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Neural Network-Based Numerical Analysis of Maize Streak Epidemic Model with Linear Control

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Abstract

Objectives: The aim of the present study is to conduct a numerical analysis of the performance of various neural architectures in solving the maize streak epidemic model with linear control. A supervised neural network approach is employed to obtain solutions for the maize streak epidemic under linear control. The mathematical model categorizes the maize population into two groups—susceptible and infected—and the vector population into susceptible and infected groups. **Method**: We compute the numerical solutions of the maize streak epidemic model with linear control using a proficient Bayesian regularization neural network, which is known for effectively solving nonlinear problems. The dataset is generated using the Adams method, with input values ranging from 0 to 1 and a step size of 0.01. The division into training, validation, and testing sets follows appropriate proportions to minimize the mean square error. During training, we apply Bayesian regularization with varying numbers of neurons and a log-sigmoid activation function. **Finding**: The correctness of the proposed stochastic computing scheme is observed through the overlapping of the results, best authentication values, and insignificant absolute error. Moreover, the statistical representations based on regression, transition state, error histogram, and function fitness also approve the reliability of the designed solver. **Analysis**: The numerical solutions of the maize streak epidemic model have been analyzed using different numbers of neurons to solve three distinct cases of the model. **Novelty**: The neuron analysis, along with the designed Bayesian regularization neural network, is proposed for the first time to solve the maize streak epidemic model with linear control.

Keywords: Maize streak virus; Bayesian regularization; neural networks; control model; numerical simulation.

1 Introduction

Maize, widely known as corn, is a cereal grain that was first domesticated approximately 9,000 years ago by the early inhabitants of southern Mexico [1]. Today, it holds global significance, playing key roles in the food, agriculture, and industrial sectors. In 2022, the Food and Agriculture Organization (FAO) reported that global maize production exceeded 1.2 billion metric tons, making it the most-produced staple cereal ahead of wheat and rice [2]. This made maize the primary driver of cereal production growth, contributing to a 2.1% year-on-year increase in global cereal output in 2021 [3]. This remarkable level of production highlights maize's versatility and its essential role in global food systems. However, maize serves as a dietary staple in many regions, a significant portion of the harvest is used as livestock feed. It is also processed into various products, including corn oil, corn syrup, biofuel ethanol, and starches used in food and biodegradable materials [4].

Economic sustainability in maize production relies on maintaining stable yields, minimizing losses from pests and diseases, and ensuring efficient use of resources. Investing in resilient crop varieties, integrated pest management, and improved farming practices can enhance long-term profitability and reduce vulnerability to market and environmental shocks [5]. With its importance, maize productivity

is threatened by a combination of environmental pressures. Maize cultivation faces several abiotic challenges, such as extreme temperatures, heavy metal pollution, and many more. At the same time, biotic threats like fungal, bacterial, and viral diseases such as maize streak virus (MSV) and insect pests attack both shoots and roots, further compromising plant vitality and grain quality [6].

Among the most devastating viral threats to maize production Maize Streak Disease (MSD) is caused by Maize streak virus. This is characterized by narrow, chlorotic streaks on the leaves that can coalesce into necrotic patches, ultimately leading to stunting and plant death. Epidemic outbreaks of MSD are driven by seasonal surges in populations of Cicadulina leafhoppers, which carry and spread the virus via a stable circulative transmission pathway and can infect new plants for up to two weeks after acquisition. In sub-Saharan Africa, incidence peaks during the rainy season when vector (leafhopper) abundance is highest, and the predominance of susceptible cultivars can precipitate yield losses approaching 100 percent in heavily infested fields. Historical epidemics, such as those recorded in Nigeria and Kenya during the 1970s and 1980s underscore the critical need for integrated control strategies combining resistant hybrids, adjusted planting dates, and vector-management tactics to avert devastating crop losses [7].

Decline in maize production per hectare, resulting from MSV infections, can have profound economic consequences, particularly for smallholder farmers who depend heavily on maize as a staple food and a primary source of income. The compounded effects of repeated outbreaks may also discourage investment in maize cultivation, leading to shifts toward less productive or less nutritious crops, further weakening agricultural resilience and economic sustainability [8]. Moreover, outbreaks of MSV can significantly reduce crop yields, diminishing food availability and contributing to increased risks of hunger, malnutrition, and food insecurity, particularly among vulnerable populations [9]. The dependence on maize as a mono-crop in many subsistence farming systems exacerbates the impact of such outbreaks, as households often lack alternative sources of nutrition and income. Ensuring food security under these conditions requires effective disease control strategies and broader investments in agricultural resilience [10]. The advancement of maize cultivars with resistance to MSV is a critical strategy for sustainable disease management and yield stabilization. Advances in both conventional breeding and molecular genetic techniques have enabled researchers to identify and incorporate resistance genes into elite maize germplasm. These resistant cultivars reduce the need for chemical control and vector management and provide long-term protection against recurring MSV epidemics in endemic regions. Marker-assisted selection, which utilizes specific DNA markers to identify and select for desirable traits, along with transgenic approaches, has further accelerated the development of highly resistant lines offering a scalable solution to enhance maize productivity and improve food security in sub-Saharan Africa [11].

Mathematical modeling plays a vital role in understanding and managing maize streak virus by providing insights into the dynamics of disease transmission and control [12]. When utilizing models, researchers can predict how MSV spreads across maize fields and regions by incorporating variables such as infection rates, vector behavior, and environmental conditions [13]. This predictive capacity supports early warning systems and timely interventions. Additionally, models enable the evaluation of control strategies, such as the deployment of resistant maize varieties, vector management, or changes in planting schedules, allowing to compare outcomes without the need for costly field trials [14]. By simulating the interactions between the virus, host plants, and insect vectors, mathematical models contribute to a deeper understanding of disease mechanisms. Furthermore, they aid in optimizing resource allocation by identifying high-risk areas and the most effective times for intervention, which is particularly valuable for resource-limited farmers. In the long term, modeling also supports strategic planning by exploring future scenarios under climate change or shifting agricultural practices. Overall, mathematical models are essential tools in combating MSV and enhancing the resilience of maize production systems [15, 16]. Authors in [17] represented a discrete fractional mode that captures the complex temporal dynamics of maize streak virus transmission more accurately than classical models. By incorporating linear control strategies, the model offers practical insights into the timing and intensity of interventions needed to effectively curb the spread of MSV.

The current numerical investigation explores the performance of various neural networks in modeling maize streak epidemics using a linear control framework, employing a robust Bayesian Regularization Neural Network (BRNN). This solver has demonstrated strong capabilities in handling nonlinear problems. Notably, the BRNN has not previously been applied to address the maize streak epidemic within this control model. In recent years, neural network solvers have been effectively utilized in a

range of applications, including models for malaria [18], fractional-order cholera and Buruli ulcer [19], modified gravity in an accelerating universe [20], and chickenpox [21]. Motivated by these successful applications, the authors aim to numerically solve the maize streak epidemic model with linear control using the BRNN approach. Some novel contributions of this research are outlined as follows:

- Solving nonlinear problems using traditional numerical schemes can be challenging; therefore, an optimization-based BRNN framework is adopted to address nonlinear systems of equations.
- A single hidden-layer neural network with a log-sigmoid activation function is employed to compute numerical solutions for the model with linear control.
- Networks with 10, 20, and 40 neurons are considered to investigate the influence of network size on the numerical solution process.
- Model validation is carried out using result comparisons and absolute error (AE) metrics.

The remaining structure of the paper is organized as follows: Section 2 presents the mathematical formulation of the maize streak epidemic model with linear control. Section 3 outlines the design of the neural network with a single hidden layer. Section 4 discusses the numerical performance and results, while Section 5 concludes the study with final remarks.

