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RESEARCH ARTICLE

Comparative Analysis of Seasonal Mixed Integrated Autoregressive Moving Average and Feed-Forward Neural Networks Models in Predicting United State Natural Hazard Casualties

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ABSTRACT

Improving the statistical and predictive accuracy, especially of the data on natural hazards, is important in addressing these issues. Therefore, policymakers urgently need a reliable forecasting methodology that provides decision-makers with early estimates of future and resulting healthcare expenditures based on historical time series data, so that they can assess potential risks. Researchers in the field of time series face the problem of choosing the best model for analysis from among several available models. Hence, this study compares the most effective model between a time series structure and a neural network model. Therefore, this research compares the predictive performance of the seasonal Mixed Autoregressive and Moving Average models, and feed-forward neural networks using the Back Propagation algorithm. It includes applying these methods to real data representing monthly injuries and deaths resulting from natural hazards in the United States. The best model is determined using the MAE criterion for forecast accuracy by leaving the last 12 observations of the data series as an evaluation set to examine the predictive performance and perform a comparison to determine the most effective one.

Keywords: Artificial neural networks, Back propagation algorithm, FFNN, Multiplicative seasonal model, Natural hazards, Validation checks

Introduction

Over the past five decades, attention has been paid to time series models. Research and science have highlighted the importance of time series. The reality of the changes depends on the observed values of the phenomenon. It also depends on how it changes over equal periods. Knowing its causes and the factors affecting it is essential. They are needed to build a math model for the time series of the phenomenon. The model has a key role in forecasting. [1]

The seasonality problem is important for researchers. It is a key issue when analyzing time series. Researchers have developed several models to address this type of problem. These include the Seasonal Autoregressive Moving Average model and the Multiplicative Seasonal Autoregressive Integrated Moving Average model (SARIMA). Stability in the average is key for building these models. Many studies have been carried out on them. Adhikari and Ramesh, for instance, presented a study on improving the predictive performance of some models, including

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SARIMA models.[2] Cong et al. presented a study based on SARIMA models to predict seasonal influenza in mainland China from 2005 to 2018,[3] while Luo et al. presented a study that fully considers an expanding landscape with vegetable prices.[4] Fang and Lahdelma presented a heat demand forecasting study essential for production and operation planning in the region's heating systems (DH) using SARIMA models.[5] Again, Divisekara et al. presented a study to predict the market price of red lentil commodities using SARIMA models.[6] Vagropoulos and others presented a comparative study between SARIMA models and other models, as well as a comparison with short-term neural networks.[7]

The methods used to improve prediction are important. They have caused a big leap in the use of computers. Prediction has improved through artificial neural networks and genetic algorithms. Predictive neural networks have found applications. They have become widely used for their high ability to make accurate predictions. This is true in cases where it is understood to understand the relationship between inputs and outputs. The first neural networks appeared in the forties of the last century. Specifically, in 1943, McCulloch and Walter introduced the concept. According to their design, a neural network is a group of simple neurons. The neurons are interconnected with the attached training weights.[8] Since then, many studies have followed. For example, Bebis and Michael asked a more important question about the network size that is most appropriate for a particular problem in a 1994, study on feed-forward neural networks.[9] Lui and William in 2019 presented a numerical methodology for the construction of reduced order models.[10] Ozanich et al. developed a nonlinear, deep, feed-forward neural network (FFNN) for direction-of-arrival (DOA) estimation.[11] Haldorai and Arulmurugan presented a study of neural network classification using feed-forward neural network.[12] Chen presented it in a 2022 study that used a Feed-forward Neural Network.[13]

This study had several sections. The first was about seasonal time series models. The second was about neural networks and their parts. It was about the FFNN. The third was about analyzing the monthly count of injuries and deaths from US natural disasters. It used storm data for 50 states, in addition to Puerto Rico, Guam and the Virgin Islands. The NWS Office of Climate, Water, Weather and Climatic Data Services in the USA issued the data. It covers the period from January 2000 to December 2022. The data was split into two sets. The first set covered the start of the observations until December 2021 and it was used to build the model's structure and analyze the time series. The second set covers all 12 months of 2022. This was done using the MATLAB-R2020 program to conduct the analysis stages of the studied models. It is the last 12 observations for comparison. The last section of the paper results and the discussion includes the most compared and important results that the study came up with.

Seasonal time series models

It means a set of linked observations. They are generated in accordance with the continuity of time. They contain a seasonal phenomenon. This indicates a repeating pattern in the time series in the next time. This period is called the seasonal period and is symbolised by S. It may represent a year, season, or month. It is hard to distinguish seasonality, especially when it is combined with the general trend. But you can overcome this problem and find seasonality when the data is stable. You do this by using difference transformation to convert the data into stable data. Then, you can see the seasonality. The existence of the general trend shows the data series is not stable.[14]

After getting stable data and finding the seasonality by checking the lags' Autocorrelations,[15] if the time correlations have big differences at fixed periods (the length of the season), then the time series is seasonal.[16] Some statistical standards describe the quality of time series and help with its modeling. They include Autocorrelation (AC) and Partial Autocorrelation (PAC).

The seasonal Mixed Autoregressive and Moving Average model of order (p, q) is denoted by a symbol $\mathrm{ARMA}(p,q)_S$, and is given by the formula:[1]

$$x_t = \gamma_S x_{t-S} + \gamma_{2S} x_{t-2S} + \cdots + \gamma_{pS} x_{t-pS} + Z_t - \theta_S Z_{t-S} - \theta_{2S} Z_{t-2S} - \cdots - \theta_{qS} Z_{t-qS} \quad (1)$$

These seasonal models are applied when the time series $\{x_t\}$ is stable, while in the case of the time series $\{x_t\}$ being unstable, the model can be found after finding the seasonal differences required to find the stable series, as the seasonal difference factor of degree d is: $\nabla_S^d = (1 - B^S)^d$.

And so, have an unstable Seasonal Mixed Integrated Autoregressive Moving Average model of order (p, d, q), $\mathrm{ARIMA}(p,d,q)_S$, and it is given by the formula:[1]

$$\gamma_p(B^S)\ \nabla_S^d\ x_t = \theta_q(B^S) \quad (2)$$

where

$$\gamma_p(B^S) = \left(1 - \gamma_S B^S - \gamma_{2S} B^{2S} - \cdots - \gamma_{qS} B^{qS}\right) x_t$$
$$\theta_q(B^S) = \left(1 - \theta_S B^S - \theta_{2S} B^{2S} - \cdots - \theta_{qS} B^{qS}\right) Z_t$$

While the multiplicative Seasonal Model (SARIMA): This model of order $(P, D, Q) * (p, d, q)_S$ is given by the formula:

$$\emptyset_P(B)\gamma_p(B^S)\ \nabla^D\nabla_S^d\ x_t = \vartheta_Q(B)\theta_q(B^S)Z_t \tag{3}$$

where P, D, and Q are the order of the non-seasonal Autoregressive, difference and moving average models, respectively, $\emptyset_P(B)$, ∇^D, and $\vartheta_Q(B)$ the parameters of the non-Seasonal Autoregressive model, the parameters of non-Seasonal difference in time D where $\nabla = 1 - B$. It is used to convert an unstable series into a stable series and the parameters of the non-Seasonal Moving Average model, respectively, where p, d, and q are the orders of the Seasonal Autoregressive model, Seasonal difference, and Seasonal Moving Average model, respectively, $\gamma_p(B^S)$, ∇_S^d, and $\theta_q(B^S)$ the parameters of the Seasonal Autoregressive model, the parameters of Seasonal difference in time d where $\nabla_S = 1 - B^S$. It is used to convert an unstable series into a stable series and the parameters of the Seasonal Moving Average model, respectively.[1] A common application of this form is $(0, 1, 1) * (0, 1, 1)_{12}$, which is in its general form:

$$\nabla^1\nabla_{12}^1\ x_t = \frac{\vartheta_1(B)\theta_1(B^{12})Z_t}{\emptyset_1(B)\gamma_1(B^{12})} \tag{4}$$

$$(1-B)(1-B^{12})x_t = \left(1 - \theta_{12}B^{12} - \vartheta_1 B + \vartheta_1\theta_{12}B^{13}\right) Z_t$$

where $\vartheta_1, \theta_{12} \in [-1, 1]$.

