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# Application of Artificial Neural Network in Predicting Direct Economic Losses Due to Earthquake

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**ABSTRACT**

Accurately predicting the direct economic losses caused by earthquakes is important for policy makers for disaster budgets. Before a disaster strikes, it is important to consider the public policy costs associated with disaster relief and recovery. The aim of this study is to provide a risk assessment approach, which can benefit all parties involved. Artificial neural networks are widely used for time series forecasting, especially financial forecasting. Therefore, this study proposes a cutting-edge forecasting method such as backpropagation neural network (BPNN) and other prediction methods: neural network autoregressive (NNAR) and ARIMA-GARCH to obtain the best prediction results. This paper applies interpolation data to increase the amount of data used. Two interpolations were applied to amplify the original small sample with virtual points, namely cubic splines and further piecewise interpolation using. The results of this study are the cubic spline interpolation is the most effective way to solve the small sampling problem to predict direct economic losses due to the Indonesian earthquake and the BPNN method outperforms other traditional methods with an RMSE of 0.024 in the training period and 0.174 in the testing period, significantly lower than other methods. The results of this research can be used as reference material for the government in estimating the level of earthquake losses and can be used to develop risk reduction strategies

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## A. INTRODUCTION

Indonesia is one of the nations that is relatively vulnerable to natural disasters, and according to National Disaster Management Agency (BNPB) data, total damages from catastrophes totaled IDR 1.06 trillion in 2022 and IDR 11.06 trillion the year before. In Indonesia, earthquakes are a common type of natural disaster (Rais, 2021). There are earthquake-prone regions on almost all of Indonesia's islands. According to the (BNPB), Indonesia will experience 500 earthquakes on average per month. Several studies have suggested that 500,000 earthquakes happen annually. Six of Indonesia's strongest earthquakes are known to have happened. as

Aceh in 2004, Sumatra in 2005, Pangandaran and Jogjakarta in 2006, Padang in 2009, and Donggala, Palu in 2018. The greatest earthquake in Aceh registered a magnitude of 9.1 on the Richter scale, with the average earthquake strength exceeding 7.5 (Hartono et al., 2021).

This seismic catastrophe caused some considerable losses. State losses totaling IDR 51.4 trillion were primarily caused by the 2015 Aceh tsunami tragedy. Additionally, the damage from the Yogyakarta earthquake disaster in 2006 totaled IDR 29.15 trillion, the damage from the Padang earthquake disaster in 2009 totaled IDR 28.5 trillion, the damage from the Central Sulawesi earthquake and tsunami in 2018 totaled IDR 23.1 trillion, and the damage from the NTB earthquake in 2018 totaled IDR 18.2 trillion (Meilano et al., 2022). The ability to accurately estimate the direct economic damage caused by an earthquake in Indonesia is crucial for risk mitigation during earthquake disasters. In order for governments to create disaster mitigation strategies and lessen the risk of natural disasters in the insurance industry, it is important and educational to anticipate annual economic loss accurately and correctly (Utomo and Marta, 2022).

There are several types of forecasting methods, namely traditional methods and machine learning methods. Traditional methods include Moving Average (Hayuningtyas and Sari, 2021), Exponential Smoothing (Lusiana and Yuliarty, 2020), Autoregressive Integrated Moving Average (ARIMA) (Yu et al., 2013). The ARIMA method is good for analyzing linear pattern data. Apart from ARIMA, there is another method that can be used in disaster prediction, namely Artificial Neural Network (NN). NN makes it easy to analyze data with linear and nonlinear patterns (Zhang et al., 2017). One of the NN network architectures is Backpropagation Neural Network (BPNN) (Bai et al., 2016).

