ISSN: 2633-4828 Vol. 5 No.4, December, 2023

International Journal of Applied Engineering & Technology

GRASSHOPPER OPTIMIZATION BASED DNN-IMC FOR A NON-LINEAR PH PROCESS

[1]K. Anu Nivetha, [2]S.Abraham lincon, [3] R.Selvaraj and [4]E. Sivaraman

[1]Research Scholar, Department of Electronics and Instrumentation Engineering, Annamalai University, Annamalainagar

[2]Professor, Department of Electronics and Instrumentation Engineering, Annamalai University, Annamalainagar

[3]Assistant Professor, Department of Instrumentation and Control Engineering, Dr.Dharmambal Government Polytechnic College for women, Thramani, Chennai

[4]Associate Professor, Department of Electronics and Communication Engineering, Government College of Engineering, Tirunelveli

[3,4](On Deputation from Annamalai University, Department of Electronics and Instrumentation Engineering, Faculty of Engineering & Technology, Annamalai Nagar, Chidambaram, 608 002, Tamil Nadu, India.)

ABSTRACT

This paper introduces a novel approach to pH process control by combining the Grasshopper Optimization Algorithm (GOA) with a Deep Neural Network (DNN) Internal Model Controller (IMC). This synergistic framework leverages GOA's optimization capabilities to fine-tune DNN weights and enhancing control performance. The IMC structure models pH process dynamics, while the DNN captures complex patterns in data for adaptive control. The proposed method involves formulating the control problem, configuring the DNN architecture, implementing GOA-based optimization, iteratively updating weights, and extracting optimal DNN configurations. Simulations validate the GOA DNN-IMC approach's effectiveness in achieving precise pH regulation under varying operating conditions and load disturbances. Results show improved control compared to GOA DNN Direct Inverse Controller (DIC).

Keywords: pH process, Non-linear, Grasshopper optimization and Controller.

1 INTRODUCTION

The control of pH processes is of paramount importance in a multitude of industrial and scientific contexts, spanning from wastewater treatment and chemical manufacturing to biological research and pharmaceutical production. pH, a logarithmic measure of the hydrogen ion concentration in a solution, profoundly influences various chemical reactions, enzyme activities, and biological processes. Achieving precise pH regulation is crucial to ensure product quality, process efficiency, and environmental compliance [1].

However, pH processes often exhibit complex and nonlinear dynamics, influenced by factors such as reaction kinetics, buffering effects, and external disturbances [2]. Traditional proportional-integral-derivative (PID) control strategies, while effective for linear systems, may struggle to maintain accurate pH levels in the presence of such intricate dynamics. Consequently, researchers have been motivated to explore advanced control methodologies that can adapt to these complexities and variations. The effective control of complex processes, such as pH regulation, is a crucial challenge in various industrial applications. Traditional control methods often struggle to handle the intricate dynamics of such systems. In response, researchers have explored innovative approaches that merge optimization algorithms and advanced control strategies to achieve superior control performance.

The selected research papers provide valuable insights into the dominion of pH process control, shedding light on the challenges, strategies, and advancements in this crucial area. These papers collectively offer a comprehensive overview of the diverse approaches employed to tackle the complexities associated with pH regulation. Henson, M. A., & Seborg, D. E [3] and Sivaraman et.al [4] discusses various control methodologies, emphasizing the significance of adapting traditional techniques to nonlinear pH processes. It highlights the need for innovative solutions beyond conventional methods. Abdullah et.al [5] delves deeper into advanced strategies. The paper introduces advanced control techniques for pH neutralization, offering insights into optimizing processes through improved control methodologies.

Siddique, N [6] explores the realm of intelligent control. This paper delves into how machine learning and intelligent algorithms enhance pH control accuracy, shedding light on the intersection of control and artificial intelligence.

Anderson and Johnson [7] introduces model predictive control to pH processes, highlighting the potential of predictive modeling in achieving precise control in dynamic pH environments. Selvasankari et al., [8] bridges the gap between neural networks and pH control. This paper showcases the transformative impact of neural networks in capturing complex pH dynamics and improving control accuracy. In summary, these papers collectively underscore the evolving landscape of pH process control. From conventional strategies to advanced techniques involving AI, machine learning, and predictive modeling, they pave the way for more robust and adaptive pH regulation approaches. The comprehensive insights offered by these papers serve as a foundation for implementing innovative control strategies in real-world pH processes.