This series is used in seasonal time series because its self-correlations have non-zero values, and after taking the differences for $\nabla^1\nabla_{12}^1$ at the time $(1,\ 11,\ 12,\ 13)$, the expression of the resulting series is in $(y_t,\ t = 1, 2, \ldots, N - T)$, where T represents the number of observations subtracted from the original series, which is the result 13.

It is possible to derive the prediction equation for $SARIMA(0, 1, 1) * (0, 1, 1)_{12}$ model by using the differential equation get:[17]

$$x_{t+r} = x_{t+r-11} + x_{t+r-12} - x_{t+r-13} + Z_{t+r} - \vartheta Z_{t+r-11} - \theta Z_{t+r-12} + \vartheta\theta Z_{t+r-13} \tag{5}$$

Where r represents the future values, and by substituting the values of r into Eq. (5) to get the predictions as follows:[18]

$$x_{t+1} = x_t + x_{t-11} - x_{t-13} - \vartheta Z_t - \theta Z_{t-11} + \vartheta\theta Z_{t-12}$$

$$x_{t+2} = x_{t+1} + x_{t-10} - x_{t-11} - \theta Z_{t-10} + \vartheta\theta Z_{t-11}$$

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$$x_{t+12} = x_{t+11} + x_t - x_{t-1} - \theta Z_t + \vartheta\theta Z_{t-1}$$

$$x_{t+13} = x_{t+12} + x_{t+1} - x_t + \vartheta\theta Z_t$$

$$x_{t+R} = x_{t+R-1} + x_{t+R-12} - x_{t+R-13},\ R > 13 \tag{6}$$

From this result, can generate the required predictions and in the same way, the predictive function of the general model can be obtained

Artificial neural networks

Artificial Neural Networks are abbreviated by ANN. They are an information-processing system based on simple math models. These models have certain performance traits. They simulate neural networks (the brain's system) using many linked processors. These networks consist of simple processing boards called neurons. The neurons store scientific knowledge and make it available to the user by adjusting the weights. They have many uses. For example, control, signal processing, pattern recognition and speech recognition.[19]

A neural network has input and output layers. Sometimes, there is a complex relationship between them. To understand this relationship, hidden layers exist between the input and output. These layers also contain neurons. This neuron connects to another nearby neuron. Fig. 1 shows the components of a neural network.[20] One advantage of each neural network over another is its: - neuron interconnection form (architecture) - method for setting the weights for this interconnection (training algorithm) - type of activation function used.

The input layer is the one in which the data is entered, so that each value of the series is considered one input layer which is expressed in the form above as $\{x_1, x_2, \ldots x_m\}$. As for the hidden layers in which the data is activated and trained, the last layer of the neural network training stages represents the results of the training stage.

The Artificial Neural Network Structure is the method of arranging neurons in layers and the form of interdependence between layers, where networks are classified according to their layers. There are two types: single-layer networks (this type does not contain a hidden layer, meaning it consists of an input layer that receives signals from the outside and an output layer from which is obtained network response and clarifies the interconnections between them) and multi-layer networks (this type has one or more hidden layers that increase the ability of the neural network to process data for any complex network, but it has a disadvantage which is the slow processing process).[19]

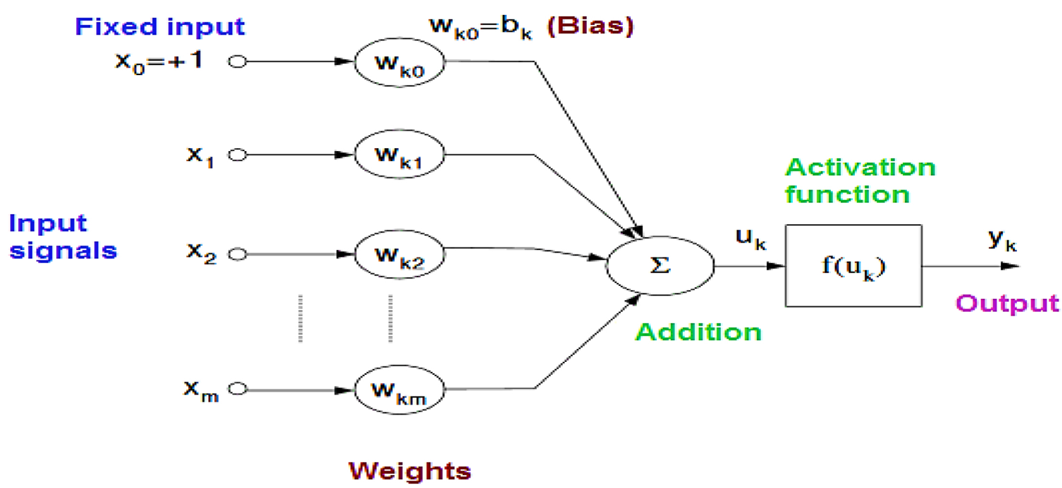

Fig. 1. Artificial neural network components.[20]

1. Feed-Forward Neural Networks using the Back-Error Propagation Algorithm:

The signals enter the network and move forward. They do this if the lines that connect the layers go in one direction. Thus, the signal coming out of each neuron depends only on the signal coming.[21] A certain type of FFNN will be used in this study. The Back-Propagation Algorithm, also known as (BPA), uses it. The steps for training FFNN using BPA are:

1. Initializing initial values for the weights and selecting the training pair from the training set.
2. Forward Propagation stage of the error. It is done in three steps, as follows:
   i. Each neuron in the input layer receives its input signal as $x_i,\ i = 1, 2, \ldots, n$ and then sends it to the collection of neurons of the hidden layer.
   ii. Each neuron in the hidden layer collects its weighted input values and signals as in the equation:

$$\mathcal{H}_j = \mathcal{V}_{0j} + \sum_{i=1}^{n} x_i \mathcal{V}_{ij} \tag{7}$$

where $\mathcal{V}_{ij}$ are the weights of the input layers to the hidden layers.

By apply the activation function with the equation:

$$\hslash_j = f\left(\mathcal{H}_j - \vartheta_j\right) \tag{8}$$

where $\mathcal{H}_j$ represents the hidden layer unit of the index j, while the output of this unit (activated) represents $\hslash_j$, while ϑ is the threshold (a nonlinear function known as the activation function by which the output of each neuron is processed)

To search for its output values, then all activation values are sent to the neuron of the output layer.

   iii. Each neuron in the hidden layer collects its weighted input values and signals as follows:

$$\mathcal{Y}_k = w_{0k} + \sum_{j=1}^{p} \hslash_j w_{jk},\ k = 1, 2, \ldots, n \tag{9}$$

Then by apply the activation function to calculate the output for each neuron in the output layer as follows:

$$y_k = f\left(\mathcal{Y}_k - \vartheta_k\right) \tag{10}$$

Where $\mathcal{Y}_k$ represents the output layer unit of the index k, while the output of this unit (activated) represents y_k.

3. Backward Propagation stage of the error.
   i. Calculate the error for the output neuron through the relation:

$$E_k = t_k - y_k \tag{11}$$

Where t_k represents the true value of the neurons and y_k represents the output value of the neurons.

