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PREDICTION INDONESIA COMPOSITE INDEX USING INTEGRATION DECOMPOSITION- NEURAL NETWORK ENSEMBLE DURING VUCA ERA

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ABSTRACT

The Volatility, Uncertainty, Complexity, and Ambiguity (VUCA) era causes turmoil in the capital markets, stocks, commodities, etc. The impact is a decline in the Composite Stock Price Index (IHSG) in 2020. Therefore, future data is needed to inform investors and business people when making portfolio decisions. This paper develops a decomposition and Neural Network (NN) integration model to predict ICI during the VUCA era. The results are presented empirically to show the model's effectiveness in reducing prediction errors. First, the actual data is converted into three components; second, with the Neural Network Ensemble (NNE) approach where the initial step of decomposition results is trained using artificial NN with architecture, training data, and topology to produce individual networks; The output is selected using Principal Component Analysis (PCA) and becomes input to the ensemble model, then combined using a simple average and weighted average. The empirical results from ICI predictions illustrate: (1) decomposition has the potential to overcome data that is characterized by high volatility; (2) NNE is able to reduce errors (MSE≤0.100e-4, MAE≤0.01) compared to individual networks (MSE=0.0024 MAE=0.0376); (3) ensemble combinations using weighted averages (MSE≤3.00e-5,MAE≤0.002) are superior to simple averages (MSE≤5.00e-5,MAE≤0.01); (4) the integration carried out shows effectiveness in predicting ICI and provides better prediction results.

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1. INTRODUCTION

The emergence of COVID-19 impacted not only the health sector but also the economic sector, which was marked by negative signals on financial markets that caused losses for the whole world, including Indonesia [1], [2]. The VUCA era presents challenges and threats from various directions. It causes a business environment that is increasingly fluctuating, complex, and increasingly uncertain, such as uncertainty in the capital market caused by technological disruption, high competition, market instability, and changing consumer desires, and this is a challenge that must be faced by every business person and investor, where both must always be prepared for all possibilities that may occur.

Many countries have experienced a decline in stock prices due to economic uncertainty and stated that the stock market belongs to a VUCA environment [3]. Insignificantly, the VUCA era affected the movement of stock exchanges in Indonesia. The impact of the global economy can be seen from the data released by the Intrinsic Mode Function (IMF) in October, during which a decline of -4.4% and a global trade volume of -10.4% [4]. In the meantime, Indonesia had economic growth in the first quarter of 2020, down 2.97% from economic growth in the same period of 2019 [5]. The stock exchange indicated by ICI also experienced a decrease of -28.21%, which was recorded for May 18, 2020, of Rp. 4,511 from the price on January 2, 2020, of Rp. 6,284. The high level of economic uncertainty resulting from the VUCA era makes investors and business people sell their investment portfolios to countries with more robust economic fundamentals or countries with a low level of risk. This fact shows a strong relationship between the VUCA era and capital market conditions, and ICI continues to experience sharp fluctuations and tends to decline. Financial data predictions, especially ICI, are a series of continuous predictions because stock prices will continue to change over time [6].

Many business people and investors routinely need several time series data from various sources to make decisions and more strategic planning by making predictions [7]. The data can be developed to provide scientific information that can support decision-making. Forecast data will only be ultimately able to provide accurate future predictions sometimes. Still, if investors and business people only rely on judgment or wrong estimates, the consequence is that business people and investors will suffer losses. Therefore, one of the roles of prediction is to deal with future uncertainties by analyzing trends and variations in data [8].

ICI time series data experiences fluctuations with nonstationary and nonlinear characteristics; this is a challenge in predicting this data for the future. Experts have used many prediction approaches, including using statistical and econometric methods [9], [10], artificial intelligence methods [11], [12] and integration approaches [13], [14]. The three methods have their advantages and disadvantages. Statistical and econometric methods can produce good predictive results based on the assumptions of linearity and stationarity in time series. However, in reality, statistical and econometric methods need help capturing data's nonlinear and nonstationary characteristics. Because of these limitations, many researchers have used artificial intelligence to predict. This method is used because it is considered to have adaptive training capabilities [15], [16], and can provide increased accuracy and stability of prediction results. However, in reality, single artificial intelligence methods still have limitations, such as sensitivity to the parameters used, which often causes overtraining, especially in some complex models such as Neural Networks (NN). Because both methods have limitations and advantages, many researchers have used integration methods to overcome these problems. Purohit *et al.* stated that the integration method provides better results than individual models in predicting crop prices [17], Albari *et al.* concluded that the integration method provides low residual performance for predicting the value of Indonesian exports [18].

Statistical and econometric methods commonly applied include exponential smoothing, ARIMA, and decomposition, and artificial intelligence uses include NN and Long Short Term Memory (LSTM). Research that has used both methods in integrating, among others, Qian *et al*. used an integration approach between decomposition methods (wavelet transformation, empirical mode decomposition, other decomposition methods) with three types, then continued with several methods in artificial intelligence approaches (NN, LSTM) to predicting wind energy, this research only combines the two approaches where an artificial intelligence approach is used even though this approach requires many parameters that are carried out repeatedly to get the best model performance which can cause overtraining in the training process [19]. Subsequent research uses variational mode decomposition to transform time series data and NN with the same architecture, then continues with an ensemble approach by adding up all the prediction results to predict product future prices. Still, the ensemble approach used in this research only adds up the results from each model obtained [20]. Sun *et al*.'s research integrates through recombination decomposition using Fast

Ensemble Empirical Mode Decomposition (FEEMD) to decompose non-stationary data followed by Partial Autocorrelation Function (PACF) analysis. It ends by using the Stacking Driven Ensemble Model (SDEM) from several artificial intelligence approaches (BPNN, IBPNN, GRNN, ELM). Still, this research only compares the performance results of the decomposition process with various artificial intelligence approaches [21]. Jamei *et al*. use multiple decomposition training algorithms to estimate monthly rainfall. The data collection was decomposed into Intrinsic Mode decomposition Functions (IMFs) using the TVF-EMD method, and substantial delays were identified using the Partial Autocorrelation Function (PACF). Meanwhile, machine training algorithms include Bidirectional Encoder-Decoder (EDBi-LSTM), Adaptive Boosting Regression (Adaboost), Generalized Regression Neural Network (GRNN), and Random Forest (RF). Furthermore, the study assesses the error performance of the machine training algorithms used [22]. Li *et al*. apply four decomposition methods to break down Electroencephalogram (EEG) data into components of various complexity, followed by a Convolutional Neural Network (CNN) architecture and an averaging approach [23].

