PREDICTION OF NATIONAL STRATEGIC COMMODITY PRICES BASED ON MULTIVARIATE NONPARAMETRIC TIME SERIES ANALYSIS

ELLY PUSPORANI[*], M. FARIZ FADILLAH MARDIANTO, SEDIONO, AMELIATUL 'IFFAH, AULIA RACHMA FIRDAUSY, ERLY WIDYATAMA, M. FATKHUL HUDA

Department of Mathematics, Faculty of Science and Technology, Universitas Airlangga, Surabaya 60115, Indonesia

Abstract: Artificial Neural Network (ANN) or often referred to as artificial neural networks is a method inspired by the awareness of the complex learning system in the brain consisting of sets of neurons that are closely interconnected. While the Fourier series is a trigonometric polynomial function that has a very high degree of flexibility to overcome data that has a repeating pattern. In the time series data, both models can be used for nonparametric approaches that have many advantages, one of which is that they are more flexible and not tied to certain classical assumptions. In this study, a comparative study will be carried out between the ANN model and the Fourier series model to obtain forecasting results on national strategic food commodity prices simultaneously, with initial commodity prices referring to the website of Pusat Informasi Harga Pangan Strategis (PIHPS). The selection of the best model is selected based on the model that results in the smallest rate of prediction error in a commodity price prediction data by comparing the Mean Absolute Percentage Error (MAPE) values. The results of this test get the smallest MAPE value on the ANN model of 0.05974244, while the smallest MAPE value on the Fourier series model is 0.000325423. The results show that the Fourier series model is the best model for predicting the price of strategic commodities in Indonesia.

Keywords: artificial neural network; prediction; Fourier; national strategic commodities; nonparametrics; time series.

2010 AMS Subject Classification: 68T07, 62M20, 62G05, 62M10.

---

[*]Corresponding author

E-mail address: elly.pusporani@fst.unair.ac.id

1. INTRODUCTION

According to the Pusat Informasi Harga Pangan Strategis (PIHPS) Nasional, there are 10 national strategic commodities. These commodities are rice, shallots, garlic, red chilies, cayenne pepper, beef, purebred chicken meat, purebred chicken eggs, granulated sugar, and cooking oil [1]. The price of these strategic commodities has a significant contribution in the formation of inflation rates, especially for inflation of volatile foods. According to Bank Indonesia (BI), volatile food inflation or volatile components is inflation that is predominantly influenced by shocks in the food group such as harvests, natural disturbances, or the developments of domestic food commodity prices as well as international food commodity prices [2]. In addition, currently the amount of inflation is also influenced by the impact of the Coronavirus Disease-2019 (Covid-19) pandemic in various related sectors. For example, inflation in November 2020, which was around 0.28%, was higher than in November 2019, which was 0.14%. BI considers this development was influenced by low core inflation amidst rising inflation in volatile foods and administered prices [3]. Therefore, it is necessary to predict the price of national strategic commodities to control inflation, especially inflation of volatile foods, at a low and stable level.

Simultaneous national strategic commodity prices can be predicted using nonparametric time-related analysis. Time-guided analysis is a method of making observations over several periods taken over time sequentially with fixed time intervals [4]. Analysis using a nonparametric approach has many advantages, one of which is that it is more flexible and not tied to certain classical assumptions. Therefore, a nonparametric approach is used in this study, namely nonparametric regression with a Fourier series estimator simultaneously and forecasting using Artificial Neural Network (ANN). Fourier series estimators are generally used if the data pattern is not known and there is a tendency towards seasonal patterns [5]. While the ANN method can be used in various data pattern conditions by adjusting the use of the activation function during data processing. This is commonly referred to as architecture. An ANN model requires the right architecture if it wants to produce an optimal output. A deeper architecture will result in better forecasts [6].

The objectives to be achieved in this study are to get an overview of national strategic commodity prices; forming a Fourier series model; forming an ANN architecture; comparing the performance of the two models based on mean squared error (MSE) values; as well as helping related parties to predict the prices of national strategic commodities based on a comparison of

selected methods.

Several studies related to the prediction of national strategic commodity prices have been carried out using several statistical methods. Anggraeni et al., [7] predict the price of one of the national strategic commodities, namely rice using a hybrid method between Artificial Neural Network (ANN) and Autoregressive Integrated Moving Average with Exogenous variables (ARIMAX). Mardianto et al., [5] predicted the production of 11 strategic commodities in East Java with a nonparametric approach, namely the multi response Fourier series estimator. The conclusion from the study is that the multi response Fourier series estimator is suitable for predicting the production of strategic commodities in East Java.

Mardianto et al., [8] conducted price predictions of 10 national strategic commodities using a nonparametric approach, namely with kernel estimators and Fourier series simultaneously. The results of this study show that the Fourier series estimator is more suitable for making predictions by looking at the comparison of the values of the model's goodness criteria. This study predicts national strategic commodity prices by comparing two nonparametric approaches, namely the ANN method and the Fourier series estimator simultaneously. These results will be the basis for controlling volatile food inflation rates.

2. PRELIMINARIES

This study focuses on predicting national strategic commodity prices by comparing two nonparametric approaches, namely the Artificial Neural Network (ANN) method and the Fourier series estimator simultaneously.

A. National Strategic Commodities

National strategic commodities are commodities that have high economic value and making a significant contribution to the national According to the National PIHPS, there are 10 strategic economic commodities, including rice, shallots, garlic, red chilies, cayenne pepper, beef, purebred chicken meat, chicken eggs, granulated sugar, and cooking oil. The prices of these strategic commodities have a significant contribution to the formation of inflation rates, especially for volatile food inflation [1]. Therefore, this study uses prices data for 10 national strategic commodities obtained from the PIHPS website from the first week of January 2018 to the second week of January 2022 as the in sample and the third week of January 2022 to the forth week of

February 2022 as the out sample.

B. Simultaneous Nonparametric Regression Using a Fourier Series Estimator

Fourier series is a trigonometric polynomial function that has a very high level of flexibility to deal with data that has repetitive patterns. The Fourier series estimator is usually used if after investigation the pattern of research data is unknown and there is a tendency to repeat the pattern[9].

