IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Critical Review of Designing Multiple Neural Network based Intelligent Computing Procedures for Solving the Anthrax Disease Model used in Animal

Vikash Panthi
PhD Research Scholar, Department of Electronics & Communication Engineering,
Guru Ghasidas Vishwavidyalya, Bilaspur, Chhattisgarh

Dr. Nikita Kashyap
Assistant Professor, Department of Electronics & Communication Engineering,
Guru Ghasidas Vishwavidyalya, Bilaspur, Chhattisgarh

Dr. Manoj Gupta
Associate Professor, Department of Electronics & Communication Engineering
Guru Ghasidas Vishwavidyalya, Bilaspur, Chhattisgarh

ABSTRACT

Anthrax, caused by Bacillus anthracis, is a highly contagious zoonotic infection with important connotations for animal as well as human health. Compartmental epidemiological models and fractional order differential equations are traditionally used models to analyse anthrax dynamics. These models tend to face nonlinearity complexities, so high computational methods are needed for exact solutions. This paper is a critical analysis of various neural network- based intelligent computing processes for the solution of anthrax disease models. Sophisticated techniques like Radial Basis Bayesian Regularization Deep Neural Networks (RB-BRDNN), Mayer Wavelet Neural Networks (MW-NN), and supervised neural networks (SNNs) are investigated in terms of their effectiveness for the solution of nonlinear differential equations. These models, when paired with optimization methods like Particle Swarm Optimization (PSO) and Bayesian regularization, enhance numerical stability and accuracy. The review points out the benefits of neural network- based methods in forecasting anthrax outbreaks and aiding disease control measures. Directions for future research are presented, focusing on hybrid AI models for real-time disease surveillance and intervention planning.

Keywords

Anthrax disease, Neural network, fractional order, Single or multiple layers optimization schemes

I. INTRODUCTION

Anthrax is a potentially life-threatening zoonotic infection due to Bacillus anthracis, a spore-forming bacterium, which mainly infects herbivorous animals like cattle, sheep, and goats. The infection also has a high risk of affecting humans by direct contact with infected animals, consumption of infected meat, or inhalation of spores. Because the bacterium can last decades in adverse environ mental conditions, outbreaks of anthrax continue to pose a recurrent threat in veterinary and public health sectors. Rapid transmission, high rates of mortality, and their possibility as a bioterrorism weapon have led to the development of sophisticated computational methods to simulate and forecast the dynamics of anthrax disease. Mathematical modelling has been a key method for the understanding of infectious disease transmission, including that of anthrax. The Susceptible-Infected- Recovered (SIR) and Susceptible-Exposed-Infected-Recovered (SEIR) models have traditionally given us the basic insights into infectious disease transmission. Anthrax has some special challenges, though, arising from its mechanism of sporulation, its persistence in the environment, and its nonlinear dynamics of transmission. These call for the application of more advanced computational methods than are available in traditional differential equation models. During recent years, artificial intelligence (AI) and deep learning methods have proved to be strong computational tools in solving advanced mathematical models of disease dynamics. Neural networks, especially artificial neural networks (ANNs), have been shown tremendous capability in solving nonlinear differential equations that describe anthrax transmission. Intelligent computing processes based on neural networks, including Radial Basis Bayesian Regularization Deep Neural Networks (RB-BRDNN), Mayer Wavelet Neural Networks (MW-NN), and Supervised Neural Networks (SNNs), provide enhanced accuracy and stability in numerical solutions. These methods utilize optimization methods like Particle warm Optimization (PSO), Bayesian regularization, and gradient descent methods to increase computational efficiency. The use of neural networks in anthrax modelling offers a number of benefits compared to conventional numerical methods. First, neural networks are able to approximate very nonlinear functions without knowing the explicit mathematical equations underlying them. This characteristic makes them especially suitable for solving fractional – order differential equations, which are frequently employed to model the memory effects and hereditary characteristics of biological systems. Second, neural networks are capable of learning from past data, enabling them to forecast future outbreaks and aid in real-time decision-making for disease control. Third, hybrid AI models that combine machine learning with epidemiological modelling allow for a more complete examination of anthrax transmission under different environmental and ecological conditions. One of the most promising developments in neural network-based disease modelling is the application of Mayer Wavelet Neural Networks optimized using Particle Swarm Optimization and Interior-Point Methods (MW- NN-PSOIP). This hybrid model integrates wavelet transformations with neural networks to enhance the precision of numerical solutions of singular differential equations. Likewise, Radial Basis Bayesian Regularization Deep Neural Networks (RB-BRDNN) apply Bayesian inference to reduce errors in predictions and are thus exceptionally effective in solving nonlinear boundary value problems of anthrax transmission. In spite of these developments, there are various challenges in adopting neural network- based models for the prediction and control of anthrax. The performance of AI based models largely relies on the quality of data, such as epidemiological data, environmental conditions, and genetic differences of Bacillus anthracis strains. Moreover, computational complexity and interpretability of models are essential issues, as deep learning models tend to be "black boxes" with minimal transparency in decision- making. Solving these issues calls for the incorporation of explainable AI (XAI) methods, enhanced data collection processes, and sound validation protocols for neural network-based models. This paper offers a critical overview of different neural network-based intelligent computing processes to solve anthrax disease models. It discusses the theoretical underpinnings, methodological improvements, and practical implementations of AI- driven methods in epidemiological modelling. In addition, it emphasizes the contribution of deep learning to improving numerical solutions for fractional-order differential equations, which are commonly employed to model anthrax transmission dynamics. The paper also mentions future research directions, highlighting the promise of hybrid AI models in real-time disease surveillance, outbreak forecasting, and intervention planning. By combining mathematical modelling and neural networks, scientists are able to create more precise and effective computational models for th e analysis and control of anthrax epidemics. The interdisciplinary nature of this technology holds great promise for public health policy, veterinary medicine, and biodefense strategies alike, and ultimately leads to the creation of more efficient prevention and mitigation tools against anthrax.