Based on previous research, research gaps were found in integrating and overcoming overtraining from using artificial intelligence models. In particular, this study suggests using decomposition techniques to divide accurate data into three components that explain time series data. Decomposition separates data into three components: seasoning, trending, and random, a unique characteristic (non-stationary and non-linear) of time series data. This method was chosen because of the severe volatility of the ICI time series data. In contrast, previous research used a decomposition methodology that transformed the original data into numerous signals by focusing on the correlation value of each data point without paying attention to the characteristics of the data. The second portion of this study involved an ensemble with many steps. First, individual network generation employs NN with a combination of architecture, training data, and topologies to predict all components separately; second, personal networks are selected using the PCA technique; and third, a combination of individual networks with simple average (selected dimensions are combined by taking the average) and weighted average (selected dimensions are weighted according to their performance) to produce a model capable of correcting bias and systematic errors in data distribution. The ensemble in this work concentrates on the parameters of the NN to be trained and develops a predictor to overcome the NN's overtraining problem and provide optimal prediction outputs.

2. RESEARCH METHODS

2.1 Architecture Models

This section describes the integration developed in detail. The study includes two parts: actual data transformation using decomposition techniques and NNE, while NNE consists of four steps: individual network generation using NN, network selection with PCA, a network combination (weight and simple average), and evaluation of prediction results. **Figure 1** shows the implementation procedure of the proposed model and is the result of a modification from [19], [20], [21] for the integration approach. Part 1, the actual data transformation. This section divides the data into three components: seasonal, trend, and random, with two types of decomposition. The goal is to reduce the volatility and complexity of the actual data while minimizing the computational burden. Part 2, NNE. NNE consists of four steps. The first is generating individual networks by varying parameters related to the design of network training (architecture, algorithm, and training data set). The algorithm used in this section is a backpropagation neural network (BPNN), which trains each component of the decomposition results. BPNN is used to train decomposition components because of its powerful ability to model complex nonlinear relationships, which is critical for accurately capturing the underlying structure in decomposed data. BPNN is very flexible and can be adapted to various tasks, making it suitable for multiple types of decomposition, whether for capturing trends, seasonality, or noise. Gradient-based optimization ensures efficient learning and convergence, allowing the network to adjust and minimize errors effectively. Additionally, the universal approximation capabilities of BPNNs mean they can approximate any continuous function, providing a powerful tool for modeling complex patterns in components. Its scalability and an established body of research and practical applications further support its use, making BPNN a reliable choice for tasks involving complex data parsing. Second, network selection. PCA is used to select individual networks. Third, network combination. The NNE is built by integrating the selected networks and combining the best networks using averaging techniques. Fourth, the prediction results (MSE and MAE) are evaluated. The resultant error is used to assess performance.

