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Fuzzy Control of Gun Barrel Movement: Fuzzy Logic and the Gun Barrel's Precision Dance

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The scientific and technical aspects of gun barrel movement for effective attack and defense are of ultimate significance. The precise control of the gun barrel is of strategic importance during targeting, especially in changing environmental conditions. Fuzzy logic control offers a powerful alternative to classical and manual solutions to deal with the complexity and uncertainties of dynamic systems, thus increasing targeting accuracy and precision. This approach provides adaptability and intuitive parameterization while simplifying system design and implementation. On the other hand, in fuzzy control management, accurate modeling and visualization of gun barrel movement is essential to achieve efficient aiming and performance. Many papers and realizations can be found on the (automatic) fuzzy control of cannon barrels. In this paper, the authors also suggest an implementation of a fuzzy-controlled cannon barrel. The novelty of this approach is the application of new defuzzification methods, resulting in an accurate solution for the problem. The article starts with a review of the theory and literature on the control of cannon barrels. It is followed by a comparison of different implementations, including simulation tests on the accuracy, and a discussion of some practical issues.

topics: fuzzy set theory, cannon control, optimization, Hopfield neural networks

1. Introduction

The art of moving the gun barrel is a sophisticated combination of science and technical applications. In addition to the precise application of physical principles, the purpose of moving the gun barrel is to provide an effective attack or defense. This process is not only a technical solution but also reflects strategic decisions, while the aim of the cannon is to achieve accuracy and precision, whether it is for attack or defense. Adapting to changes in the environment and accurately assessing conditions are essential to achieve optimal performance.

Precise control of the movement of the gun barrel is a key issue in many fields, such as military cannons [1, 2], industrial automation [3], or robotics [4, 5]. Fuzzy logic control offers a powerful approach to dealing with task-related uncertainties and complexities [6]. Traditional control methods [2, 7] often have difficulty dealing with these dynamic variations, which can lead to lower performance and reduced accuracy. Fuzzy set theory is represented in many fields, be it decision systems [8], environmental applications [9], or some kind of expert system [10]. The application of fuzzy control in gun barrel motion offers several advantages over traditional methods. It increases adaptability to changing environmental conditions, improves accuracy on targets, and reduces the impact of uncertainties in ballistic systems. Fuzzy control enables intuitive parameter setting and reduces the need for complex mathematical modeling, simplifying system design and implementation.

There are many articles in the literature about fuzzy-controlled cannon barrels. It is reported that the performance of adaptive neural fuzzy models outperforms (mean squared error MSE = 0.002, coefficient of determination $R^2 = 0.9998$, mean absolute error MAE = 1.6) the predictive ability of artificial neural networks [11]. Surprisingly, even in the 21st century, many military cannons are still operated manually, as pointed out in several articles [12] (it is well known that the more human intervention in a system is minimized, the less the possibility of error), but the use of fuzzy logic algorithms or*fuzzy-proportional–integral–derivative* (fuzzy-PID) control methods in these fields is becoming more and more widespread. Furthermore, several papers report on new control methods that combine elements of machine learning [13, 14] to achieve a more optimal result.

For our model, we use the Denavit–Hartenberg convention [20, 21] to define the joint parameters and the transformation matrices. The parameters shown in Table I were defined using the

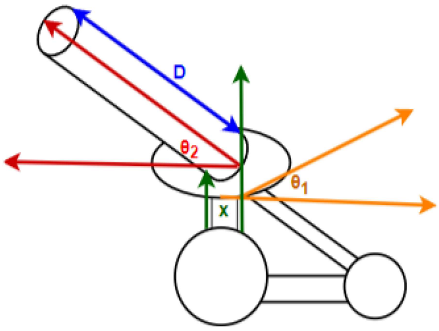

Fig. 1. System schematic.

TABLE I

System joints.

	Joints		
	A	B	C
Angle [°]	θ_1	0	θ_2
Linear displacement (d)	0	0	0
Distance (a)	0	x	D
Angular displacement (α)	90°	0	0

Denavit–Hartenberg convention with the help of the transformation matrix, and Fig. 1 shows the schematic of the cannon system itself. Explanations of the abbreviations are given in Table I.

In the article, the authors illustrate the potential of fuzzy logic in cannon control, highlighting new perspectives and, after presenting the theoretical model, combine machine learning methods within the framework of comparison. The fuzzy-controlled cannon system performance is compared with the performance of a system augmented with a Hopfield neural network.