Research on forecasting economic losses in the world using the Backpropagation Neural Network (BPNN) method that has been carried out is an analysis of direct economic losses due to marine disasters for case studies in China from 1989 to 2016. The data used are direct economic loss data obtained from China Oceanic Information Network. The result of this research is that forecasting using BPNN obtains a smaller MAPE than other traditional forecasting methods, such as ARIMA, which is 3.29. As well as an estimated direct loss of around 157 billion RMB Yuan (Zhao et al., 2019). In Indonesia, the authorized data system for Indonesia's direct economic loss was established in 1989, which is a short period for our study. In other words, the sample size is insufficient for BPNN to predict the direct economic loss from an earthquake. Fortunately, interpolation can answer the problem of a small sample by adding virtual points and is successfully used to make up for the lack of data in ANN.

Additionally, Monsalve-Giraldo et al. (2018) developed a hybrid Interpolation method and Neural Network methods for predicting steel risers. They used a Hybrid Parabolic Interpolation Artificial Neural Network Method (HPI ANNM) has been applied to for long-term extreme response estimation of steel risers (Monsalve-Giraldo et al., 2018). Requia et al. (2019) suggested that hybrid interpolation and machine learning methods can estimate the PM2,5 constituent over space (Requia et al., 2019). In submarine field, Rao and Yang (2017) used hybrid RBF Interpolation and numerical prediction for a submarine (Rao and Yang, 2017).

Studies on the estimation of direct economic loss forecasting in Indonesia due to earthquakes have not been widely carried out and the application of hybrid and interpolation systems has also not been used. Therefore, in this paper, we are developing an interpolation-based backpropagation neural network (BPNN) to predict the direct economic loss of an Indonesian earthquake. The difference between this research and previous research is the method and data used. Similar research with similar data uses different methods, namely NNAR and ARIMA-GARCH (Azmi et al., 2022). Meanwhile, similar research uses the same method with different research data (Zhao et al., 2019). Therefore, the novelty of this research is applying the BPNN method to cases of economic losses due to earthquake in Indonesia. The purpose of this paper is to adapt the BPNN forecasting procedure to data on the direct economic damage of annual earthquakes across the 1989-2021 dataset. The International Disaster Database (EM-DAT) is intended to be the source of the data for the study variable, and secondly, the data on direct earthquake-related losses used are in billion Rupiah.

This study aims to forecast the direct economic losses in the event of an earthquake in Indonesia in the near future. Therefore, after knowing the predicting results, all stakeholders can develop risk reduction strategies. This benefit helps disaster risk reduction and mitigation for helps policy makers effectively decide how much to invest in a disaster risk reduction fund. In addition, other advantages show the strength of simple prediction methods in terms of accuracy and complex methods, the application of prediction methods using the backpropagation neural network (BPNN) method, and the selection of models to generate predictions is minimum root mean square error (RMSE). Interpolation, on the other hand, is used to solve the problem of inadequate sample size for the predicted direct economic loss of earthquake prediction. In particular, the interpolation method is used to extend the sample by adding virtual values of the expected direct economic loss due to the earthquake, making the expanded sample more satisfying for BPNN.


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## B. RESEARCH METHOD

The International Disaster Database, or EM-DAT, which is run by the Centre for Research on the Epidemiology of Disasters (CRED), Universit Catholique de Louvain, Brussels, Belgium, was used for this study's annual data on direct economic losses caused by earthquakes in Indonesia from 1898 to 2021. There are several important points in this paper, such as:

1. The original samples have 33 observations $\left(\sum_{i=1}^{33} x_i\right)$ and we applied and extended four virtual point interpolations for each year and got a new sample of 129 observations $\left(\sum_{i=1}^{129} x_i\right)$. From annual data, the new data samples are converted into quarterly data.
2. We use 8 input vectors and 1 output vector. The first eight data in a set is a set of input vectors, the ninth data of the bundle are output vectors. Namely, $(X_1, X_2, \ldots, X_{N-8}), (X_2, X_3, \ldots, X_{N-7}), \ldots, (X_{N-8}, X_{N-7}, \ldots, X_{N-1})$, are input vectors, and $(X_9, X_{10}, \ldots, X_N)$ are the corresponding output vectors. There are $N_8$ bundles of input and output vectors.
3. The data from the first quarter of 1989 to 4th quarter of 2016 is acquired as training data, and the rest is acquired as testing data. Analysis is performed using R Studio.
4. By applying the interpolation method, it is possible to generate negative numbers for large fluctuations in direct economic loss. Considering the non-negative characteristics of the data, the prediction replaces the negative number with zero.