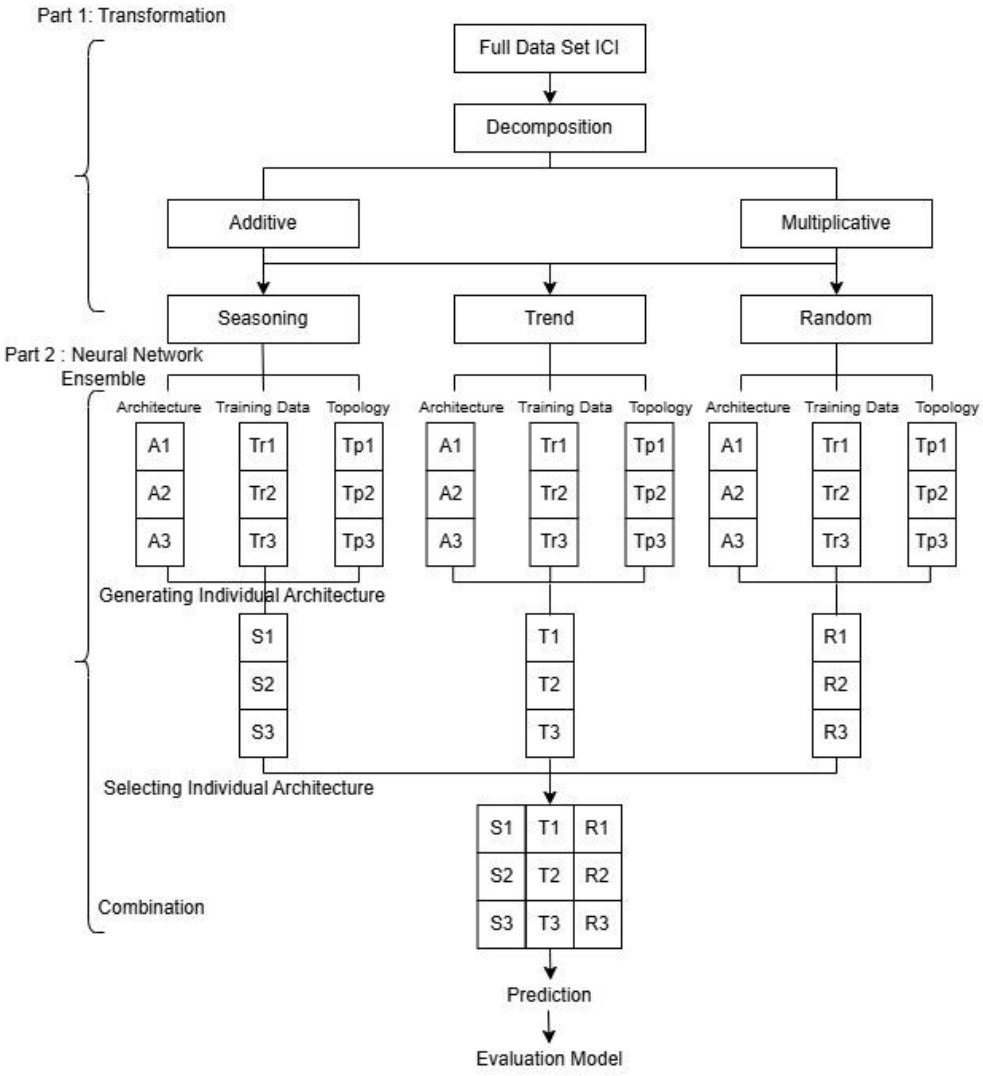

Figure 1. Structures of decomposition-NNE based approach

2.2 Decomposition Techniques

Researchers frequently employ decomposition models to partition big data sets [24]. Several prior researchers have investigated the goal of sharing this data to address issues with time series data. As Wu and Huang stated, using decomposition techniques can reduce the overall complexity of predictions without requiring additional data so that it can improve prediction performance [25]; Altan *et al.* stated that the decomposition technique was able to reduce volatility problems and was able to increase prediction accuracy decomposition technique was able to reduce volatility problems and was able to increase prediction accuracy [26]; Huang *et al.* noted that the divide and conquer strategy is the central concept for solving prediction problems [27].

Since its introduction in the 1920s, economists have utilized the decomposition approach extensively to recognize and manage business cycles. In practice, the decomposition technique divides the data into several components and identifies these components separately to obtain high accuracy [28]. Data distribution consists of three components: trend, seasonality, and random. Decomposition modeling is presented in the following equation [29]:

$$y_t = f(I_t, T_t, C_t) + E_t \quad (1)$$

2.3 Neural Network Ensemble

Many parameters are required to create a BPNN network architecture, such as a hidden layer, initial random weights, learning rate, and momentum rate. Parameter selection and small changes in the training set can significantly change prediction output. Many studies show that individual network generalizations are not unique or that networks are unstable. The instability of individual networks is a problem in predictions using individual networks [28], [29]. Hence, instead of training many individual networks, it is more optimal to combine several individual networks. Combining several individual networks is known as the NNE technique.

NNE has been widely used in many studies. The purpose of doing NNE is to avoid overtraining when carrying out training by combining several individual networks that have been trained. The proposed NNE approach consists of three stages: individual network generation, individual network selection, and network combination, as shown in **Figure 2.**

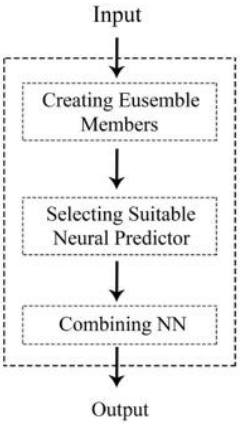

Figure 2. Neural network ensemble framework

Step 1: Generation of Individual Networks

NN is an algorithm designed according to the work of brain function [30], [31], [32], which consists of three layers [33], [34], [35]. Each layer consists of a certain number of neurons that will connect one layer to another. The relationship between neurons will be calculated iteratively in the training stage [36], [37], [38]. The network will initialize randomly in the training process, and the training process is obtained based on adjusting the weights until the desired criteria are met [39]. NN is a (nonlinear) function with many parameters where the parameters and functions are arranged in layers [40]. NN network modeling can be mapped in the following equations [19], [41], [42]:

$$\hat{y}_t = \psi_k \left(w_{k0} + \sum_{j=1}^{p} w_{kj} \psi_j \left(v_{j0} + \sum_{i=1}^{n} v_{ij} x_i \right) \right) \quad (2)$$

This study uses the type of BPNN. The BPNN used consists of three layers: the input layer, the hidden layer, and the output layer, each consisting of neurons. The input layer consists of p neurons, a hidden layer of p neurons, and an output layer of k neurons. Based on equation (2), BPNN can be mathematically derived as the following equation [43].

$$\hat{y}_{(t+1)} = \begin{bmatrix} \widehat{y_1}(t+1) \\ \widehat{y_2}(t+1) \\ \vdots \\ \widehat{y_k}(t+1) \end{bmatrix}$$

$$= \begin{bmatrix} f_2\left[\sum_{i=1}^{q} f_1\left(\sum_{j=1}^{p} w_{ij}(t)x_j(t) + w_{i0}(t)v_{1i}(t) + v_{10}(t)\right)\right] \\ f_2\left[\sum_{i=1}^{q} f_1\left(\sum_{j=1}^{p} w_{ij}(t)x_j(t) + w_{i0}(t)v_{2i}(t) + v_{20}(t)\right)\right] \\ \vdots \\ f_2\left[\sum_{i=1}^{q} f_1\left(\sum_{j=1}^{p} w_{ij}(t)x_j(t) + w_{i0}(t)v_{ki}(t) + v_{k0}(t)\right)\right] \end{bmatrix}$$

$$= \begin{bmatrix} f_2\left[\sum_{i=1}^{q} f_1\left(\sum_{j=1}^{p} w_{ij}(t)x_j(t)\right)v_{1i}(t)\right] \\ f_2\left[\sum_{i=1}^{q} f_1\left(\sum_{j=1}^{p} w_{ij}(t)x_j(t)\right)v_{2i}(t)\right] \\ \vdots \\ f_2\left[\sum_{i=1}^{q} f_1\left(\sum_{j=1}^{p} w_{ij}(t)x_j(t)\right)v_{ki}(t)\right] \end{bmatrix}$$