2 Mathematical maize streak epidemics with linear control model

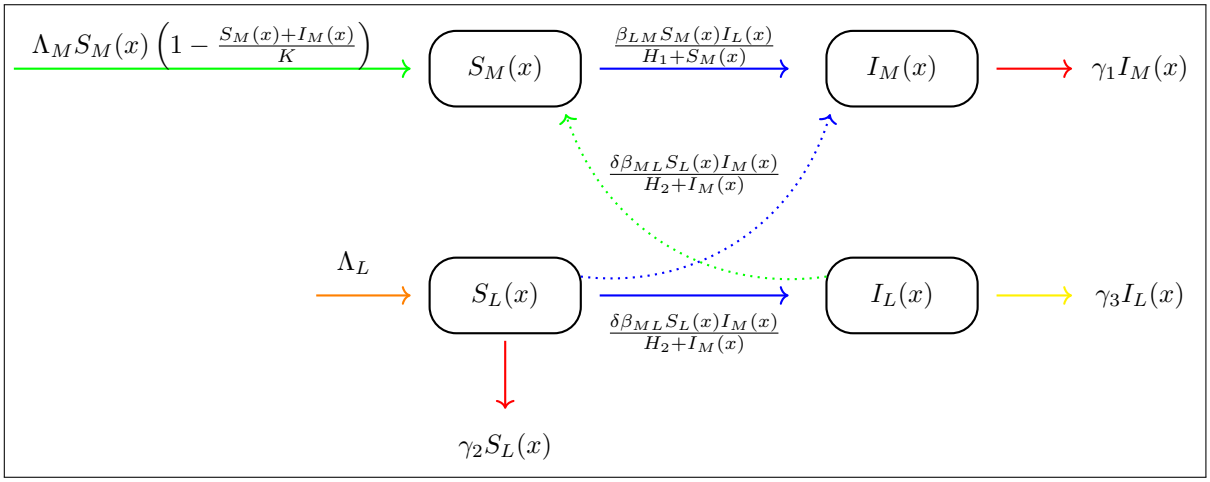


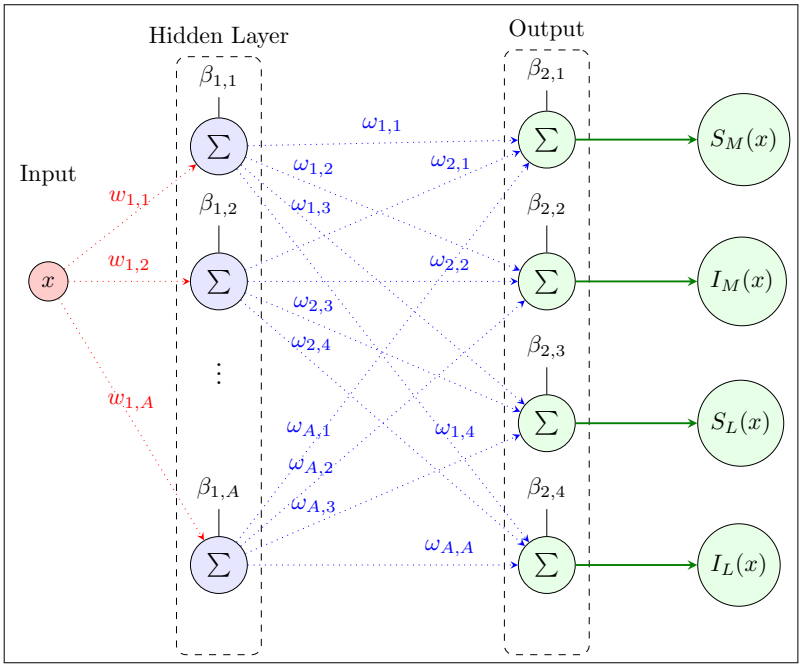
Figure 1: Systemic diagram of the maize streak epidemics with linear control model

This section presents the mathematical formulation of the maize streak epidemic model with linear control. The population is categorized into four compartments: susceptible and infected maize plants, and susceptible and infected vectors. The resulting system of first-order differential equations representing the maize streak epidemic model with linear control is given as [17]:

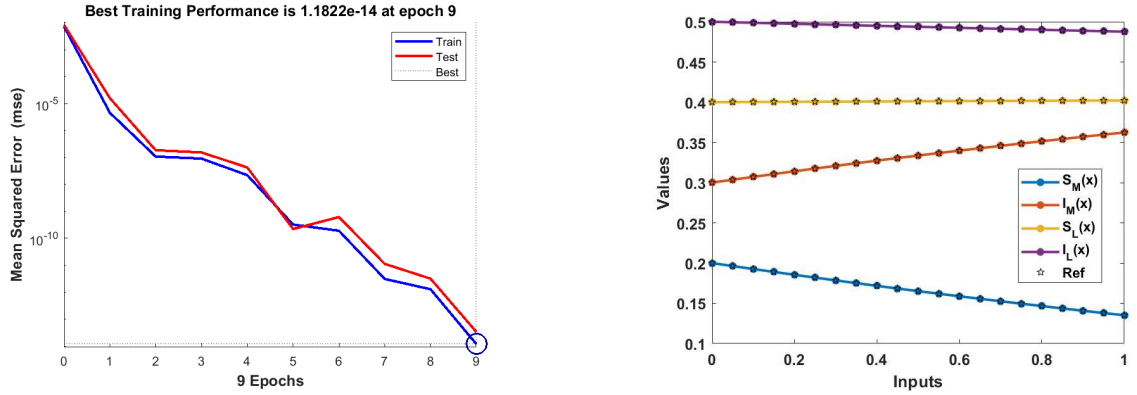
$$\begin{cases} \frac{dS_M(x)}{dx} = \Lambda_M S_M(x)\left(1-\frac{S_M(x)+I_M(x)}{K}\right) - \frac{\beta_{LM}S_M(x)I_L(x)}{H_1+S_M(x)}, & S_M(0)=i_1, \\ \frac{dI_M(x)}{dx} = \frac{\beta_{LM}S_M(x)I_L(x)}{H_1+S_M(x)} - \gamma_1 I_M(x), & I_M(0)=i_2, \\ \frac{dS_L(x)}{dx} = \Lambda_L - \frac{\beta_{ML}S_L(x)I_M(x)}{H_2+I_M(x)} - \gamma_2 S_L(x), & S_L(0)=i_3, \\ \frac{dI_L(x)}{dx} = \frac{\delta\beta_{ML}S_L(x)I_M(x)}{H_2+I_M(x)} - \gamma_3 I_L(x), & I_L(0)=i_4. \end{cases} \tag{1}$$

Where i_1, i_2, i_3 and i_4 are positive initial conditions (ICs), $S_M(x)$ and $I_M(x)$ are the susceptible and infected categories of maize, while $S_L(x)$ and $I_L(x)$ are the susceptible and infected categories of vectors. The parameter Λ_M is the inherent rate of growth based $N(x)$, K is the size of maximum population, β_{LM} is the rate of infection through $I_L(x)$ to $S_M(x)$, H_1 is the half rate of saturation based infected class $S_M(x)$, γ_1 is the rate of death based infected class $I_M(x)$, Λ_L is the recruitment rate based leafhopper, β_{ML} is the rate of infection through sustainable $S_M(x)$ to infected $I_M(x)$, H_2 is the rate of half-saturation from the categories of susceptible $S_L(x)$ to infected $I_M(x)$, γ_2 is the rate of death based $S_L(x)$, δ is the conversion rate of $I_L(x)$, and γ_3 is the death rate of $I_L(x)$. The systematic diagram of the maize streak epidemics with linear control model is shown in Figure 1.

3 Methodology



(a) Design of different layers for the maize streak epidemics with a linear control model



(b) Some result curves for the mathematical model based on the maize streak epidemics with a linear control, design of neural network

Figure 2: The first figure illustrates the layered structure of the model with linear control, while second presents representative solution curves

This section presents the designed stochastic single-layer structure by using $10, 20$, and 40 neurons, while the activation log-sigmoid function is used in the hidden layer as

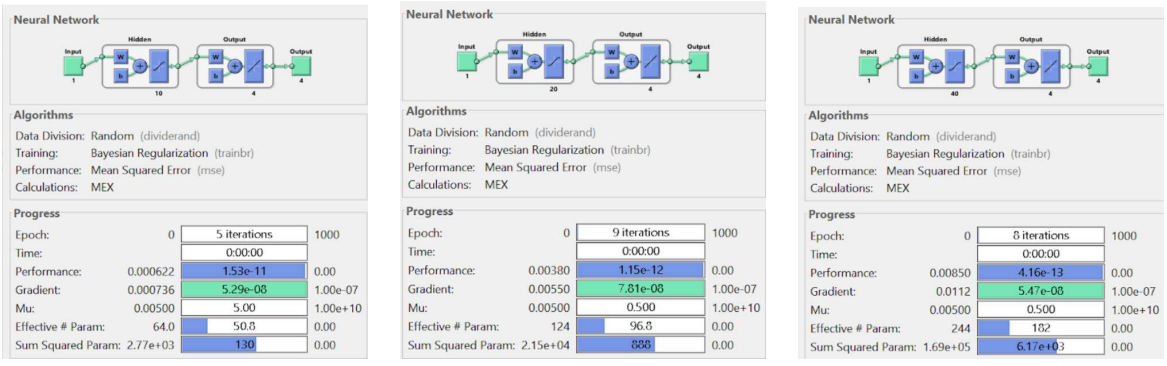
$$\begin{bmatrix} L_1 \\ L_2 \\ L_3 \\ \vdots \\ L_A \end{bmatrix} = T\left(\begin{bmatrix} w_{1,1} \\ w_{1,2} \\ w_{1,3} \\ \vdots \\ w_{1,A} \end{bmatrix}[x] + \begin{bmatrix} b_{1,1} \\ b_{1,2} \\ b_{1,3} \\ \vdots \\ b_{1,A} \end{bmatrix}\right) \tag{2}$$

$$\begin{bmatrix} S_M(x) \\ I_M(x) \\ S_L(x) \\ I_L(x) \end{bmatrix} = \begin{bmatrix} \omega_{1,1} & \omega_{2,1} & \omega_{3,1} & \cdots & \omega_{A,1} \\ \omega_{1,2} & \omega_{2,2} & \omega_{3,2} & \cdots & \omega_{A,2} \\ \omega_{1,3} & \omega_{2,3} & \omega_{3,3} & \cdots & \omega_{A,3} \\ \omega_{1,4} & \omega_{2,4} & \omega_{3,4} & \cdots & \omega_{A,4} \end{bmatrix} \begin{bmatrix} L_1 \\ L_2 \\ L_3 \\ \vdots \\ L_A \end{bmatrix} + \begin{bmatrix} B_{2,1} \\ B_{2,2} \\ B_{2,3} \\ B_{2,4} \end{bmatrix}. \tag{3}$$