The BPNN forecasting system relies on interpolation, which expands the initial samples using imaginary points. This enables the system to overcome the issue of having few samples. Input and output vectors are created based on expanded data, and training and validation samples are obtained. The accuracy of the model is increased by using the training data that was used to train the BPNN. The trained BPNN model predicted the testing samples. The research methodology as shown in Figure 1:

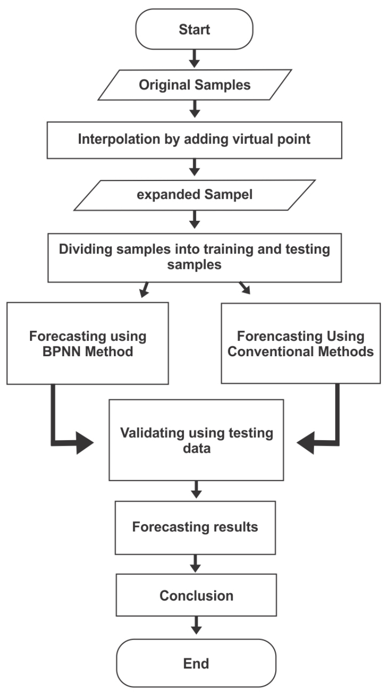


Figure 1. Procedure of Economic Losses Forecasting using Interpolation-BPNN

The study phases employed in the methodology mentioned in Figure 1 are as follows:

### 1. Piecewise Linear Interpolation

Using a discrete set of existing data, interpolation is a technique for creating new points in a range. In this study, we employ the piecewise linear interpolation method and the cubic spline interpolation method, two different types of interpolation methods.

The Piecewise polynomial approximation combines the graph of the low-degree polynomial for $N+1$ points $\{(x_k, y_k)\}_{k=0}^{N}$ and interpolates between $x_k, y_k$ and $(x_{k+1}, y_{k+1})$, the following nodes. Piecewise A polygonal path made up of line segments passing through these spots is produced by a linear polynomial. Considering points $(x_k, y_k)$ and $(x_{k+1}, y_{k+1})$, the formula for a line segment's slope is $P_k(x) = y_k + d_k(x - x_k)$ where $d_k = (y_{k+1} - y_k)/(x_{k+1} - x_k)$. The output of the piecewise linear function can be expressed in the form 1.

$$(x) = \begin{cases} y_0 + d_0(x - x_0) & \text{for } x \text{ in } [x_0, x_1] \\ y_1 + d_1(x - x_1) & \text{for } x \text{ in } [x_1, x_2] \\ \vdots & \\ y_k + d_k(x - x_k) & \text{for } x \text{ in } [x_k, x_{k+1}] \\ \vdots & \\ y_{N-1} + d_{N-1}(x - x_{N-1}) & \text{for } x \text{ in } [x_k, x_{k+1}] \end{cases} \tag{1}$$

### 2. Cubic Splines Interpolation

According to Anton and Rorres (2013), Cubic Spline is an approximation method by interpolating at points x which are located between two points and assuming that the function is in the form of a triple polynomial. If given n data points $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$ with $i = 1, 2, \ldots, n-1$, then the cubic spline that interpolates these points is shown in the Equation 2.

$$S_i(x) = a_i(x - x_i)^3 + b_i(x - x_i)^2 + c_i(x - x_i) + d_i \tag{2}$$

where:

| | |
|---|---|
| $S_i(x)$ | : Cubic polynomial function that represents a curve in the domain$x_i \leq x \leq x_{i+1}$ |
| $n$ | : Number of observation data points (there are $n-1$ cubic polynomial interpolations) |
| $a_i, b_i, c_i, d_i$ | : unknown Cubic Spline coefficients in the ith interval for any point $x$ in the interval. |

In determining the coefficient values $a, b, c, d$ for $i = 1, 2, \ldots, n-1$, it is necessary to fulfill the following assumptions.

