behaviors of gorilla troops. This heuristic algorithm balances exploration and exploitation by impersonating the natural foraging, movement, and survival approaches of gorillas. It is mainly well suited for solving complex optimization problems such as parameter identification in IN-OES models.

The significant parts of the study are as follows

- The Artificial Gorilla Troops Optimization Algorithm (AGTOA) is applied for the identification of the input non-linear output error system (IN-OES).
- A fitness function based on minimizing the mean square error is formulated to reduce the gap between the predicted response and the actual response in the IN-OES model.
- An auxiliary model combined with the key term is utilized to manage the indeterminate and cross-product terms within the IN-OES structure, simplifying the identification process.
- The performance is evaluated based on parameter estimation accuracy, learning curve, i.e., convergence speed, and consistent results in identifying actual parameters.

A graphical picture of the proposed methodology is provided

Manuscript received February 25, 2025; revised April 14, 2025; accepted May 3, 2025.

[1] Master's Student, Department of Computer Science and Information Engineering, National Yunlin University of Science and Technology, Taiwan, R.O.C.

[2*] Assistant Professor (corresponding author), Future Technology Research Center, National Yunlin University of Science and Technology, Taiwan, R.O.C. (email: chaudni@yuntech.edu.tw)

[3] Master's Student, Department of Economics, S3H, National University of Sciences and Technology, Islamabad, Pakistan.

[4] Student, Department of Computer Science, COMSATS University Islamabad, Pakistan.

in Figure 1. The structure of the input non-linear output error system (IN-OES) is provided in Section 2. The working principles of the AGTOA are discussed in section 3, and the analysis, results, and conclusion are provided in sections 4 and 5, respectively.

2. INPUT NON-LINEAR OUTPUT ERROR SYSTEMS (IN-OES)

Input non-linear output error system (INO-ES) [52] is represented in Figure 2 and numerically shown in Equation (1) [53]

$$X(\mathrm{i}) = \frac{C(j)}{D(j)}\ddot{\mathrm{k}}(\mathrm{i}) + \Theta(\mathrm{i}), \tag{1}$$

where, $X(\mathrm{i})$ presents the outcome of the system, $\frac{C(j)}{D(j)}$ shows polynomial operators, $\ddot{\mathrm{k}}(\mathrm{i})$ shows the non-linear outcome and shows noise. The noise-free portion of IN-OES is represented in Equation (2) [53]

$$\tau(\mathrm{i}) = \frac{C(j)}{D(j)}\ddot{\mathrm{k}}(\mathrm{i}), \tag{2}$$

The resultant equation of the mathematical model of the IN-OES is shown in Equation (3) [53]

$$Z(\mathrm{i}) = \boldsymbol{\rho}^{\mathbf{T}}(\mathrm{i})\mathbf{X} + \Theta(\mathrm{i}). \tag{3}$$

where, $Z(\mathrm{i})$ is the resultant vector, $\boldsymbol{\rho}^{\mathbf{T}}$ shows the transposition of parameters and $\mathbf{X}$ shows the information vector.