Grasshopper Optimization Algorithm (GOA) is a nature-inspired optimization technique that mimics the swarming behavior of grasshoppers. It's used to solve optimization problems by iteratively adjusting solutions to improve their fitness according to a defined objective function [9]. The integration of advanced control techniques with optimization algorithms has gained traction as a potential solution. Such approaches aim to optimize controller parameters in simulation, enabling the system to respond effectively to changing conditions [10]. In this context, this paper proposes the utilization of the Grasshopper Optimization Algorithm (GOA) in tandem with a Deep Neural Network (DNN) Internal Model Controller (IMC) to tackle the challenges of pH process control. By combining the optimization capabilities of GOA with the adaptive learning of DNNs, this integrated approach aims to provide robust and efficient control in the face of intricate pH process dynamics. The subsequent sections delve into the details of this novel approach and its implications for enhancing pH regulation across various applications.

2 Process Description and Mathematical Modeling

The described process involves the interaction between a Sodium Hydroxide (NaOH) solution and an Acetic Acid (CH3COOH) solution in a titration setup. This results in a neutralization reaction, producing salt and water as products. The equivalence point, where the concentrations of acid and base are equal, represents the maximum process gain and typically occurs at pH 7 for a strong acid/strong base system, which is the neutralization point. For effective control near pH 7, high precision in the control system and a wide range of reagent delivery are essential. This is particularly challenging in a weak acid/strong base system due to the moderately high gain around pH 7. Interestingly, the equivalence point may not always align perfectly with neutrality, emphasizing the intricacies of the process. To address this complexity, the study focuses on a strong base-weak acid neutralization process.

McAvoy et al. have contributed to understanding the dynamic physico-chemical behavior in continuous stirred tank reactors. They have derived dynamic equations for the neutralization process involving acetic acid and sodium hydroxide. These equations are based on mass balances of ionic species in the CSTR solution, often referred to as reaction invariants. By comparing their derived equations with experimental results, the study enhances comprehension of the behavior of pH in such neutralization processes. The complexities arising from the relationship between pH and concentrations of the reacting components are addressed through dynamic equations and experimental comparisons. This contributes to advancing the understanding of pH control in neutralization processes, particularly in cases where the equivalence point deviates from neutrality.

The linear algebraic equation of pH process is expressed as

$$[H^+]^3 + (K_A + \zeta)[H^+]^2 + K_A(\zeta - \xi) - K_W[H^+] - K_A K_W = 0 \qquad (1)$$

The reaction invariants, ζ and ξ are found from the following mass balances

$$F_A C_A - (F_A + F_B)\xi = V\left(\frac{d\xi}{dt}\right) \quad (2)$$

$$F_B C_B - (F_A + F_B)\zeta = V\left(\frac{d\zeta}{dt}\right) \quad (3)$$

where F_A is the acid flow rate (LPH), F_B is the base flow rate (LPH), C_A is the acid concentration (mol/L), C_B is the base concentration (mol/L), $[H^+]$ is the hydrogen ion concentration and V is the liquid volume (L^3). Finally the pH is calculated as

$$pH = -\log_{10}([H^+]) \quad (4)$$

The analysis of the acid-base system involves obtaining the steady-state titration curve through the simulation of equations (1), (2), (3), and (4) using MATLAB software. The simulation is conducted over a range of acid flow rates (FA) from 0 to 0.5 L/min. Remarkably, the results reveal a distinct static nonlinear behavior in the system when the acid flow rate is approximately 0.2 L/min. Within this region, even a slight alteration in the acid flow rate, ranging from 0.19702 LPH to 0.202225 LPH, leads to a significant shift in pH value, transitioning from 11 to 7. The process reaction curve, a widely adopted technique for process identification, is derived by subjecting the manipulated variable to a step change. This method is pivotal for parameter identification in the pH process across different zones. Each zone entails variations in pH process parameters, and this method involves introducing step changes in the acid flow rate, both positive and negative, to observe the corresponding reaction curves.

The results from different zones are tabulated in Table 1, presenting a comprehensive overview of process parameters in various operational zones. The information garnered from these reaction curves serves as a foundation for further control design and optimization. Based on these process parameters, a Proportional-Integral (PI) controller is designed using the pole placement technique. The PI controller aims to regulate the system by adjusting the manipulated variable, leveraging the insight gained from the process reaction curves and their associated parameters.