$$= \begin{bmatrix} f_2\left[V_1^T(t)F_1\left(W(t)X(t)\right)\right] \\ f_2\left[V_2^T(t)F_1\left(W(t)X(t)\right)\right] \\ \vdots \\ f_2\left[V_k^T(t)F_1\left(W(t)X(t)\right)\right] \end{bmatrix}$$

$$\hat{y}_{(t+1)} = F_2[V^T(t)F_1\left(W(t)X(t)\right)]$$

and the following equation is obtained:

$$\hat{y}_{(t+1)} = F_2[V^T(t)F_1\left(W(t)X(t)\right) \quad (3)$$

BPNN trains individual networks by altering the architecture, training data, and topology.

1) Architectural variations

Selection of the optimal number of neurons in the hidden layer is one of the important problems in determining an NN. Many previous studies have found approaches to determine the number of hidden neurons. Meng, *et al* with the equation $\frac{3^{N_i}}{(N_i+3)}$, proposed a strategy to determine the number of hidden neurons in predicting wind speed, and the results showed good performance [44], Wang and Hu used the equation $\frac{\sqrt{N_i+N_o}}{2}$ to determine the number of neurons from the hidden layer and the research results show an increase in prediction accuracy so that it can be used for predictions [45], and Sheela and Deepa uses the equation $\frac{4N_i}{N_i-2}$ in selecting the number of hidden neurons in the NN network, and the results of the approach used can increase network stability and can reduce errors with N_i being the number of input neurons and N_o being the output neurons [46].

2) Variation of training data

They used different training data when training could provide different prediction results. This study generated various training data by resampling (cross-validation) and preprocessing the time series data.

3) Topology variations

Each trained network undergoes topological changes by altering its initial random weights, learning, and momentum rates.

Step 2: Network Selection

The selection of parameters as a variation in the generation of individual networks, with each experiment three times, gives different individual network performances. PCA is used to select and train individual networks to avoid correlations from each network. Using the PCA, a multivariate technique, several associated individual networks are transformed into uncorrelated networks while keeping their maximum variance [47].

PCA is applied to reduce the dimensionality of a data set [48]. In individual network selection, PCA is used to find a new coordinate system from several networks that have been trained so that they are concentrated on a few coordinates. Simply put, PCA will find an orthonormal basis as a new basis from a set of trained individual networks. The procedure for selecting several individual networks follows the following steps.

1) Compute the average vector of all data in the individual network.

$$\bar{\boldsymbol{y}} = \frac{\boldsymbol{1}}{\boldsymbol{N}}\sum_{\boldsymbol{n=1}}^{\boldsymbol{N}} \boldsymbol{y_n} \tag{4}$$

2) Subtract the average vector from each data point for all data.

$$\hat{y} = y_n - \bar{y} \tag{5}$$

3) Let $\hat{\boldsymbol{y}} = \left[\hat{\boldsymbol{y}}_{\boldsymbol{1}}, \hat{\boldsymbol{y}}_{\boldsymbol{2}}, \cdots, \hat{\boldsymbol{y}}_{\boldsymbol{p}}\right]$, an orthonormal matrix with a covariance matrix:

$$\boldsymbol{S} = \frac{\boldsymbol{1}}{\boldsymbol{N}}\hat{\boldsymbol{y}}\hat{\boldsymbol{y}}^{\boldsymbol{T}} \tag{6}$$

4) Calculate the eigenvalues and eigenvectors of the covariance matrix and arrange them in descending order.

5) Choose the $\boldsymbol{L}$ eigenvector that corresponds to the largest $\boldsymbol{L}$ eigenvalue to build the $\boldsymbol{V_L}$matrix by forming an orthogonal system column. The vector $\boldsymbol{L}$ is called the principal component which forms a subspace close to the orthonormal matrix.

6) Project the orthonormal data matrix into the obtained subspaces.

7) New data is the coordinates of data points in new space.

$$Z = V_L^T \hat{y} \tag{7}$$

The original data will be approximated by the new data with the following equation:

$$y \approx V_L Z + \hat{y} \tag{8}$$

Step 3: Network Combination

Ensembling combines prediction results [49], [50]. In this research, the ensemble preparation uses training data samples that have been decomposed first, as shown in **Figure 1**. In the first step, several networks are built using three different variations. In the second stage, the individual networks formed are then selected using PCA, and finally, in the third stage, a network combination is carried out using the averaging technique.

Assume that the function $f: \boldsymbol{R^N} \rightarrow \boldsymbol{R^M}$, with p samples, (x^u, y^u) for a particular problem where $y^u = f(x^u)$ where $u = 1,2,\cdots,p$. The sample is assumed to be taken randomly from the distribution of $p(x)$. The ensemble of individual networks consists of n forecast results of a single NN network and the output of the ith single network at input x is called $f_i(x)$. Then the ensemble technique with weighted averaging in the following form.

$$\hat{f}(x) = \sum_{i=1}^{n} w_i f_i(x) \tag{9}$$

Step 4: Evaluation of Predictive Results

Evaluation of the prediction results of this research is measured using Mean Absolute Error (MAE) and Mean Square Error (MSE) which are error metrics used in time series data predictions [51], [52].

$$MAE = \frac{1}{N}\sum_{i=1}^{N}(y_i' - y_i),$$
$$MSE = \sum_{i=1}^{N}\frac{(y_i' - y_i)^2}{N} \tag{10}$$

where y_i is the predicted output, y_i' is the actual output, and N N is the number of samples used. The network design process plays an important role in determining network performance.