Before moving on to the Fourier series estimator, it is necessary to test the correlation between variables. One of the correlation tests that can be applied is the Bartlett Sphericity Test.

The principle of the Bartlett Sphericity Test is that the variables X_1, $X_2,...,X_p$ are said to be independent if the correlation matrix between variables forms an identity matrix. So that this test can be used as an independence test with the following hypothesis:

$H_0: \rho = I =$ There is a correlation

$H_1: \rho \neq I =$ There is no correlation

The results of the Bartlett Sphericity Test obtained must be significant (p-value <0.05) so that the factor analysis is appropriate [10]. Therefore, the decision that can be taken from this test is that H_0 ditolak if p-value $< \alpha$ (0.05).

This is because the Fourier series is a curve that shows the sine cosine function [11]. For example, with the observation data of (t_r, y_r) that follows the regression model as follows.

$$y_r = m(t_r) + \varepsilon_r; \quad \varepsilon_r \sim IID\ (0, \sigma^2) \tag{1}$$

Where $r = 1,2,...,n$ show the number of observations.

The regression function $\widehat{m}(t_r)$ in equation (1) is unknown and will be estimated using a Fourier eries estimator approach, $\widehat{m}(t_r)$ can be written as follow.

$$m(t_r) = \sum_{j=1}^{\infty} \beta_j x_j (t_r) \tag{2}$$

Where β_j is the parameter of the j-th regression coefficient which has a scalar value.

Therefore, model (2) can change to:

$$y_r = \sum_{j=1}^{\infty} \beta_j x_j (t_r) + \varepsilon_r; \quad \varepsilon_r \sim IID\ (0, \sigma^2) \tag{3}$$

If equation (3) is written based on the Fourier series estimator approach, it becomes:

$$y = X_\lambda \beta_\lambda + \varepsilon \tag{4}$$

If the estimation method used is Least Square which minimizes the number of squared errors, then $\hat{\beta}_\lambda$ is :

$$Q = \varepsilon^t \varepsilon = y^t y - 2\beta_\lambda^t X_\lambda^t y + \beta_\lambda^t X_\lambda^t X_\lambda \beta_\lambda \tag{5}$$

$$\frac{\partial Q}{\partial \beta_\lambda} = 0 - 2X_\lambda^t y + 2X_\lambda^t X_\lambda \beta_\lambda = 0 \tag{6}$$

$$\hat{\beta}_\lambda = (X_\lambda^t X_\lambda)^{-1} X_\lambda^t y \tag{7}$$

where:

$$X_\lambda^t X_\lambda = nxI$$

$$(X_\lambda^t X_\lambda)^{-1} = \frac{1}{n} I$$

$$X_\lambda^t y = \sum_{r=1}^{n} y_j e^{-2\pi i j\, t_r}$$

Thus, the estimator of the Fourier series or $\hat{m}(t_r)$ is as follow

$$\begin{aligned}
\hat{m}(t_r) &= \sum_{j=-\lambda}^{\lambda} \hat{\beta}_j\, x_j(t_r) \\
&= \sum_{j=-\lambda}^{\lambda} \hat{\beta}_j\, e^{2\pi i j\, t_r} \\
&= \sum_{j=-\lambda}^{\lambda} \left(\frac{\sum_{r=1}^{n} y_r\, e^{\wedge}{-2\pi i j t_r}}{n} e^{2\pi i j\, t_r} \right)
\end{aligned} \tag{8}$$

Taking [a,b] = [0,1] and t_r equidistant at [0,1], the notation of t_r can be written as $t_r = \frac{r-1}{n}$.

The first study related with Fourier series estimators in nonparametric regression was carried out by Bilodeau [12]. Several subsequent studies on the Fourier series estimator in nonparametric regression were carried out by Biedermann et.al., [13], namely examining the optimal design to obtain oscillation parameters from nonparametric regression models with Fourier series. Dette et.al., [14] developed the study of Biedermann et.al., [13] using several constraints. Tjahjono et.al., [15] proposed a Fourier series estimator in the case of biresponse and applied it to predict electricity consumption. Mardianto et.al., [16] applied the Fourier series estimator to determine the prediction of rice production in in Indonesia Provinces.

C. Forecasting Using Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a method that is inspired by the awareness of the complex learning system in the brain which consists of closely related sets of neurons. ANN is the right tool

to model the relationship between several variables, based on experimental observations that should be sufficient, numerous, and representative. The ANN method belongs to a set of nonlinear parametric functions that are used in various fields, especially to perform complex modeling processes with very powerful computational techniques.

ANN modeling is determined by network architecture, learning algorithm, and activation function. Some of the various kinds of activation functions that can be used to get the output can be seen in Table 1.

Activation Fuction	Equation
Linear/ Identity	$f(x) = x$
Hyperbolic Tangent	$f(x) = \tanh(x)$
Sigmoid	$f(x) = (1 + exp(-x))$

TABLE 1. Activation Function

The algorithm commonly used in ANN is the general delta rule, which calculates the derivative by applying a chain rule called backpropagation (BP) [17]. BP is an algorithm that consists of two steps. The first is to feedforward the input value and the second is to calculate the error and recalculate the previous layer. The layer in this step is one of the network architecture type. An example of an architecture that is often used is FFNN which consists of an input layer, a hidden layer connected to an output layer. According to Taylor, the equation to get the output of the FFNN architecture is as follows [18].

$$\hat{Y}_t = f^0 \left\{ v_0 + \sum_{k=1}^{K} \left(v_k f^h \left(\sum_{i=1}^{I} w_{ik} x_{i,t} \right) \right) \right\}$$

(9)

where v_k is the weight of the k-th neuron in the hidden layer, w_{ik} is the weight of the i-th input to the k-th neuron in the hidden layer, $f^h( )$ and $f^0( )$ are the activation functions of the hidden layer and the output layer. Another architecture is DLNN which uses two hidden layers to connect the input and output layers.

The emergence of the ANN domain was in the 1940s, while the first concrete applications occurred in the late 1950s with the invention of the Perceptron network. n 1988, ANN was developed through the invention of the BP algorithm, this algorithm is an answer to the criticisms Minsky and Papert made in the late 1960s (McCulloch and Pitts, [19]; Rumelhart et al., [20]; Gallant, [21]). ; Smith, [22]). ANN is considered a nonlinear estimation tool based on data that has

been successfully applied in various fields including ecological science (Trichakis et al., [23]), water science (Makaya and Hense, [24]; Manu and Arun Kumar, [25]), hydrological sciences (Grid and Uncuoglu, [26]; Nourani et al., [27]), etc.