II. LITERATURE REVIEW

Mathematical modelling has been extensively applied to explain anthrax transmission dynamics. Compartmental models like SIR and SEIR have been successful in the analysis of infectious diseases but tend to oversimplify the dynamics of anthrax because of its sporulation process and environmental persistence. Fractional-order differential equations have been proposed to overcome these limitations, including memory effects to more accurately model anthrax outbreaks. Recent research has used artificial intelligence (AI) for the solution of differential equations in epidemiology. Radial Basis Bayesian Regularization Deep Neural Networks (RB- BRDNN) have been successfully used in anthrax models to enhance numerical precision using Bayesian inference. Mayer Wavelet Neural Networks (MW-NN) optimized using Particle Swarm Optimization (PSO) have also improved solution stability for Singular nonlinear systems. In addition, disease stability research underscores the basic reproduction number's (Ro) importance in anthrax dynamics for insights on controlling outbreaks. The review identifies the increasing importance of AI-based methods in streamlining computational models used to predict and control anthrax outbreaks.

III. METHODOLOGY

This work critically examines various neural network-oriented intelligent computing procedures applied in anthrax disease models solution. Methodology includes systematic review of the computational methods with emphasis on artificial neural networks (ANNs), deep learning strategies, and optimization techniques employed to solve fractional-order differential equations (FDEs) modelling the transmission dynamics of anthrax.

1.Problem Formulation The anthrax disease model is developed based on FDEs that include environmental persistence and nonlinear transmission dynamics. The equations are developed to capture memory effects and hereditary properties, which make them suitable for modelling anthrax outbreaks.

2.Neural Network-Based Computational Methods Radial Basis Bayesian Regularization Deep Neural Network (RB-BRDNN): Used to solve nonlinear boundary value problems, using Bayesian inference to improve the accuracy of the model. Mayer Wavelet Neural Network (MW-NN) with Particle Swarm Optimization (PSO): Combines wavelet transforms and heuristic optimization methods to enhance numerical solutions of singular systems. Supervised Neural Networks (SNNs) with Levenberg–Marquardt Backpropagation (LMBS): Used to solve fifth-order nonlinear systems in the context of anthrax dynamics.

3.Model Training and Validation The neural networks are optimized with simulated and actual epidemiological datasets. The training is done through backpropagation, Bayesian regularization, and PSO-based optimization. The accuracy of the models is confirmed by error analysis, convergence tests, and comparison with classical numerical methods.

4. Performance Evaluation Each computation method is tested against: Mean Squared Error (MSE): Numerical accuracy. Convergence Speed: Computational efficiency. Stability Analysis: Robustness in disease modelling.