Table 1. pH process parameters for various zones.

Zone	Nominal operating point	Process Gain			Time constant		
		K_p (+F_A)	K_p (-F_A)	K_p (Average)	τ (+F_A)	τ (-F_A)	τ (Average)
1 (13to11)	12	-37	-12	-24.5	22	9.6	15.8
2 (11to 9.5)	10.25	-3520	-1012	-2266	20.5	10.5	15.5
3 (9.5 to 8)	8.75	-2416	-7702	-5059	10.1	15.1	12.6
4 (8 to 6.5)	7.25	-98	-136	-117	10.2	19.5	14.85
5 (6.5 to 4.5)	5.5	-27	-97	-62	10.25	21.4	15.83

4 Design of Grosshopper Optimization Algorithm based DNN-IMC

The optimization of complex systems has been a focal point in various scientific and engineering disciplines. In this pursuit, nature-inspired algorithms have gained traction as effective tools to tackle intricate optimization challenges. One such algorithm that has garnered attention is the Grasshopper Optimization Algorithm (GOA). The GOA draws inspiration from the collective behavior of grasshoppers in their search for optimal feeding spots. Just as grasshoppers adapt their positions based on interactions with neighboring individuals, the GOA applies similar principles to iteratively fine-tune solutions in optimization problems. By mimicking these natural behaviors, the GOA offers a unique and effective approach to optimization that can be applied across diverse domains.

The algorithm leverages the concepts of exploration and exploitation, dynamically adjusting its search strategy to balance the exploration of new solution spaces with the exploitation of promising regions. This adaptability enables the GOA to navigate complex solution landscapes and converge towards optimal or near-optimal solutions. In the context of optimization problems, including parameter tuning, function optimization, and neural network weight optimization, the GOA has demonstrated its capability to surpass traditional optimization techniques in terms of convergence speed and solution quality. Its ability to handle both continuous and discrete domains, along with its versatility across various problem types, makes it a versatile tool for researchers and practitioners alike.

Deep Neural Network (DNN) capable of modeling the pH process dynamics. The DNN takes inputs like acid flow rates, present pH value and predicts the future pH level of the solution.

Step 1: Data Collection

Dataset is collected with input-output pairs of the pH control process. This dataset encompass a range of conditions, including disturbances and variations in input flow rates.

Step 2: DNN Training

DNN forward model and inverse models are trained using the dataset to minimize the difference between predicted and actual levels. DNN's performance is validated on a separate validation dataset.

Step 3: Grosshopper Weight Updation

(a) Initial population of candidate solutions are generated (control inputs).

(b) Each solution's performance is evaluated by calculating the pH error based on the DNN prediction.

(c) Weights of the DNN are updated using the Grosshopper-inspired weight update mechanism New generation of candidate solutions are generated using updated DNN weights.

Step 4 Optimized control inputs are applied to the pH process.

Step 5 Actual pH level resulting from the control inputs and the process dynamics are measured.

Step 6 Repeat steps 2 to 5 iteratively, allowing the optimization algorithm to refine the control inputs and update DNN weights.

5 Modeling using GOA-DNN Algorithm

Hybrid GOA-DNN approach combines Grosshopper Optimization Algorithm with Deep Neural Networks for both forward and inverse modeling, enhancing accuracy in predicting process outputs and optimal control inputs.Forward modeling involves training the GOA-DNN algorithm to predict current process outputs based on past inputs and outputs.

Input vectors : $[pH(k-1) \quad pH(k-2) \quad F_A(k-1)]$

Output vector : $p\hat{H}(k)$

The inverse GOA-DNN model, employing present and delayed outputs along with delayed inputs, requires specific training parameters for accurate prediction of optimal control inputs in the pH process.

Input vectors : $[F_A(k-1) \quad pH(k) \quad pH(k-1)]$

Output vectors : $\hat{F}_A(k)$

The GOA based DNN-DIC structure is built using the previously developed inverse model. The inverse neural model developed is connected in cascade with the pH process model as shown in Figure 1.