One of the architectur of Neural Network model is as follow.
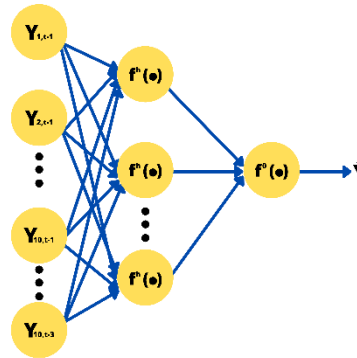

FIGURE 1. Example of Neural Network Architecture

3. MAIN RESULTS

A. *Data Exploration*

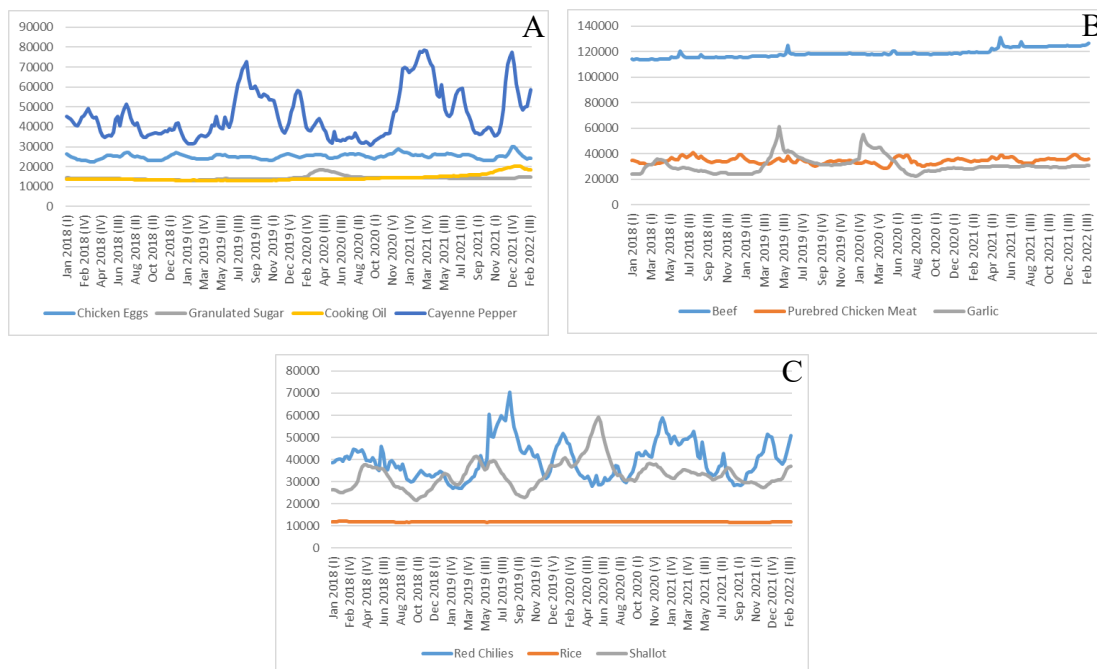In modeling using time series data, the component that must be considered is the data pattern.

FIGURE 2. Time Series Plots of (A) Chicken Eggs, Granulated Sugar, Cooking Oil, and Cayenne Pepper, (B) Beef, Purebred Chicken Meat, and Garlic Commodities, and (C) Red Chilies, Rice, and Shallots

Figure 2A shows the development of commodity prices in Indonesia, consisting of chicken eggs, granulated sugar, cooking oil, and cayenne pepper. Based on Figure 2A, the commodity prices in Indonesia have been fluctuating up and down. A clear upward trend is occurring in cooking oil commodities. In the case of cayenne pepper, fluctuations are very noticeable, while the case of purebred chicken eggs there are fluctuations but not too steep and the price of granulated sugar commodities tends to be stable.

Figure 2B shows the development of commodity prices consisting of beef, purebred chicken meat, and garlic. It can be seen that the beef prices have been increasing. The price of garlic, also have very obvious fluctuations. However, for the price of purebred chicken meat, the price of this commodity fluctuates slightly but tends to be stable. Figure 2C shows commodity prices consisting of red chilies, rice, and shallots. it can be seen that there is a clear fluctuation pattern for red chilies and shallots, while for rice prices tend to be stable without fluctuations.

In the time series analysis, it is also very important to know the linearity relationship of each commodity to the time period. Therefore, the linearity testing using the Terasvirta test of each commodity is carried out to determine the linear relationship of each commodity to the time period. The Terasvirta test is tested on the price data of each commodity at lags 1, 2, and 3. Based on Table 2, the test results using the Terasvirta test showed that in lag 1 data of each commodity tends to have a linear relationship, while in lag 2 and 3 data of each commodity tends to have a nonlinear relationship.

Variable	Lag	P-value	Variable	Lag	P-value
Chicken Eggs	1	0.4145	Purebred Chicken Meat	1	0.1375
	2	0.01151		2	0.002522
	3	0.05347		3	7.85×10^{-5}
Granulated Sugar	1	0.6687	Garlic	1	1.24×10^{-6}
	2	2.20×10^{-16}		2	2.20×10^{-16}
	3	2.20×10^{-16}		3	2.20×10^{-16}
Cooking oil	1	2.61×10^{-12}	Red Chilies	1	0.2187
	2	2.20×10^{-16}		2	7.24×10^{-7}
	3	2.20×10^{-16}		3	1.31×10^{-6}
Cayenne Pepper	1	0.8127	Rice	1	0.3091
	2	0.7217		2	2.41×10^{-5}
	3	0.1406		3	0.0005783
Beef	1	1.01×10^{-6}	Shallot	1	0.706
	2	3.67×10^{-12}		2	9.63×10^{-6}
	3	4.24×10^{-12}		3	7.12×10^{-6}

