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Research article

Intelligent computing knacks for infected media and time delay impacts on dynamical behaviors and control measures of rumor-spreading model

Muhammad Asif Zahoor Raja[1], Adeeba Haider[2], Kottakkaran Sooppy Nisar[3,4,]* and Muhammad Shoaib[5]

[1] Future Technology Research Center, National Yunlin University of Science and Technology, 123 University Road, Section .3, Douliou, Yunlin 64002, Taiwan, R.O.C
[2] Department of Mathematics, COMSATS University Islamabad, Attock Campus, Pakistan
[3] Department of Mathematics, College of Science and Humanities in Alkharj, Prince Sattam bin Abdulaziz University, Al Kharj, Saudi Arabia
[4] Saveetha School of Engineering, SIMATS, Chennai, India
[5] Yuan Ze University, AI Centre, Taoyuan 320, Taiwan

* **Correspondence:** Email: n.sooppy@psau.edu.sa.

Abstract: Artificial neural networks (ANNs) have transformed machine learning and computational intelligence by providing unprecedented powers in modeling complicated data and addressing a wide range of challenges. In the field of ANNs, back propagation is a key approach for training neural networks. However, obtaining optimum network efficiency while tackling over fitting and controlling uncertainty is a difficult task. The present study employs the Bayesian Regularization Method with Neural Network Backpropagation (BRM-NNB) technique to investigate the rumors spreading delay model. With their rapid spread, rumors have the potential to cause fear and even financial loss. Thus, we must take decisive actions to stop the rumor from spreading. Nowadays, rumors can spread through instant messaging, emails, or publishing, thanks to the development of the internet. In this research, an XY-SIR rumors spreading delay model (XY-SIR-RS-DM) is investigated in relation to the novel spreading pattern. Media networks can be categorized into susceptible and infected media, while friendship networks can be categorized into three groups: spreaders (S, I, and R), who actively disseminate rumors, those who are ignorant and those who have no desire to do so. To estimate the solution of the suggested model, the Bayesian regularization method with neural network back propagation (BRM-NNB) is used. The data set is generated by applying the explicit Runge-Kutta method. The computing BRM-NNB strategy is implemented for three different performances, where the training, testing, and verification data are reported as 80%, 15%, and 5%, respectively, with 10 hidden neurons. To verify the validity of the developed artificial intelligence (AI) approach represented by the BRM-NNB, outcome comparisons are presented. The result is compatible with obtaining a minimal absolute error that is nearly equal to zero, thereby proving the efficacy of the proposed method.

Keywords: Bayesian regularization method; regression; neural networks backpropagation; rumors spread model

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Nomenclature: BRM-NNB: Bayesian Regularization Method with Neural Networks Backpropagation; MSE: Mean Square Error; X(t): susceptible media that isn't rumor-infected; Y(t): infected media that is rumor-infected; S(t): spreaders; who know and actively disseminate rumors; I(t): those who are ignorant and have never heard of rumors; R(t): those who know but have no desire in spreading rumors; τ_i: time delays; A_1: susceptible media's probability; ω: infected media's specific probability; ε_1: probability of leaving system by individuals; δ: the media action rate; A_2: friendship network layer's probability; υ: probability of changing the ignorant person to spreader; ε_2: the migration rate; γ: Probability of changing the spreader into the stifler; EHs: Error Histograms; AI: Artificial Intelligence

1. Introduction

Artificial neural networks (ANNs) have emerged as a critical tool in the fields of data mining, modeling, and predicting. They have become critical components of current technology and the problem-solving abilities of adaptable computer models, which are based on the architecture and operations of the human brain and have spread across a wide range of disciplines and applications. In this study, we explore how artificial intelligence (AI) plays a critical role in addressing complicated challenges and enhancing knowledge in today's fast changing world. Their ability to replicate and analyze complicated trends in data makes them highly useful to a wide range of fields, including epidemiology and the study of data dispersion. In this work, we explore the application of AI to the interesting topic of rumor-spreading dynamics, with a particular focus on the influence of infected media and time delays. Ongoing pushing factors in the ever-advancing science of AI include achieving goals of greater efficiency, increasing generalization, & an improved model resilience. The back propagation technique, which is a key component of neural network training, is at the center of this search. Recognizing the mechanisms of rumor propagation is critical in modern society, as data can quickly move via multiple media outlets. Understanding the mechanisms, variables, and control measures governing this process is critical for both social and epidemiological purposes. It has the ability to capture non-linear interactions and to learn from data, which provides a robust foundation for modeling and analyzing such intricate processes. We investigate using advance techniques on analyses and forecast the dynamical behaviors of rumor propagation, thereby considering the presence of infected media alongside the temporal element provided by a time delay.

Rumors are a type of social phenomenon that have existed throughout human evolution, in which a statement spreads widely and quickly through networks of communication [1]. In a most basic sense, rumors are unreliable information that haven't been verified. Typically, they are spread by some individuals to achieve a specific goal, such as defaming others, generating momentum, deflecting attention, inciting panic, etc. [2,3]. Over the past few decades, there has been a lot of attention on rumor spreading as a significant type of social communication. Online social networks play a crucial role in the dissemination of information, which has a significant impact on our way of life. This is due to the rapid development of online social media platforms in the past few years, such as Sina Weibo, WeChat, and others.

In December 2019, Wuhan& Hubei reported a string of unidentified pneumonia cases, also known as the coronavirus disease 2019 (COVID-19) pneumonia cases. Numerous cases of illness have currently been confirmed in China, Italy, the United States, and other nations [4,5]. Since the beginning of 2020, COVID-19 has spread throughout the world and has become a pandemic, thus posing serious problems for healthcare systems and contributing to a downturn in the economy. The etiology, prevention, and treatment of the disease have all been the subject of numerous rumors and false facts that have concurrently been circulated on social media [6]. People across the world now face the possibility of infection, as COVID-19 has grown to be a big global issue; this has changed people's actions and produced emotional changes [7]. There were a lot of emotional remarks and sporadic rumors made on the internet during the COVID-19 breakouts in various regions of the world.