Where A shows the numbers of neurons, which are taken as 10, 20 and 40, the outputs are $S_M(x), I_M(x), S_L(x)$ and $I_L(x)$, the weights are w and ω, the biases are b and B present, whereas T is an activation log-sigmoid function, which is taken in 0 and 1. This activation function has S-shaped curve, which shows the nonlinear association of inputs and outputs, shown as:

$$\Delta = (1 + e^{-x})^{-1} \tag{4}$$

This design methodology enables the distribution of performance through system parameters, effectively distributing the computational load of the neural network. It facilitates the exploration of Bayesian probabilistic frameworks for practical knowledge acquisition. Common choices for the distribution models include Gaussian and scale mixture distributions, which incorporate regularization mechanisms to control the network's complexity. Figure 2a illustrates the neural outcome and design of the maize streak epidemics model with a linear control approach. The BRNN stochastic scheme is implemented to generate numerical results for the maize streak epidemics using the 'nftool' command in MATLAB, with optimization carried out in the same software. The model settings include 1000 epochs, a tolerance of 10^{-8}, cross-validation through n-folding, a step size of 0.01, and varying neuron counts of $10, 20$, and 40. The activation function used is a log-sigmoid function, and the Bayesian Regularization (BR) scheme is applied. The maize streak epidemics model with linear control plays a crucial role in managing and predicting the spread of the disease. The BRNN-based approach facilitates understanding of the design and provides insights into disease incidence statistics, thereby improving the efficiency of control actions. This approach, considering uncertainties, can enhance the accuracy and robustness of the system. The linear control model optimizes BRNN predictions to enhance disease management strategies, including identifying optimal intervention points, executing targeted control actions to mitigate the impact of maize streak epidemics on crop yields, and allocating resources effectively. In recent years, BR-based approaches have been applied in various fields, including quantitative susceptibility map reconstruction using MR phase data [22], analysis of explosion risks in fixed offshore platforms [23], animal breeding [24], and sensorless measurement of pump operational states [25].



(a) Diagram for 10 neurons (b) Diagram for 20 neurons (c) Diagram for 40 neurons

Figure 3: Neural network diagrams for 10, 20, and 40 neurons

The design of input, hidden, and output layers is presented in Figure 3 based on 10, 20 and 40 numbers of neurons for solving the maize streak epidemics model with a linear control.

4 Results and discussion

This section presents the numerical performance of the maize streak epidemic model incorporating a linear control approach. The parameter values used are derived from the literature [17], which are fixed in all three cases and presented in Table 1. The differences between the three cases are the initial value conditions given in Table 2.

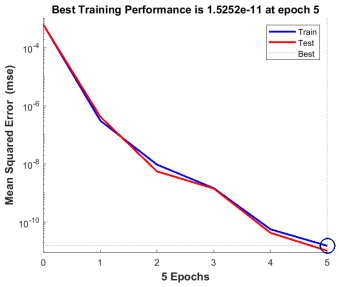
Table 1: Parameter values used for System (1)

Λ_M	K	β_{LM}	H_1	γ_1	Λ_L	β_{ML}	H_2	γ_2	δ	γ_3
0.0005	10000	0.45	0.4	0.008	0.02	0.04	0.6	0.0303	0.45	0.0303

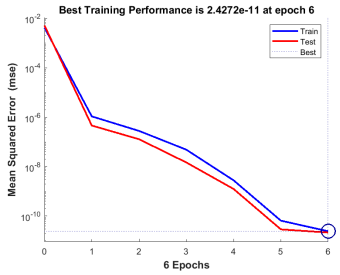
Table 2: Initial conditions for different cases of System (1)

Case	$S_M(0)$	$I_M(0)$	$S_L(0)$	$I_L(0)$
1	0.1	0.2	0.3	0.4
2	0.2	0.3	0.4	0.5
3	0.3	0.4	0.5	0.6

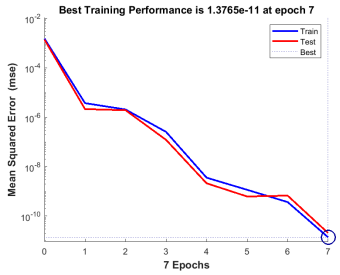
4.1 Discussion of the results



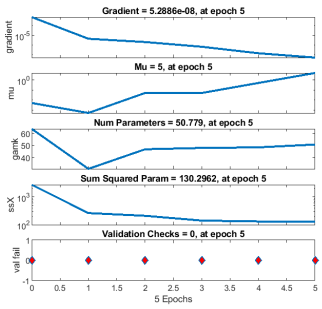
(a) BTF for Case 1



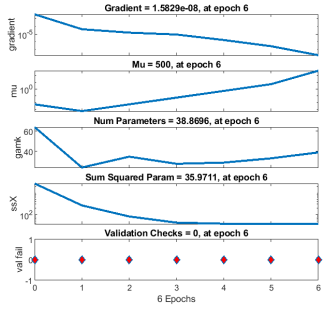
(b) BTF for Case 2



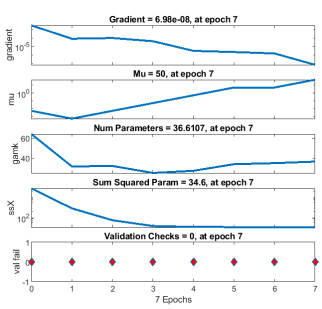
(c) BTF for Case 3



(d) TS for Case 1



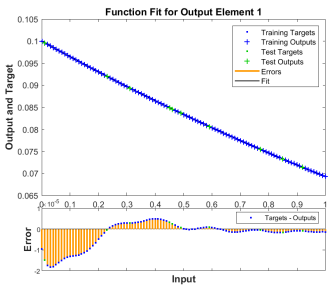
(e) TS for Case 2



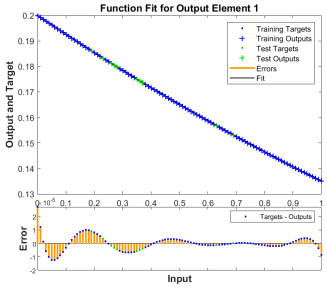
(f) TS for Case 3

Figure 4: BTF and TS values for Case 1 to 3 of maize streak epidemics with linear control using 10 neurons

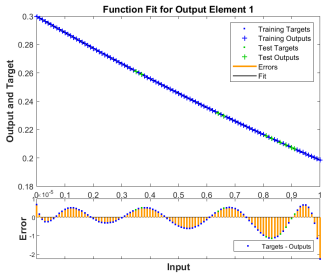
The numerical performance of the maize streak epidemics model with linear control, using the BRNN structure, is presented in Figures 4-18. Figures 4-8 display the results with 10 neurons, Figures 9-13 show the outcomes with 20 neurons, and Figures 14-18 illustrate the results with 40 neurons, all for Cases 1–3. The best training fitness (BTF) performances for 10, 20, and 40 neurons, as



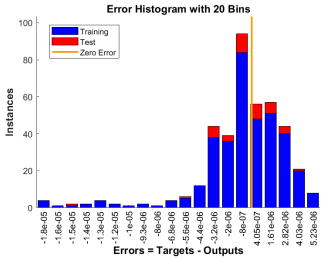
(a) FFOE for Case 1



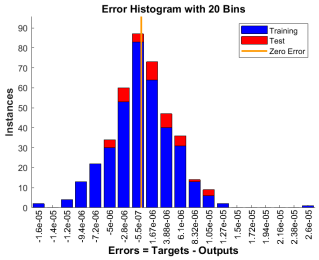
(b) FFOE for Case 2



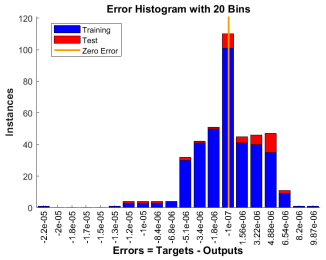
(c) FFOE for Case 3



(d) Err. Hist for Case 1



(e) Err. Hist for Case 2



(f) Err. Hist for Case 3

Figure 5: FFOE and Err. Hist for respective cases of maize streak epidemics with linear control using 10 neurons