2. Theoretical principles of control

First, the model is presented in a theoretical framework. Our cannon system is based on modern cannon systems [15, 16], which consist of several *direct current* (DC) motors, pivots, arms, and possibly a turning pad [17, 18].

The theoretical model can be interpreted as a multidisciplinary model, which requires the combination of the disciplines of fuzzy set theory, cybernetics, physics, and mathematics to construct it.

2.1. Factors of joints

The Denavit–Hartenberg convention is essentially a reference framework that allows the spatial location and displacement of each segment of the robot arm to be described [19].

2.2. System equations

For accurate modeling and implementation, our model must include the total kinetic energy of the system, the total potential energy, and the dissipation function due to damping [22–24]. The dynamic behavior of the system is described using the Lagrangian equations of motion, which model the motion of the arm and other parts of the system in detail [25, 26]. The equations are related to the total kinetic and potential energy of the system, as well as the dissipation function. The kinetic energy of different components and the gravitational potential part of the potential energy are analyzed. In determining the equations of motion, we consider the system's total kinetic and potential energy, as well as the virtual work done by the forces acting on the system. The resulting differential equations describe the motion and behavior of the system, which vary depending on the available parameters [27]. The relationships between the generalized forces and equations of motion of the system, including the system's total kinetic and potential energies, as well as damping, are expressed by

$$\frac{\mathrm{d}}{\mathrm{d}t}\left(\frac{\partial E_k}{\partial q_i}\right)-\left(\frac{\partial E_k}{\partial q_i}\right)+\left(\frac{\partial E_p}{\partial q_i}\right)+\left(\frac{\partial F_d}{\partial q_i}\right)=F_i, \quad (1)$$

where E_k is the total kinetic energy of the system, E_p is the total potential energy of the system, F_d is the dissipation function due to damping, F_i is the generalized force corresponding to the i-coordinate [28]. The generalized coordinate q_i describes the configuration or position of the system in relation to its degrees of freedom. The kinetic energy is given by the generalized formula of the form

$$E_k=\sum_{i=1}^{n} E_{ki}, \quad (2)$$

where n is the total number of moving parts in the system, E_{ki} is the kinetic energy of the i-th moving part. This summation notation can be applied in a general way to express the total kinetic energy of the system, regardless of the number of moving parts present in the system, since it depends on the implementation of how many moving parts are to be used [28, 29].

The gravitational potential energy of the arm, the charge, and the motors represent the potential energy of the whole system since the stretching energy of the arm is neglected because it is considered a rigid body [30]. Based on this, the gravitational potential energy of the charge is given by

$$V_p=mr^T g_z, \quad (3)$$

where V_p is the potential energy at the point, m is the mass of the mass point, r^T is the position vector of the mass point, g is the gravitational acceleration [31, 32]. The total potential energy is given by

$$E_p=E_{ka}+E_t, \quad (4)$$

where E_p is the total potential energy, E_{ka} is the arm potential energy, and E_t is the projectile potential energy [28, 29, 33]. If there is no external force acting on the end device, the generalized force of the system comes from the virtual work [34]

$$\delta W = Q_1\theta_1 + Q_2\theta_2 \ , \tag{5}$$

where Q_1 and Q_2 are the generalized forces θ_1 and θ_2, which are the torques applied by the motors; $\delta\theta_1$ and $\delta\theta_2$ are the virtual displacements θ_1 and θ_2 [34, 35].

The physical model, which we will apply in our implementation, has been completed. The following sections will discuss fuzzy set theory [36–38], which can be considered the heart of the system, as it is crucial for the operation and accuracy of our model.

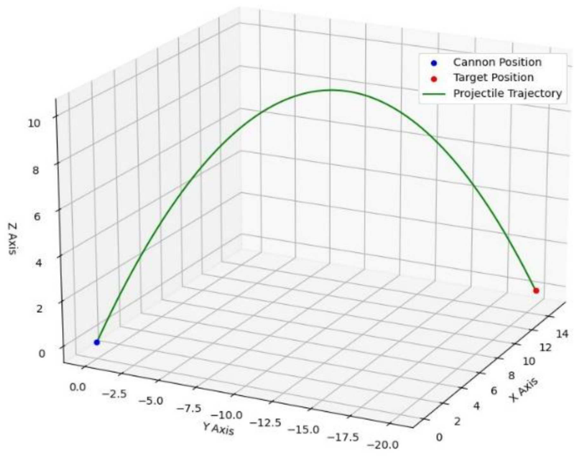

Fig. 2. Visualization of the fuzzy-controlled system.