Many researchers have evaluated various rumor-spreading models in an effort to better manage rumor dissemination. Initially, infectious epidemic models were used to create and assess the rumor-spreading model. The traditional rumor spreading model (i.e., the Daley-Kendall (DK) model) was first put forth by Daley and Kendal in 1965 [8], which marked a significant advance in rumor transmission research. The DK model divided all closed and homogeneous populations into three groups: spreaders (i.e., those who heard the rumor and actively spread it), ignorant (i.e., those who were ignorant of the rumor), and stiflers (i.e., those who knew about the rumor but never spread it). This division was largely derived from the susceptible-infected-removed (SIR) model of epidemics [9]. In recent years, there has been significant advances in the study of rumor dissemination. Some researchers have updated the susceptible-exposed-infected-removed (SEIR) model by taking hesitant mechanisms of complex social networks into consideration [10,11]. In order to better understand how rumors travel in both homogeneous and heterogeneous networks, Zhao et al. investigated a new SHIR rumor spreading model [12]. Cheng and Zhao [13] and Ghosh and Das [14] conducted studies on the rumor propagation dynamics of infected media, time delay, and social networks, thereby offering valuable insights.

The goal of this study is to develop numerical solvers using the Bayesian regularization method with neural network back propagation (BRM-NNB) method, which is based on AI that leverages either soft computing or machine learning to solve an improved rumor XY-SIR spreading model. This model was developed to investigate the novel aspects of the rumor-spreading process, while taking the delay of the interactive system into account [15]. ANNs are a versatile and flexible idea that has been explored and provided as one of many choices in the literature for credit scoring. They can be used to handle clustering, time series, and function approximation issues, as well as classification challenges [16]. They are the most efficient and reliable numerical approach and have many real-world applications. Using Bayesian regularization, the squares of the errors and weights are reduced linearly. In addition, the linear combination is altered such that the final network can effectively generalize after training. Compared to traditional back-propagation networks, BRM-NNB is more resilient and can

reduce or perhaps do away with the need for significant cross-validation. One main advantage of the Bayesian approach is its tremendous flexibility. Realistic models can be easily fitted to complex data sets with estimation errors, filtered or incomplete information, multilayer or regression analysis patterns, and many outcomes using BRM-NNB approaches. Recently, numerous studies utilized AI computing for solving different types of real-life problems [17−24]. Their capacity to learn from information, deal with transforming trends, and generalize facts makes them important in a wide range of industries, from robot learning and the recognition of trends to data evaluation and decision-making. In the context of COVID-19, the use of ANNs is growing as an exciting avenue for comprehending and handling the complexity involved with the epidemic. As a subtype of machine learning, ANNs have the capacity to discover sophisticated patterns and relationships among large datasets, thus making them particularly useful in analyzing the virus's multiple characteristics, such as propagation dynamics, infection rates, and probable outcomes. Atangana [25,26] made a significant contribution to COVID-19 modeling. Sindhu et al. provided an important investigation in the pursuit for an in-depth understanding of the COVID-19 pandemic [27] and boost validity by combining the exponentiated inverse Weibull distribution and the inverse power law [28]. The investigation focuses on the dependability of the exponentiated Weibull distribution employing the inverse power law (IPL), which utilizes a combination of numerical computations and ANN modeling. This combines accurate numerical insights with the modeling capability of ANNs to grasp complicated patterns in data. Shafiq et al. presented detailed evidence to suggest the design of COVID-19 statistical modeling [29−31] by completely analyzing the efficiency of ANNs, in contrast with standard parametric techniques, and the enhanced robustness by integrating the exponentiated inverse Weibull distribution and the IPL [32].
The suggested BRM-NNB investigates the dynamic of XY-SIR-RS-DM and adds the following novel features:

- By utilizing BRM-NNB, a unique embedded computational intelligence framework is created to investigate the XY-SIR-RS-DM.
- The exact solutions for three different model variations of XY-SIR-RS-DM are contrasted with the results produced by the BRM-NNB approach.
- To provide a more accurate solution to the XY-SIR-RS-DM model, an intelligent computing analysis with BRM-NNB is applied.
- The outcomes of generated solutions and those that were referred to are compared using the explicit Runge-Kutta method approach. The data set is generated from the ND Solver tool using deterministic numerical computing in the processes of training, testing, and validation to acquire the approximation solution and compare it to the standard solution.
- The neural network's decision variables are learned with the use of backpropagation via Bayesian regularization, which effectively optimizes the merit function at each epoch.
- Statistical analyses demonstrate the accuracy and reliability of BRM-NNB; additionally, the predicted mean square error (MSE)-based measures predicted are precise and trustworthy.
- The MSE graph depicts either the convergence of the model or the consistency, in the form of best performances up to 10^{-9}.
- The result corresponds with producing a minimal absolute error that is approximately close to zero, thereby demonstrating the usefulness of the proposed approach.

1.1. Organizational structure

The study's organization structure is as follows. The mathematical model for the nonlinear XY-SIR-RS-DM is investigated in relation to the novel spreading pattern is described in the second section. A synopsis of the suggested algorithms and examples of its execution are provided in the third section. The suggested scheme's results are outlined in the fourth section's concluding remarks, which also include recommendations for additional research.