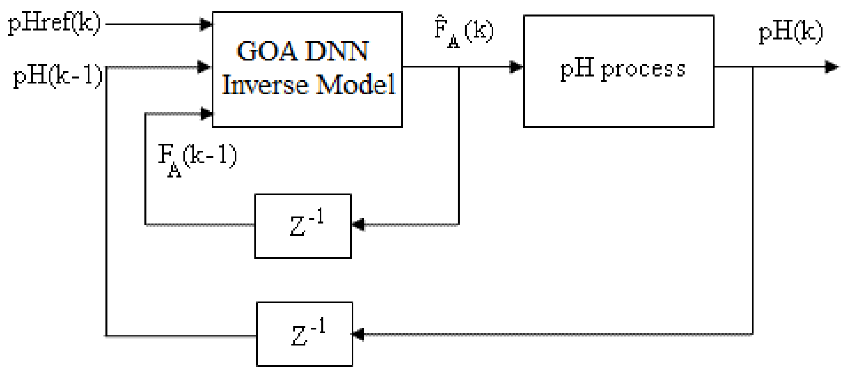

Fig.1. GOA-DNN Direct Inverse Controller for a pH process.

The effectiveness of the direct inverse neural control is verified for set point tracking as shown in Figure 3. The controlled system could follow the set point trajectory very well at all operating points. GOA DNN-IMC is failed to produce satisfactory result when load disturbance applied to the process. It is clearly visible in Figure 5. This necessitates the design of GOA DNN-IMC for a nonlinear pH process. The GOA DNN IMC structure is built using the previously developed forward and inverse models. The resulting IMC structure is depicted in Figure 2.

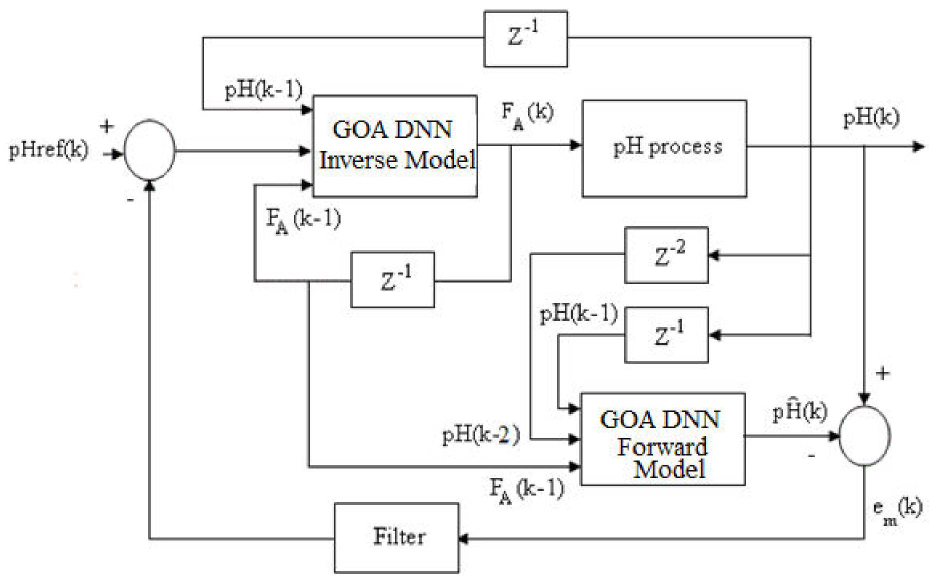

Fig.2. GOA-DNN Internal Model Controller for a pH process.

6 RESULTS AND DISCUSSION

The servo response of pH process is shown in Figure 3. Figure 3 and Figure 4 compare pH profiles (controlled variable) and F_A profiles (manipulated variable) for GOA based DNN-DIC and GOA-based DNN-IMC. Figure 3 highlights GOA-DNN DIC and GOA DNN-IMC's accurate control at the target point.