Then compare the output of the neural network with the real values to estimate the error through the form:

$$\delta_k = \left(t_k - y_k\right) .\ f'\left(\mathcal{Y}_k - \vartheta_k\right) \tag{12}$$

As for the following, by calculate the amount of change in the size of the error according to the equation:

$$\Delta w_{jk} = \gamma.\delta_k.\hbar_j \tag{13}$$

where δ_k is the error correction factor for weight tuning w_{jk}, while γ represents the learning unit and is used to synthesise the weight at each step of the training.

After that calculate its bias correction term used to update the weight w_{0k} later, where w_{0k} is the bias on the output layer unit of index k.

$$\Delta w_{0k} = \gamma.\delta_k \tag{14}$$

ii. Each neuron in the hidden layer collects the δ_k weighted input signals as in the formula:

$$\Delta_k = \sum_{k=1}^{m} \delta_k w_{jk} \tag{15}$$

Then it count $\delta_j = \Delta_k.f'(\mathcal{H}_j - \vartheta_k)$, in order to calculate the change in the magnitude of the error through the equation:

$$\Delta \mathcal{V}_{ij} = \gamma.\delta_j.x_i \tag{16}$$

where δ_j is the error correction factor for weight tuning $\mathcal{V}_{ij}$.

After that, The bias correction term value is calculated by used to update the weight $\mathcal{V}_{0j}$ later, where $\mathcal{V}_{0j}$ is the bias on the hidden layer unit of index j.

$$\Delta \mathcal{V}_{0j} = \gamma.\delta_j \tag{17}$$

4. The stage of updating weights and biases
   i. The weights and biases for each neuron in the hidden and output layers are updated with the following equations, respectively:

$$\mathcal{V}_{ij}(N) = \mathcal{V}_{ij}(O) + \Delta \mathcal{V}_{ij},\ i = 1, 2, \ldots, n \tag{18}$$

$$w_{jk}(N) = w_{jk}(O) + \Delta w_{jk},\ j = 1, 2, \ldots, p \tag{19}$$

Then the activation function is applied to estimate the hidden layer neurons.

   ii. The neural network continues to update the weights until the optimal weights are obtained, and then the desired output is obtained (testing the stopping condition).[22–24]

As for the advantages of each neural network over another, including the following: the form of interconnection between neurons that decides the shape of the neuron (architectural), the method that determines the weights for this interconnection (algorithm training) and the type of activation function used.[25]

Methodology

In previous studies, various traditional methods have been applied to estimate and forecast many time series. Researchers have often used Seasonal Autoregressive Integrated Moving Average (SARIMA) to forecast time series, and the advantage of this model is that it is easy to model and requires little data. Other researchers have used linear models, grey models and other forecasting methods. The results obtained from this type of research are not very accurate and can reflect limited information. In recent years, with the widespread use of machine learning techniques, more researchers have used machine learning models to research natural hazard prediction.

The use of models such as extreme gradient boosting (XGBoost K), recurrent Elman neural networks, and long and short-term memory networks has led to significant improvements in prediction. The introduction of machine learning techniques provides more options for predictive natural hazards research. The relatively complex modeling approach of machine learning models, however, makes it necessary to model different problems individually. This study applies two models, one is the linear and seasonal autoregressive model (SARIMA) and the other is the FFNN neural network model.

Modelling

The data used in this study represent the monthly number of injuries and deaths caused by US natural hazards in storm data for 50 states in addition to Puerto Rico, Guam and the Virgin Islands issued by the National Weather Service (NWS) Office of Climate, Water, Weather and Climatic Data Services in the USA. Table 1 represents the values of the data series used.

The data was divided into two groups: the first group until the end of 2021, which was relied upon to build the series structure for the analysis, while the second group represented (last 12 observations) the evaluation group during which the analysis results for each model were compared.

1. Modelling by SARIMA model

The first step in modelling in all-time series is to draw the time series to see the nature of the time

Table 1. The data series used.

Year	Months											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	37	40	38	11	32	51	99	68	31	7	9	53
2001	22	33	21	34	16	66	82	118	17	11	41	17
2002	17	14	33	24	44	45	181	68	22	22	48	22
2003	23	29	21	21	68	38	67	48	27	32	33	31
2004	42	17	19	23	42	34	26	42	73	13	16	22
2005	63	5	13	12	19	37	116	1035	71	20	35	25
2006	26	17	51	52	28	40	160	144	28	4	11	5
2007	23	74	49	29	50	52	43	108	38	25	2	30
2008	58	76	35	18	65	87	61	52	63	12	6	36
2009	38	30	13	27	33	54	35	20	56	21	17	29
2010	39	17	20	19	60	79	109	73	28	5	5	37
2011	24	33	15	413	210	43	162	124	35	5	22	10
2012	16	32	64	19	21	59	157	41	17	84	6	22
2013	28	17	12	22	88	61	104	32	20	13	26	25
2014	50	32	58	53	26	32	45	22	17	16	8	29
2015	33	47	38	27	85	39	67	34	43	18	15	78
2016	37	23	17	34	21	99	78	52	16	48	9	24
2017	62	14	18	34	24	53	73	148	31	19	6	26
2018	61	14	22	26	29	42	93	49	47	35	96	16
2019	38	22	44	40	46	73	116	62	43	18	18	14
2020	32	19	41	63	36	44	187	180	89	34	21	11
2021	22	133	38	24	41	239	113	125	107	20	10	112
2022	13	19	38	20	27	105	115	39	154	3	20	73

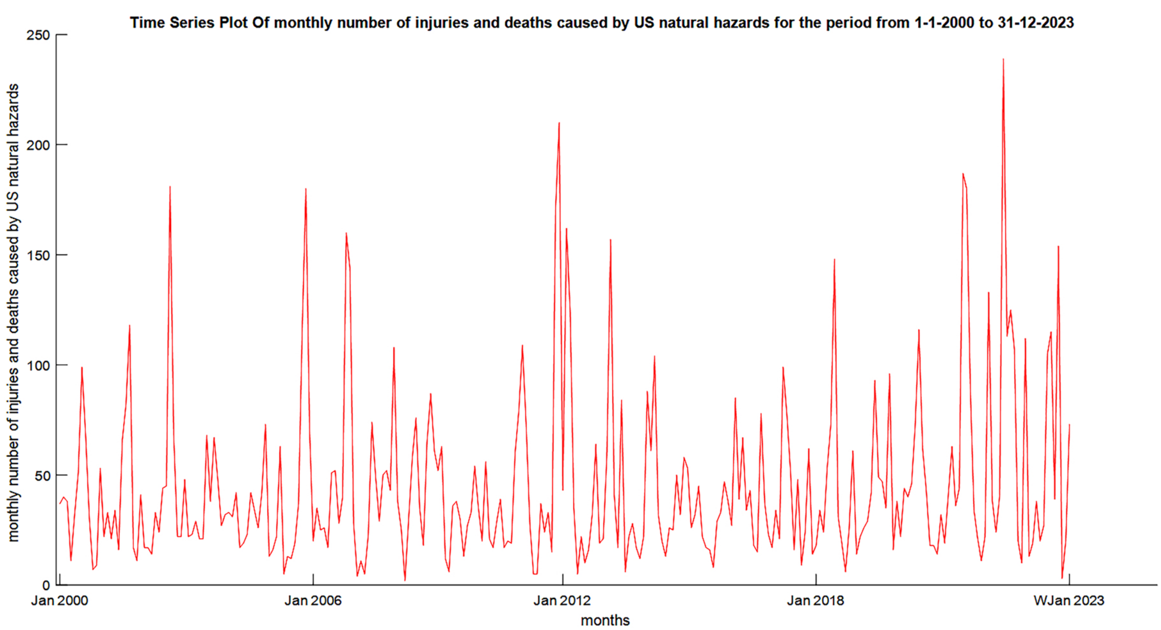

Fig. 2. Monthly number of injuries and deaths caused by US natural hazards in storm data.

series, Fig. 2 represents a plot of Data series represented by monthly number of injuries and deaths caused by US natural hazards in storm data.