2.3. Defuzzification

To perform fuzzy calculations, inputs must be transformed from crisp values into linguistic forms, and outputs must be defuzzified from linguistic forms back into crisp values. There are numerous defuzzification methods for this purpose, but we recommend a method mentioned by Piegat and Tomaszewska [39] (2017), which addresses the shortcomings and imperfections of existing methods.

This method does not involve aggregation; instead, it determines the best, optimal fuzzy representation and the optimal crisp representation of the activated inferences [39, 40]. Additionally, the authors emphasize that *"the OpR method is well-suited for both fuzzy modeling and control problems, as well as for fuzzy inferences. Its 'democratic' approach takes into account all rule inferences and their degrees of significance (competence)."* [39].

3. Implementation

We implemented our model using the Python programming language because, through fuzzy libraries, it seemed to be the most suitable for the task [41], and it is also excellently suited for creating fuzzy control systems.

It was necessary to define antecedents (latitude, depth, etc.) and consequents (horizontal adjustment, vertical adjustment, etc.). We automatically generated several fuzzy sets (poor, average, good, etc.) for the antecedents. For the consequents, we defined unique triangular fuzzy sets (negative, zero, positive, etc.), which are included in the rules. We then defined rules for the fuzzy control system. We used multiple rules that describe the relationships between antecedents and consequents. For example, if the latitude and/or depth are poor or average, we applied the corresponding horizontal and vertical adjustments. We defined the positions of the cannon and the target and calculated the trajectory from the initial position to the target, utilizing the precise implementation of the physical model in practice. Finally, we output the horizontal and vertical adjustment values.

The fuzzy sets assigned to the antecedents and consequents represent the fuzzy sets used to interpret the values of input and output variables. The rules describe logical relationships that determine the adjustments needed to reach the target based on the values of the input variables. During the simulation, the adjustments are computed based on fuzzy logic and then applied during trajectory adjustments to reach the target.

The model is a good example of how fuzzy set theory can be applied to a specific problem, such as aiming a cannon. The fuzzy control system helps to handle variable conditions flexibly and regulates the achievement of the target. A 3D visualization was created to represent the projectile, the target positions, and the trajectory (Fig. 2).

Overall, the use of fuzzy set theory in this model effectively demonstrates its efficiency in handling specialized problems such as weapon targeting. The fuzzy control system enhances adaptability to variable conditions and facilitates accurate target acquisition, encouraging the use of fuzzy logic in similar systems.

4. Testing

During the accuracy assessment, we applied several statistical methods to obtain a comprehensive view of the system's performance for both fixed and dynamically moving targets. Each test was run 100 times to ensure reliability and statistical significance.

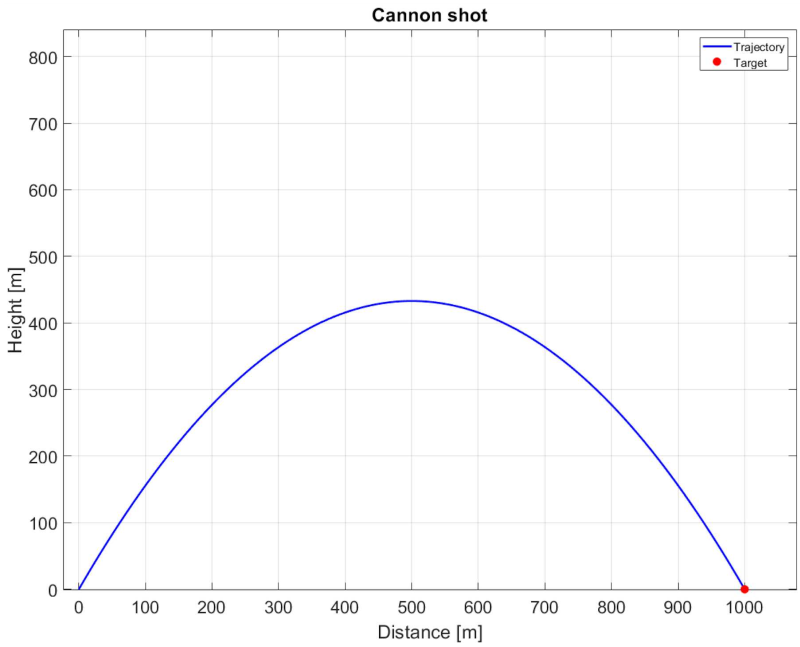

Fig. 3. Visualization of the fuzzy-controlled Hopfield logic system.