1. $S(x) = S_i(x)$ is defined on the subinterval $[x_i, y_i]$
2. $S(x)$ is a continuous function and can be derived on the interval $[x_i, y_i]$
3. There are points $x_i$ (nodes of $S(x)$) such that it is known that point $a = x_0 < x_1 < \cdots < x_n = b$

### 3. Backpropagation Neural Network Model

An input layer, a hidden layer, and an output layer make up a single hidden layer backpropagation neural network (BPNN), depicts in Figure 1. Using weights, adjacent layers are connected, this class is distributed from 1 to 1. The number of input nodes and hidden layer nodes cannot be calculated theoretically. However, several academics have suggested some heuristic methods. However, no one solution can solve every issue. Trial and error based on the experimental data's least squares error is the most typical method for determining the right amount of input nodes and hidden nodes.

For one step-ahead forecasting in the present investigation, a single hidden layer BPNN is employed. To forecast the current value, a number of earlier observations are used. Therefore, the input is $y_{t-n}, y_{t-n+1}, \ldots, y_{t-2}, y_{t-1}$ and $y_t$ is the output.

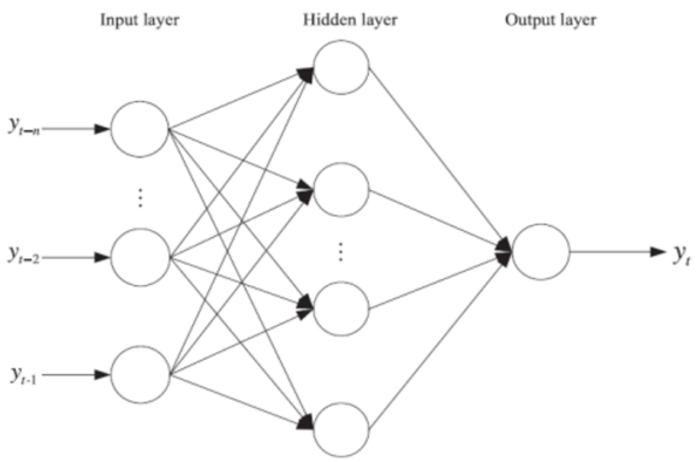


Figure 2. Single hidden layer BPNN structure


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Each node in the same layer generally has the same activation function. The linear activation function is the one that is most frequently utilized for the output layer since the nonlinear activation function can generate distortion in the expected output. The activation function on hidden layer generally uses Logistic and Hyperbolic function (Asaad and Ali, 2019).

The convergence of a training method is significantly influenced by a network's initial weights and the minimum MSE between forecasted and actual values generated from the output of the neural network. The initial values of the connection weights should be randomly assigned, and the error between the estimated value and the actual value is communicated through the network to update the weights. In theory, any kind of fully trained model can be simulated using a neural network. Before the model is used for prediction, it must be trained first. Assuming that the number of input neurons, hidden neurons, and output neurons are n, m, and one, respectively, the neural network's training procedure is described in the following steps.