2. Description and analysis of XY-SIR-RS-DM

A new XY-SIR-RS-DM model was established to study the dynamics of rumor spreading [33], taking the interaction between media websites and friendship networks into account, as well as factors such as delay and cost in the spreading process, to more accurately describe the mechanism of rumor spreading under the influence of social media. The following are the model's presumptions:

A1: Information flowing between individuals has a certain time delay due to the ad hoc nature of Internet browsing and the fact that various people have varied thought processes when it comes to accepting information.

A2: The media has a specific ratio of registration to removal in the media website network layer. It is introduced to the susceptible media with the probability A_1. It is assumed that the susceptible media is contaminated and will be transformed into the infected media with a specific probability ω, which is referred to as the infection rate of spreaders to websites when the spreader visits the susceptible media and leaves either a message or comment. Both the susceptible media and the infected media are simultaneously likely to leave the system with a probability of ε_1 due to the healthy competition between media.

A3: When an uninformed person sees an infected media, they will change into a rumor spreader with a probability of δ, which is known as the media action rate, with a probability of A_2 in the friendship network layer. When an ignorant person is connected to a rumor spreader during the course of an offline interaction, the ignorant person will be persuaded by the spreader and change into the spreader with the probability υ, which is known as the general spreading rate. According to the migration rate ε_2, which is similar to the population's death rate, a particular set of individuals have been eliminated from the population for some cause.

A4: The spreader will eventually change into the stifler with the probability γ, which is known as the stifling rate, due to forgetfulness, losing interest, and other factors over time.

The media in the network of media websites can be separated into two categories: susceptible media that isn't rumor-infected (expressed as X) and infected media that is rumor-infected (expressed as Y). The susceptible media does not contain any rumor information. The susceptible media will become infected and turn into an infected media when the extruders access the susceptible media and either post or leave comments regarding rumors on the media network. In the friendship network, individuals are categorized into three groups: those who know and actively disseminate rumors (denoted by S), those who are ignorant and have never heard of rumors (denoted by I), and those who know about rumors but have no desire to spread them (represented as R).

$$
\begin{aligned}
&\frac{dX(t)}{dt} = A_1 - \omega X(t)S(t-\tau_1) - \varepsilon_1 X(t), && X(0)=c_1 \\
&\frac{dY(t)}{dt} = \omega X(t)S(t-\tau_1) - \varepsilon_1 Y(t), && Y(0)=c_2 \\
&\frac{dS(t)}{dt} = \delta I(t)Y(t-\tau_2) + \upsilon I(t)S(t-\tau_3) - \gamma S(t) - \varepsilon_2 S(t), && S(0)=c_3 \\
&\frac{dI(t)}{dt} = A_2 - \delta I(t)Y(t-\tau_2) - \upsilon I(t)S(t-\tau_3) - \varepsilon_2 I(t), && I(0)=c_4 \\
&\frac{dR(t)}{dt} = \gamma S(t) - \varepsilon_2 R(t), && R(0)=c_5
\end{aligned}
\tag{1}
$$

3. Proposed methodology

Table 1. Description of default values of parameters and initial conditions.

Parameter or Classes	τ_i	A_1	ω	ε_1	δ	A_2	υ	ε_2	γ	X(t)	Y(t)	S(t)	I(t)	R(t)
Value or Initial Conditions	1.6	0.05	0.8	0.1	0.5	0.2	0.8	0.2	0.5	0.99	0.01	0.001	0.995	0.004

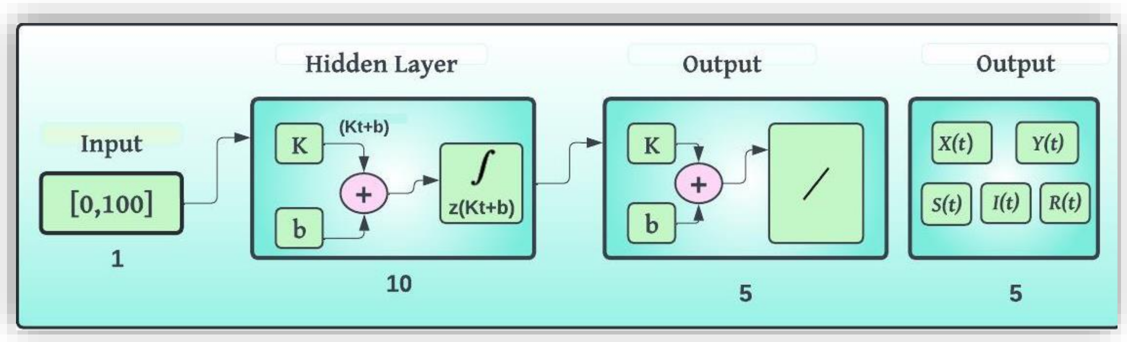

Figure 1. Neural network created for the BRM-NNB.

Three phases constitute the suggested methodology. The dataset used as a reference input for ANNs is created by running explicit Runge-Kutta calculations for three different scenarios that are caused by variations in the various parameters of XY-SIR-RS-DM in phase one, formulating the BRM-NNB's two-layer structure in phase two, and training the BRM-NNB using the Bayesian regularization technique in phase three.