For fixed-position targets, the average deviation from the target was 0.12 m, with a 95% confidence interval ranging between 0.4 and 0.6 m. The average standard deviation was 0.118 m. Additionally, the mean absolute error (MAE) was 0.25 m, while the root mean square error (RMSE) was 0.12 m. For dynamically moving targets, the average distance from the target was 1500 m, changing within 5 s. Based on these values, the system was able to track dynamically moving targets, although the accuracy decreased by 3.21% due to the dynamic behavior.

Overall, these results demonstrate high accuracy for both fixed and dynamically moving targets and confirm the effectiveness of the fuzzy control system in achieving targets.

5. Comparison with other methods

For comparison purposes, we created an additional model, in which we initialized a Hopfield network used for solving optimization tasks. The network helps to fine-tune the angle of the cannon and then iteratively updates the network's states to find the most effective firing angle. Numerous studies use Hopfield networks for similar tasks [42–45].

Based on the results from the Hopfield network, we selected the optimal firing angle and calculated the required initial velocity to ensure that the projectile reaches the target at the specified distance, considering the physical motion equations

$$s_i\,(t{+}1) = \operatorname{sign}\Big(\sum_{j\neq i} s_j(t)\Big), \tag{6}$$

where $s_i(t{+}1)$ is the state of the i-th neuron at the next time step, and $s_j(t)$ represents the current state of the other neurons. The iterative steps in the model are described, where each neuron's state is updated based on the aggregation of the current states of all other neurons (excluding its own state), i.e.,

$$E = -\frac{1}{2}\sum_{i\neq j} w_{ij} s_i s_j, \tag{7}$$

where E denotes energy, w_{ij} represents the weight of the connection between neurons i and j, and s_i and s_j are the states of the respective neurons. In the case of the model using a Hopfield network (Fig. 3), accuracy improved on average by 4.32%. This suggests that integrating machine learning typically results in better performance, in our case accuracy, which is supported by several studies [46–48].

6. Model validation

Our fuzzy logic control model was validated using a structured framework that included comparison with experimental data and sensitivity analysis. We used experimental data from the Janes defense [49] website to validate the model, as similar models are not fully comparable to ours. The system was tested under various conditions, including target ranges of 1000–6000 m and wind speeds of 5, 10, and 15 m/s. For example, the model suggested a muzzle angle of 28° for a target at 400 m, the gun was set to that angle and the actual projectile trajectory was recorded. The measured angle was 27.9°, and the projectile landed 0.05 m from the target. The mean absolute error (MAE) between the model and experimental data was 0.09 m and the *root mean square error* (RMSE) was 0.08 m, indicating a high degree of agreement with the experimental results.

In the sensitivity analysis, key parameters such as membership functions and ranges of rule weights were varied. For example, a 20% increase in the wind compensation rule weight resulted in an improvement in targeting accuracy of 0.02 m, reflecting the sensitivity of the model to parameter changes. The model was also evaluated under extreme conditions, such as wind speeds of 20 m/s, and we showed that accuracy remained within 0.05 m, demonstrating robustness under varying environmental conditions.

7. Modeling conditions and limitations

The model was optimized for wind speeds up to 15 m/s; higher wind speeds may reduce accuracy. Simulations were conducted using Python libraries, such as scikit-fuzzy, on a high-performance computer cluster with 64 GB of RAM and 8 core CPUs.

The model assumes ideal conditions, neglecting factors such as mechanical wear, friction, or barrel misalignment. These simplifications may limit the model's applicability in long-term operations. Additionally, the model requires significant computational resources and is optimized for average projectile speeds between 700 and 1000 m/s; deviations from this speed range may affect performance.

8. Conclusions

In this research, we investigated the fuzzy logic control of cannon tube movement for effective targeting tasks and defense. The results indicate that the fuzzy control system effectively tracked both fixed and dynamically moving targets.