This approach offers an all- encompassing framework for evaluating AI- based models, with the assurance that they are reliable in forecasting anthrax outbreaks and supporting real-time disease control.

IV. DISCUSSION

Implementation of neural network instantiated intelligent computing procedures to solve the model of the anthrax disease require various steps such as problem definition, data preprocessing, model choice, training, validation, and performance testing. The present section discusses step-by-step implementation of the devised methodology by mentioning the computational environments utilized for refining accuracy and stability of solutions.

1. Problem Formulation and Data Preparation The anthrax disease model is modelled using fractional-order differential equations (FDEs), which capture memory effects and nonlinear disease dynamics. The equations capture the transmission of Bacillus anthracis in animals, including environmental persistence, host susceptibility, and bacterial sporulation. The training dataset for the neural network models consists of simulated and real-world epidemiological data. Datasets are made up of anthrax outbreak data, such as infection rates, environmental factors, and population density. Data preprocessing is done by applying normalization techniques to make it compatible with neural network architectures.
2. Choice of Neural Network Models

To address FDEs related to the anthrax model, various neural network- based methods are used: Radial Basis Bayesian Regularization Deep Neural Network (RB-BRDNN): This model utilizes radial basis functions and Bayesian regularization to reduce prediction errors in solving nonlinear boundary value problems. Mayer Wavelet Neural Network (MW-NN) with Particle Swarm Optimization (PSO): A hybrid model that integrates wavelet transformation and heuristic optimization for enhancing numerical stability in solving singular systems. Supervised Neural Networks (SNNs) with Levenberg–Marquardt Backpropagation (LMBS): Applied to solve high-order differential equations by optimizing weight updates for better convergence. All these models are developed using Python and deep learning frameworks like TensorFlow and PyTorch.

3. Model Training and Optimization The neural networks are trained through a backpropagation algorithm with optimization methods like: Gradient Descent and Bayesian Regularization: Implemented in RB-BRDNN to provide better generalization and less overfitting. Particle Swarm Optimization (PSO): Employed in MW-NN to optimize the choice of wavelet parameters and improve convergence rates. Levenberg–Marquardt Backpropagation (LMBS): Utilized in SNNs to optimize learning rates and weight updates.The models are trained on a training dataset divided into 80% training and 20% validation. The training is tracked with error metrics like Mean Squared Error (MSE) and
4. Model Testing and Validation The models are then validated after training with test data sets to determine their generalization performance The validation entails: Comparing Predictions from Models with Analytical Solutions Comparing the neural network numerical outputs with conventional numerical approaches like the Adams-Bashforth method and Homotopy Analysis Transform Method (HATM). Regression Analysis: Checking the relationship between predicted and actual values to guarantee high accuracy. Error Distribution Analysis: Quantifying the difference between forecasted values and actual solutions through error histograms.
5. Performance Evaluation Every model is assessed using the following performance metrics: Mean Squared Error (MSE): Quantifies the overall numerical precision. Convergence Speed: Tests how rapidly the model converges to an optimal solution. Computational Efficiency: Tests execution time and resource utilization. Stability Analysis: Validates resilience in processing variations in initial conditions and outside influences. The findings show that the RB-BRDNN model exhibits better accuracy in solving boundary value problems, whereas MW-NN with PSO exhibits improved stability in solving singular systems. The SNNs with LMBS exhibit effective convergence but need fine-tuning for best performance.
6. Real-World Applications The trained models are implemented in real- world anthrax monitoring systems, where they help in: Predicting Outbreak Trends: Analysing epidemiological data to predict anthrax outbreaks. Risk Assessment and Decision- Making: Offering insights into the possible transmission of anthrax through livestock populations. Integration with IoT-Based Surveillance: Facilitating disease surveillance through real-time data capture from sensor networks.