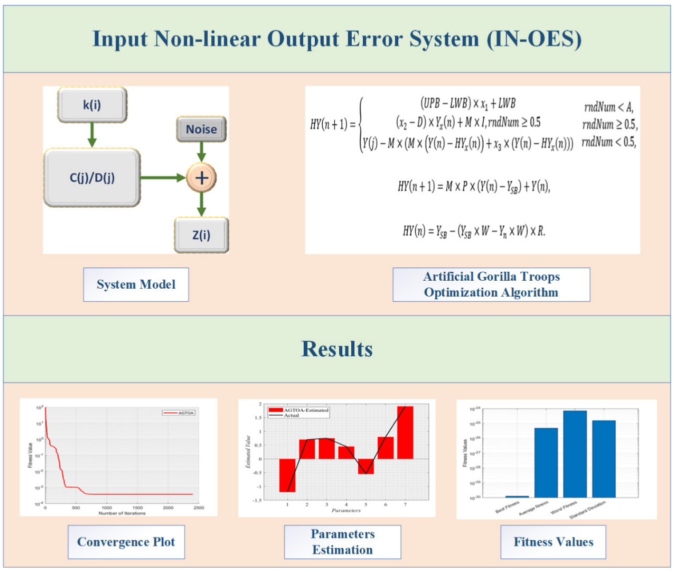


Fig. 1 Graphical representation of the study

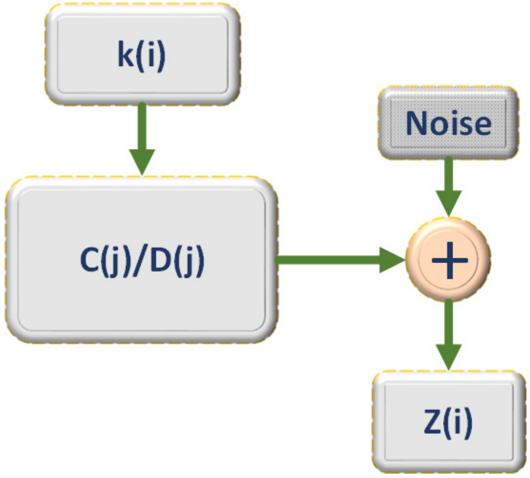


Fig. 2 Input non-linear output error systems (IN-OES) model's visual representation

3. ARTIFICIAL GORILLA TROOPS OPTIMIZATION ALGORITHM (AGTOA)

The Artificial Gorilla Troops Optimization Algorithm (AGTOA) [51] takes inspiration from the shared intellect and societal activities of gorilla troops. This algorithm balances exploration and exploitation by mimicking the natural foraging, movement, and survival approaches of gorillas [54]. The update rules of the AGTOA are shown in Equations 4, 5, and 6.

$$HY(n+1) = \begin{cases} (UPB - LWB) \times x_1 + LWB & rndNum < A, \\ (x_2 - D) \times Y_x(n) + M \times I, rndNum \geq 0.5 & rndNum \geq 0.5, \\ Y(j) - M \times (M \times (Y(n) - HY_x(n)) + x_3 \times (Y(n) - HY_x(n))) & rndNum < 0.5, \end{cases} \tag{4}$$

$$HY(n+1) = M \times P \times (Y(n) - Y_{SB}) + Y(n), \tag{5}$$

$$HY(n) = Y_{SB} - (Y_{SB} \times W - Y_n \times W) \times R. \tag{6}$$

4. RESULTS AND DISCUSSIONS

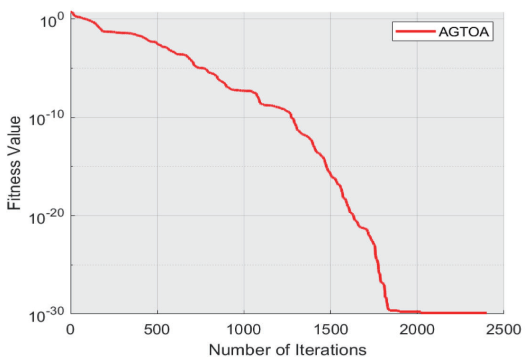
The results of the study for identifying the parameters of the input non-linear output error system (IN-OES) are presented in this section. The simulations are executed on 2400 number of iterations with 24 independent runs and 75 population size. The results are executed on the MATLAB tool with system specifications of Intel Core i-5 12th generation with 24 GB of RAM. The results are shown in table and figure form, showcasing the robustness of the artificial gorilla troops optimization algorithm (AGTO) for the IN-OES model. Table 1 shows the accuracy achieved by the AGTO in multiple noise levels, such as .0, 0.00021, 0.0022, 0.023. From Table 1, we can say that the AGTOA achieved high accuracy with no noise, and accuracy becomes low as we increase the noise level. table 1 shows the best fitness value, average fitness value, standard deviation value, and worst fitness value. The parameters of the system are taken from [55].