3. RESULTS AND DISCUSSION

3.1 Indonesia Composite Index Price

The data in this study is time series data from ICI data from 1 July 2021 to 15 July 2022, with a total of 253 observations. Researchers only took data from the past year to see the impact of the pandemic and the arrival of the VUCA era in Indonesia. Hence, the data became unstable and experienced rapid changes marked by data volatility [53], [54]. ICI time series data was obtained from the website finance.yahoo.com and is presented in Figure 3.

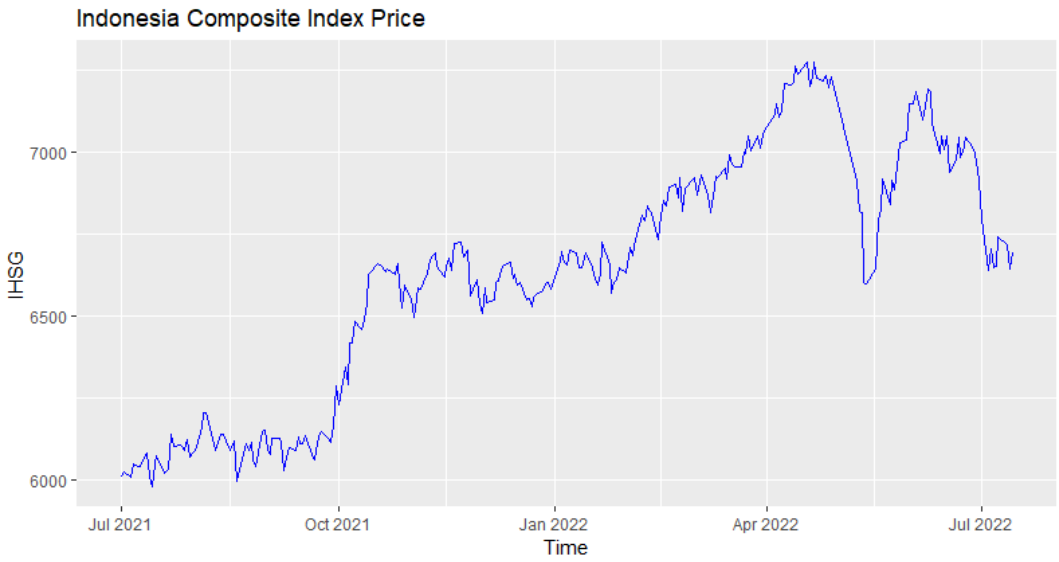

Figure 3. Indonesia composite index 2021-2022

Figure 3 shows very volatile fluctuations from the ICI data that will be studied, marked by a very high 29-time spike for rising and falling prices. This surge continued until the end of this research data was used. Extreme increases occur at the end of 2021, and extreme decreases around May 2022.

Table 1. Statistical Parameters of Daily ICI Using Observations 2021-2022

Number of data points	Value
Minimum	5979.21
Maximum	7276.19
Mean	6620.9
Median	6647.06
Standard deviation	363.86
Skewness	-0.21
Kurtosis	-1

Table 1 shows the statistical parameters of the data used. It can be seen from the table that the range between the lowest and highest data is 1,296.98 points; this shows quite a long movement. For the centralization measure, it can be seen that the average value is smaller than the median, so the frequency distribution curve formed is left skewed or negatively skewed. The standard deviation number is the measure of dispersion. In Table 1, this value is relatively significant, showing that prices change substantially daily, demonstrating the price volatility in the data. For a skewness value smaller than zero, this indicates that the ICI data is distributed skewed to the left, indicating a high level of fluctuation in the data. For a kurtosis size smaller than 3, the curve formed is platykurtic (tends to be flat).

3.2 Empirical Result and Discussion

This section presents empirical results and discusses the effectiveness of decomposition models and ensembles with an integration approach between decomposition techniques and the NNE approach. The performance of each model will be measured using MSE and MAE. In addition, different models were used for comparison. Several experimental results are discussed to demonstrate the superiority of the decomposition and NNE approaches. Daily data spanning one year with a total of 253 observations were used for the empirical study.

According to the model development step, part 1 transforms the data using decomposition to break down the original ICI data set into three components: seasonal, trend, and random. In general, the component with the highest frequency factor is the random component, the middle component is seasonal, which has sinusoidal solid fluctuation characteristics, and the lowest component is a trend, which will show the trend of time series data for the long-term in the future. This research uses additive (type 1) and multiplicative (type 2) decomposition. The results of the first decomposition are presented **Figure 4** and **Figure 5**.