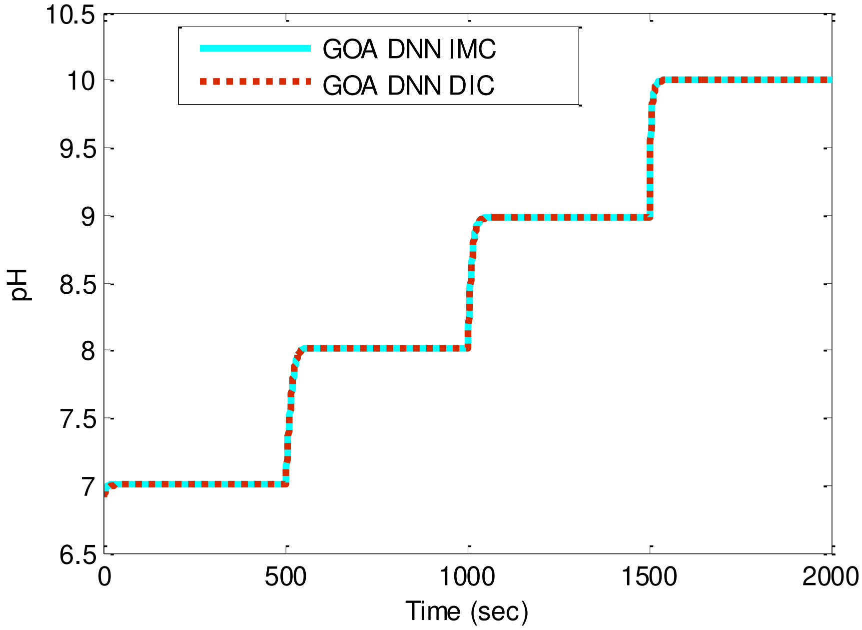

Fig.3. Servo response of pH process using GOA DNN-DIC and GOA DNN-IMC.

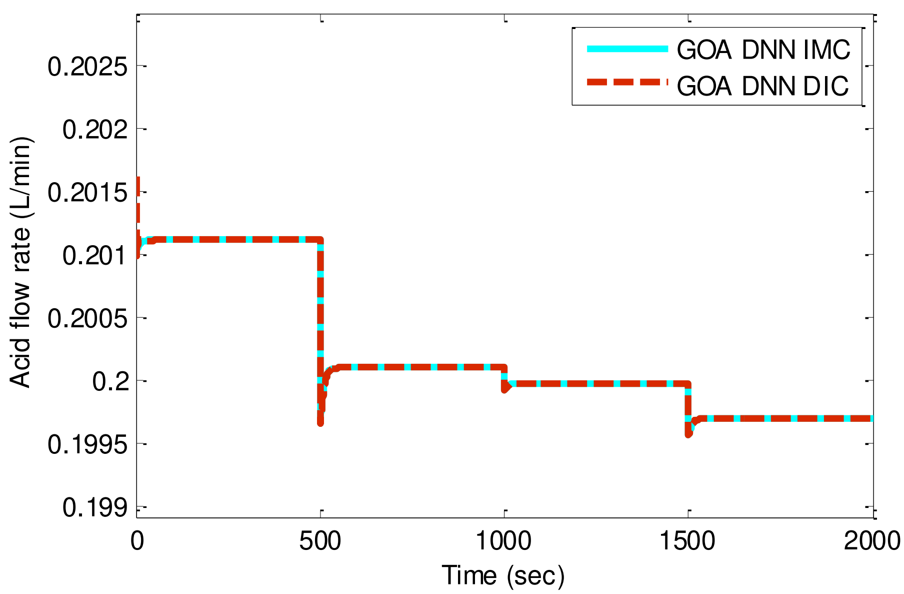

Fig.4. Controller output of pH process using GOA DNN-DIC and GOA DNN-IMC.

The regulatory responses of pH process using GOA-DNN DIC and GOA DNN-IMC are shown in Figs.5 for the operating point of pH value at 10. It is observed from Figure 5 GOA-DNN DIC fails to work for load disturbance in base flow rate and the GOA DNN-IMC has the ability to regulate the disturbance in the base flow rate.