Table 1 Best-fitness (B.F), Average-fitness (A.F), and Worst-fitness (W.F) of AGTO

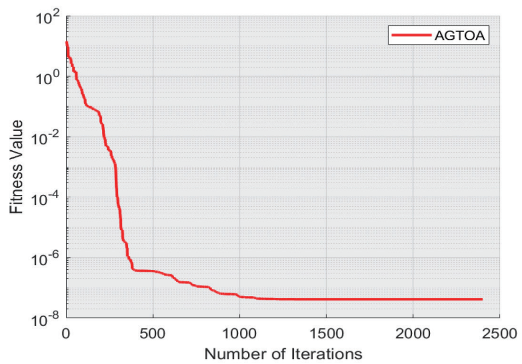
Algorithm	Noise level	B.F	A.F	W.F	S.T.D
AGTOA	.0	1.2942E-30	4.8623E-26	7.1733E-25	1.5734E-25
		4.2028E-08	4.2028E-08	4.2028E-08	3.5513E-17
		6.1374E-06	6.1374E-06	6.1374E-06	6.0145E-16
		3.8209E-04	3.8209E-04	3.8209E-04	5.3807E-15

The learning curves represented in Figure 3 show the convergence speed of the AGTO, how quickly and consistently it converges to achieve the highest accuracy, and how well it performs in different noise scenarios, i.e., .0, 0.00021, 0.0022, 0.023. From Table 1, we can clearly state that with no noise, the AGTOA gives a fitness of 1.2942E-30, and as we implemented the noise and increased it, the fitness values decreased, such as for the noise cap theta equals, .00021, 0.0022, 0.023, the best fitness values are 4.2028E-08, 6.1374E-06, and 3.8209E-04.

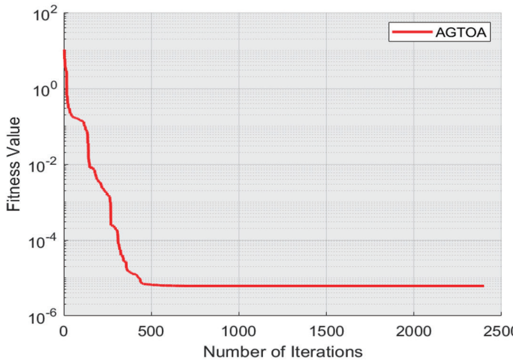
Table 2 and Figure 4 show that the AGTOA performed exceptionally well at identifying the parameters of the input non-linear output error system (IN-OES). By increasing the noise, the performance of the algorithm gets low, but it still accurately predicts the system parameters. From these results, we can say that the AGTOA performance is well enough to identify the parameters of IN-OES.