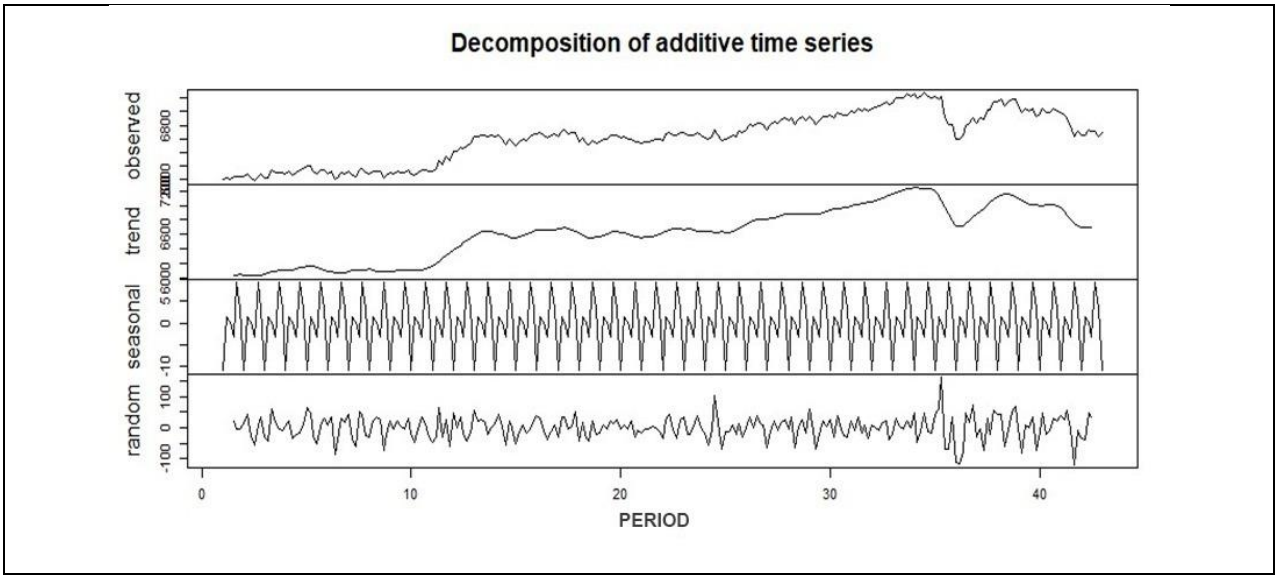

Figure 4. Daily ICI price after decomposition process with additive decomposition

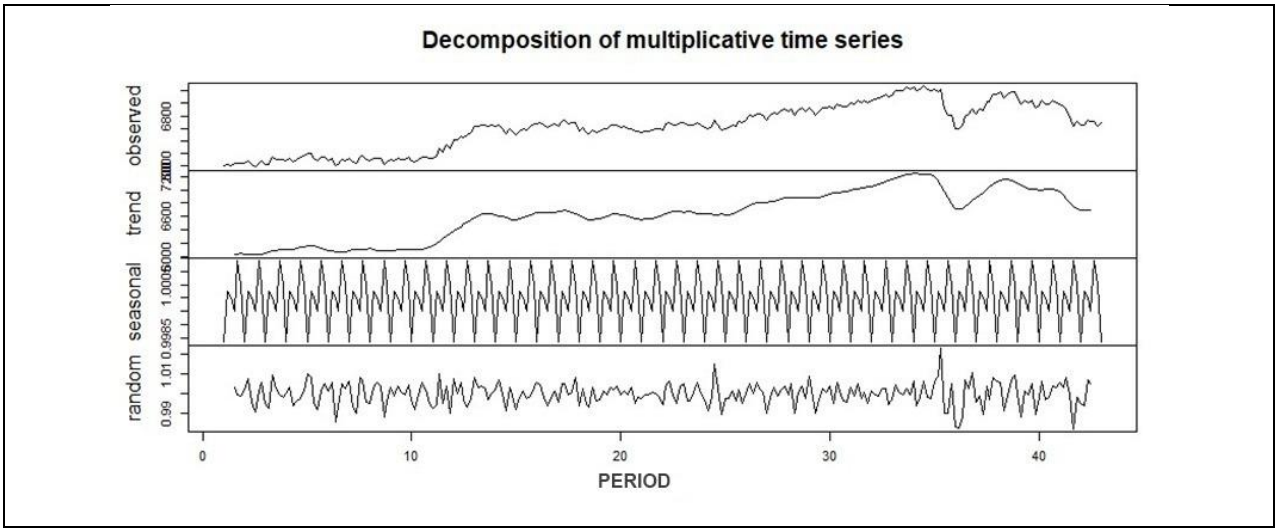

Figure 5. Daily ICI price after decomposition process with multiplicative decomposition

Figure 4 and **Figure 5** show the results of the transformation using decomposition. The two types of decomposition provide almost the same picture, such as an upward trend in the data with three spikes; for seasonal, the cycle is visible, while for random data, the data set is volatile, and the data is mostly found in the random component. This is because decomposition aims to separate the main elements of the data, such as trend, seasonality, and noise, even though the methods are different.

Part 2 of individual network development begins with single network prediction, accompanied by phases of constructing ensemble members for the three previously stated components. **Table 2** provides a complete report of the results of the ensemble model for training and testing groups, as well as the results of creating ensemble members. Three different methods were used to create ensemble members. They are as follows: (1) architectural variations, carried out using the three approaches described previously, neurons obtained from hidden layers were 5, 1, and 12; (2) variations in training data, carried out using cross-validation with variations of 60%, 70%, and 80% training and 40%, 30% and 20% testing **[55]**; and (3) topology variations, this variation is carried out by varying initial random weights, activation function, different training rates for each network being trained. This stage is carried out to train a single network with various variations, demonstrated by empirical results from the performance of each single network. The **Table 2** and **Table 3** uses the terms $\boldsymbol{A}$ for architecture, $\boldsymbol{T_r}$ for training data, and $\boldsymbol{T_p}$ for topology.

Table 2. The MSE and MAE of Decomposition-NNE Approach for Different Creating Ensemble Members Type 1