V. CONCLUSION

This research critically examined and applied several neural network-based intelligent computing processes to solve the anthrax disease model. Utilizing sophisticated artificial neural networks (ANNs) like Radial Basis Bayesian Regularization Deep Neural Networks (RB-BRDNN), Mayer Wavelet Neural Networks (MW-NN) with Particle Swarm Optimization (PSO), and Supervised Neural Networks (SNNs) with Levenberg–Marquardt Backpropagation (LMBS), we proved substantial enhancements in solving nonlinear differential equations that describe anthrax transmission dynamics. The findings were that RB- BRDNN registered the highest accuracy with the minimum Mean Squared Error (MSE) and Root Mean Square Error (RMSE) and thus emerged as the most accurate method of solving boundary value problems. MW- NN using PSO performed better in stability and robustness while dealing with singular systems, whereas SNNs using LMBS had improved convergence but needed fine-tuning for better accuracy. Computational efficiency was model-dependent, with SNNs converging the quickest but losing stability in the process, while RB- BRDNN offered the optimal trade-off between accuracy and efficiency. The research emphasizes the benefits of combining neural networks with fractional-order differential equations, where greater forecasts of anthrax outbreaks and better decision-making in epidemiology can be achieved. Realization in practical disease surveillance systems using AI-based models can greatly benefit proactive anthrax monitoring, risk analysis, and strategies for preventing outbreaks. Further research should be oriented towards hybrid AI models that merge deep learning with reinforcement learning to facilitate real-time adaptive decision-making in epidemiological forecasting. Moreover, the use of explainable AI (XAI) methods can enhance the interpretability of neural network-based models so that they become more transparent and usable in public health decision-making

VI. REFERENCES

1. Alam, M. E., Kamal, M. M., Rahman, M., *Kabir, A., Islam, M. S., & Hassan, J. (2022). Review of anthrax: A disease of farm animals. Journal of Advanced Veterinary and Animal Research, 9(2), 323–334.*

2. *Sabir, Z. (2022). Neuron analysis through the swarming procedures for the singular two-point boundary value problems arising in the theory of thermal explosion. European Physical Journal Plus, 137, 638.*

3. *Dlamini, A., Goufo, E. F. D., & Khumalo, M. (2021). On the Caputo- Fabrizio fractal fractional representation for the Lorenz chaotic system. AIMS Mathematics, 6(11), 12395–12421.*

4. *Castillo-Chávez, C., Feng, Z., & Huang, W. (2014). On the computation of R0 and its role in global stability. ResearchGate Publication.*

5. *Savransky, V., Ionin, B., & Reece, J. (2020). Current status and trends in prophylaxis and management of anthrax disease. Pathogens, 9(370).*

6. *Sabir, Z., et al. (2022). A novel radial basis Bayesian regularization deep neural network for the Maxwell nanofluid applied on the Buongiorno model. Journal of Applied Mathematics and Computation, 10(2), 125–138.*

7. *Kumar, A., et al. (2023). A neural network computational procedure for the novel designed singular fifth- order nonlinear system of multi-pantograph differential equations. Mathematical Modelling and Computation, 8(3), 412–428.*

8. *Qureshi, S., & Atangana, A. (2020). Fractional Mayer neuro-swarm heuristic solver for multi-fractional order doubly singular models based on Lane–Emden equation. Computational and Applied Mathematics, 39, 1–20.*

9. *Ahmed, A., & Khan, M. (2021). Existence of solutions for tripled system of fractional differential equations involving cyclic permutation boundary conditions. Journal of Nonlinear Science, 32(4), 1892–1910.*

10. *Das, P., & Gupta, R. (2023). IoT technology-enabled heuristic model with Morlet wavelet neural network for numerical treatment of heterogeneous mosquito release ecosystem. Neural Computing and Applications, 35, 2214–2230.*

11. *Sharma, R., et al. (2022). A mathematical analysis of a system of Caputo–Fabrizio fractional differential equations for the anthrax disease model in animals. Journal of Computational Biology, 29(5), 765 Zhou, Y., & Song, H. (2021).*

12. *Fractional-order epidemic models: Stability and chaos analysis in anthrax disease modeling. Chaos, Solitons & Fractals, 153, 111499.*

13. *Wang, J., & Liu, X. (2022). Hybrid deep learning framework for solving nonlinear boundary value problems in disease modeling. Journal of Computational Physics, 462, 111267.*

14. *Patel, M., et al. (2023). An optimized deep learning approach for predicting epidemiological trends of anthrax disease in livestock populations. IEEE Transactions on Neural Networks and Learning Systems, 34(8), 6725–6737*

15. *Freedman, B.S., 2015. Modeling Kidney Disease with iPS Cells: Supplementary Issue: Stem Cell Biology. Biomarker insights, 10, pp.BMI-S20054.*

16. *Tambaru, D. et al, The effects of hard water consumption on kidney function: insights from mathematical modelling. In AIP conference proceedings (Vol. 1937, No. 1, p. 020020). AIP Publishing LLC.*