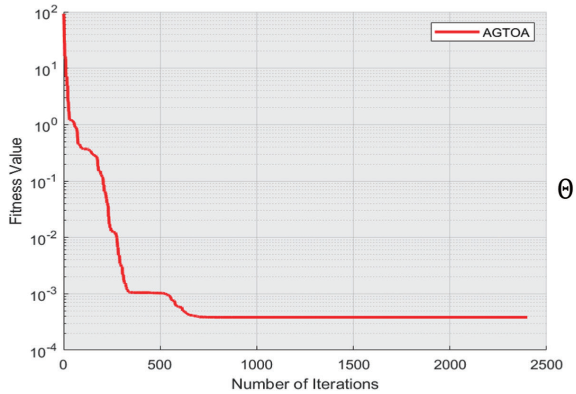
$\Theta = 0.0$



$\Theta = 0.00021$

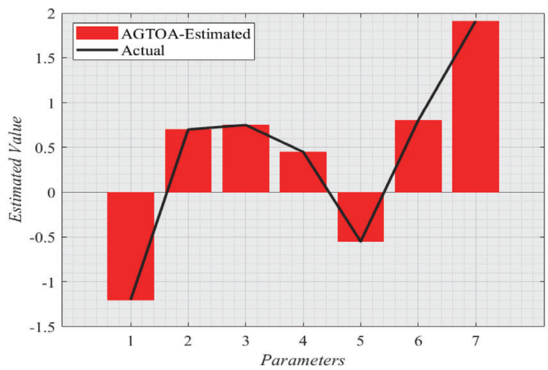


$\Theta = 0.0022$

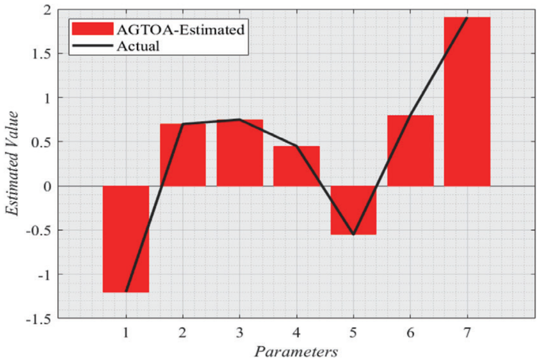


$\Theta = 0.023$

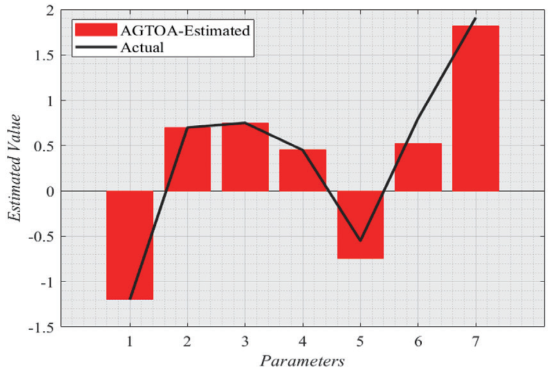
Fig. 3 Learning curves of AGTOA



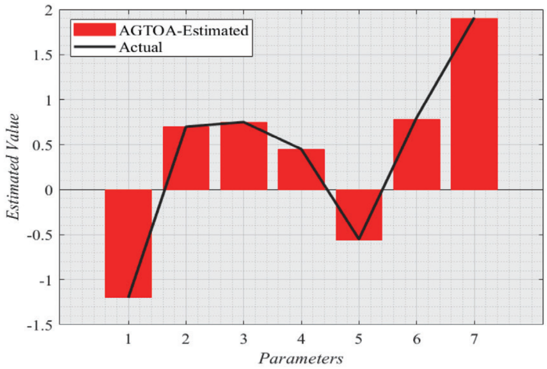
$\Theta = 0.0$



Θ = 0.00021



Θ = 0.023



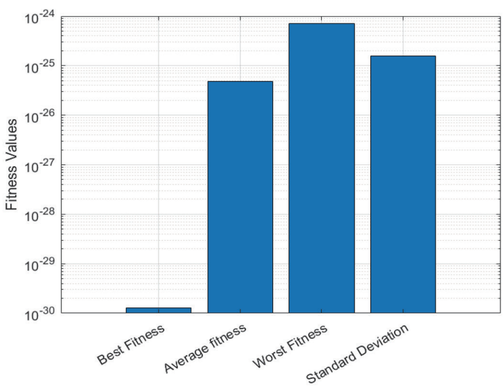
Θ = 0.0022

Fig. 4 Parameter's estimation of AGTOA

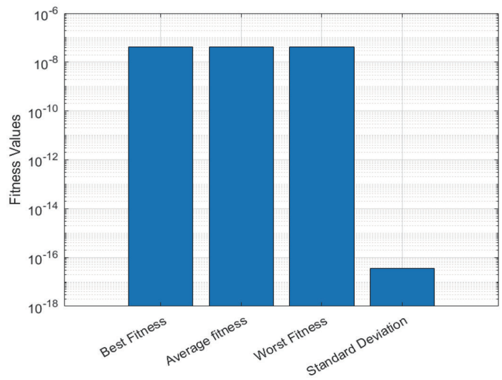
Table 2 Weight approximation of AGTOA

Algorithm	Noise level	P.1	P.2	P.3	P.4	P.5	P.6	P.7
AGTOA	.0	-1.200	0.700	0.750	0.450	-0.550	0.800	1.910
		-1.200	0.700	0.750	0.450	-0.552	0.797	1.909
		-1.200	0.700	0.750	0.450	-0.560	0.780	1.901
		-1.198	0.698	0.748	0.452	-0.747	0.524	1.820
Actual Parameters		-1.2	0.7	0.75	0.45	-0.55	0.8	1.91

Figure 5 shows the best, average, and worst fitness values, and standard deviation bar plots showcasing how the AGTOA performs in different noisy and no-noise scenarios, i.e., .0, 0.00021, 0.0022, 0.023. The plots show that AGTOA performs well in all noisy and no-noise scenarios.