Creating Ensemble	Criteria	Training		Testing	
		MSE	MAE	MSE	MAE
Seasonal Component					
Architecture	A_1	2.5344e-07	4.3028e-04	4.1994e-06	0.0013
	A_2	0.1269	0.2822	0.1274	0.2755
	A_3	5.5546e-08	1.9031e-04	3.9932e-09	5.5743e-05
Training Data	T_{r1}	8.1826e-07	6.6954e-04	1.1130e-08	7.0378e-05
	T_{r2}	4.2613e-07	4.3515e-04	4.4819e-07	5.4105e-04
	T_{r3}	1.7767e-07	2.9704e-04	1.2715e-07	2.7980e-04
Topology	T_{p1}	8.7841e-07	5.7118e-04	3.8067e-05	0.0029
	T_{p2}	3.4593e-0 8	1.7597e-04	0.0094	0.0634
	T_{p3}	1.2641e-18	8.0822e-10	6.3088e-19	3.5139e-10
Trend Component					
Architecture	A_1	0.0198	0.0292	0.0010	0.0175
	A_2	0.0209	0.0392	0.0028	0.0360
	A_3	0.0196	0.0306	2.5669e-04	0.0124
Training Data	T_{r1}	0.0198	0.0282	0.0012	0.0162
	T_{r2}	0.0099	0.0222	9.0560e-04	0.0221
	T_{r3}	0.0050	0.0145	6.1836e-04	0.0184
Topology	T_{p1}	0.0199	0.0350	0.0014	0.0191
	T_{p2}	0.0202	0.0303	0.0020	0.0311
Creating Ensemble	Criteria	Training		Testing	
		MSE	MAE	MSE	MAE
Random Component					
Architecture	T_{p3}	0.0179	0.0326	1.3954e-04	0.0087
	A_1	0.0043	0.0158	0.0010	0.0177
	A_2	0.0049	0.0265	0.0022	0.0301
	A_3	0.0042	0.0148	5.5842e-04	0.0140
Training Data	T_{r1}	0.0042	0.0149	0.0016	0.0231
	T_{r2}	0.0099	0.0235	0.0016	0.0219
	T_{r3}	0.0051	0.0159	4.4501e-04	0.0146
Topology	T_{p1}	0.0042	0.0154	0.0013	0.0163
	T_{p2}	0.0044	0.0208	0.0017	0.0275
	T_{p3}	0.0035	0.0115	1.6386e-04	0.0098

Overall, the table presented can be explained that **Table 2** shows an evaluation of the performance of the type 1 model. The best variation of neurons in the hidden layer is 12 neurons, the most significant variation in training data is 80% with 202 observations for training and 51 testing data, and for topological variations, it is using the bipolar sigmoid activation function (tansig), training rate 0.1.

Table 3 shows the performance results of type 2 decomposition continued with individual networks. Seasonal components and network performance trends that provide optimum values for different architectures are architecture type 3, training data 2, and topologies 3 and 1, while for the optimum network performance evaluation components are architecture 3, training data 1, and topology 3.

Table 3. The MSE And MAE of Decomposition-NNE Approach for Different Creating Ensemble Members Type 2

Creating Ensemble	Criteria	Training		Testing	
		MSE	MAE	MSE	MAE
Seasonal Component					
Architecture	A_1	7.04E-09	8.03E-05	4.41E-09	4.72E-05
	A_2	0.0791	0.1923	0.0799	0.1936
	A_3	2.60E-09	3.89E-05	5.26E-09	6.78E-05
Training Data	T_{r1}	5.21E-09	5.79E-05	9.02E-09	7.61E-05
	T_{r2}	4.48E-09	4.99E-05	1.87E-15	3.85E-08
	T_{r3}	6.80E-09	5.27E-05	3.88E-27	4.35E-14
Topology	T_{p1}	2.11E-09	4.25E-05	3.87E-11	4.80E-06
	T_{p2}	1.07E-04	0.0098	3.71E-15	5.11E-08
	T_{p3}	5.47E-17	5.40E-09	2.21E-19	4.14E-10

Creating Ensemble	Criteria	Training		Testing	
		MSE	MAE	MSE	MAE
Seasonal Component					
Trend Component					
Architecture	A_1	9.37E-08	1.95E-04	2.03E-06	0.001
	A_2	1.06E-09	2.54E-05	1.25E-09	3.31E-05
	A_3	2.28E-08	8.30E-05	5.73E-09	3.06E-05
Training Data	T_{r1}	2.50E-06	1.10E-03	9.76E-09	9.01E-05
	T_{r2}	1.31E-07	1.52E-04	1.83E-06	0.0012
	T_{r3}	3.80E-07	4.42E-04	3.13E-10	1.49E-05
Topology	T_{p1}	6.93E-07	2.85E-04	9.19E-11	8.82E-06
	T_{p2}	5.12E-07	3.95E-04	5.43E-16	1.56E-08
	T_{p3}	3.47E-15	3.16E-08	8.75E-07	6.46E-04
Random Component					
Architecture	A_1	3.66E-09	5.18E-05	7.98E-09	7.49E-05
	A_2	0.0865	0.1978	0.0845	0.193
	A_3	2.63E-09	3.62E-05	4.37E-09	5.45E-05
Training Data	T_{r1}	2.92E-10	1.46E-05	2.15E-09	3.89E-05
	T_{r2}	8.29E-10	2.07E-05	2.25E-10	1.33E-05
	T_{r3}	3.09E-09	4.05E-05	1.08E-09	2.99E-05
Topology	T_{p1}	1.36E-13	2.81E-07	8.26E-09	8.44E-05
	T_{p2}	1.01E-09	2.31E-05	3.51E-09	5.26E-05
	T_{p3}	3.77E-17	4.83E-09	1.57E-22	1.00E-11

Table 3 shows the performance evaluation of type 2. The results show that the best variation of architecture with neurons in the hidden layer in an individual network is 12 neurons. For the best variation of training data, a variety of three cross-validations were carried out, as well as for variations of network architecture topology, which provides performance. The best is the third type, which 5 hidden layer neuron variations, a training rate of 0.1, bipolar sigmoid activation function (tansig), and a training method called Lavenberg Marquat.

Empirical results in **Table 2** and **Table 3** show that the use of a single network can result in overtraining if the network is continuously trained. At the same time, this research aimed to overcome the occurrence of overtraining to provide optimal predictions by performing an ensemble so that a single network is selected that represents the characteristics of the data next based on the results of observations from each type of model development. It was found that individual networks became more complex due to an increase in neurons in the hidden layer, and MSE and MAE in the training and testing groups using the PCA approach decreased when measuring the error of each network. Using the PCA technique, the table findings are then used to identify an appropriate NN predictor. The PCA method is used to select individual networks while eliminating correlation between separate networks. The PCA results were then combined using simple, average, and weighted averages, and the performance results were evaluated using MSE and MAE, which are presented in **Table 4**.