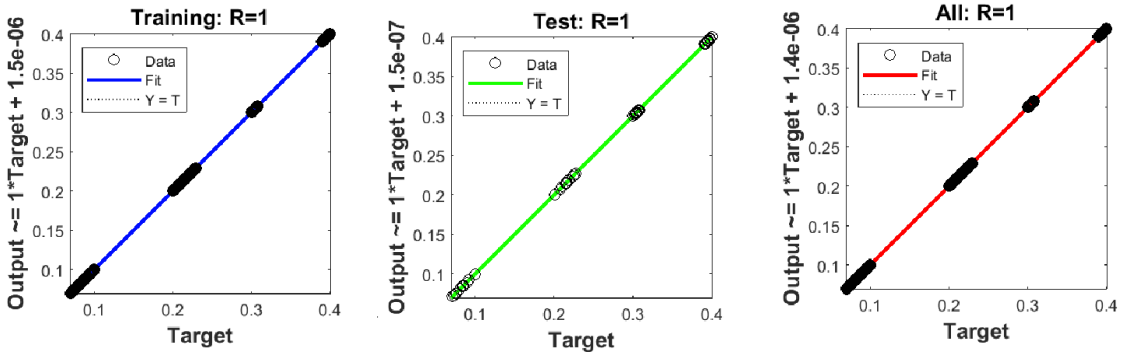


Figure 6: Reg. performances for Case 1 of maize streak epidemics with linear control using 10 neurons

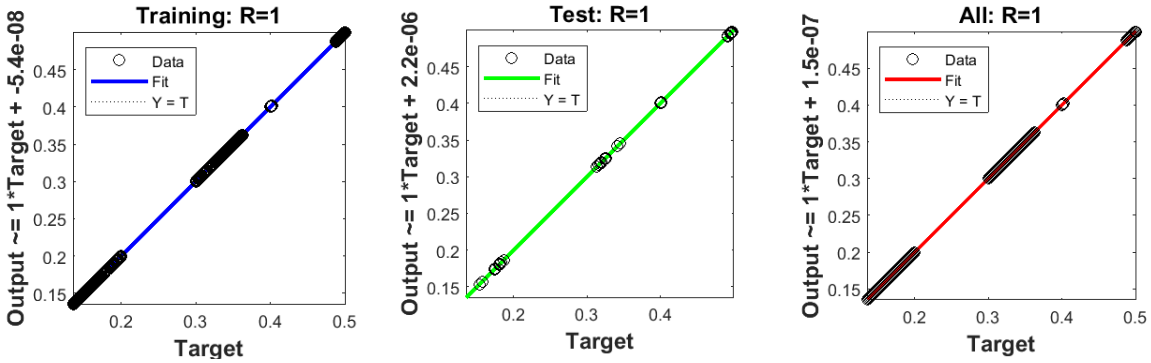


Figure 7: Reg. performances for Case 2 of maize streak epidemics with linear control using 10 neurons

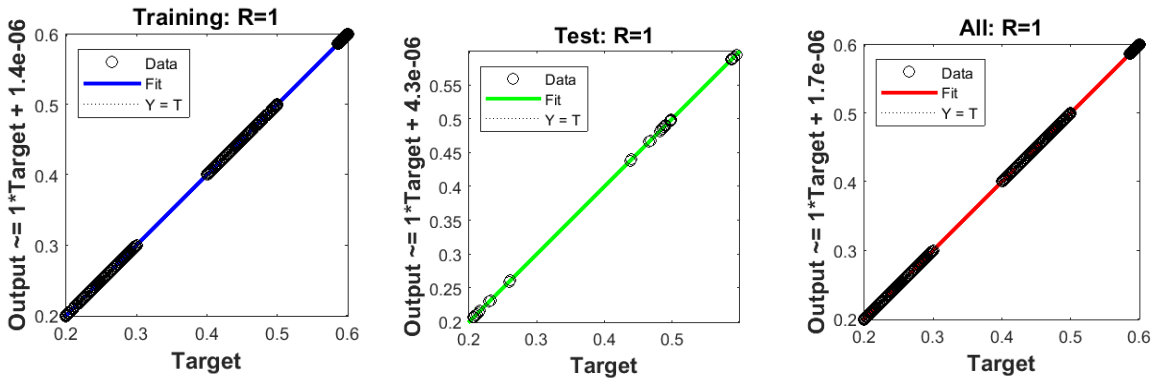
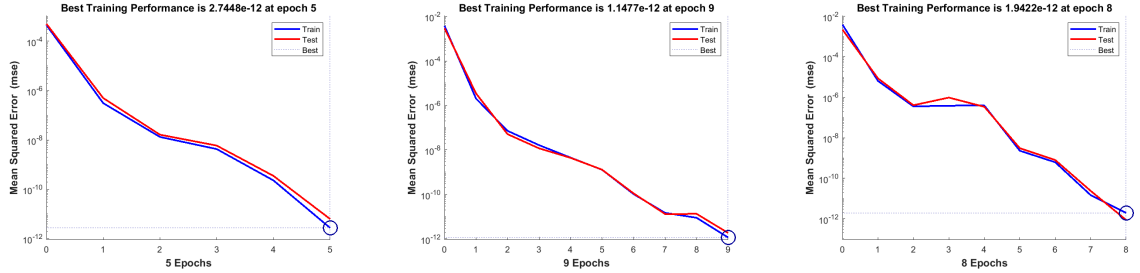
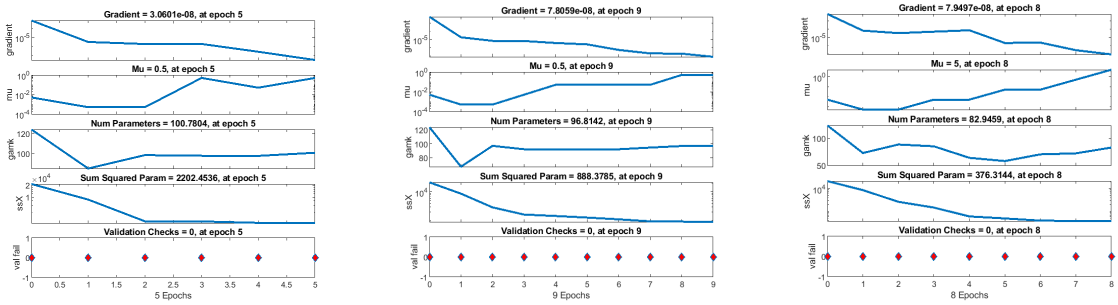


Figure 8: Reg. performances for Case 3 of maize streak epidemics with linear control using 10 neurons

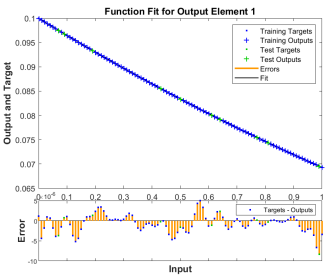


(a) BTF for Case 1 (b) BTF for Case 2 (c) BTF for Case 3

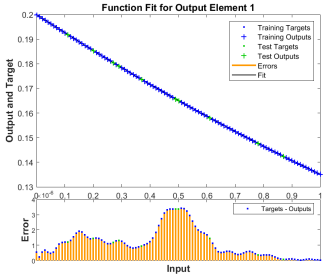


(d) TS for Case 1 (e) TS for Case 2 (f) TS for Case 3

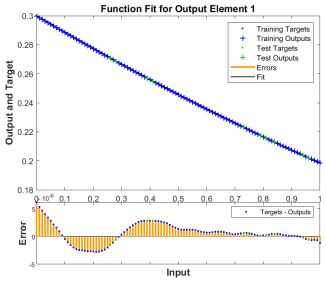
Figure 9: BTF and TS values for Case 1 to 3 of maize streak epidemics with linear control using 20 neurons



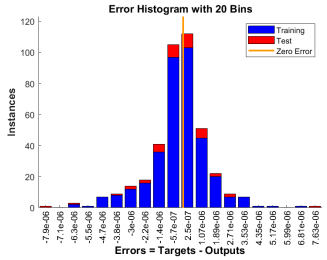
(a) FFOE for Case 1



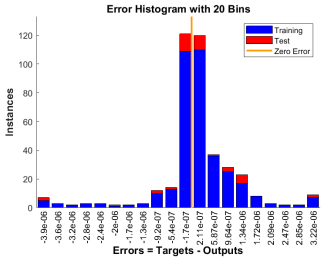
(b) FFOE for Case 2



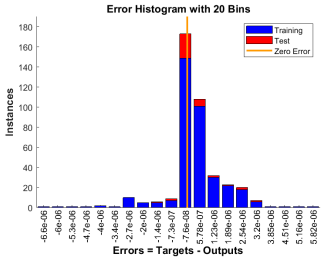
(c) FFOE for Case 3



(d) Err. Hist for Case 1



(e) Err. Hist for Case 2



(f) Err. Hist for Case 3

Figure 10: FFOE and Err. Hist for respective cases of maize streak epidemics with linear control using 20 neurons