**Step 1.** Hidden layer stage: The first step in hidden layer step is calculate the outputs of all neurons in the hidden layer using the Equation 3 and 4.

$$net_j = \sum_{i=0}^{n} v_{ij} x_i \qquad i = 1, 2, \ldots, n \tag{3}$$

$$y_j = f_H(net_j) \qquad j = 1, 2, \ldots, m \tag{4}$$

where $net_j$ is the activation value of the jth node, $j = 1, 2, \ldots, m$ is the output of the hidden layer, and fH is the activation function of the node. The commonly used activation function is log-sigmoid activation using Equation 5:

$$f_H(x) = \frac{1}{1 + \exp(-x)} \tag{5}$$

**Step 2.** Output layer stage: The output of a neuron in the output layer is represented using Equation 6:

$$O = f_0 \left( \sum_{j=0}^{m} \omega_{jk} y_j \right) \tag{6}$$

where $f_O$ is the activation function, which is usually a linear function. All weights are initially assigned a random value, then the weights are changed according to the delta rule based on the training samples.

## C. RESULTS AND DISCUSSION

Data on direct economic losses were explored using time series plots prior to doing forecasting analysis with BPNN. Figure 3 displays the real facts on the direct economic losses caused by the earthquake in Indonesia. On the other hand, Figure 4 shows the time series plot of interpolation data with cubic spline and piecewise interpolation. Following the data exploration process with visualization time series plots, analysis using the BPNN approach, which uses interpolated data, is the next step.

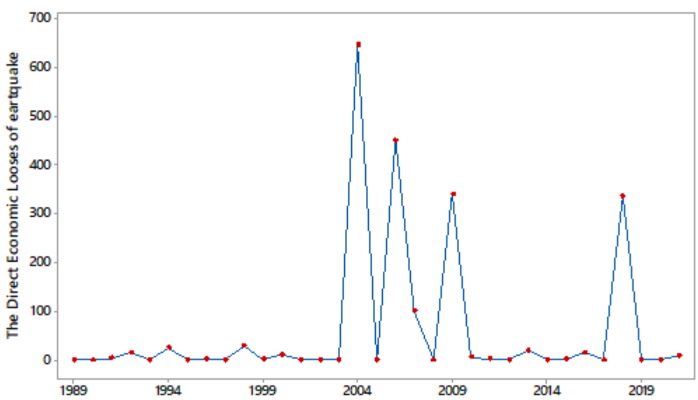


Figure 3. The Time Series Plot of Actual Direct Economic Losses of Earthquake in Indonesia from 1989-2021 (Unit: 100 billion Rupiah)

Figure 3 indicates that the year with the largest losses was 2004, even though it is known that Aceh experienced an earthquake at the end of 2004 with a magnitude of 9.1 on the Richter scale. At that time, Indonesia's economic losses were over 64 billion


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Rupiah, or Rp 64,467.574,400.000. Then, following the greater losses, earthquakes with magnitudes greater than 6 on the Richter scale occurred in Jogjakarta, Padang, and Palu, respectively, in 2006, 2009, and 2018.