Θ = 0.0



Θ = 0.00021

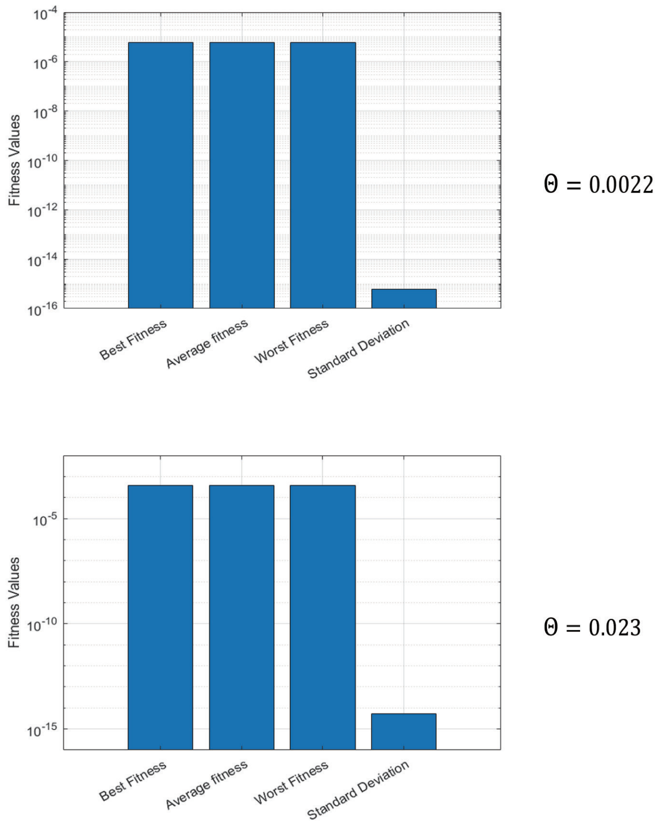


Fig. 5 Fitness values of AGTOA

5. Conclusion

In this research study, for the input non-linear output error system (IN-OES), the heuristic optimization algorithm, artificial gorilla troops optimization algorithm (AGTOA) is exploited. The results show that the AGTOA gives promising outcomes in terms of fast convergence and high fitness values, such as best fitness values, average fitness values, worst fitness values, and standard deviation values. AGTOA predicts the parameters of the system in no-noise and multiple-noise scenarios, such as .0, 0.00021, 0.0022, 0.023. By increasing the noise, a slight variation in predicting the original parameters is observed, but it is still considered to be a very well-performing algorithm on that system and gives expected outcomes. In future work, fractional calculus on the system model INO-ES or algorithm AGTOA can be implemented with different nonlinearities such as geometry, material, and contact nonlinearities, or different noise types such as asymmetric noise, Gaussian noise, etc.

References

[1] Alessandri, A. (2025). “Robust moving horizon estimation for nonlinear systems: From perfect to imperfect optimization.” *Automatica,* **175**, 112187.

[2] Abdelhamid, B., & Mohamed, C. (2025). “Robust Fuzzy Adaptive Fault-Tolerant Control for a Class of Second-Order Nonlinear Systems.” *International Journal of Adaptive Control and Signal Processing,* **39**(1), 15-30.

[3] Zhao, G. H., & Liu, S. J. (2025). “Decentralized adaptive finite-time stabilization for a class of non-local Lipschitzian large-scale stochastic nonlinear systems.” *Automatica,* **171**, 111900.

[4] Liang, Y., Zhu, L., Wang, X., & Yang, Y. (2022). “A simple episodic linear probe improves visual recognition in the wild.” In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 9559-9569).

[5] Syawahid, M., & Prahmana, R. C. I. (2024). “Figural and Non-Figural Linear Pattern: Case of Primary Mathematical Gifted Students’ Functional Thinking.” *Mathematics Teaching Research Journal,* **16**(4), 94-115.

[6] Goswami, S., Giovanis, D. G., Li, B., Spence, S. M., & Shields, M. D. (2025). “Neural Operators for Stochastic Modeling of Nonlinear Structural System Response to Natural Hazards.” *arXiv preprint arXiv:*2502.11279.