TABLE 2. Terasvirta Test Result

B. Forecasting with Fourier Series Estimator

Simultaneous modeling with Fourier series estimators for ten commodities must fulfill the assumption that statistically all ten commodities have a correlation with each other. Therefore, a calculation of the correlation between commodity prices must be done and the result can be seen in Figure 3 which shows that not all variables relationships have a high correlation. Because of this, Bartlett Sphericity test must be done to determine the correlation between commodities.

$$
\begin{aligned}
G^2 &= -\left\{n - 1 - \frac{2q + 5}{6}\right\}\ln|R| \\
&= -\left\{218 - 1 - \frac{2(10) + 5}{6}\right\}\ln|0.01435781| \\
&= 903,15
\end{aligned}
$$

Based on the results, the test statistical value of 903.15 was obtained, which was further compared with the value of $\chi^2_{0.05.1.80} = 202.304$, due to value $G^2 > \chi^2$ then it fails to reject H_0 which means that the variables have a correlation with each other. Thus, simultaneous modeling can be carried out for all commodities.
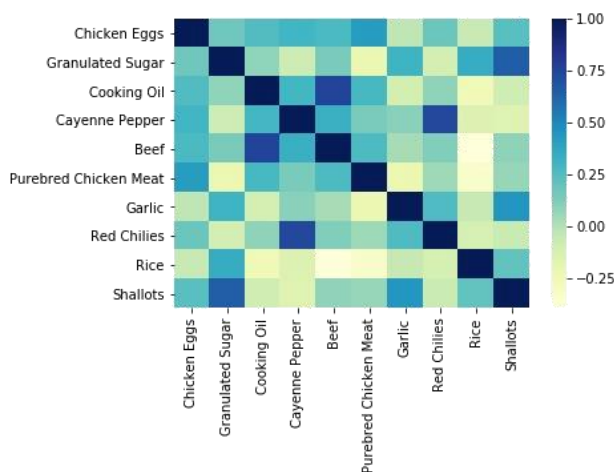
FIGURE 3. Correlation Between 10 National Strategic Commodities

The best Fourier series estimators of the three forms of Fourier series components namely the Fourier cosine series, the Fourier sine series, and the Fourier series with the sine cosine component are used to predict commodity prices simultaneously. Before making predictions, the model must be build based on training data first. The GCV calculation results using the Fourier series estimator of the cosine, sine, and sine cosine using training data are shown in Table 3. The Fourier series with a cosine sine component in the oscillation parameter of value (k) 6 has a minimum GCV value of 17,324,005,817, with an MSE value of 2,073 and an R-square value of 96.29%. The

Fourier series with a sine component when valued at k 6 has a minimum GCV value of 17156004709, with an MSE value of 1.935 and an R-square value of 96.07%. The Fourier series with a cosine component when valued at k 6 has a minimum GCV value of 18348564269, with an MSE value of 2,089 and an R-square value of 96.26%.

k	Sine Cosine	Sine	Cosine
1	18.966.129.039	18.046.282.385	19.291.832.336
2	18.500.027.539	17.739.686.348	19.071.103.470
3	18.090.433.100	17.568.583.835	18.757.965.799
4	17.703.184.015	17.368.083.128	18.534.176.198
5	17.324.005.817	17.156.004.709	18.348.564.269
6	17.082.366.231	16.889.446.261	18.091.275.913

TABLE 3. The Changes of CGV Value in Fourier Series Estimator

Based on the parsimony model principle, the estimator chosen for prediction is the Fourier series estimator which includes a sine component with small oscillatory parameters, the smallest MSE and GCV values when compared to the Fourier series estimator which contains only cosine or the Fourier series estimator containing the cosine and sine. Comparison of estimators is presented in Table 4.

Fourier Series Estimator	k	GCV	MSE	R-Square
Sine Cosine	5	17.082.366.231	2,08609	0,963598
Sine	5	16.889.446.261	1,92341	0,961066
Cosine	5	18.091.275.913	2,08063	0,962883

TABLE 4. Estimators Performance Comparison for Fourier Series

Commodity price predictions are carried out simultaneously based on testing data. The prediction uses a Fourier series estimator with a sine component for multi response cases. The form of a Fourier series *estimator with a sine component and an oscillation parameter (k) of* 6 can be expressed into equations (10). The estimated values for each parameter are shown in Table 4.

$$
\begin{cases}
\hat{y}_{i1} = \dfrac{\hat{\alpha}_{01}}{2} + \hat{\gamma}_1 t_{i1} + \displaystyle\sum_{k=1}^{6} \left(\hat{\beta}_{k1} \sin k \, t_{i1} \right) \\[2mm]
\hat{y}_{i2} = \dfrac{\hat{\alpha}_{02}}{2} + \hat{\gamma}_2 t_{i2} + \displaystyle\sum_{k=1}^{6} \left(\hat{\beta}_{k2} \sin k \, t_{i2} \right) \\[2mm]
\qquad\qquad\vdots \\[1mm]
\hat{y}_{i10} = \dfrac{\hat{\alpha}_{010}}{2} + \hat{\gamma}_{10} t_{i10} + \displaystyle\sum_{k=1}^{6} \left(\hat{\beta}_{k10} \sin k \, t_{i10} \right)
\end{cases}
\qquad (10)
$$

PREDICTION OF NATIONAL STRATEGIC COMMODITY PRICES

j	Parameter						
	$\hat{\gamma}_j$	$\hat{\beta}_{1j}$	$\hat{\beta}_{2j}$	$\hat{\beta}_{3j}$	$\hat{\beta}_{4j}$	$\hat{\beta}_{5j}$	$\hat{\beta}_{6j}$
1	25271.02	321.54	255.8	18.19	-199.32	-272.28	-490.99
2	14226.45	4.24	4.13	-6.77	6.56	4.21	-89.28
3	14174.2	20.92	8.72	-22.94	10.74	9.28	-179.64
4	42408.5	201.86	-215	-37	72.95	-207.85	-2268.3
5	118715.5	-6.5	-34.82	-89.03	33.67	15.44	-158.95
6	34511.22	-37.68	-14.56	-17.76	-20.97	-74.52	-35.17
7	31081.32	64.15	27.77	-21.96	23.32	174.33	-708.17
8	39518.79	-52.29	-209	-70.19	40.46	-363.56	-364.29
9	11776.67	-3.94	-1.69	1.2	-0.37	1.8	-7.02
10	33183.57	-34.17	-62.72	-14.37	2.93	-19.5	1970.17

TABLE 5. Parameter Estimate

Predictions of national strategic commodity production were carried out simultaneously using a Fourier series estimator based on a sine component with an oscillation parameter of 6 on the out sample. The next step is to compare the testing data with the prediction results in the period corresponding to the out sample data. The prediction results obtained by this method are very good because the prediction value is close to the out sample value and produces a Mean Absolute Percentage Error (MAPE) value of 0.000325423%, which means that the prediction accuracy is very good. Thus, Fourier series estimators based on those that include a sine component with an oscillation parameter of 5 can be used to predict commodity prices in Indonesia from the present to the future.