Examined metrics, such as average deviation, *mean absolute error* (MAE), and *root mean square error* (RMSE), show low values, indicating high accuracy of the system for both static and dynamic targets.

The results confirm the adaptive nature and intuitive parameterization of fuzzy control, which enable the system to effectively adapt to varying environmental conditions. Additionally, the application of fuzzy set theory offers significant advantages in managing dynamic systems, as it simplifies system design and implementation while increasing accuracy and efficiency. The flexibility and accuracy provided by fuzzy control highlight its importance in precisely modeling and controlling cannon tube movement under changing environmental conditions. Furthermore, the incorporation of the Hopfield network and the resulting increase in accuracy support the fact that integrating machine learning is crucial for precision.

Overall, it can be concluded that the fuzzy control system is an effective tool for achieving targets through cannon tube movement and offers potential for broad application in other dynamic systems where precision and efficiency are key factors.

Future work will involve conducting additional tests under various environmental and operational conditions and exploring the integration possibilities of other fuzzy logic and machine learning methods.

References

[1] A. Żyluk, K. Kuźma, N. Grzesik, M. Zieja, J. Tomaszewska, *Sensors* **21**, 7913 (2021).

[2] M.A. Muslim, D. Minggu, J. Saputra, R.N. Hasanah, *ARPN J. Eng. Appl. Sci.* **10**, 9765 (2015).

[3] Z. Zhao, X. Xu, X. Hao, *SPIE Proc.* **12492**, 124920B (2022).

[4] A.I.E. Yakzan, A.A. Khan, E.L. Hines, D. Iliescu, in: *UKSim 14th Int. Conf. on Computer Modelling and Simulation*, 2012.

[5] M.J. Er, Y. Gao, *IEEE Trans. Ind. Electron.* **50**, 620 (2003).

[6] L. A. Zadeh, *Fuzzy Sets Syst.* **11**, 199 (1983).

[7] H.W. Pout, in: *The Applications of Radar and other Electronic Systems in the Royal Navy in World War 2*, Ed. F.A. Kingsley, Palgrave Macmillan, London 1995.

[8] M.H. Homaei, F. Soleimani, S. Shamshirband, A. Mosavi, N. Nabipour, A. Varkonyi-Koczy, *IEEE Access* **8**, 20628 (2020).

[9] A.R. Varkonyi-Koczy, B. Tusor, *IEEE Trans. Instrum. Meas.* **60**, 1505 (2011).

[10] A. Dineva, A.R. Varkonyi-Koczy, J.K. Tar, in: *IEEE 18th Int. Conf. on Intelligent Engineering Systems (INES 2014)*, 2014, p. 163.

[11] M.A. Koç, *Arab. J. Sci. Eng.* **47**, 8829 (2022).

[12] M.A. Muslim, D. Minggu, J. Saputra, R.N. Hasanah, *J. Eng. Appl. Sci.* **10**, 9765 (2015).

[13] Q. Yang, Q. Yan, J. Cai, J. Tian, X. Guan, *IEEE Access* **8**, 72179 (2020).

[14] Y. Zhang, Q. Yan, J. Cai, X. Wu, *IEEE Access* **8**, 63443 (2020).

[15] T. Fan, J. Zhou, Y.J. Tian, K. Huang, *J. Phys. Conf. Ser.* **2460**, 012113 (2023).

[16] Y.-F. Xu, B. Gu, J.-P. Lei, C.-L. Shan, H. Liang, *J. Phys. Conf. Ser.* **2460**, 012021 (2023).

[17] V.H. Pinto, J. Gonçalves, P. Costa, *Appl. Syst. Innov.* **3**, 24 (2020).

[18] R.F.K. Tagne, R.T. Fotsa, P. Woafo, *Int. J. Bifurc. Chaos* **31**, 2150178 (2021).

[19] C.R. Rocha, C.P. Tonetto, J.M. Bernardes, *Robot. Comput.-Integr. Manuf.* **27**, 723 (2011).

[20] S. Shim, S. Lee, S. Joo, J. Seo, *J. Mech. Robot.* **14**, 054505 (2022).

[21] M.J. Thomas, M.M. Sanjeev, A.P. Sudheer, M.L. Joy, *Ind. Robot Int. J.* **47**, 683 (2020).