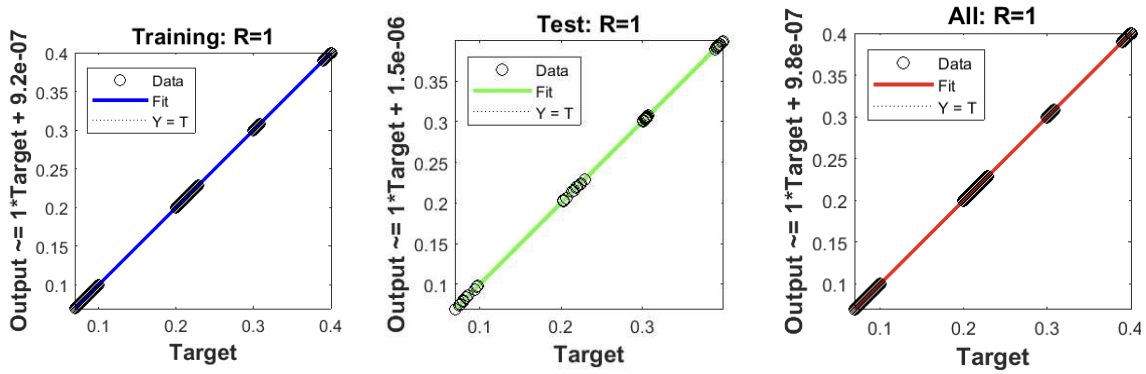


Figure 11: Reg. performances for Case 1 of maize streak epidemics with linear control using 20 neurons

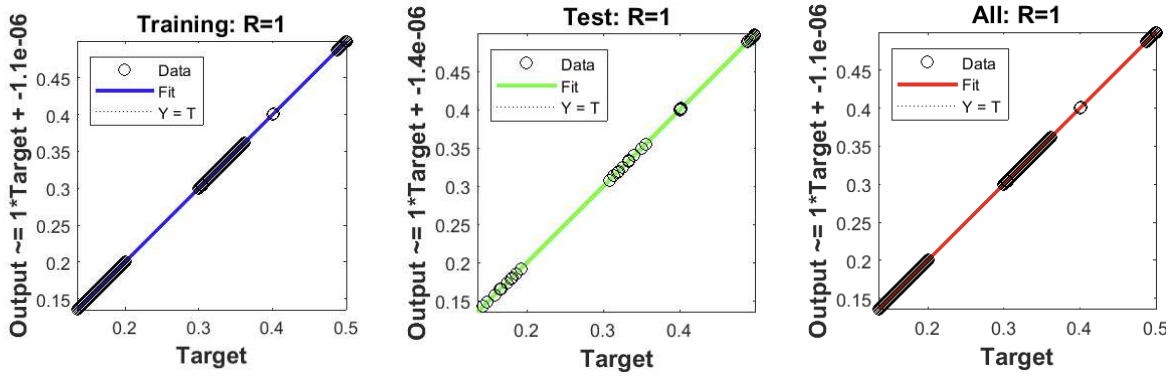


Figure 12: Reg. performances for Case 2 of maize streak epidemics with linear control using 20 neurons

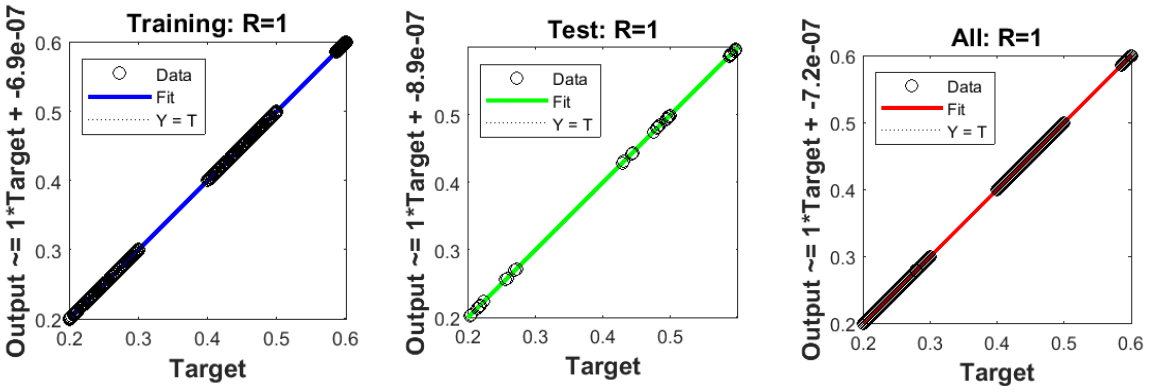
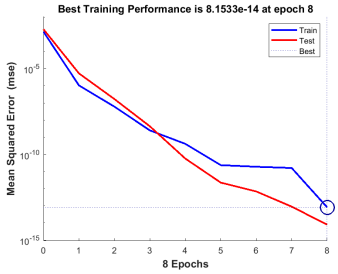
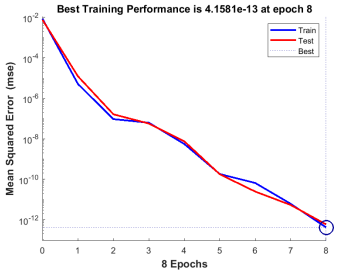


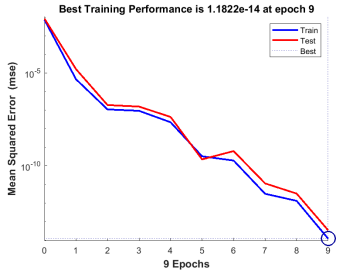
Figure 13: Reg. performances for Case 3 of maize streak epidemics with linear control using 20 neurons



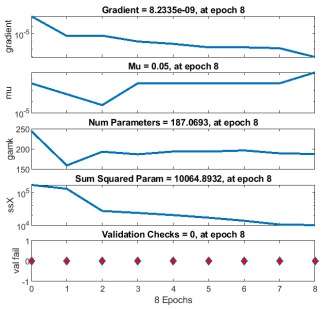
(a) BTF for Case 1



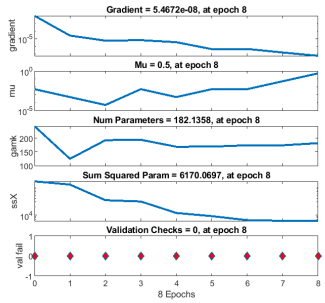
(b) BTF for Case 2



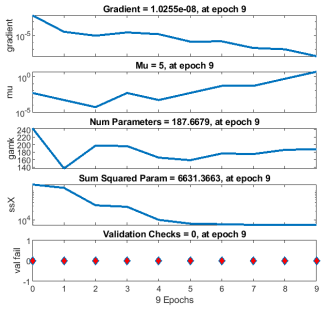
(c) BTF for Case 3



(d) TS for Case 1

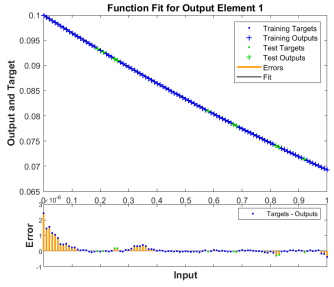


(e) TS for Case 2

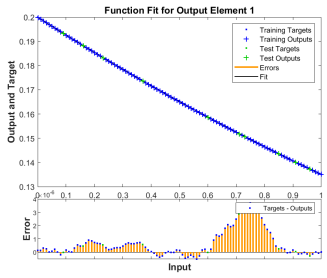


(f) TS for Case 3

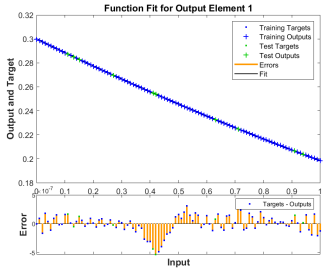
Figure 14: BTF and TS values for case 1 to 3 of maize streak epidemics with linear control using 40 neurons



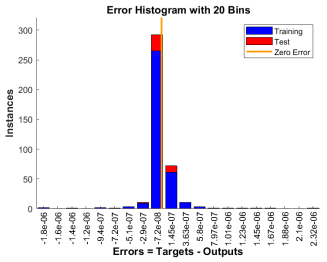
(a) FFOE for Case 1



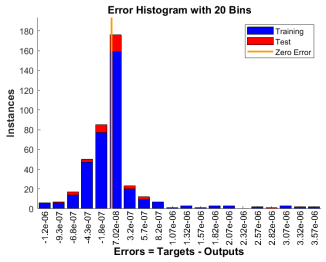
(b) FFOE for Case 2



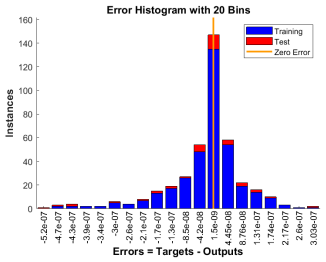
(c) FFOE for Case 3



(d) Err. Hist for Case 1



(e) Err. Hist for Case 2



(f) Err. Hist for Case 3

Figure 15: FFOE and Err. Hist for respective cases of maize streak epidemics with linear control using 40 neurons