In Fig. 2, notice that the time series is unstable in variance and mean, and in order to give it stability, and by take a log transformation of the series, whereas Fig. 3 represents the transformation of the series.

By observing the figure above, it is known that the time series has stabilized, but the mean is still unstable. So again by take the first difference, and Fig. 4 represents the first difference of the transformation of the series.

Now draw the ACF and PACF for 20 lags, Fig. 5 represents a plot of the total and partial autocorrelation functions.

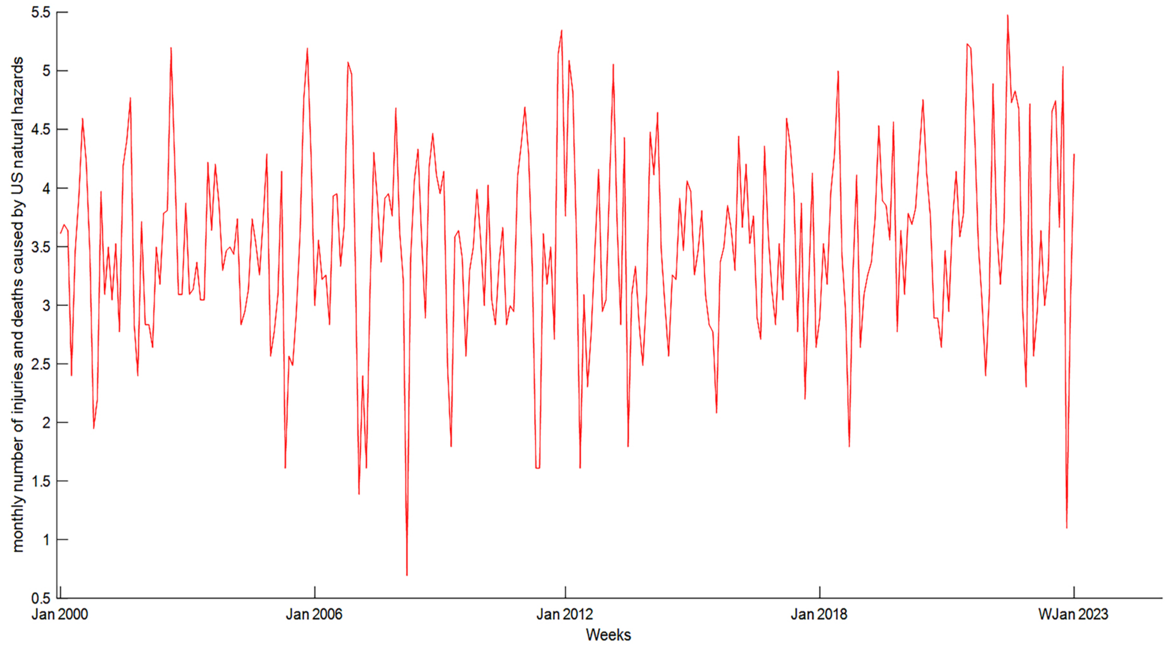

Fig. 3. Log transformation of the series.

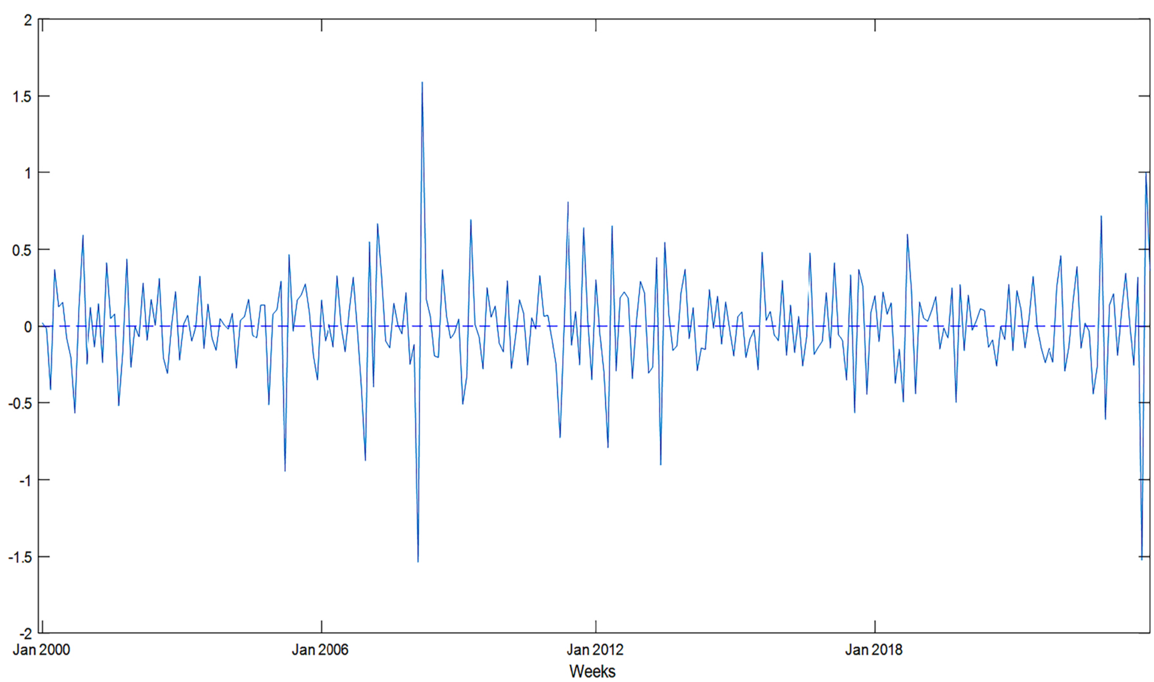

Fig. 4. The first difference of the log transformation of the series.

From Fig. 5 notes that the ACF values at lags $=$ 1, 2, 5, 8, 11, 12, 16 and the PACF values at lags $=$ 1, 2, 3, 5, 6, 8, 9, 10, 11 are all outside the confidence interval.

Now by apply the $\text{SARIMA}(p, d, q)(P, D, Q)_{12}$ model while adjusting the model ranks (fitting) of the model to obtain the best order.

Therefore, it is get that the best model as:

$$(1-\text{Ø}L)(1-\gamma_{12}L^{12})(1-L)x_t$$
$$= c + (1+\vartheta)(1+\theta_{12}L^{12})Z_t \quad (20)$$

According to AIC and BIC criteria, such that AIC $=$ 581.5544, BIC $=$ 602.9644. The parameter values are shown in the Table 2:

Table 2. The parameter values.

Parameters	Value	Standard Error	T-Statistic	P-Value
Constant	0.0006	0.0003	2.2958	0.0217
AR1$\{\emptyset\}$	0.1.86	0.0570	1.9043	0.0569
SAR1 $\{\gamma_{12}\}$	0.8381	0.0176	47.6438	0
MA1 $\{\vartheta\}$	–9.0301	0.0186	–53.7259	0
SMA $\{\theta_{12}\}$	–0.6028	0.0582	–10.3502	0.0000
Variance	0.4610	0.0394	13.1926	0.0000

Table 3. Training progress.

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	7	1000
Elapsed Time	–	00:00:04	–
Performance	9.6E+05	28.7	0
Gradient	1.89E+06	144	1E–07
Mu	0.001	1	1E+10
Validation Checks	0	6	6

Since the analysis included the use of log transformation, an inverse transformation must be performed, which is the use of the exponential transformation after inferring the results and then predicting the future values of the time series. The Fig. 6 represents the time series into the inferred by SARIMA, and Real Data series, While Fig. 7 represents the inferred series and the predicted series.