[22] S. Ayık, K. Sekizawa, *Phys. Rev. C* **102**, 064619 (2020).

[23] J. Kaur, A. Ghosh, M. Bandyopadhyay, *Physica A Stat. Mech. Appl.* **625**, 128993 (2023).

[24] P. Zhao, J. Liu, Y. Li, C. Wu, *Nonlinear Dyn.* **105**, 1437 (2021).

[25] A.M. Bersani, P. Caressa, *Math. Mech. Solids* **26**, 785 (2020).

[26] V.S. Erturk, E. Godwe, D. Baleanu, P. Kumar, J. Asad, A. Jajarmi, *Acta Phys. Pol. A* **3**, 265 (2021).

[27] B. Pardo, N. T. Maia, *Phys. Rev.* **102**, 124020 (2020).

[28] A.B. Tatar, B. Taşar, O. Yakut, *Arab. J. Sci. Eng.* **45**, 5191 (2020).

[29] X. Ma, W. Deng, S.S. Yuan, J. Yao, G. Yang, *J. Phys. Conf. Ser.* **1507**, 052001 (2020).

[30] L. Fu, H. Nakamura, S. Chi, Y. Yamamoto, T. Miura, *J. Adv. Concr. Technol.* **19**, 1245 (2021).

[31] T.L. Hubbard, *Psychonom. Bull. Rev.* **27**, 36 (2019).

[32] S. Sarkar, B. Fitzgerald, *Struct. Control Health Monitor.* **27**, e2471 (2019).

[33] J.L. Bradshaw, *Eur. J. Phys.* **44**, 025001 (2022).

[34] S.E. Lyshevski, *Electromechanical Systems, Electric Machines, and Applied Mechatronics*, CRC Press eBooks, 2018.

[35] E. Fable, C. Angioni, *Plasma Phys. Controll. Fusion* **65**, 115007 (2023).

[36] S. Laengle, V. Lobos, J.M. Merigó, E. Herrera-Viedma, M.J. Cobo, B. De Baets, *Fuzzy Sets Syst.* **402**, 155 (2021).

[37] S. Das, D. Chakraborty, L.T. Kóczy, *Iran. J. Fuzzy Syst.* **20**, 127 (2023).

[38] M.-W. Tian, A. Mohammadzadeh, J. Tavoosi, S. Mobayen, J.H. Asad, O. Castillo, A.R. Varkonyi-Koczy, *Acta Polytech. Hung.* **19**, 152 (2022).

[39] A. Piegat, K. Tomaszewska, *Przegląd elektrotechniczny* **2017**, 110 (2017).

[40] A. Piegat, K. Tomaszewska, in: *Uncertainty and Imprecision in Decision Making and Decision Support: Cross-Fertilization, New Models and Applications*, Eds. K.T . Atanassov, J. Kacprzyk, A. Kałuszko, M. Krawczak, J. Owsiński, S. Sotirov, E. Sotirova, E. Szmidt, S. Zadrożny, 2017 p. 71.

[41] S. Spolaor, C. Fuchs, P. Cazzaniga, U. Kaymak, D. Besozzi, M. S. Nobile, *Int. J. Computat. Intell. Syst.* **13**, 1687 (2020).

[42] G. Joya, M. Atencia, F. Hernández, *Neurocomputing* **43**, 219 (2002).

[43] X. Li, J. Wang, S. Kwong, *IEEE Trans. Neural Networks Learn. Syst.* **33**, 5116 (2021).

[44] S.S.M. Sidik, N.E. Zamri, M.S.M. Kasihmuddin, H.A. Wahab, Y. Guo, M.A. Mansor, *Mathematics* **10**, 1129 (2022).

[45] T. Kmeť, M. Kmetová, in: *Artificial Neural Networks*, Eds. P. Koprinkova-Hristova, V. Mladenov, N. Kasabov, 2015, p. 315.

[46] J. Krepel, M. Kircher, M. Kohls, K. Jung, *Stat. Anal. Data Mining* **15**, 112 (2021).

[47] V. Stamatis, M. Salampasis, K.I. Diamantaras, *Data Technol. Appl.* **58**, 363 (2023).

[48] N.S. Chang, K. Bai, C.F. Chen, *J. Environ. Manag.* **201**, 227 (2017).

[49] Janes website, 2024.