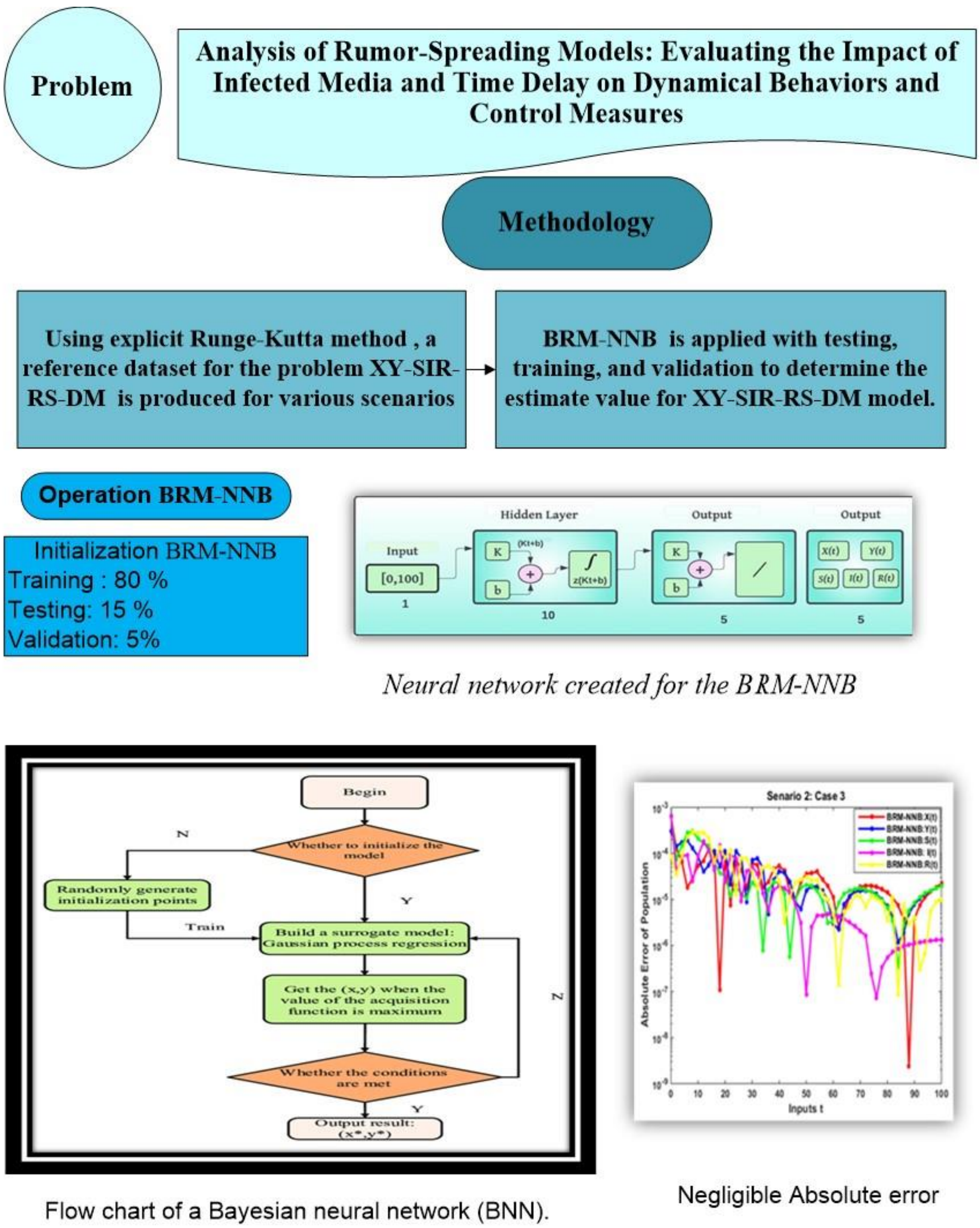

Figure 2. Flowchart of the designed technique.

In the literature, these AI algorithm-based approaches have a wide range of modern applications for solving differential equations across many different disciplines. The "nftool" function in MATLAB provides access to the BRM-NNB processes, which uses the following data configuration: 80% for training, 15% for assessment, and 5% for validation. Figure 1 shows the topology of the neural network created for the BRM-NNB, while Figure 2 shows a thorough flowchart of the design technique. Table 1 shows the default values of parameters and the initial conditions of classes involved in the model, which are taken from [33].

3.1. Bayesian regularization

A mathematical technique, known as Bayesian regularization, turns a nonlinear regression into a "well-posed" statistical problem similar to a ridge regression. An ANN variant called BRNN (Bayesian Regularization Neural Networks) is substantially more durable than a traditional ANN. Over-fitting of the model results from these networks with an immature convergence. The Bayesian approach is used to regularize networks by allowing optimization of characteristics using prior information. Theoretically intricate input-output relationships can be revealed by BRNN, thus making it a useful prediction model. The parameters of the presented study are adjusted to analyze the presented mathematical model after numerous experiments, experience, and over/under fitting scenarios. Moreover, the methodology is selected since it is responsible for calculating the gradient of a loss function with respect to all of the network weights.

As a result of its probabilistic nature, Bayesian networks aid in event prediction and the identification of links among numerous variables or occurrences, which is why the following researchers have recently used these techniques in their work: Pantograph DDE [34], magneto rheological radiative hybrid Nano fluid flow [35], short-term wind forecasting [36], SEIR model for zika virus spreading [37], and a nonlinear model of the influenza virus [38].

4. Results and analysis

This section includes numerical simulations with detailed descriptions for three distinct situations, each of which consists of three instances of the system (1) that represents the nonlinear XY-SIR-RS-DM when using the suggested BRM-NNB.

Figure 3 shows the use of the developed BRM-NNB in terms of the graphical outputs for scenario 1 case 2. The fundamental performance function that directly impacts the network is the MSE factor. An effective system will come from minimizing this error. A smaller MSE suggests that the model's forecasts are more accurate. It is a measurement of reliability that indicates how well the model fits the data. A minimal MSE indicates an accuracy in forecasting the results and is essential when performing tasks that require precision (e.g., forecasting). Obtaining a minimal MSE is critical for assuring the forecast models' precision and dependability, as well as giving those making decisions the trust they need to use the model's results for better decision-making.