2. Modelling by FFNN

The data was divided into three sets, the first set constitutes the training set for the network which constitutes 80% of the observations; the second set is the investigation set which constitutes 10% of the data set; and the third set is the testing set which constitutes 10% of the data set, given that the upper bound on the number of hidden layers is 200 and that the number of inputs is one variable with one time difference, by iterating it for 1000 epochs, where Table 3 represents the values for Epoch, Elapsed Time, Performance, Gradient, Mu and Validation Checks.

As for the training plot, it was obtained that the best validation Performance is 3262.6489 at epoch 3, while Gradient is 48.5325, Mu is 1 and Validation Checks is 6 at epoch 9. Where Figs. 8 to 10 represent best validation performance, Validation Checks, and Validation target, respectively.

The Fig. 11 represents the values of the data series with the trained neural network. From this, notice that the data in the trained check appears almost identical to the original sequence, which means that the network completed its work perfectly, while

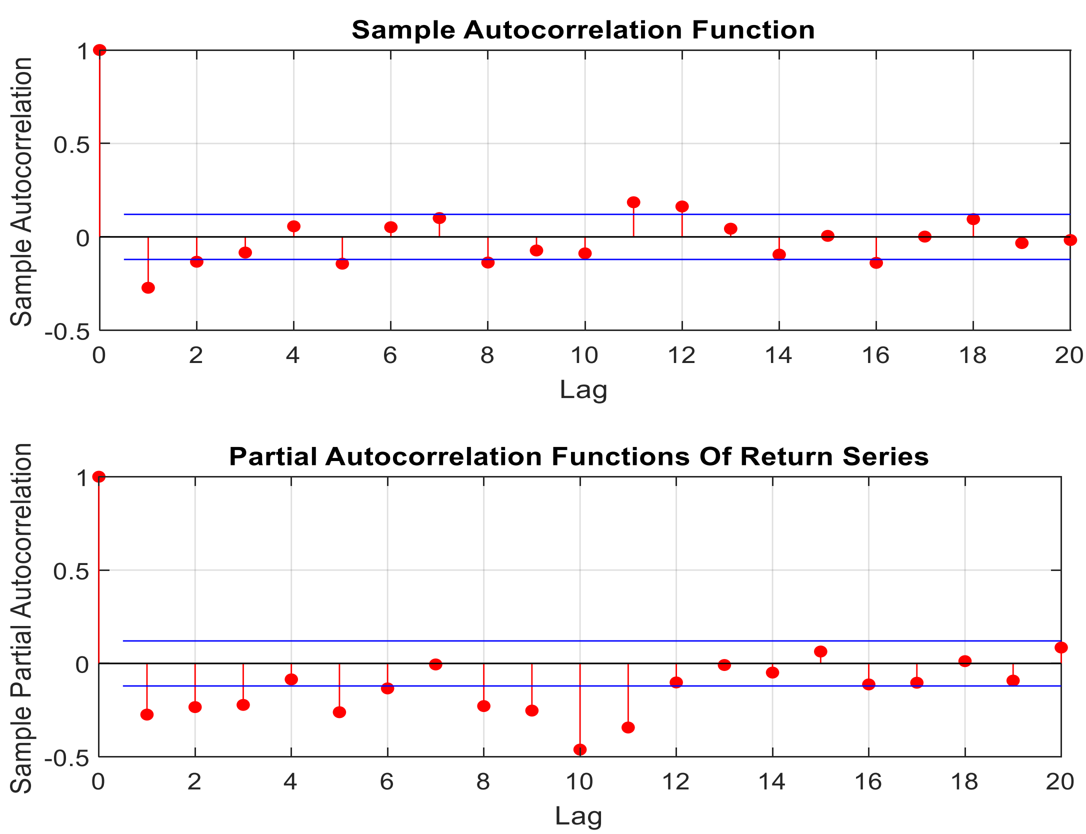

Fig. 5. ACF and PACF.

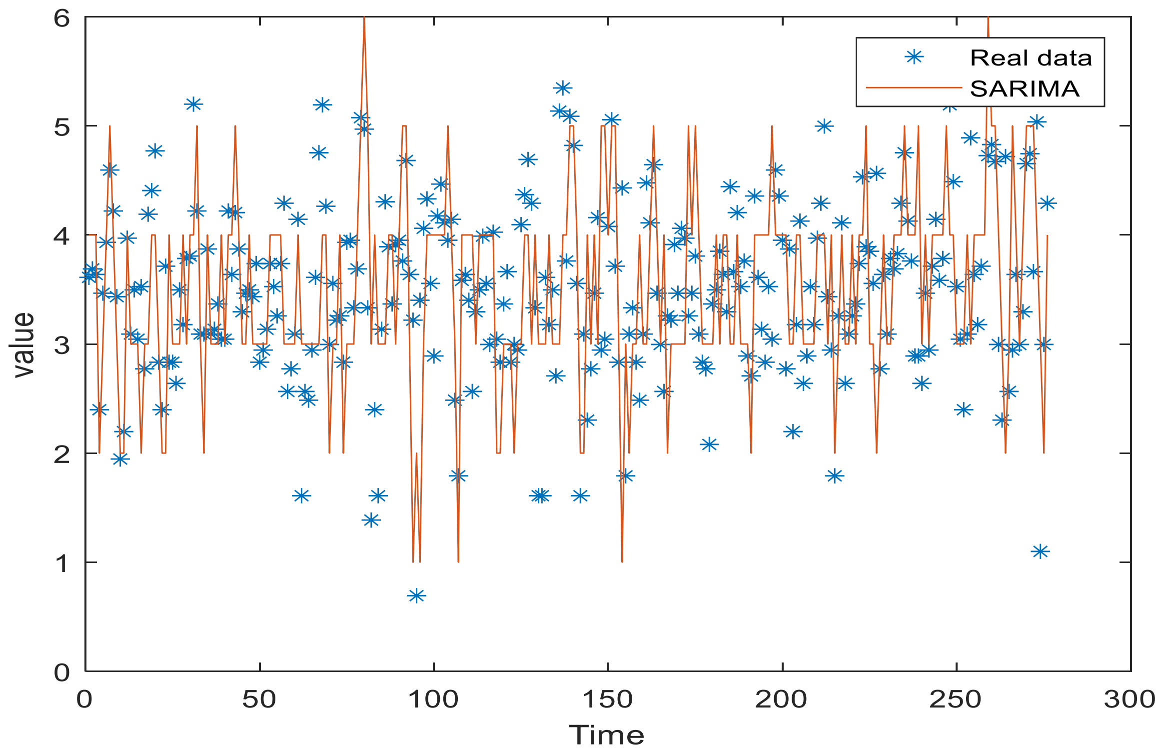

Fig. 6. The inferred series by SARIMA, and Real Data.