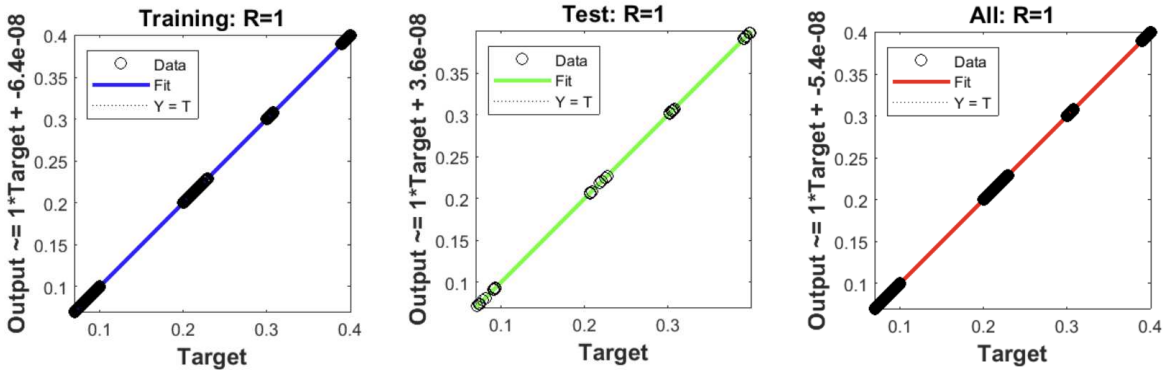


Figure 16: Reg. performances for Case 1 of maize streak epidemics with linear control using 40 neurons

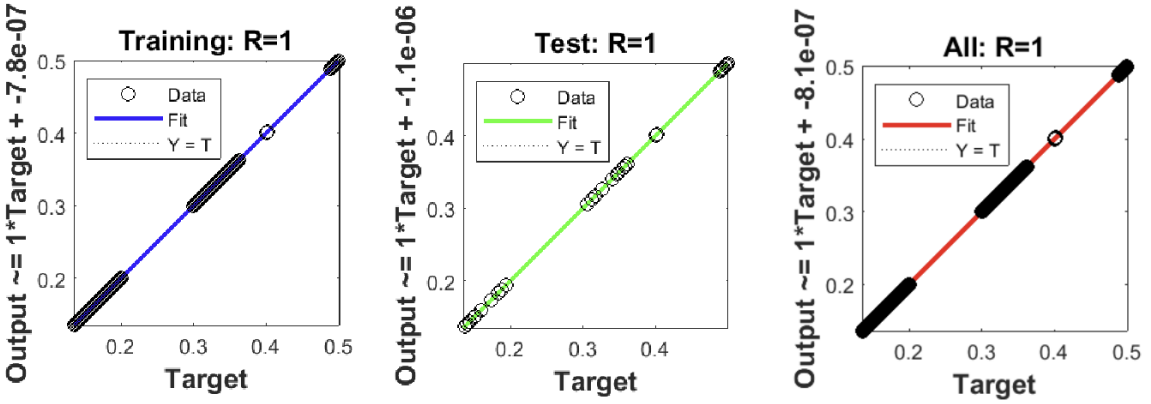


Figure 17: Reg. performances for Case 2 of maize streak epidemics with linear control using 40 neurons

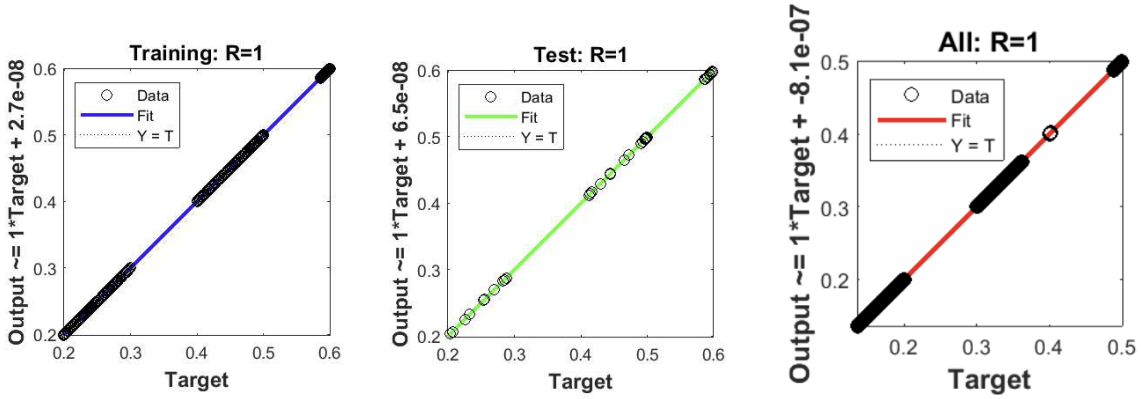


Figure 18: Reg. performances for Case 3 of maize streak epidemics with linear control using 40 neurons

well as the transition state (TS) values, are shown in Figures 4, 9 and 14 (a to c) and Figures 4, 9 and 14 (d to f), respectively. The BTF values for Cases 1 to 3 with 10 neurons are approximately $1.525211 \times 10^{-11}, 2.4272 \times 10^{-11}$, and 1.3765×10^{-11} at iterations 5, 6, and 7, respectively. For Cases 1 to 3 with 20 neurons, the BTF values are $2.7448 \times 10^{-12}, 1.1477 \times 10^{-12}$, and 1.9422×10^{-12} at iterations 5, 9, and 8. Similarly, the BTF performances for 40 neurons are $8.1533 \times 10^{-14}, 4.1581 \times 10^{-13}$, and 1.1822×10^{-14} at iterations 8, 8, and 9. The BTF values in the neural network process for solving the maize streak epidemics with a linear control model depend on several factors, including data quantity and quality, model structure, and hyperparameters. To determine the optimal training values, it is essential to experiment with different combinations of learning rates, epochs, and batch sizes. Regularization techniques, such as L1/L2 regularization and dropout, are used to prevent overfitting. Additionally, selecting the right optimization algorithm and activation function—such as the sigmoid function—can significantly impact the system's performance. To fine tune these values and evaluate the model effectively, researchers can measure the BTF values based on relevant metrics to address the specific problem. The TS performances are reported in terms of gradient values, as illustrated in the earlier figures. For Cases 1 to 3 using 10 neurons, the gradients are 5.2886×10^{-8}, 1.5829×10^{-8}, and 6.980×10^{-8} at iterations 5, 6, and 7, respectively. For Cases 1 to 3 with 20 neurons, the gradient values are measured as 3.0601×10^{-8}, 7.8059×10^{-8}, and 7.9497×10^{-8} at iterations 5, 9, and 8, respectively. Similarly, for 40 neurons, the gradients are reported as 8.2335×10^{-9}, 5.4672×10^{-8}, and 1.0255×10^{-8} at iterations 8, 8, and 9, respectively. In the neural network process for solving the model, the gradient performances are primarily calculated through backpropagation. The gradients represent the rate of change in the cost function with respect to the model's parameters. To compute these gradient values, the system first calculates the error between the actual and predicted outcomes, then propagates this error backward through the network to adjust the weights and biases. The gradient values are used to adjust the system's parameters, enabling it to improve and refine its predictions. The direction and magnitude of these gradients provide valuable information for optimizing the model's performance. The Fitness Function of Output Element (FFOE) for 10, 20, and 40 neurons is presented in Figures 5, 10, and 15 (a to c), while the Error Histogram (Err. Hist) is displayed in the corresponding subfigures (d to f). The FFOE values in the neural network process for solving the maize streak epidemics with a linear control model represent the outputs of the model. These values compare the predicted results with the actual outcomes, typically using a cost function such as cross-entropy or Mean Square Error (MSE). The FFOE reflects the accuracy of the system's predictions, providing a quantitative measure of its ability to capture underlying patterns and relationships in the data. By minimizing the cost function, the system adjusts its parameters to improve the performance of the model in simulating maize streak dynamics. In Subfigures 5, 10 and 15 (d to f), the Error Histogram (Err. Hist) values for Cases 1 to 3 are reported as 4.05×10^{-7}, -5.50×10^{-7}, and -1×10^{-7} for 10 neurons; 2.50×10^{-7}, 2.11×10^{-7}, and -7.60×10^{-8} for 20 neurons; and -7.2×10^{-8}, 7.02×10^{-8}, and 1.50×10^{-9} for 40 neurons, illustrating the distribution of prediction errors across the different network configurations. As discussed previously, these values represent the frequency of errors obtained by comparing actual and predicted outcomes, providing insights into the model's performance. By analyzing the shape of the Err. Hist, researchers can identify patterns such as outliers

or biases and assess the accuracy of the system. A histogram with values close to zero indicates good predictive performance, whereas a skewed or wider histogram may suggest that the model requires improvement. The Regression (Reg) performances are shown in Figures 6–8, 11–13, and 16–18 for 10, 20, and 40 neurons, respectively. In the neural network process, regression analysis is used to evaluate the relationship between actual and predicted outcomes. A regression plot illustrates this relationship, indicating how well the predictions align with the real data. By examining these plots, researchers can assess the accuracy of the model and identify any deviations or patterns. Strong correlation between actual and predicted values indicates better model performance, whereas outliers or deviations highlight areas that may require improvement. These analyses support the improvement of the system to achieve more accurate predictions of maize streak epidemics, as well as provide information on effective control strategies. The performance results for the maize streak epidemics model with linear control using 10, 20, and 40 neurons are summarized in Tables 3, 4, and 5, respectively.