We acquired the fitness of the data points in terms of the MSE for training in the range of $1.37\text{E}-08$ and the testing data points in the range of $1.44\text{E}-08$, thereby demonstrating a very low margin of error among the predicted and actual values. The presented MSE values indicate that the model obtained an exceptionally high level of efficiency on both data sets used for training and testing, with minimal errors. These results suggest that the model is stable, and its effectiveness in producing superior results is outstanding. Table 3 shows the MSE values for training and testing, as well as the best performance values. As shown, the values indicate a more powerful system result convergence.

After the neural network is trained, the error histogram shows the discrepancies between the goal values and the predicted/output values. A histogram layer for ANNs is presented; the maximum samples hit an error at 1.67E-06, which is really close to the zero error. The identification of characteristics that illustrate the value distribution in certain local regions of space is a crucial component of the texture analysis. The spatial distribution of features is taken advantage of by the suggested histogram layer for the texture analysis, and the parameters for the layer are determined by backpropagation.

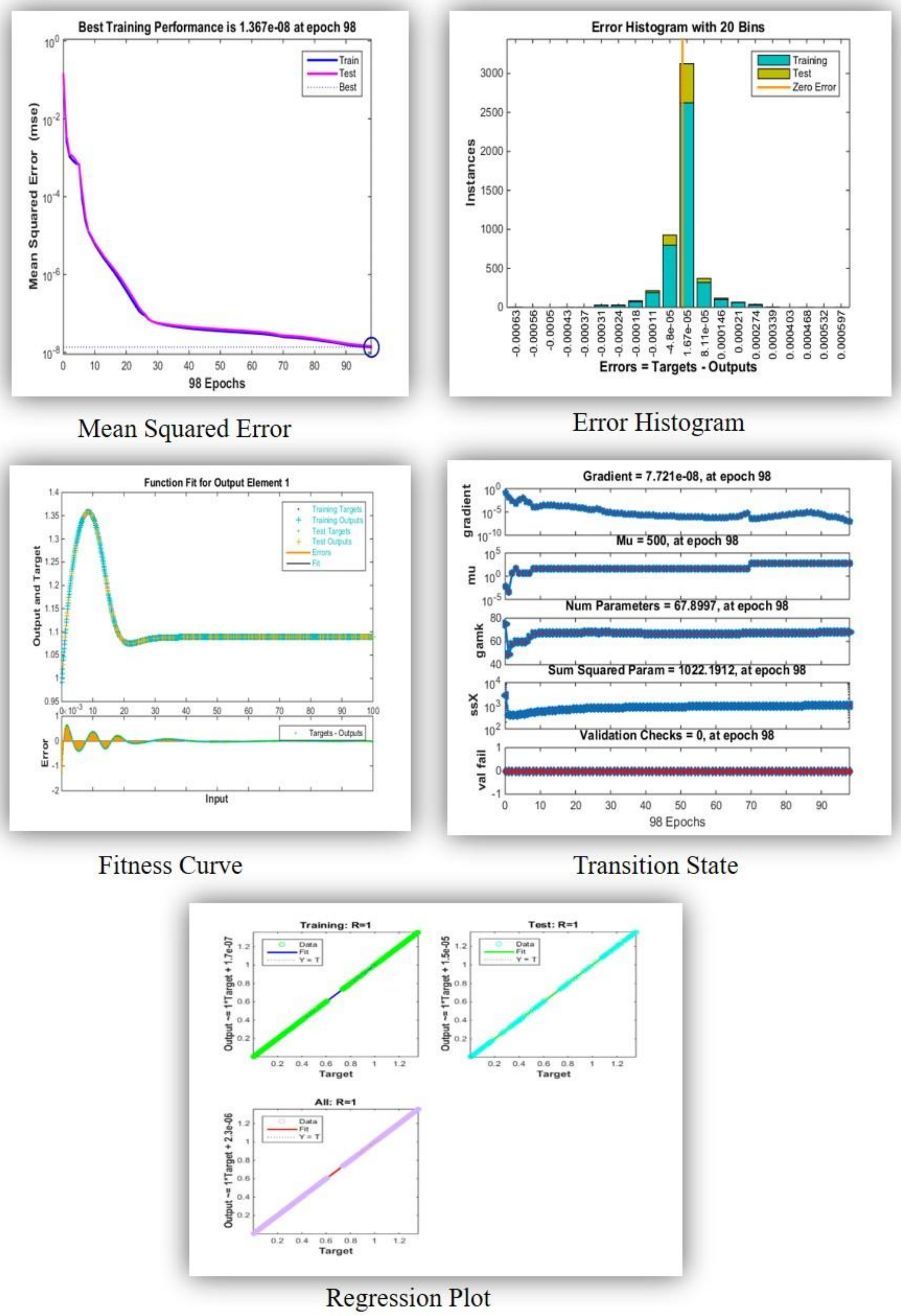

Figure 3. BRM-NN's outputs for scenario1 case2.

The fitness function determines how closely a particular solution adheres to the ideal solution of the desired problem and establishes a solution's suitability. Each member of the population possesses all of the BRM-NNB network's weights and thresholds. Fitness functions can be used to determine individual fitness values. In order to limit the error until the BRM-NNB integrates the training data, the backpropagation technique starts with random weights. Conventional backpropagation, which is a gradient decent technique, moves the network weights along the performance function's gradient's inverse. The learning problem is thought to have been solved by selecting a set of weights that minimize the error function. The values of mu and the gradient in the transition state at 500 epochs are 500 and 7.78E-08, respectively. Additionally, a regression plot is illustrated, which shows that the regression is linearly distributed.