[7] Gao, C., Liu, F. F., Fan, Z. Q., Fan, L., Zhang, R., & Cao, C. (2024). “Quantum-squeezing-engineered third-order kerr nonlinearity and optical high-order sideband comb in a composite resonator-atom system.” *IEEE Journal of Selected Topics in Quantum Electronics.*

[8] Liang, Z., Wu, Y., & Li, J. (2024). “Polarization-engineered photon statistics and its tomography via optomagnonic interaction.” *Optics Letters,* **49**(10), 2749-2752.

[9] Pios, S. V., Gelin, M. F., Ullah, A., Dral, P. O., & Chen, L. (2024). “Artificial-intelligence-enhanced on-the-fly simulation of nonlinear time-resolved spectra.” *The Journal of Physical Chemistry Letters,* **15**(9), 2325-2331.

[10] Saleem, S., Ahmad, I., Ahmed, S. H., & Rehman, A. (2024). “Artificial intelligence based robust nonlinear controllers optimized by improved gray wolf optimization algorithm for plug-in hybrid electric vehicles in grid to vehicle applications.” *Journal of Energy Storage,* **75**, 109332.

[11] Lv, J., Ju, X., & Wang, C. (2025). “Neural network prescribed-time observer-based output-feedback control for uncertain pure-feedback nonlinear systems.” *Expert Systems with Applications,* **264**, 125813.

[12] Farooq, U., Saqib, S. U., Khan, S. A., Liu, H., Fatima, N., Muhammad, T., & Faiz, Z. (2025). “Mathematical modeling of radiative nanofluid flow over nonlinear stretching sheet using artificial neural networks and Levenberg-Marquardt scheme: Applications in solar thermal energy.” *Solar Energy Materials and Solar Cells,* **281**, 113265.

[13] Jain, V., & Bhatia, R. (2025). “A survey on machine learning schemes for fiber nonlinearity mitigation in radio over fiber system.” *Journal of Optical Communications,* **45**(s1), s1157-s1163.

[14] Desmedt, E., Jacobs, M., Alonso, M., & De Vleeschouwer, F. (2025). “Deciphering nonlinear optical properties in functionalized hexaphyrins via explainable machine learning.” *Physical Chemistry Chemical Physics,* **27**(3), 1256-1273.

[15] Tao, K., Cao, J., Wang, Y., & Ma, W. (2025). “Disentangling and interpreting nonlinear molecular and isotopic variations in petroleum using machine learning.” *Marine and Petroleum Geology,* **171**, 107175.

[16] Hildebrandt, M., Sunder, S. S., Mogoreanu, S., Joblin, M., Mehta, A., Thon, I., & Tresp, V. (2019). "A recommender system for complex real-world applications with nonlinear dependencies and knowledge graph context." *In The Semantic Web: 16th International Conference, ESWC 2019, Portorož, Slovenia, June 2–6, 2019, Proceedings* **16** (pp. 179-193). Springer International Publishing.

[17] Behera, G., & Nain, N. (2022). "DeepNNMF: deep nonlinear non-negative matrix factorization to address sparsity problem of collaborative recommender system." *International journal of information technology,* **14**(7), 3637-3645.

[18] Zhang, Y. (2023). "Application of nonlinear clustering optimization algorithm in web data mining of cloud computing. " *Nonlinear Engineering,* **12**(1), 20220239.

[19] Du, W., Li, A., Li, Q., & Zhou, P. (2021). "Privacy-preserving and secure cloud computing: A case of large-scale nonlinear programming." *IEEE Transactions on Cloud Computing,* **11**(1), 484-498.

[20] Raja, M. A. Z., Mehmood, J., Sabir, Z., Nasab, A. K., & Manzar, M. A. (2019). "Numerical solution of doubly singular nonlinear systems using neural networks-based integrated intelligent computing." *Neural Computing and Applications,* **31**, 793-812.

[21] Quaranta, G., Lacarbonara, W., & Masri, S. F. (2020). "A review on computational intelligence for identification of nonlinear dynamical systems." *Nonlinear Dynamics,* **99**(2), 1709-1761.