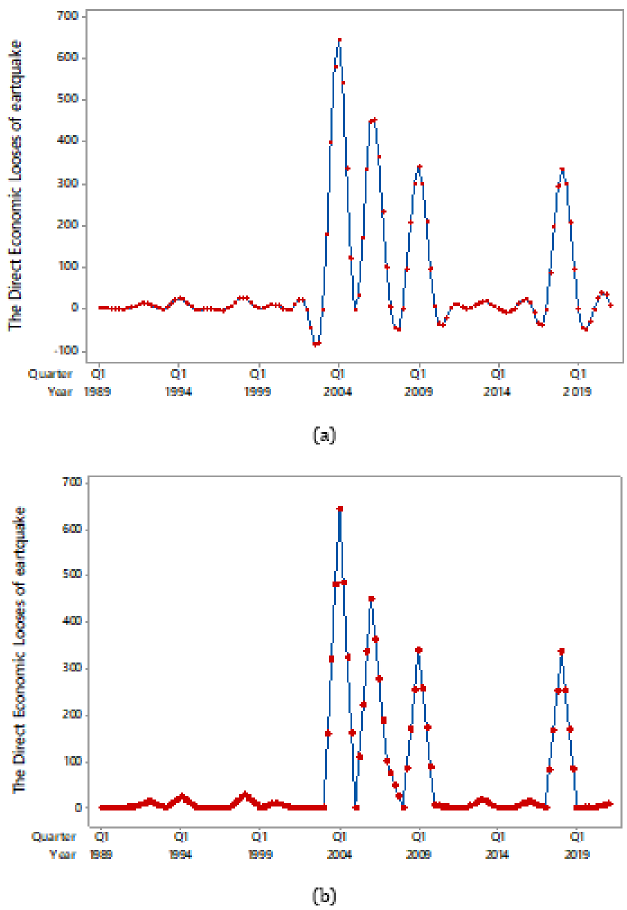


Figure 4. The series created by (a) Cubic Spline Interpolation (b) Piecewise Linear Interpolation

Figure 4 illustrates how the results of piecewise interpolation and cubic spline modelling are quite comparable. We used four virtual points as an interpolation in both. As a result, the fresh data samples from the annual data become quarterly data. The first step of ANN analysis is normalizing the data. The original data cannot be used directly as input variables when using the Neural Network method for prediction. Moreover, when the magnitude of the original data is very different, it is easy to lose information when we enter the original data directly into the model. Therefore, to overcome this problem, the data normalization is carried out first with the scale function in the R software. The normalization formula used is $X_{norm} = \dfrac{x - \min(x)}{\max(x) - \min(x)}$, such that the normalized value is between 0 and 1 or -1 and 1. The next step is to analyze the normalized data on cubic and piecewise interpolation data by applying the BPNN method. The data is divided into two groups, namely training data and testing data. Testing data is data for the last 5 years, while training data is the rest. Analysis of the BPNN method using the R software and the neuralnet function. This paper uses only 1 hidden layer. By doing some trial and error on the number of nodes. The following results were obtained:

Table 1. The result of BPNN Model in Training Period

| **Number of Nodes in the hidden layer** | **RMSE** | |
|---|---|---|
| | **Cubic** | **Piecewise** |
| 2 | 0.04508033 | 0.1654886 |
| 3 | 0.03266983 | 0.1437526 |
| 5 | 0.02836103 | 0.1331682 |
| 10 | 0.02578031 | 0.1325532 |
| 20* | 0.02386881* | 0.1322275* |
| 25 | 0.02389295 | 0.1324868 |

By choosing multiple numbers, specifically ranging from 2 to 25, to determine the number of nodes in the hidden layer by trial and error, the number of nodes chosen is determined by taking the minimum RMSE value. Table 1 shows that the number of nodes 20 gives the most optimal prediction error results, both for cubic and piecewise interpolation data, this is indicated by the smallest RMSE value for the number of nodes 20 in the hidden layer. Furthermore, BPNN analysis was carried out and the predicted value was obtained, then the predicted value was compared with the original data value (in training and testing data), so that the results obtained as shown in Figure 5 - Figure 7 below.

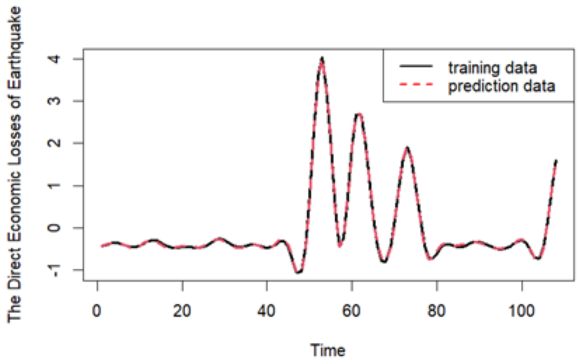


Figure 5. The series created by (a) Cubic Spline Interpolation (b) Piecewise Linear Interpolation