Similarly, we have obtained these outputs for all three scenarios with three cases each, which are described in Table 2, and the numerical outcomes obtained by BRM-NNB for all cases are illustrated in Table 3.

Table 2. Default parameter setting of all scenarios for XY-SIR rumors propagating dynamical model.

Scenarios	Parameters	Case 1	Case 2	Case 3
S1	A_1	$A_1 = 0.04$	$A_1 = 0.03$	$A_1 = 0.02$
	A_2	$A_2 = 0.4$	$A_2 = 0.3$	$A_2 = 0.2$
S2	δ	$\delta = 0.3$	$\delta = 0.5$	$\delta = 0.7$
	υ	$\upsilon = 0.7$	$\upsilon = 0.5$	$\upsilon = 0.3$
S3	τ	$\tau = 0.5$	$\tau = 1.5$	$\tau = 2.5$

Table 3. Numerical Outcomes of BRM-NN for all scenarios.

Scenarios	Cases	MSE		Performance	Gradient	Mu	Epoch	Time
		Training	Testing					(s)
I	**I**	4.20E-08	3.88E-08	4.20E-08	9.68E-07	50.0	1000	53s
	II	1.37E-08	1.44E-08	1.37E-08	7.78E-08	500	98	5s
	III	9.04E-07	8.74E-07	9.04E-07	5.87E-06	500	1000	54s
II	**I**	1.53E-08	2.11E-08	1.53E-08	9.95E-08	5000	729	40s
	II	1.11E-08	1.25E-08	1.11E-08	9.98E-08	5000	648	35s
	III	4.72E-09	3.47E-09	4.72E-09	9.95E-08	500	814	44s
III	**I**	1.17E-07	1.29E-07	1.17E-07	4.92E-05	50.0	1000	58s
	II	4.40E-07	4.47E-07	4.40E-07	1.01E-06	50.0	1000	57s
	III	6.41E-06	6.52E--6	6.41E-06	2.18E-06	50.0	1000	59s

Comparative studies of BRM-NN results with reference results obtained by explicit Runge-Kutta numerical method utilize the following variables: X(t), which represents the susceptible media that isn't rumor-infected, Y(t), which represents the infected media that is rumor-infected, S(t), which represents spreaders (i.e., individuals who know and actively disseminate rumors), I(t), which represents individuals who are ignorant and have never heard of rumors, and R(t), which represents individuals who know about rumors but have no desire to spread them. Figures (4−6) make it clear that BRM-NN solutions overlap with the explicit Runge-Kutta results, and the resultant values of absolute error (AE) for scenarios 1 to 3 for the nonlinear XY-SIR-RS-DM are astonishingly low in each case. For all scenarios of the nonlinear XY-SIR-RS-DM, the results of the BRM-NN characterize the accuracy and convergence of the proposed method.