C. Forecasting with Artificial Neural Network (ANN)

To get the best forecasting results using the ANN model, there are some modeling steps that need to be done. That step is presented in Figure 4 below.
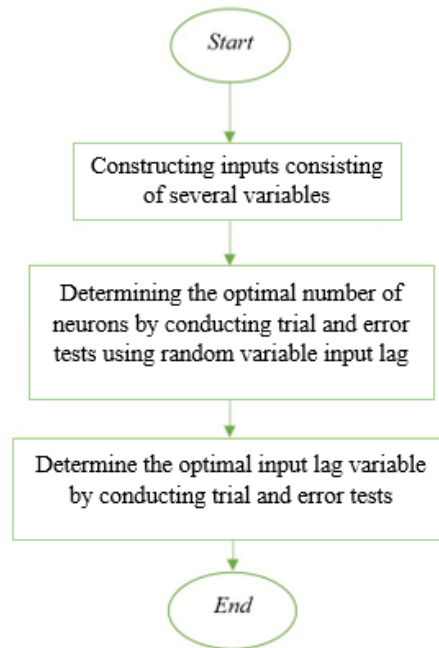
FIGURE 4. Artificial Neural Network (ANN) modeler flow chart

Artificial Neural Network (ANN) is a network formed based on human neural networks. A nerve cell (neuron) consists of a sum function, an activation function, and an output. The neurons in an ANN are arranged in a layer, generally consisting of an input layer, hidden layer, and output layer. The input in this Artificial Neural Network (ANN) modeling is lag variables that will be predicted.

To determine the optimal number of neurons a trial and error test is carried out, in this case the number of neurons used is 1 to 10. This study use Tanh activation function in the hidden layer to connect input to the output. The Tanh function is chosen because the results of data testing using Terasvirta test show that several of the show some nonlinear pattern.

In this study, *the lag* used as an input variable is *lag* 1, 2 and 3, this is based on the output results of *the Akaike Information Criterion* (AIC) based on *vector autoregressive* model and *the Parsimony* principle.

Lag	MA (0)	Lag	MA (0)
AR (0)	151,08235	AR (3)	120, 93881
AR (1)	123,68169	AR (4)	120,98535
AR (2)	121,11258	AR (5)	120,86465

TABLE 6. VAR Model AIC Value

The next process is that the selection of the best ANN model based on the Mean Absolute Percentage Error (MAPE) on each ANN model. MAPE results from the modeling process based on the activation function that has been run according to its lag variable can be seen in Table 7.

Neuron	Lag		
(C)	1	2	3
1	0.091397931	0.331371739	0.465377468
2	0.157060724	0.239488938	0.287582443
3	0.154367035	0.230948299	0.158139318
4	0.162746058	0.161154476	0.227234162
5	0.090994103	0.116756724	0.195317818
6	0.067107766	0.09605743	0.121440984
7	0.120817461	0.093314936	0.104398975
8	0.105714426	0.08194467	0.205105179
9	0.093691192	0.104982497	0.143582534
10	0.05974244	0.108619402	0.141732528

TABLE 7. MAPE Values with Different Amounts of Lag and Neurons

Based on table 1, the smallest MAPE was obtained, when the models use input with only lag 1 and the number of neurons 10. The MAPE obtained is 0.05974244. It showed that the model had a very high level of prediction accuracy. The model of the ANN modeling estimator using lag 1 and 10 neurons can be expressed in equation (11) for the input layer to the hidden layer and equation (12) for the hidden layer to the output layer.

$$f(x_1) = 0.240 + 0.483 \tanh\left(y^*_{1,1,t-1}\right) + 0.483 \tanh\left(y^*_{2,1,t-1}\right) + 0.378 \tanh\left(y^*_{3,1,t-1}\right) + \cdots -$$
$$0.231 \tanh\left(y^*_{10,1,t-1}\right) - 0.315 \tanh\left(y^*_{1,2,t-1}\right) + \cdots + 0.081 \tanh\left(y^*_{10,2,t-1}\right) -$$
$$0.365 \tanh\left(y^*_{1,3,t-1}\right) + \cdots + 0.074 \tanh\left(y^*_{10,10,t-1}\right)$$

$$f(x_2) = -0.303 + 0.240 \tanh\left(y^*_{1,1,t-1}\right) + 0.047 \tanh\left(y^*_{2,1,t-1}\right) + 0.313 \tanh\left(y^*_{3,1,t-1}\right) + \cdots -$$
$$0.116 \tanh\left(y^*_{10,1,t-1}\right) + 0.146 \tanh\left(y^*_{1,2,t-1}\right) + \cdots + 0.318 \tanh\left(y^*_{10,2,t-1}\right) -$$
$$0.057 \tanh\left(y^*_{1,3,t-1}\right) + \cdots + 0.117 \tanh\left(y^*_{10,10,t-1}\right)$$

$$f(x_3) = 0.255 + 0.217 \tanh\left(y^*_{1,1,t-1}\right) - 0.502 \tanh\left(y^*_{2,1,t-1}\right) + 0.004 \tanh\left(y^*_{3,1,t-1}\right) + \cdots +$$

$$0.058 \tanh\left(y^*_{10,1,t-1}\right) + 0.192 \tanh\left(y^*_{1,2,t-1}\right) + \cdots - 0.061 \tanh\left(y^*_{10,2,t-1}\right) -$$