Table 3: Different data performances for the maize streak epidemics with linear control model using 10 neurons

Case	MSE (Testing)	MSE (Training)	Gradient	Performance	Epoch	Time
1	1.02565×10^{-11}	1.52520×10^{-11}	5.29×10^{-8}	1.53×10^{-8}	5	01 Sec
2	2.14579×10^{-11}	2.42722×10^{-11}	1.58×10^{-8}	2.43×10^{-8}	6	01 Sec
3	2.05134×10^{-11}	1.37648×10^{-11}	6.98×10^{-8}	1.38×10^{-8}	7	01 Sec

Table 4: Different data performances for the maize streak epidemics with linear control model using 20 neurons

Case	MSE (Testing)	MSE (Training)	Gradient	Performance	Epoch	Time
1	6.29449×10^{-12}	2.74477×10^{-12}	3.06×10^{-8}	2.74×10^{-12}	5	01 Sec
2	1.84293×10^{-12}	1.14769×10^{-12}	7.81×10^{-8}	1.15×10^{-12}	9	01 Sec
3	8.63302×10^{-13}	1.94221×10^{-13}	7.95×10^{-8}	1.94×10^{-12}	8	01 Sec

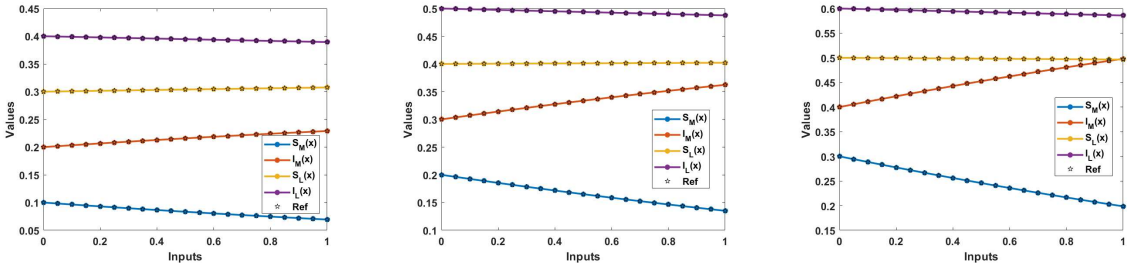
Table 5: Different data performances for the maize streak epidemics with linear control model using 40 neurons

Case	MSE (Testing)	MSE (Training)	Gradient	Performance	Epoch	Time
1	7.90538×10^{-15}	8.15331×10^{-14}	8.23×10^{-9}	8.15×10^{-14}	8	01 Sec
2	5.83682×10^{-13}	4.15806×10^{-13}	5.47×10^{-8}	4.16×10^{-13}	8	01 Sec
3	3.35247×10^{-14}	1.18218×10^{-14}	1.03×10^{-8}	1.18×10^{-14}	9	01 Sec

The comparison of the results for each case of the model using 10, 20, and 40 neurons is presented in Figures 19 and 20. It is evident that the results overlap for each case and category of the model with linear control, which demonstrates the accuracy of the BRNN scheme. Figure 20 presents the AE values for each case of the model corresponding to all neuron configurations. The AE provides a quantitative measure of the performance difference between the reference and proposed approaches. It offers a straightforward indication of the magnitude of the error, enabling easy comparison across different systems, algorithms, and prediction techniques.

4.2 Analysis of the neurons

In this section, a neuron-based analysis is presented using 10, 20, and 40 neurons to solve the linear control model. For the 10-neuron configuration, the MSE-based Case 1 training performance reaches 10^{-8} after two iterations, while the best training fitness (BTF) converges to 10^{-11} after five iterations. In Case 2, the MSE decreases to 10^{-6} within one iteration, and the BTF attains 10^{-11} after six iterations. Similarly, in Case 3, the MSE values are observed to be 10^{-6} after one iteration, 10^{-5} after two iterations, and 10^{-9} after four iterations, with the BTF reaching 10^{-11} after seven iterations.

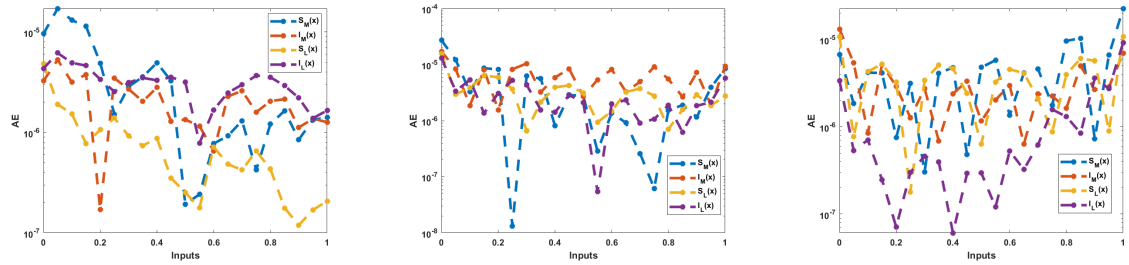


(a) Outcomes for Case 1 based 10, 20 and 40

(b) Outcomes for Case 2 based 10, 20 and 40

(c) Outcomes for Case 3 based 10, 20 and 40

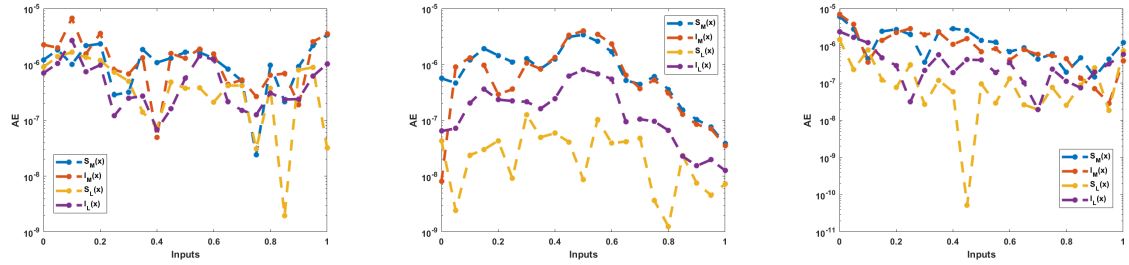
Figure 19: Matching of the results for 10, 20 and 40 numbers of neurons based on the maize streak epidemics with linear control model



(a) AE for 10 neurons: Case 1

(b) AE for 10 neurons: Case 2

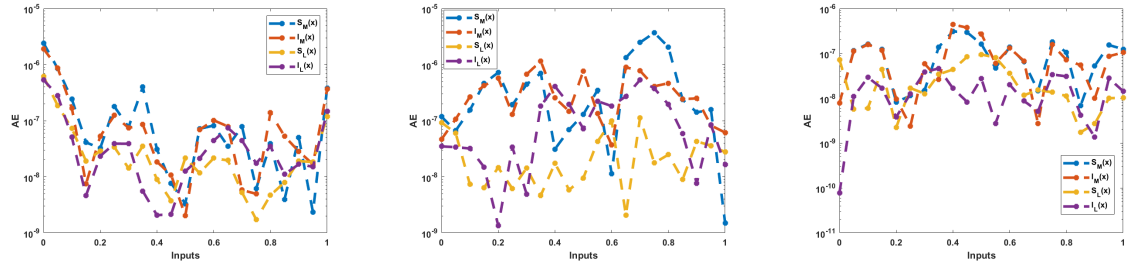
(c) AE for 10 neurons: Case 3



(d) AE for 20 neurons: Case 1

(e) AE for 20 neurons: Case 2

(f) AE for 20 neurons: Case 3



(g) AE for 40 neurons: Case 1

(h) AE for 40 neurons: Case 2

(i) AE for 40 neurons: Case 3

Figure 20: AE performances for 10, 20 and 40 numbers of neurons based on the maize streak epidemics with linear control model

For 20 neurons, the training results show improved convergence. In Case 1, the MSE decreases to 10^{-8} after two iterations and further to 10^{-11} after four iterations, while the BTF reaches 10^{-12} after five iterations. For Case 2, the MSE values are 10^{-7} after two iterations and 10^{-11} after seven iterations, with the BTF obtained as 10^{-12} after nine iterations. Similarly, in Case 3, the MSE reaches 10^{-6} between two and four iterations and further decreases to 10^{-11} after seven iterations, while the BTF reaches 10^{-12} after eight iterations.

Finally, for 40 neurons, the training performance further improves. In Case 1, the MSE reaches 10^{-10} after five iterations, and the BTF achieves 10^{-14} after eight iterations. For Case 2, the MSE decreases to 10^{-7} after two iterations and 10^{-10} after five iterations, with the BTF reaching 10^{-13} after eight iterations. Similarly, for Case 3, the MSE attains 10^{-7} between two and four iterations and 10^{-10} after five iterations, while the BTF reaches 10^{-14} after nine iterations.