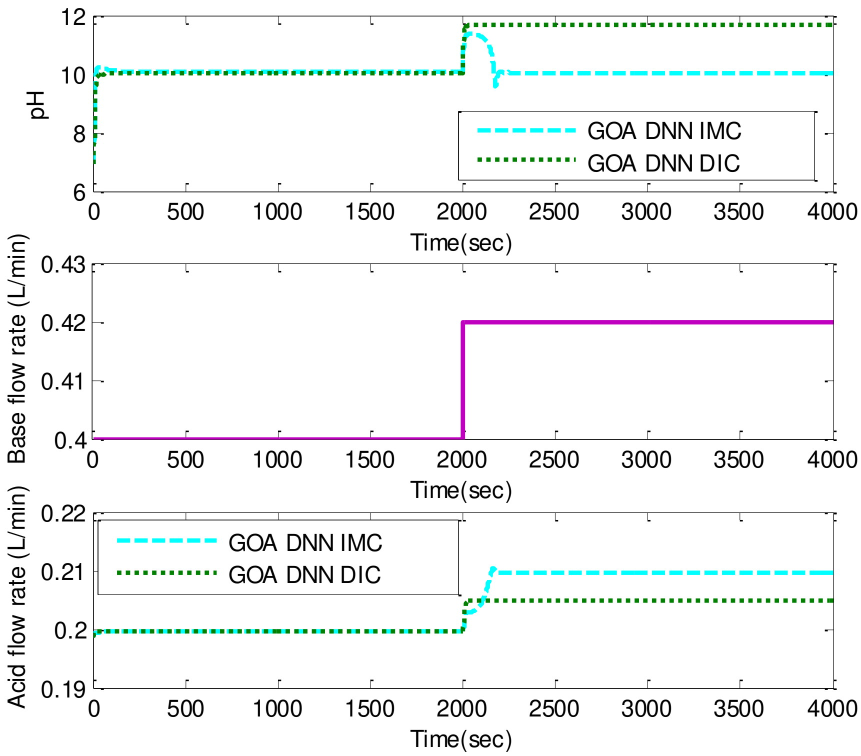

Fig.5. Regulatory response of pH process using GOA DNN-DIC and GOA DNN-IMC.

7 CONCLUSION

In this work, a novel approach, the Grasshopper Optimization Algorithm (GOA) based Deep Neural Network Internal Model Controller (DNN IMC), is formulated and applied to the pH process. The GOA DNN-IMC is designed to enhance the control performance of the pH process by leveraging the optimization capabilities of GOA and the modeling power of DNNs. Simulation results demonstrate that the GOA DNN-IMC significantly outperforms the GOA DNN-DIC approach. The proposed method achieves superior control accuracy, stability, and robustness, effectively handling the nonlinearities and dynamic complexities of the pH process. This innovative controller shows great promise for industrial applications.

REFERENCES

1. Amaral-Silva, N., Martins, R. C., Castro-Silva, S., & Quinta-Ferreira, R. M. (2016). Integration of traditional systems and advanced oxidation process technologies for the industrial treatment of olive mill wastewaters. *Environmental technology*, *37*(19), 2524-2535.
2. E.Sivaraman and S.Arulselvi, "Neuro modeling and control strategies for a pH process", International Journal of Engineering Science and Technology , 2011.
3. Henson, M. A., & Seborg, D. E. (1997). *Nonlinear process control* (pp. 5-8). Upper Saddle River, New Jersey: Prentice Hall PTR.
4. Sivaraman, E., Arulselvi, S., & Babu, K. (2011, March). Data driven fuzzy c-means clustering based on particle swarm optimization for pH process. In *2011 International Conference on Emerging Trends in Electrical and Computer Technology* (pp. 220-225). IEEE.
5. Abdullah, N. H. S., Karsiti, M. N., & Ibrahim, R. (2012, June). A review of pH neutralization process control. In *2012 4th International conference on intelligent and Advanced Systems (ICIAS2012)* (Vol. 2, pp. 594-598). IEEE.

6. Siddique, N. (2013). *Intelligent control: a hybrid approach based on fuzzy logic, neural networks and genetic algorithms* (Vol. 517). Springer.
7. Anderson, K. J., & Johnson, J. R. (2018). The effects of substrate pH on growth and survival of recently metamorphosed marbled salamanders (Ambystoma opacum). *Herpetological Conservation and Biology*, *13*(1), 70-79.
8. Selvasankari, T., Lincon, S. A., Sivaraman, E., & Thirumavalavan, R. (2022). BFA-LOLIMOT based Internal Model Controller for a nonlinear pH process–Real Time Approach. *NeuroQuantology*, *20*(5), 3001.
9. Okwu, M. O., Tartibu, L. K., Okwu, M. O., & Tartibu, L. K. (2021). Grasshopper Optimisation Algorithm (GOA). *Metaheuristic Optimization: Nature-Inspired Algorithms Swarm and Computational Intelligence, Theory and Applications*, 95-104.
10. Mirjalili, S. Z., Mirjalili, S., Saremi, S., Faris, H., & Aljarah, I. (2018). Grasshopper optimization algorithm for multi-objective optimization problems. *Applied Intelligence*, *48*, 805-820.