[22] Raja, M. A. Z., Shah, F. H., & Syam, M. I. (2018). "Intelligent computing approach to solve the nonlinear Van der Pol system for heartbeat model." *Neural Computing and Applications,* **30**(12), 3651-3675.

[23] Ding, F., Xu, L., Zhang, X., & Ma, H. (2024). "Hierarchical gradient-and least-squares-based iterative estimation algorithms for input-nonlinear output-error systems from measurement information by using the over-parameterization." *International Journal of Robust and Nonlinear Control,* **34**(2), 1120-1147.

[24] Ali, M. A., Chaudhary, N. I., Khan, T. A., Mao, W. L., Lin, C. C., & Raja, M. A. Z. (2024). "Design of key term separated identification model for fractional input nonlinear output error systems: Auxiliary model based Runge Kutta optimization algorithm." *Chaos, Solitons & Fractals,* **189**, 115696.

[25] Xu, H., Xu, L., & Shen, S. (2024). "Online identification methods for a class of Hammerstein nonlinear systems using the adaptive particle filtering." *Chaos, Solitons & Fractals*, **186**, 115181.

[26] Yao, J. (2018). "Model-based nonlinear control of hydraulic servo systems: Challenges, developments and perspectives. " *Frontiers of Mechanical Engineering,* **13**, 179-210.

[27] Lyshevski, S. E. (1998). "Nonlinear control of servo-systems actuated by permanent-magnet synchronous motors." *Automatica,* **34**(10), 1231-1238.

[28] Kaddissi, C., Kenne, J. P., & Saad, M. (2007). "Identification and real-time control of an electrohydraulic servo system based on nonlinear backstepping." *IEEE/ASME Transactions on Mechatronics,* **12**(1), 12-22.

[29] Bhoir, N., & Singh, S. N. (2004). Output feedback nonlinear control of an aeroelastic system with unsteady aerodynamics. " *Aerospace science and technology,* **8**(3), 195-205.

[30] Baldelli, D. H., Lind, R., & Brenner, M. (2005). "Nonlinear aeroelastic/aeroservoelastic modeling by block-oriented identification." *Journal of guidance, control, and dynamics,* **28**(5), 1056-1064.

[31] Zhang, Q., Wang, H., & Liu, X. (2025). "Auxiliary model maximum likelihood least squares-based iterative algorithm for multivariable autoregressive output-error autoregressive moving average systems." *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering,* 09596518241280323.

[32] Li, Y., Zhang, J., Liu, W., & Tong, S. (2021). "Observer-based adaptive optimized control for stochastic nonlinear systems with input and state constraints." *IEEE transactions on neural networks and learning systems,* **33**(12), 7791-7805.

[33] Cohen-Addad, V., Gupta, A., Hu, L., Oh, H., & Saulpic, D. (2022). "An improved local search algorithm for k-median." In *Proceedings of the 2022 Annual ACM-SIAM Symposium on Discrete Algorithms (SODA)* (pp. 1556-1612). Society for Industrial and Applied Mathematics.

[34] D'Angelo, G., & Palmieri, F. (2021). "GGA: A modified genetic algorithm with gradient-based local search for solving constrained optimization problems." *Information Sciences,* **547**, 136-162.

[35] Gharehchopogh, F. S., Namazi, M., Ebrahimi, L., & Abdollahzadeh, B. (2023). "Advances in sparrow search algorithm: a comprehensive survey." *Archives of Computational Methods in Engineering,* **30**(1), 427-455.

[36] Abdel-Basset, M., Mohamed, R., Jameel, M., & Abouhawwash, M. (2023). "Nutcracker optimizer: A novel nature-inspired metaheuristic algorithm for global optimization and engineering design problems." *Knowledge-Based Systems,* **262**, 110248.

[37] Jiang, Z., Duan, J., Xiao, Y., & He, S. (2022). "Elite collaborative search algorithm and its application in power generation scheduling optimization of cascade reservoirs." *Journal of Hydrology,* **615**, 128684.

[38] Ji, J., Shi, D., Shen, X., Luo, Z., & Gan, W. S. (2025). "Implementation of minimum output variance filtered reference least mean square algorithm with optimal time-varying penalty factor estimate to overcome output saturation." *Applied Acoustics,* **231**, 110473.