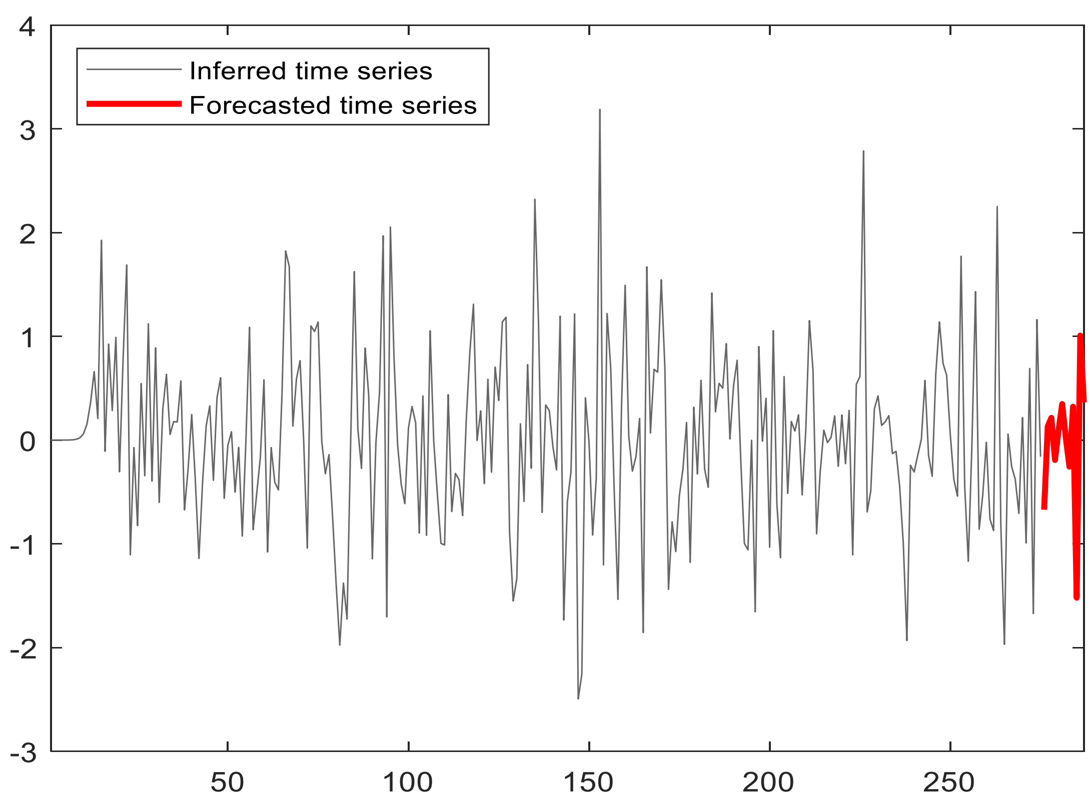

Fig. 7. The inferred series, and the predicted series.

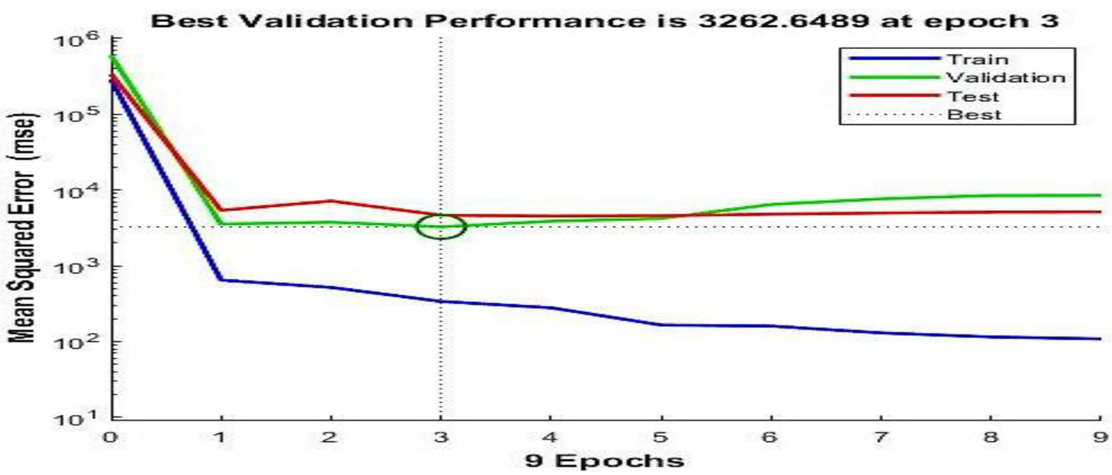

Fig. 8. Best validation performance.

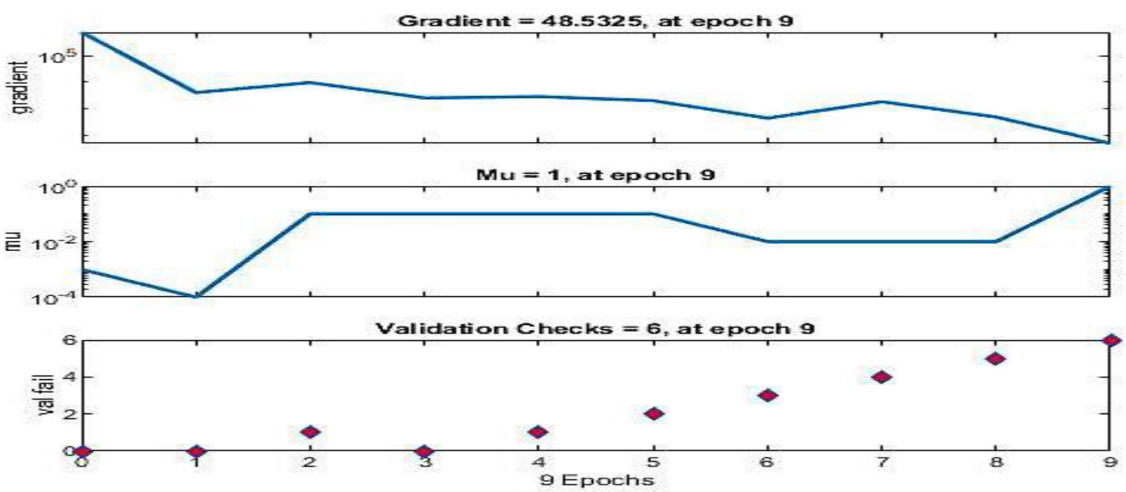

Fig. 9. Gradient, Mu, and validation checks.

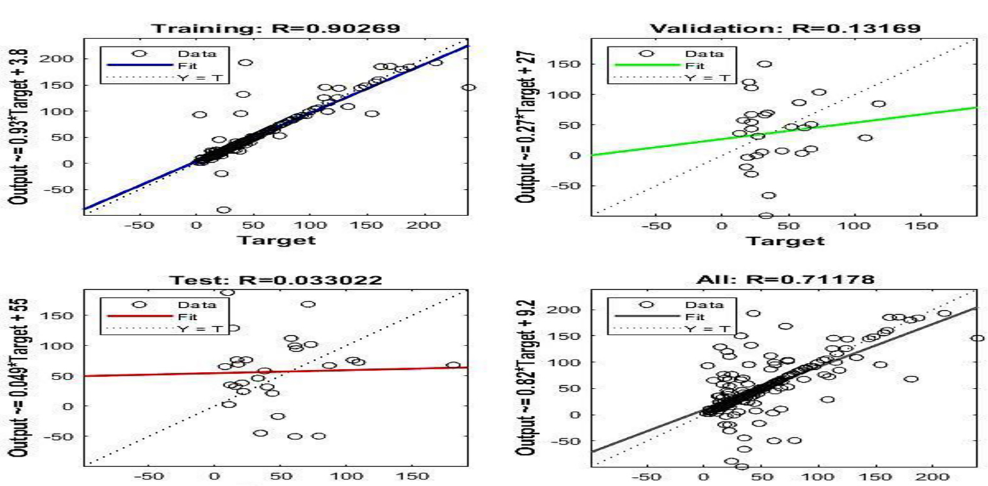

Fig. 10. Training target, and validation target.