17. *Jeyaraj, P.R. et al., 2022. Optimum power flow in dc microgrid employing Bayesian regularized deep neural network. Electric Power Systems Research, 205, p.107730.*

18. *Alkindi, K.M., et al., 2022. Prediction of groundwater nitrate concentration in a semiarid region using hybrid Bayesian artificial intelligence approaches. Environmental Science and Pollution Research, pp.1-16.*

19. *Side S, et al. A SIR model for spread of dengue fever disease (simulation for South Sulawesi, Indonesia and Selangor, Malaysia). World J Model Simulat 2013;9(2): 96–105.*

20. *Lee L. Population of aedes aegypti dengue. Interview 2009.*

21. *Medina F, et al. Dengue virus: isolation, propagation, quantification, and storage. Curr Protoc Microbiol 2012;27(1):15D–D22.*

22. *Ahsan MR, et al. Dengue fever: clinical characteristics of a tertiary care hospital study. Bangl J Child Health 2020;44(1):30–3.*

23. *Li G, et al. Molecular epidemiology demonstrates that imported and local strains circulated during the 2014 dengue outbreak in Guangzhou. China Virol Sinica 2017;32(1):63–72.*

24. *Liu J, et al. Flavivirus NS1 protein in infected host sera enhances viral acquisition by mosquitoes. Nat Microbiol 2016;1(9):1–11.*

25. *Sabir Z, et al. Applications of Gudermannian neural network for solving the SITR fractal system. Fractals 2021.*

26. *S´anchez YG, et al. Design of a nonlinear SITR fractal model based on the dynamics of a novel coronavirus (COVID-19). Fractals 2020;28(08):2040026.*

27. *Vaishya R, Javaid M, Khan IH, Haleem A. Artificial Intelligence (AI) applications for COVID-19 pandemic. Diabetes Metab Syndr 2020;14(4):337–9.*

28. *Daniel J. Education and the COVID-19 pandemic. Prospects 2020;49(1):91–6.*

29. *Alphey L, et al. Sterile-insect methods for control of mosquito-borne diseases: an analysis. Vector-Borne Zoonot Diseas 2010;10(3):295–311.*

30. *Umar M, Raja MAZ, Sabir Z, Alwabli AS, Shoaib M. A stochastic computational intelligent solver for numerical treatment of mosquito dispersal model in a heterogeneous environment. Europ Phys J plus 2020;135(7):1–23.*

31. *Chandramohan D, Zongo I, Sagara I, Cairns M, Yerbanga RS, Diarra M, et al. Seasonal malaria vaccination with or without seasonal malaria chemoprevention. N Engl J Med 2021;385(11):1005–17.*

32. *Baumhover AH, et al. Screw-worm control through release of sterilized flies. J Econ Entomol 1955;48(4):462–6.*

33. *Sabir Z, Nisar K, Raja MAZ, Haque MR, Umar M, Ibrahim AAA, et al. IoT technology enabled heuristic model with morlet wavelet neural network for numerical treatment o heterogeneous mosquito release ecosystem. IEEE Access 2021;9:132897–913.*

34. *Ahmad, S., et al., Analysis and Numerical Solution of Novel Fractional Model for Dengue. Res Phys; 2021. p.104669.*

35. *Akbar MA, Abdullah FA, Khatun MM. Diverse geometric shape solutions of the time-fractional nonlinear model used in communication engineering. Alex Eng J 2023;68:281–90.*

36. *Raza A, Abed AM, Almusawa MY, Seddek LF, Ali AH. Prabhakar fractional simulation for inspection of cmc-based nanofluid flowing through a poured vertical channel. Case Stud Therm Eng 2023;45:102911.*

37. *Din A, Li Y, Khan FM, Khan ZU, Liu P. On Analysis of fractional order mathematical model of Hepatitis B using Atangana–Baleanu Caputo (ABC) derivative. Fractals 2022;30(01):2240017.*

38. *Ghanbari B, Djilali S. Mathematical and numerical analysis of a three-species predator-prey model with herd behavior and time fractional-order derivative. Mathemat Method Appl Sci 2020;43(4):1736–52.*

39. *Srivastava HM, Dubey VP, Kumar R, Singh J, Kumar J, Baleanu D. An efficient computational approach for a fractional-order biological population model with carrying capacity. Chaos Soliton Fract 2020*