[39] Khamis, M., Zhang, S., & Ibrahim, S. (2025). "A Synchronized Filter-s Least Mean Square (SFsLMS) algorithm for multi-channel ANC in aviation noise suppression." *Applied Acoustics,* **231**, 110552.

[40] Younis, R. A., Touti, E., Aoudia, M., Zahrouni, W., Omar, A. I., & Elmetwaly, A. H. (2024). "Innovative hybrid energy storage systems with sustainable integration of green hydrogen and energy management solutions for standalone PV microgrids based on reduced fractional gradient descent algorithm." *Results in Engineering,* **24**, 103229.

[41] Chaudhary, N. I., Raja, M. A. Z., Khan, Z. A., Mehmood, A., & Shah, S. M. (2022). "Design of fractional hierarchical gradient descent algorithm for parameter estimation of nonlinear control autoregressive systems." *Chaos, Solitons & Fractals,* **157**, 111913.

[42] Akeb, H., Hifi, M., & M'Hallah, R. (2009). "A beam search algorithm for the circular packing problem." *Computers & Operations Research,* **36**(5), 1513-1528.

[43] Meng, K., Chen, C., & Xin, B. (2022). "MSSSA: a multi-strategy enhanced sparrow search algorithm for global optimization." *Frontiers of Information Technology & Electronic Engineering,* **23**(12), 1828-1847.

[44] Gad, A. G. (2022). "Particle swarm optimization algorithm and its applications: a systematic review." *Archives of computational methods in engineering,* **29**(5), 2531-2561.

[45] Wang, F., Wang, X., & Sun, S. (2022). "A reinforcement learning level-based particle swarm optimization algorithm for large-scale optimization." *Information Sciences,* **602**, 298-312.

[46] Katoch, S., Chauhan, S. S., & Kumar, V. (2021). "A review on genetic algorithm: past, present, and future." *Multimedia tools and applications,* **80**, 8091-8126.

[47] Halim, Z., Yousaf, M. N., Waqas, M., Sulaiman, M., Abbas, G., Hussain, M., ... & Hanif, M. (2021). "An effective genetic algorithm-based feature selection method for intrusion detection systems." *Computers & Security,* **110**, 102448.

[48] Guerrero-Luis, M., Valdez, F., & Castillo, O. (2021). "A review on the cuckoo search algorithm." *Fuzzy Logic Hybrid Extensions of Neural and Optimization Algorithms: Theory and Applications,* 113-124.

[49] Yaqoob, A., Verma, N. K., & Aziz, R. M. (2024). "Optimizing gene selection and cancer classification with hybrid sine cosine and cuckoo search algorithm." *Journal of medical systems,* **48**(1), 10.

[50] Zhang, J., Jiang, W., & Zhao, K. (2024). "An improved Shuffled frog-leaping algorithm to solving 0-1 knapsack problem. " *IEEE Access.*

[51] Abdollahzadeh, B., Soleimanian Gharehchopogh, F., & Mirjalili, S. (2021). "Artificial gorilla troops optimizer: a new nature-inspired metaheuristic algorithm for global optimization problems." *International Journal of Intelligent Systems*, **36**(10), 5887-5958.

[52] Leontaritis, I. J., & Billings, S. A. (1985). "Input-output parametric models for non-linear systems part I: deterministic non-linear systems." *International journal of control,* **41**(2), 303-328.

[53] Ding, F., Ma, H., Pan, J., & Yang, E. (2021). "Hierarchical gradient-and least squares-based iterative algorithms for input nonlinear output-error systems using the key term separation. " *Journal of the Franklin Institute,* **358**(9), 5113-5135.

[54] Hussien, A. G., Bouaouda, A., Alzaqebah, A., Kumar, S., Hu, G., & Jia, H. (2024). "An in-depth survey of the artificial gorilla troops optimizer: outcomes, variations, and applications." *Artificial Intelligence Review,* **57**(9), 246.

[55] Yue, Z., & Yang, X. (2020, November). "Multi-innovation identification algorithm based on auxiliary model for Hammerstein output error systems." In *2020 Chinese Automation Congress (CAC)* (pp. 5635-5640). IEEE.