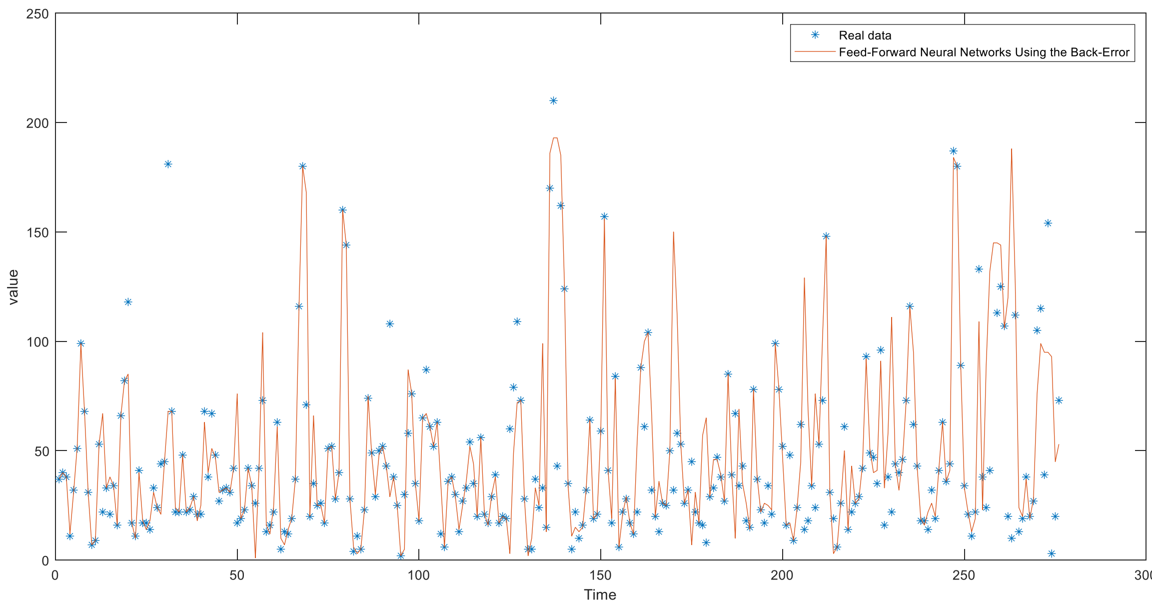

Fig. 11. Real Data to FFNN.

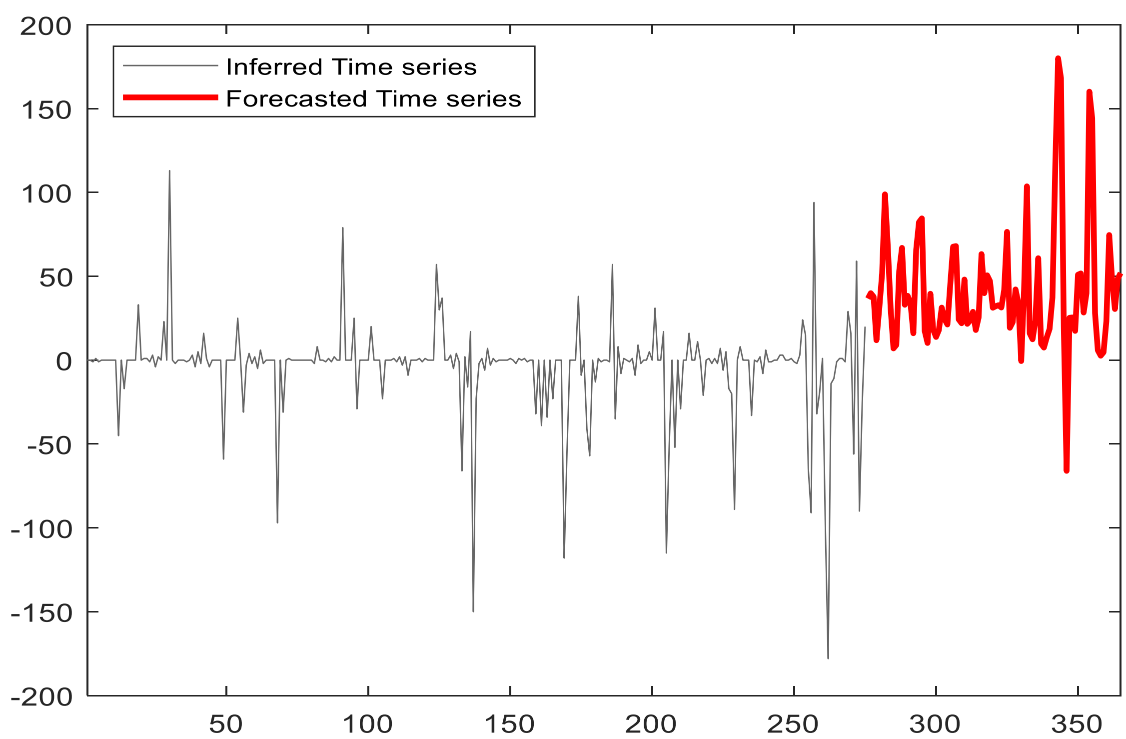

Fig. 12. Inferred and forecasting the tine series.

Fig. 12 represents the inferred and Forecasting the time series.

To ensure obtaining the best results from conducting a time series analysis using the SARIMA model and FFNN neural networks, It has been developed drawings showing the results, also have reached through analysing the two models, as well as developing a comparison table by keeping the last 12 values of the time series as an evaluation set for the predictive performance of both models. Figs. 13 and 14 represent the values of the last 12 months of the time series and their predictions using SARIMA and FFNN.

The Table 4 represents the mean absolute errors for the two models:

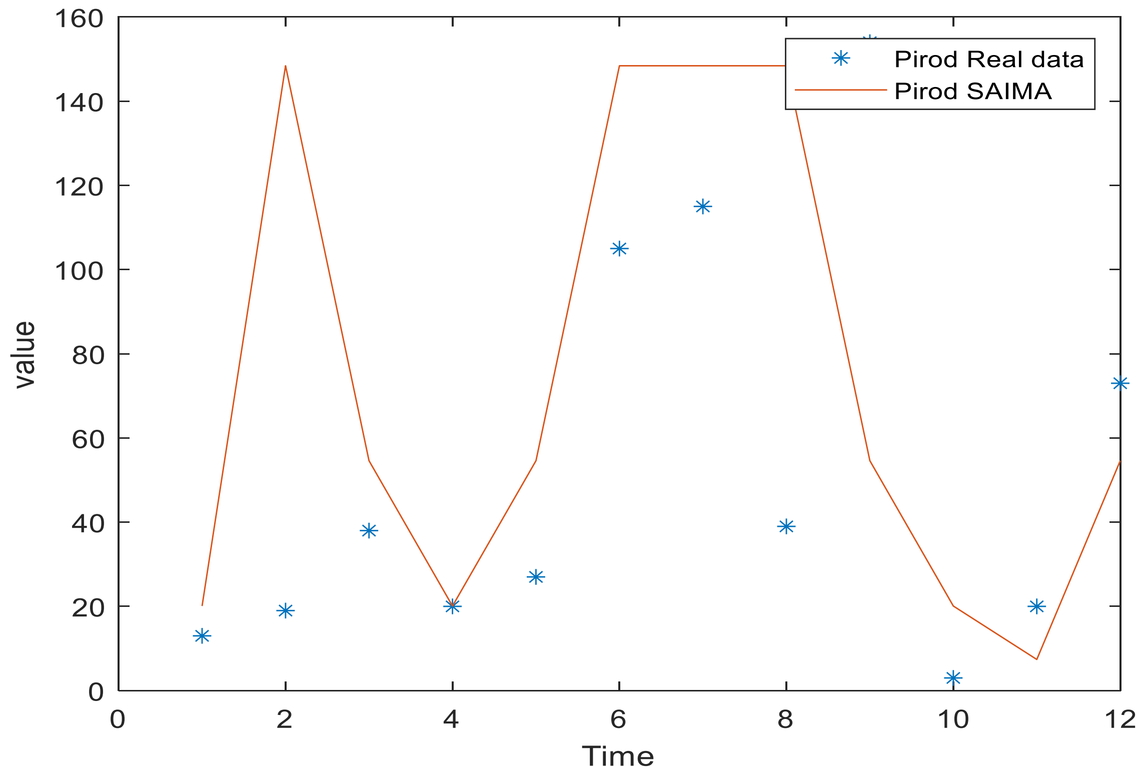

Fig. 13. Last 12 observation of Real Data to forecasting using SARIMA model.