$$0.224 \tanh\left(y^*_{1,3,t-1}\right) + \cdots + 0.665 \tanh\left(y^*_{10,10,t-1}\right)$$

$$f(x_4) = 0.255 - 0.140 \tanh\left(y^*_{1,1,t-1}\right) + 0.174 \tanh\left(y^*_{2,1,t-1}\right) + 0.173 \tanh\left(y^*_{3,1,t-1}\right) + \cdots -$$

$$0.481 \tanh\left(y^*_{10,1,t-1}\right) - 0.074 \tanh\left(y^*_{1,2,t-1}\right) + \cdots - 0.222 \tanh\left(y^*_{10,2,t-1}\right) +$$

$$0.114 \tanh\left(y^*_{1,3,t-1}\right) + \cdots + 0.404 \tanh\left(y^*_{10,10,t-1}\right)$$

$$f(x_5) = 0.470 + 0.236 \tanh\left(y^*_{1,1,t-1}\right) + 0.075 \tanh\left(y^*_{2,1,t-1}\right) + 0.232 \tanh\left(y^*_{3,1,t-1}\right) + \cdots +$$

$$0.096 \tanh\left(y^*_{10,1,t-1}\right) - 0.133 \tanh\left(y^*_{1,2,t-1}\right) + \cdots + 0.396 \tanh\left(y^*_{10,2,t-1}\right) +$$

$$0.343 \tanh\left(y^*_{1,3,t-1}\right) + \cdots + 0.391 \tanh\left(y^*_{10,10,t-1}\right)$$

$$f(x_6) = 0.143 + 0.334 \tanh\left(y^*_{1,1,t-1}\right) - 0.144 \tanh\left(y^*_{2,1,t-1}\right) + 0.328 \tanh\left(y^*_{3,1,t-1}\right) + \cdots -$$

$$0.249 \tanh\left(y^*_{10,1,t-1}\right) - 0.218 \tanh\left(y^*_{1,2,t-1}\right) + \cdots - 0.308 \tanh\left(y^*_{10,2,t-1}\right) +$$

$$0.274 \tanh\left(y^*_{1,3,t-1}\right) + \cdots + 0.238 \tanh\left(y^*_{10,10,t-1}\right)$$

$$f(x_7) = -0.028 + 0.468 \tanh\left(y^*_{1,1,t-1}\right) + 0.418 \tanh\left(y^*_{2,1,t-1}\right) - 0.162 \tanh\left(y^*_{3,1,t-1}\right) + \cdots +$$

$$0.343 \tanh\left(y^*_{10,1,t-1}\right) + 0.305 \tanh\left(y^*_{1,2,t-1}\right) + \cdots - 0.046 \tanh\left(y^*_{10,2,t-1}\right) +$$

$$0.484 \tanh\left(y^*_{1,3,t-1}\right) + \cdots - 0.705 \tanh\left(y^*_{10,10,t-1}\right)$$

$$f(x_8) = -0.187 - 0.461 \tanh\left(y^*_{1,1,t-1}\right) - 0.344 \tanh\left(y^*_{2,1,t-1}\right) - 0.059 \tanh\left(y^*_{3,1,t-1}\right) + \cdots +$$

$$0.320 \tanh\left(y^*_{10,1,t-1}\right) - 0.064 \tanh\left(y^*_{1,2,t-1}\right) + \cdots - 0.331 \tanh\left(y^*_{10,2,t-1}\right) +$$

$$0.387 \tanh\left(y^*_{1,3,t-1}\right) + \cdots + 0.373 \tanh\left(y^*_{10,10,t-1}\right)$$

$$f(x_9) = -0.221 - 0.005 \tanh\left(y^*_{1,1,t-1}\right) - 0.166 \tanh\left(y^*_{2,1,t-1}\right) + 0.113 \tanh\left(y^*_{3,1,t-1}\right) + \cdots +$$

$$0.440 \tanh\left(y^*_{10,1,t-1}\right) - 0.064 \tanh\left(y^*_{1,2,t-1}\right) + \cdots + 0.342 \tanh\left(y^*_{10,2,t-1}\right) +$$

$$0.414 \tanh\left(y^*_{1,3,t-1}\right) + \cdots - 0.737 \tanh\left(y^*_{10,10,t-1}\right)$$

$$f(x_{10}) = 0.714 + 0.390 \tanh\left(y^*_{1,1,t-1}\right) - 0.431 \tanh\left(y^*_{2,1,t-1}\right) - 0.437 \tanh\left(y^*_{3,1,t-1}\right) + \cdots +$$

$$0.255 \tanh\left(y^*_{10,1,t-1}\right) + 0.073 \tanh\left(y^*_{1,2,t-1}\right) + \cdots + 0.037 \tanh\left(y^*_{10,2,t-1}\right) +$$

$$0.364 \tanh\left(y^*_{1,3,t-1}\right) + \cdots - 0.005 \tanh\left(y^*_{10,10,t-1}\right)$$

(11)

$$\hat{y}^*_t = 0.511 - 0.268\, f(x_1) + 0.512\, f(x_2) + 0.523\, f(x_3) - 0.133\, f(x_4) - 0.386\, f(x_5) -$$

$$0.191\, f(x_6) - 0.592\, f(x_7) - 0.454\, f(x_8) - 0.144\, f(x_9) - 0.306\, f(x_{10})$$

(12)

where in this model y_t^* is the standardize value of y_t.

Based on analysis that has been done, it can be concluded that in this case ANN model with lag 1 and neuron 10 can be used as a method in predicting commodity prices in Indonesia with a very high level of accuracy.

D. *Model Comparison*

To find out the best model to be used for forecasting, a comparison of forecasting results *out sample* data with forecasting models using the *Fourier* method and the ANN method was carried out. In Table 8 are shown the MAPE Values of each commodity for the best model of the *Fourier* and ANN methods.