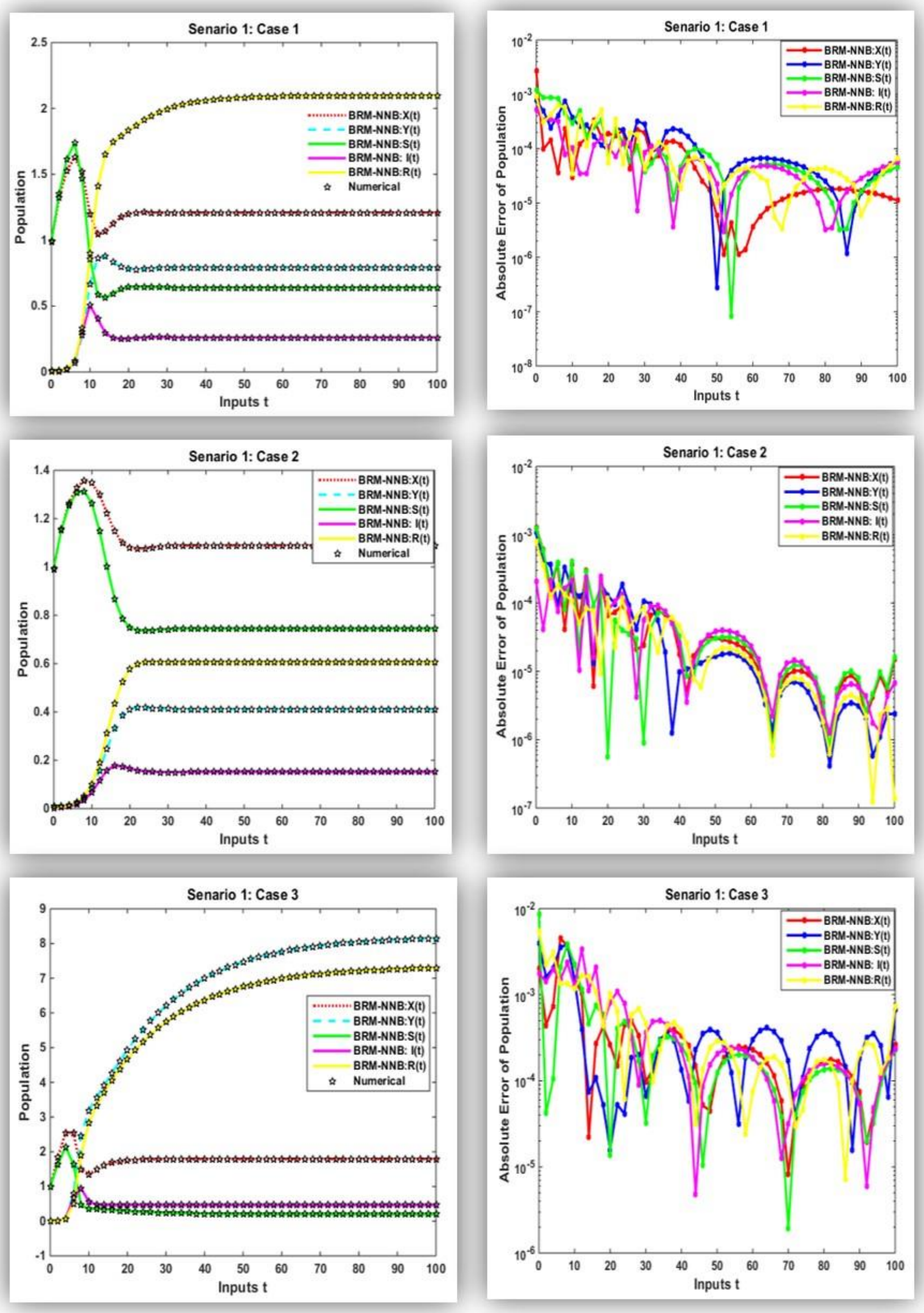

Figure 4. Comparison of results of BRM-NN and absolute error for scenario 1.

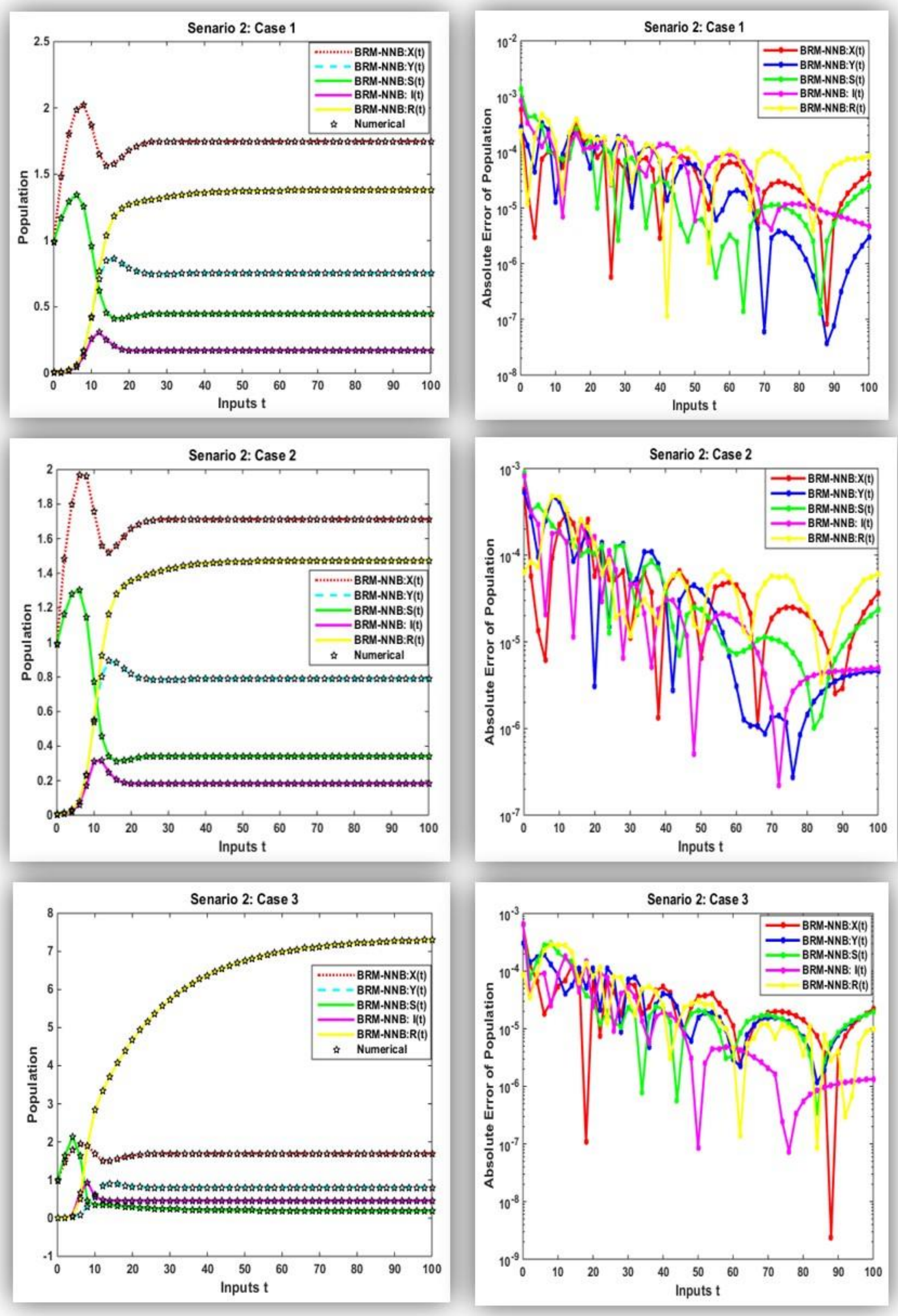

Figure 5. Comparison of results of BRM-NN and absolute error for scenario 2.