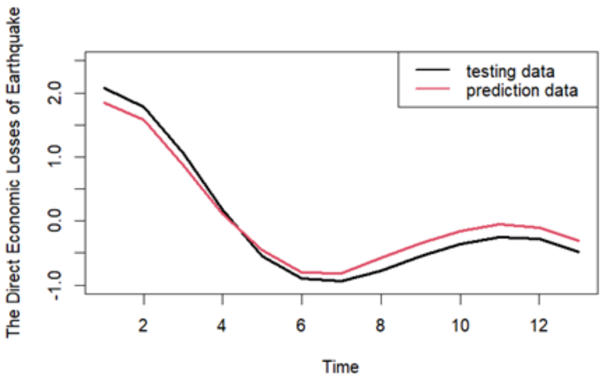


Figure 6. Forecasting Results for Indonesian Economic Losses due to the Earthquake in Indonesia on testing dataset obtained by cubic spline interpolation.

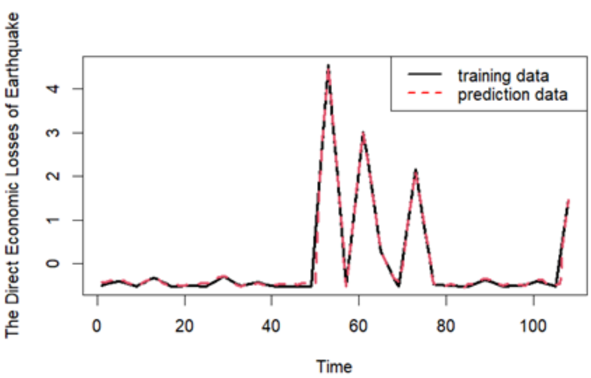


Figure 7. Forecasting Results for Indonesian Economic Losses due to the Earthquake in Indonesia on training dataset obtained by piecewise interpolation

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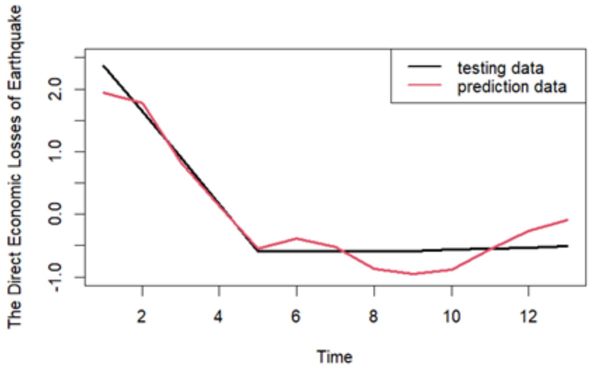


Figure 8. Forecasting Results for Indonesian Economic Losses due to the Earthquake in Indonesia on testing dataset obtained by piecewise interpolation

Based on Figure 5, Figure 6, Figure 7, and Figure 8, in the training data, the data with cubic interpolation displays prediction results that are almost like the actual data. It can be said that the prediction error is quite small compared to other models. This is reinforced by the RMSE value in cubic interpolation, which is smaller than the RMSE in piecewise interpolation, such as 0.02386881 and 0.1322275. Meanwhile, in the testing data, the RMSE of the cubic interpolation data is 0.147 and the RMSE of the piecewise interpolated data is 0.2509243.

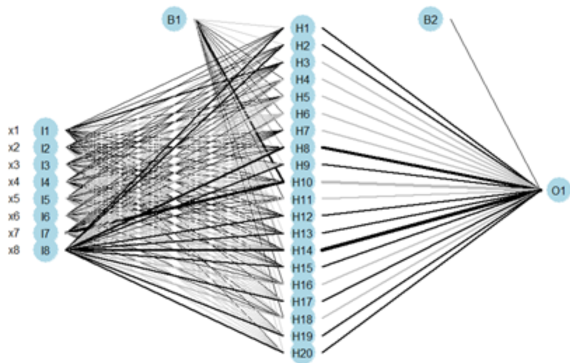


Figure 9. Architecture of the BPNN Network on Indonesian Economic Losses due to the Earthquake in Indonesia with node 20

The network architecture of the optimal BPNN model is BPNN (8-20-1), which consists of 8 nodes in the input layer, 20 nodes in the hidden layer, and 1 node in the output layer. Figure 9 shows a visual representation of the BPNN network design. The 8 nodes in the input layer represent input variables, which are Y's lag variables and namely $X_1, X_2, \ldots, X_8$. While 1 node in the output layer represents the output variable, namely $Y$.