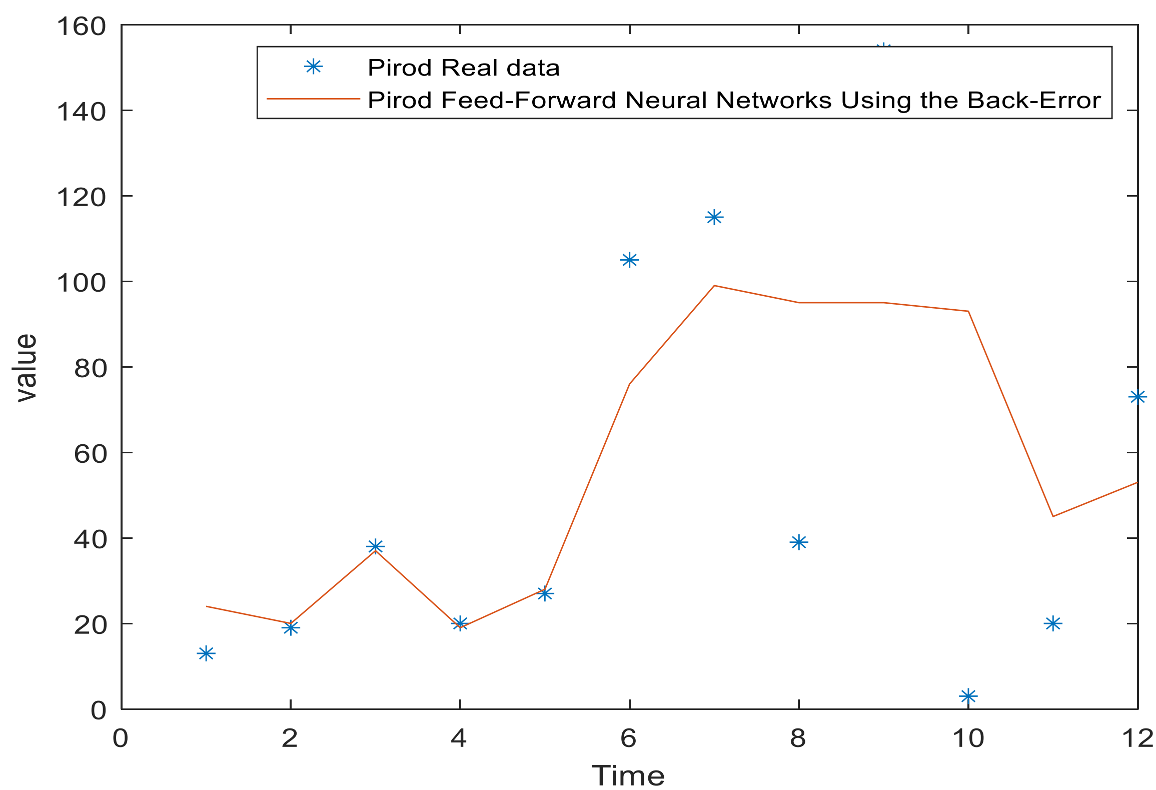

Fig. 14. Last 12 observation of Real Data to forecasting using FFNN.

Table 4. MAE of Real Data to forecasting data.

No	Real Data	Forecasting using SARIMA	Forecasting using FFNN
1	13	20.0855	13
2	19	148.413	2
3	38	54.5982	38
4	20	20.0855	20
5	27	54.5982	27
6	105	148.413	105
7	115	148.413	115
8	39	148.413	39
9	154	54.5982	154
10	3	20.0855	151
11	20	7.38906	20
12	73	54.5982	73
MAE [26]		42.9432	13.75

Results and discussion

Because most studies are concerned with one section, either time series models or neural networks, the study presented a comprehensive analysis of one time series using two different model architectures to find out which methods are better in terms of accuracy of analysis and prediction. From the previous analysis, the response to training on the seasonal model was very slow compared to the response of the neural network, and this slowness greatly caused predictive errors, as the seasonal model had a large error value compared to the small predictive errors of the neural network. The forecast evaluation set was almost identical, but it was observations 2 and 9 that generated the forecast errors, while in the seasonal model, almost no single value was identical. Despite the accuracy possessed by FFNN, it still suffers from slowness in implementing the analysis steps.

Conclusion

By adjusting the activation function and controlling the number of hidden layers of the neural network, FFNN predicts the number of casualties due to natural hazards more accurately and robustly than the other model. Comparing the two models, FFNN models still show excellent predictive performance against data with seasonal and drastic changes. FFNN can provide a better basis for planning and management in the face of natural hazards because it has a high ability to predict better in addition to the very slow response to training about the seasonal model.

Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at Anbar Education Directorate.

Author's contributions

This has been implemented work in cooperation between all authors, as the N.A.N. presented the title of the research and collected sources regarding time series and worked on the basics of the time series model, while the M.Q.I. collected sources of neural networks, while the A.A.K. took care of the applied aspect, while the A.A.M. collected application data and interpreted the results of the applied aspect.

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التحليل المقارن للنموذج الموسمي للانحدار الذاتي والاوساط المتحركة التكاملي ونماذج الشبكات العصبية ذات التغذية الأمامية في التنبؤ بخسائر المخاطر الطبيعية في الولايات المتحدة

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الخلاصة

يعد تحسين الدقة الإحصائية والتنبؤية، وخاصة البيانات المتعلقة بالمخاطر الطبيعية، أمرًا مهمًا في معالجة هذه القضايا. ولذلك، يحتاج صناع السياسات بشكل عاجل إلى منهجية تنبؤية موثوقة تزود صناع القرار بتقديرات مبكرة لنفقات الرعاية الصحية المستقبلية وما ينتج عنها من نفقات على الرعاية الصحية بناءً على بيانات السلاسل الزمنية التاريخية، حتى يتمكنوا من تقييم المخاطر المحتملة. يواجه الباحثون في مجال السلاسل الزمنية مشكلة اختيار النموذج الأفضل للتحليل من بين عدة نماذج متاحة. وبالتالي، توفر هذه الدراسة مقارنة لتحديد النموذج الأكثر فعالية بين بنية السلاسل الزمنية ونموذج الشبكة العصبية. لذلك، يركز هذا البحث على مقارنة الأداء التنبؤي لنموذج الانحدار الذاتي المختلط والمتوسط المتحرك الموسمي، والشبكات العصبية ذات التغذية الأمامية باستخدام خوارزمية الانتشار العكسي. ويتضمن تطبيق هذه الأساليب على بيانات حقيقية تمثل الإصابات والوفيات الشهرية الناتجة عن المخاطر الطبيعية في الولايات المتحدة. يتم تحديد النموذج الأفضل باستخدام معيار MAE لدقة التنبؤ من خلال ترك آخر 12 مشاهدة من سلسلة البيانات كمجموعة تقييم لفحص الأداء التنبؤي وإجراء مقارنة لتحديد الأكثر فعالية.

الكلمات المفتاحية: النموذج الموسمي المضاعف، الشبكات العصبية الاصطناعية، المخاطر الطبيعية، خوارزمية الانتشار العكسي، FFNN، اختبارات التحقق من الصحة.