Variable	Fourier	ANN	Variable	Fourier	ANN
Chicken Eggs	0.00325	0.045866	Purebred Chicken Meat	5.579×10^{-13}	0.035824
Granulated Sugar	4.478×10^{-13}	0.082386	Garlic	1.532×10^{-13}	0.021777
Cooking Oil	3.467×10^{-13}	0.120257	Red Chilies	3.619×10^{-13}	0.071226
Cayenne Pepper	1.363×10^{-12}	0.051699	Rice	3.369×10^{-13}	0.102704
Beef	3.064×10^{-13}	0.009436	Shallot	2.817×10^{-13}	0.056249

TABLE 8. MAPE Fourier and ANN Value Comparison

Table 8 shows that the model using the Fourier method with a sine component is the best model for predictions on each strategic commodity in Indonesia compared to the model using the ANN method with lag 1 and neuron 10. The results of the study using the Fourier method produced good forecasting seen from the forecast chart with the Fourier method following the graph from the out sample data. The results of the study are presented in Figure 5. Based on the Figure 5, it can be seen that the prediction using Fourier method with a sine component fit perfectly with the out sample data. This is support the statement before this that the prediction using Fourier method with a sine component is the best model to predict the commodities prices simultaneously.
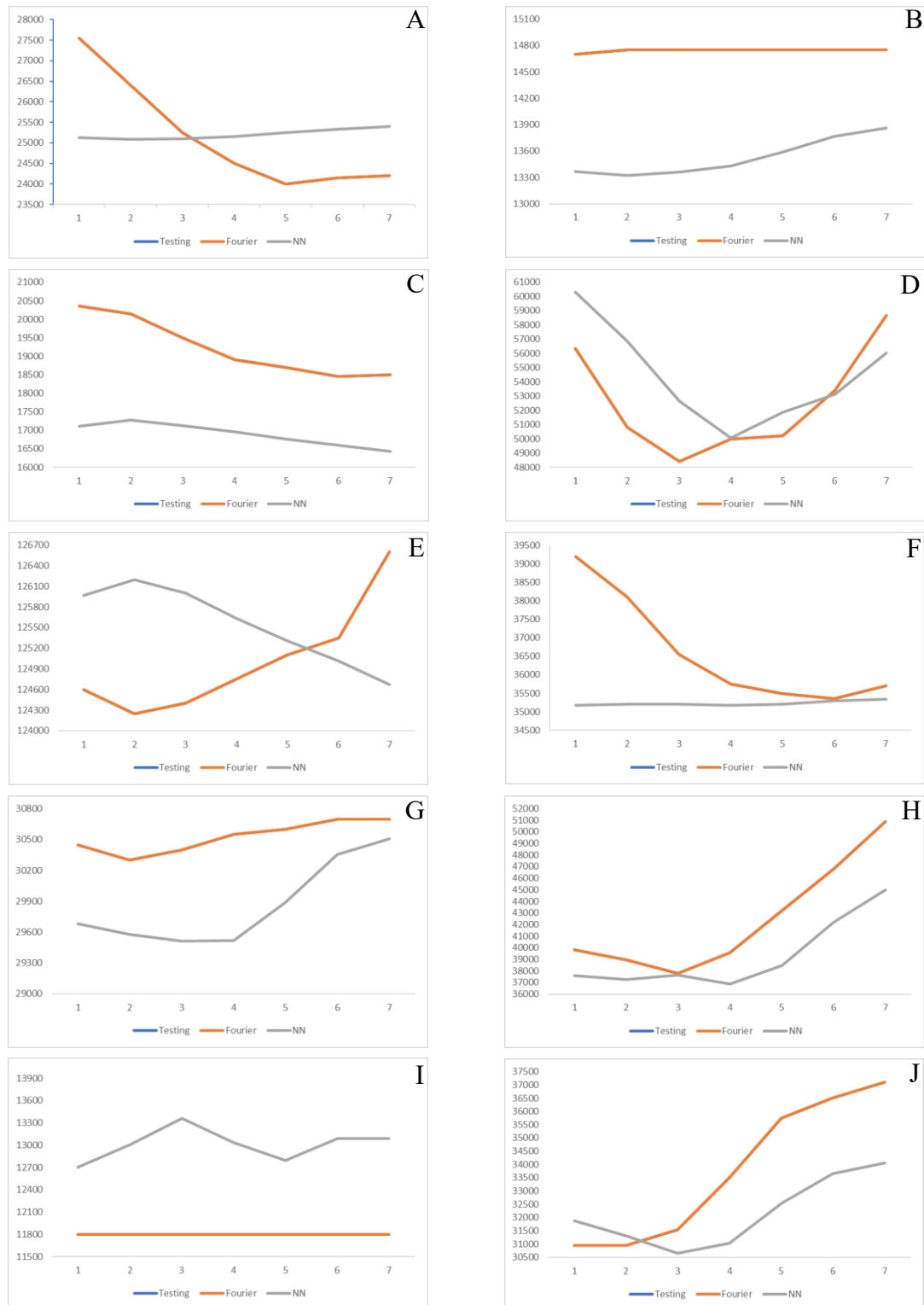
FIGURE 5. Line Plot Prediction of Testing Data, Fourier, and ANN of (A) Chicken Eggs, (B) Granulated Sugar, (C) Cooking Oil, (D) Cayenne Pepper, (E) Beef, (F) Purebred Chicken Meat, (G) Garlic, (H) Red Chilies, (I) Rice, and (J)Shallot

4. CONCLUSION

Fluctuations in commodity prices in Indonesia often occur at certain times. The Fourier method with a sine component and an oscillation parameter (k) of 6 is the best model of the Fourier method with a MAPE value of 0.000325423, while the ANN model with a lag structure of 1 and a number of neurons of 10 is the best model of the ANN method with a MAPE value of 0.05974244. The selection of the best model for commodity price prediction in Indonesia is based on the smallest MAPE value, so the best model for prediction is the Fourier model with a sine component and oscillation parameters of 6. Fourier series estimators have the flexibility to adjust regression curves based on certain patterns of data changes such as seasonality, seasonality, and oscillating or fluctuating data patterns.

CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

REFERENCES

[1] National Strategic Food Price Information Center, https://hargapangan.id/informasi/faq. [Accessed 18 February 2022].

[2] Bank Indonesia, https://www.bi.go.id/id/fungsi-utama/moneter/inflasi/default.aspx. [Accessed 20 April 2022].

[3] A.R. Farandy, Analyzing Factors Affecting Indonesian Food Price Inflation, Jurnal Ekonomi dan Pembangunan. 28 (2020), 65–76. https://doi.org/10.14203/jep.28.1.2020.65-76.