Based on this analysis, it is evident that increasing the number of neurons leads to a significant reduction in MSE values. The performance obtained with 40 neurons is superior to that of 20 neurons, while the 20 neuron configuration outperforms the 10-neuron case. Similar performance trends are observed for the gradient and error history metrics, where lower values are consistently achieved with higher neuron counts. This behavior is further confirmed by the AE analysis, which shows that most AE values for 10 neurons are in the range of 10^{-5} to 10^{-6} for all cases, while for 20 neurons they fall between 10^{-6} and 10^{-8}. In contrast, the AE values for 40 neurons are reduced to approximately 10^{-7} to 10^{-9} in all cases.

Overall, the results demonstrate that higher neuron configurations yield improved accuracy; however, this improvement is accompanied by a slight increase in the number of training iterations and computational complexity.

5 Conclusion

In this study, a comprehensive numerical investigation was carried out to analyze the performance of various neuron configurations to solve the model of maize streak epidemics with linear control. The mathematical model categorizes the maize population into two groups, susceptible and infected, and the vector population into susceptible and infected compartments. The key findings and conclusions from this work are summarized as follows:

1. A supervised intelligent neural network framework was developed specifically for the maize streak epidemics model with linear control.

2. Numerical solutions were obtained using the Bayesian Regularization Neural Network, a well-regarded method for handling nonlinear problems effectively.

3. The dataset was generated using the Adam optimization algorithm over the interval [0, 1] with a step size of 0.01, and the log-sigmoid function was employed as the activation function.

4. Data splitting was implemented into training, validation, and testing subsets with appropriate ratios to minimize the mean squared error.

5. The accuracy of the proposed stochastic technique was validated through overlapping results and by evaluating the Best Training Function Output Error.

6. Additional validation metrics—including regression plots, gradient convergence, error histograms, and first-order optimality error were utilized to confirm the solver's reliability.

7. A comparative analysis using 10, 20, and 40 neurons demonstrated that higher neuron counts yielded improved accuracy; however, this led to higher computational complexity.

Future work may explore the application of other neural training algorithms, such as Bayesian Regularization, Scaled Conjugate Gradient, and similar methods, to address nonlinear mathematical models more effectively.

Author Contributions:

Methodology, L.A. and Z.S.; Software, L.A.; Validation, Z.S.; Formal analysis, L.A. and Z.S.; Investigation, L.A. and Z.S.; Resources, L.A.; Writing—original draft, L.A.; Writing—review and editing, Z.S.; Supervision, L.A. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement:

The data can be provided by the authors on reasonable request.

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Conflicts of Interest:

The authors declare that they have no conflicts of interest.

References

[1] Dolores R Piperno and Kent V Flannery. The earliest archaeological maize (zea mays l.) from highland mexico: new accelerator mass spectrometry dates and their implications. *Proceedings of the National Academy of Sciences*, 98(4):2101–2103, 2001.

[2] Olaf Erenstein, Moti Jaleta, Kai Sonder, Khondoker Mottaleb, and Boddupalli M Prasanna. Global maize production, consumption and trade: trends and r&d implications. *Food security*, 14(5):1295–1319, 2022.

[3] FAO Joint. *Caramel Colours*, volume 11. Food and Agriculture Organization of the United Nations, 2011. Monograph 11.

[4] Peter Ranum, Juan Pablo Peña-Rosas, and Maria Nieves Garcia-Casal. Global maize production, utilization, and consumption. *Annals of the New York Academy of Sciences*, 1312(1):105–112, 2014.

[5] Sherry A. Tanumihardjo, Lindsey McCulley, Rena Roh, Santiago Lopez-Ridaura, Natalia Palacios-Rojas, and Nalika S. Gunaratna. Maize agro-food systems to ensure food and nutrition security in reference to the sustainable development goals. *Global Food Security*, 25:100327, 2020.

[6] F. Gong, L. Yang, F. Tai, X. Hu, and W. Wang. "omics" of maize stress response for sustainable food production: opportunities and challenges. *Omics: A Journal of Integrative Biology*, 18(12):714–732, 2014.

[7] S. Macfadyen, C. Paull, L.M. Boykin, P. De Barro, M.N. Maruthi, M. Otim, A. Kalyebi, D.G. Vassão, P. Sseruwagi, W.T. Tay, and H. Delatte. Cassava whitefly, bemisia tabaci (gennadius)(hemiptera: Aleyrodidae) in east african farming landscapes: a review of the factors determining abundance. *Bulletin of Entomological Research*, 108(5):565–582, 2018.

[8] A.K. Biswal, A.E. Alakonya, K.A. Mottaleb, S.J. Hearne, K. Sonder, T.L. Molnar, A.M. Jones, K.V. Pixley, and B.M. Prasanna. Maize lethal necrosis disease: review of molecular and genetic resistance mechanisms, socio-economic impacts, and mitigation strategies in sub-saharan africa. *BMC Plant Biology*, 22(1):542, 2022.

[9] F. Njeru, A. Wambua, E. Muge, G. Haesaert, J. Gettemans, and G. Misinzo. Major biotic stresses affecting maize production in kenya and their implications for food security. *PeerJ*, 11:e15685, 2023.

[10] S. Anami, M. De Block, J. Machuka, and M. Van Lijsebettens. Molecular improvement of tropical maize for drought stress tolerance in sub-saharan africa. *Critical Reviews in Plant Sciences*, 28(1-2):16–35, 2009.

[11] O.X. Dong and P.C. Ronald. Genetic engineering for disease resistance in plants: recent progress and future perspectives. *Plant Physiology*, 180(1):26–38, 2019.

[12] A.A. Elsadany, Y. Sabbar, W. Adel, and A. El-Mesady. Dynamics of a novel discrete fractional model for maize streak epidemics with linear control. *International Journal of Dynamics and Control*, 13(1):1–25, 2025.

[13] M. Emeraghi, E. G. Achigan-Dako, C. N. Nwaoguala, and H. Oselebe. Maize streak virus research in africa: an end or a crossroad. *Theoretical and Applied Genetics*, 134(12):3785–3803, 2021.

[14] H.T. Alemneh, A.S. Kassa, and A.A. Godana. An optimal control model with cost effectiveness analysis of maize streak virus disease in maize plant. *Infectious Disease Modelling*, 6:169–182, 2021.

[15] H.T. Alemneh, O.D. Makinde, and D.M. Theuri. Mathematical modelling of msv pathogen interaction with pest invasion on maize plant. *Global Journal of Pure and Applied Mathematics*, 15(1):55–79, 2019.

[16] H.T. Alemneh, O.D. Makinde, and D. Mwangi Theuri. Ecoepidemiological model and analysis of msv disease transmission dynamics in maize plant. *International Journal of Mathematics and Mathematical Sciences*, 2019(1):7965232, 2019.

[17] A. A. Elsadany, Y. Sabbar, W. Adel, and A. El-Mesady. Dynamics of a novel discrete fractional model for maize streak epidemics with linear control. *International Journal of Dynamics and Control*, 13(1):1–25, 2025.

[18] Z. Sabir, T. Ismail, H. Sleem, M. Umar, and S. Salahshour. A radial basis bayesian regularization neural network process for the malaria disease model. *Knowledge-Based Systems*, page 113722, 2025.

[19] Z. Sabir, M. A. Abdelkawy, M. A. Z. Raja, and M. R. Ali. Numerical treatment of fractional order buruli ulcer and cholera model by using neural network approach. *Knowledge-Based Systems*, page 113713, 2025.

[20] Z. Sabir, B. Souayeh, Z. Zaiour, A. Nazal, M. W. Alam, and H. Alfannakh. A machine learning neural network architecture for the accelerating universe based modified gravity. *Egyptian Informatics Journal*, 29:100635, 2025.

[21] Z. Sabir, M. A. Mehmood, M. Umar, S. Salahshour, Y. Altun, A. Arbi, and M. R. Ali. A numerical treatment through bayesian regularization neural network for the chickenpox disease model. *Computers in Biology and Medicine*, 187:109807, 2025.

[22] Ludovic De Rochefort, Tian Liu, Bryan Kressler, Jing Liu, Pascal Spincemaille, Vincent Lebon, Jianlin Wu, and Yi Wang. Quantitative susceptibility map reconstruction from mr phase data using bayesian regularization: validation and application to brain imaging. *Magnetic Resonance in Medicine*, 63(1):194–206, 2010.

[23] J. Shi, Y. Zhu, F. Khan, and G. Chen. Application of bayesian regularization artificial neural network in explosion risk analysis of fixed offshore platform. *Journal of Loss Prevention in the Process Industries*, 57:131–141, 2019.

[24] P. Pérez-Rodríguez, D. Gianola, K. A. Weigel, G. J. M. Rosa, and J. Crossa. An r package for fitting bayesian regularized neural networks with applications in animal breeding. *Journal of Animal Science*, 91(8):3522–3531, 2013.

[25] D. Wu, H. Huang, S. Qiu, Y. Liu, Y. Wu, Y. Ren, and J. Mou. Application of bayesian regularization back propagation neural network in sensorless measurement of pump operational state. *Energy Reports*, 8:3041–3050, 2022.