Table 4. The MSE And MAE of Random Component for Different Combination and Individual Networks

	Training		Testing	
	MSE	MAE	MSE	MAE
Model Development (Type 1) *Weighted Average*	3.0134e-05	0.0023	4.3090e-16	1.6773e-08
Model Development (Type 1) *Simple Average*	5.2354e-05	0.0174	5.7277e-15	2.0573e-07
Model Development (Type 2) *Weighted Average*	3.0708e-09	2.6921e-05	4.3110e-10	6.2522e-06
Model Development (Type 2) *Simple Average*	6.7429e-08	4.8733e-05	5.9330e-09	1.0834e-05
NN	0.0024	0.0376	1.0733e-04	0.0063

Table 4 compares MSE and MAE decomposition and ensemble approaches with individual networks. Based on **Table 4** MSE and MAE, the decomposition and NNE models, both type 1 or 2, can perform better than individual networks. This is because the development of decomposition and NNE techniques first decomposes the original time series data into several components periodically so that it can be predicted more efficiently and thus becomes more effective. When the results from all components are combined, the final result of the prediction is better than the original time series.

The results of the complete ensemble based on decomposition by thoroughly describing components with types 1 and 2 are presented in the table above. The two types of model development have been compared. Based on the experiments that have been carried out, it can be concluded that: (1) decomposition is able to capture seasonal, trend and random features from actual data containing high volatility, (2) in almost all cases of both types it produces good performance evaluations for all predictions, not only for during training but also on data testing when compared to individual networks; (3) integration of decomposition and NNE for both types can effectively improve prediction accuracy, and (4) the combination of using weighted average shows better performance than simple average.

Figure 6 presents the predicted results of the ICI price. This section compares prediction plots using the decomposition technique, development, NNE types 1 and 2, NN, and actual data from ICI. From the picture, it can be seen that the decomposition technique and NNE can follow the exact price of ICI compared to individual NN, which makes it difficult to follow the movement of actual ICI data with high volatility. Based on the prediction results from the developed integration, which can follow daily data from ICI, it can provide helpful information in carrying out investments in running a portfolio.

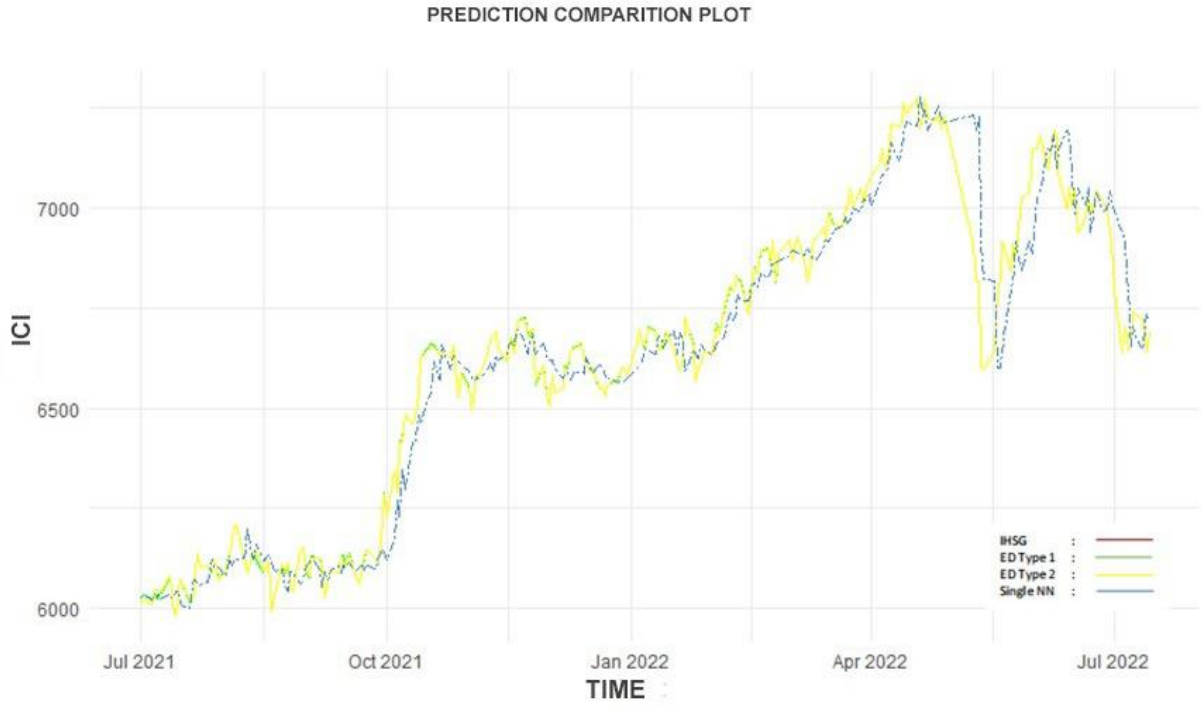

Figure 6. Predicted result plot

4. CONCLUSIONS

The amount of risk that business people and investors will accept in running portfolios in the VUCA era causes the need to predict the prices of commodities, stocks, and so on in the capital market. If business people and investors only make wrong judgments or predictions, the consequence is that business people and investors will suffer huge losses. This study uses an approach that integrates decomposition and NNE. The framework is used to predict ICI prices using two different types. The first objective of this approach is to separate time series data into three components: seasonal component, high volatility characterized by a trend component, and random component. Then, NNE is used to combine individual networks. To assess the effectiveness of this approach, network performance evaluation is carried out using MSE and MAE. The experimental results show that integrating decomposition and NNE can reduce errors and provide better performance than individual NNs. The decomposition integration and NNE approaches in this research use a linear approach; in reality, this approach still requires a nonlinear approach to the prediction output to reduce differences in prediction error.

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