[4] C. Chatfield, H. Xing, The analysis of time series: An introduction with R, CRC Press, New York, 2019.

[5] M.F.F. Mardianto, S.M. Ulyah, E. Tjahjono, Prediction of national strategic commodities production based on multi-response nonparametric regression with Fourier series estimator, Int. J. Innov. Creativity Change, 5 (2019), 1151-1176.

[6] I.M.G.M. Dana, Suhartono, S.P. Rahayu, GSTARX-ANN hybrid model for forecasting space-time data with calendar variation effects (Case study: data inflow and outflow of currency at Bank Indonesia East Java Region), Statistics ITS, Surabaya, 2018.

[7] W. Anggraeni, F. Mahananto, A.Q. Sari, et al. Forecasting the price of Indonesia's rice using hybrid artificial neural network and autoregressive integrated moving average (Hybrid NNs-ARIMAX) with exogenous variables,

Procedia Computer Sci. 161 (2019), 677–686. https://doi.org/10.1016/j.procs.2019.11.171.

[8] M.F.F. Mardianto, Sediono, I. Syahzaqi, et al. Prediction of Indonesia strategic commodity prices during the COVID-19 Pandemic based on a Simultaneous Comparison of Kernel and Fourier Series Estimator, J. Southwest Jiaotong Univ. 55 (2020), 1-10. https://doi.org/10.35741/issn.0258-2724.55.6.43.

[9] L.R. Khairunnisa, A. Prahutama, R. Santoso, Semiparametric regression modeling with Fourier series approach (Case study: Effect of Dow Jones index and BI rate on composite stock price index), J. Gauss. 9 (2020), 50–63. https://doi.org/10.14710/j.gauss.v9i1.27523.

[10] R.K. Henson, J.K. Roberts, Use of exploratory factor analysis in published research, Educ. Psychol. Measure. 66 (2006), 393–416. https://doi.org/10.1177/0013164405282485.

[11] Suparti, R. Santoso, A. Prahutama, et al. Indonesia's inflation analysis using hybrid Fourier - wavelet multiscale autoregressive method, J. Phys.: Conf. Ser. 1306 (2019), 012041. https://doi.org/10.1088/1742-6596/1306/1/012041.

[12] M. Bilodeau, Fourier smoother and additive models, Can. J. Stat. 20 (1992), 257–269. https://doi.org/10.2307/3315313.

[13] S. Biedermann, H. Dette, P. Hoffmann, Constrained optimal discrimination designs for Fourier regression models, Ann. Inst. Stat. Math. 61 (2007), 143–157. https://doi.org/10.1007/s10463-007-0133-5.

[14] H. Dette, V.B. Melas, P. Shpilev, T-optimal discriminating designs for Fourier regression models, Comput. Stat. Data Anal. 113 (2017), 196–206. https://doi.org/10.1016/j.csda.2016.06.010.

[15] E. Tjahjono, M.F.F. Mardianto, N. Chamidah, Prediction of electricity consumption using Fourier series estimator in bi-response nonparametric regression model, Far East J. Math. Sci. 103 (2018), 1251–1263. https://doi.org/10.17654/ms103081251.

[16] M.F.F. Mardianto, E. Tjahjono, M. Rifada, et al. The prediction of rice production in indonesia provinces for developing sustainable agriculture, in: Proceeding of the 1st International Conference on Food and Agriculture, 2019.

[17] W.S. Sarle, Neural network and statistical models, in: Proceedings of the Nineteenth Annual SAS Users Group International Conference, North Carolina, (1994).

[18] E. Pusporani, Suhartono, D.D. Prastyo, Hybrid multivariate generalized space-time autoregressive artificial

neural network models to forecast air pollution data at Surabaya, AIP Conf. Proc. 2194 (2019), 020090. https://doi.org/10.1063/1.5139822.

[19] W.S. McCulloch, W. Pitts, A logical calculus of the ideas immanent in nervous activity, Bull. Math. Biophys. 5 (1943), 115–133. https://doi.org/10.1007/bf02478259.

[20] D.E. Rumelhart, G.E. Hinton, R.J. Williams, Learning internal representations by error propagation. In: D.E. Rumelhart, J.L. McClelland, (Eds.), Parallel distributed processing: Explorations in the microstructure of cognition. Vol. 1: Foundations. MIT Press, Cambridge, (1985).

[21] S.I. Gallant, Neural Network Learning and Expert Systems, MIT Press, Cambridge, (1993).

[22] A.E. Smith, A.K. Mason, Cost estimation predictive modeling: regression versus neural network, Eng. Economist. 42 (1997), 137–161. https://doi.org/10.1080/00137919708903174.

[23] I.C. Trichakis, I.K. Nikolos, G.P. Karatzas, Artificial neural network (ANN) based modeling for karstic groundwater level simulation, Water Resour Manage. 25 (2010), 1143–1152. https://doi.org/10.1007/s11269-010-9628-6.

[24] E. Makaya, O. Hensel, Modelling flow dynamics in water distribution networks using artificial neural networks - A leakage detection technique, Int. J. Eng. Sci. Technol. 7 (1970), 33–43. https://doi.org/10.4314/ijest.v7i1.4.

[25] D.S. Manu, A.K. Thalla, Artificial intelligence models for predicting the performance of biological wastewater treatment plant in the removal of Kjeldahl Nitrogen from wastewater, Appl. Water Sci. 7 (2017), 3783–3791. https://doi.org/10.1007/s13201-017-0526-4.

[26] Ö. Kisi, Multi-layer perceptrons with Levenberg-Marquardt training algorithm for suspended sediment concentration prediction and estimation / Prévision et estimation de la concentration en matières en suspension avec des perceptrons multi-couches et l'algorithme d'apprentissage de Levenberg-Marquardt, Hydrol. Sci. J. 49 (2004), 1025-1040. https://doi.org/10.1623/hysj.49.6.1025.55720.

[27] V. Nourani, M.T. Alami, F.D. Vousoughi, Wavelet-entropy data pre-processing approach for ANN-based groundwater level modeling, J. Hydrol. 524 (2015), 255–269. https://doi.org/10.1016/j.jhydrol.2015.02.048.