**Comparison of ARIMA-GARCH, NNAR and BPNN Models**

Comparing the results of the accuracy of predictions is carried out to obtain the best prediction model. In this paper, the BPNN model based on interpolation is compared with NNAR (4,1,20) [4] and ARIMA(2,1,1)-GARCH(2,0). The Root Mean Square Error (RMSE) are used to assess the performances forecasting of the novel hybrid system in direct economic losses of earthquake in Indonesia. On the other hand, to evaluate the performance of the new hybrid system in predicting the direct economic damage of the earthquake in Indonesia, the BPNN model-based on interpolation was added to compare with the NNAR (4,1,20) [4] and ARIMA (2,1,1) - GARCH (2,0). These measures are defined as follows:

Table 2. Comparison of accuracy of the ARIMA, NNAR and BPNN models

| Data | Method | RMSE |
|---|---|---|
| Training | ARIMA-GARCH | 9,197 |
| | NNAR | 2,412 |
| | BPNN | 0.024* |
| Testing | ARIMA-GARCH | 8,4 |
| | NNAR | 24,66 |
| | BPNN | 0.174* |

Table 2 shows the comparison of model accuracy on ARIMA-GARCH, NNAR and BPNN for Training data and Testing data. The results obtained are that the best method for predicting direct economic losses due to earthquakes in Indonesia is to use the Backpropagation Neural Network (BPNN) method, because it produces the lowest RMSE value, both on training data and testing data, which is 0.0024 on training data and 0.174 on the testing data. The findings of this study support Zhao's earlier research (2019), which found that cubic spline interpolation produces better results and that the BPNN method outperforms other traditional methods for forecasting economic losses in Indonesia.

This study inline by Azmi et al (Azmi et al., 2022), which solely employed NNAR and ARIMA, and it also demonstrates that the BPNN model is far more effective in predicting direct economic losses due to earthquakes in Indonesia. Additionally, compared to earlier research, specifically Zhao et al (Zhao et al., 2019), where the BPNN accuracy value is only 3.29, the BPNN model used to estimate economic losses in Indonesia offers more accurate results.

## D. CONCLUSION AND SUGGESTION

In conclusion, piecewise linear interpolation and a cubic spline were also options for adding four virtual points. This work used interpolated data from 1989 to 2016 as a training period and the most recent five years, from 2017 to 2021, as a testing period to fit the BPNN model, NNAR (4,1,20) model, and ARIMA (2,1,1) - GARCH (0,2) model to anticipate the direct economic losses of earthquake in Indonesia. According to the analysis, the result of this study is that virtual points (by interpolation) are an effective way to solve the small sample problem for the direct economic loss of earthquake predictions. In the two proposed interpolation methods, namely the piecewise linear interpolation and the cubic spline interpolation. The cubic spline interpolation is the most powerful tool to predict the direct economic loss of earthquake in Indonesia. In addition, based on the small sample problem, the BPNN method effectives for predicting the non-linear direct economic losses and outperforming the other traditional methods with RMSE is 0,024 in the training period and 0,174 in the testing period, it is significantly lowest than the others. The forecasting results of direct economic loses in Indonesia for 2022 are IDR 2,930,129,000,000 and IDR 43,120,260,000,000 for 2023. In the case of forecasting, the results of this model will be used for learning and research purposes only. These findings should allow policymakers to provide a representation of the expenses associated with disaster recovery.

## DECLARATIONS

AUTHOR CONTIBUTION

All authors contributed to the writing of this article.

FUNDING STATEMENT

-

COMPETING INTEREST

The authors declare no conflict of interest in this article.

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