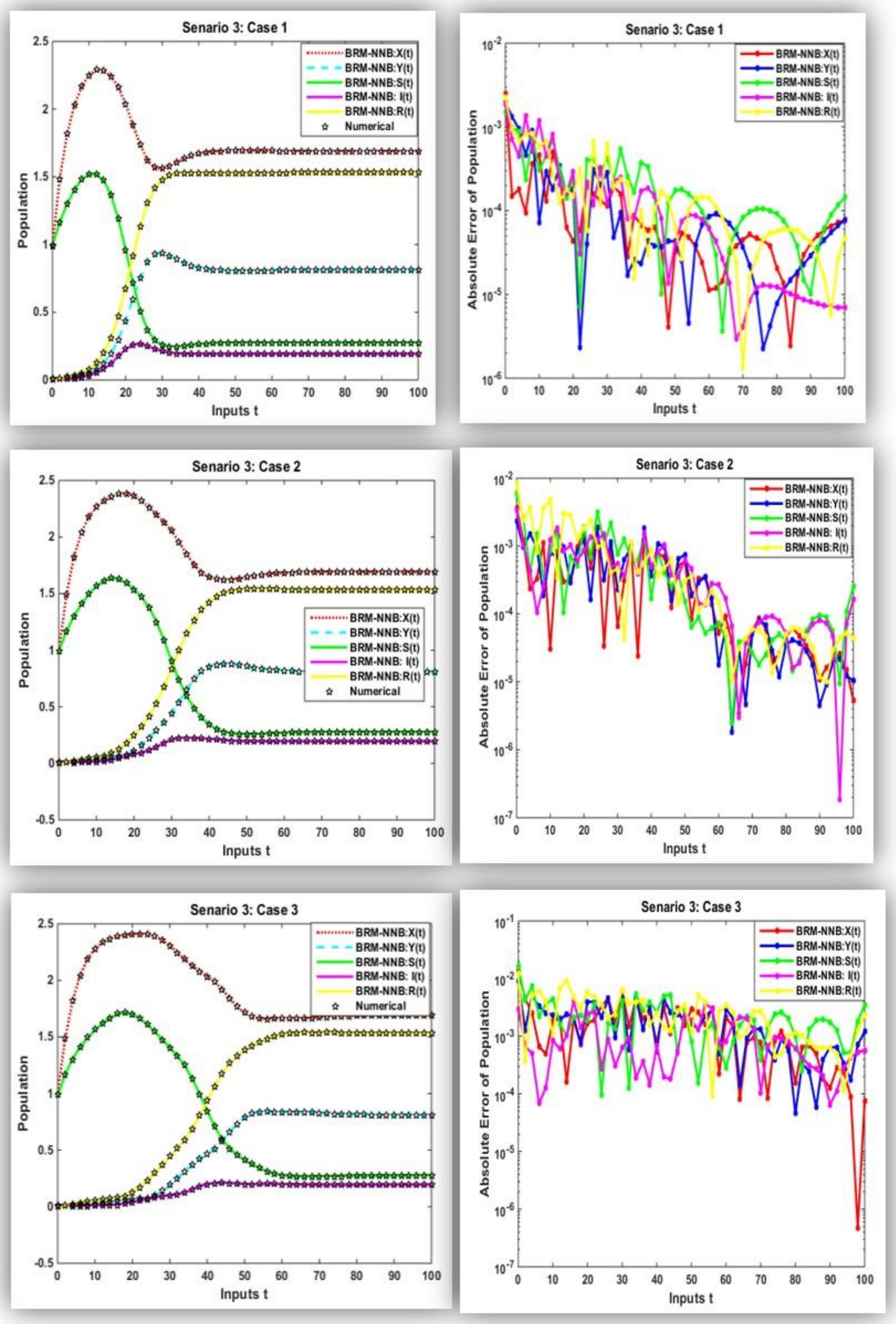

Figure 6. Comparison of results of BRM-NN and absolute error for scenario 3.

The discrepancy between a quantity's measured or inferred value and its actual value is known as the AE. The AE assists users in turning learning difficulties into optimization problems because it is one of the most widely utilized loss functions for regression situations Moreover, it serves as a simple, quantifiable way to quantify errors in regression issues. For AE, we have illustrated the graphical outcomes of each scenario with three cases. For scenario 1 the AE lies between $10^{-2} \to 10^{-8}$, $10^{-2} \to 10^{-7}$ and $10^{-2} \to 10^{-6}$ for cases 1-3, respectively. Similarly, for scenario 2, the range of AE for all three cases lies from $10^{-3} \to 10^{-9}$. Additionally, for scenario 3, the range of AE for all three cases lies from $10^{-1} \to 10^{-7}$.

5. Conclusions

The BRM-NNB is explored in relation to the unique spreading pattern for different examples of three scenarios based on the modification in different parameters and time delays, and offers a numerical solution for the XY-SIR-RS-DM. The computing BRM-NNB approach is implemented using the training, testing, and verification data with 10 hidden neurons, which are divided as 80%, 15%, and 5%, respectively. In view of the aforementioned numerical discoveries and simulations, the nonlinear XY-SIR-RS-DM has the following significant conclusions:

❖ The suggested randomized computing paradigm offered by BRM-NNB was successfully used to find the solution to the XY-SIR-RS-DM simulation problem. The behavior of XY-SIR-RS-DM is strongly influenced by changes in the parameters.

❖ Studies comparing the suggested BRM-NNB findings to the referenced numerical data produced by the explicit Runge-Kutta method displayed the planned technique's accuracy and convergence, as well as the amount of AE within the range of $10^{-3} \to 10^{-9}$. The results certify the proper training, testing, and validation modelling for the various scenarios.

❖ Regression matrices, MSE acquisition curves, and histogram error visualizations all demonstrate how effective, trustworthy, and resilient the built-in BRMNNs are for all tasks.

In the future, one may take advantage of the design computing paradigm's strengths and their deep versions for the numerical treatment of epidemic models, fractional order problems, wave radar systems, and computational fluid dynamics models [39−43].

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization: KSN, MS; Formal analysis: MAZR; Investigation: MAZR, AH, KSN, MS; Methodology: MAZR; Software: AH, KSN, MS; Validation: MAZR, MS; Visualization: AH, MS; Writing - original draft: MAZR, AH, KSN, MS; Writing - review editing: KSN, MS.

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