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A Time Series Forecasting of the Philippine Unemployment Rate Using Feed-Forward Artificial Neural Network

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ABSTRACT

Unemployment is considered as one of the major sources of social problems and it remains to be a significant challenge to every country. Hence, forecasting the trend of unemployment rate contributes to alleviating a country's unemployment problem. This study focuses on forecasting the trend of the Philippine unemployment rate using one of the types of architecture of neural network which is the Feed-forward Artificial Neural Network. Neural networks are modern statistical tools. Nowadays these are widely used in different researches because of its ability to process complex and nonlinear data sets. To generate the Philippine unemployment rate forecast, this study used twelve variables namely, Unemployment Rates, Population, Labor Force, Gross Domestic Product (GDP), Gross National Income (GNI), Gross Domestic Investment (GDI), Inflation Rate, Elementary Level Cohort Survival Rate, High School Level Cohort Survival Rate, Higher Education Graduates, Index of value of production of key manufacturing enterprises by Industry and Foreign Trade covering the year 1991-2014 obtained from Philippine Statistics Authority (PSA) Region X. Results show that the model obtained in this study for forecasting the trend of the unemployment rate in the Philippines is .875

or 87.5% accurate. A mathematical model for forecasting the unemployment rate was also formulated which can be used to generate future estimated values of unemployment rates.

***Keywords*:** Time series forecasting, unemployment rate, feed-forward artificial neural network

INTRODUCTION

According to the latest United Nations (UN) estimates, the 2017 Philippine population is about 104.92 million and it is steadily growing for so many years.

Philippines is the 12th most populated country in the world between Mexico and Ethiopia ("Philippines Population 2018," n.d.).

Based on the preliminary results of the 2017 annual estimates of Labor Force Survey (LFS) conducted by the Philippine Statistics Authority (PSA) that was released last December 18, 2017, the number of unemployed Filipinos is about 2.4 million (Bersales, 2017). An annual average of 2.4 million unemployed Filipinos from a hundred million population is still a problem.

From the updates of Asian Development Bank (ADP), the Philippine economy continued to perform strongly in the first six months of 2017.Gross Domestic Product (GDP) increased by 6.4 percent year on year in the first six months of 2017, moderating from a 7.0 percent pace in the same period last 2016 but in line with the average 6.3 percent annual expansion since 2010 ("Asian Development Outlook2017 Update," n.d). The Philippine economy under Pres. Rodrigo Duterte is said to be the world's fastest growing economy in the world in 2017 (Mourdoukoutas, 2017). In fact, GDP grew by 6.9 percent in the third quarter of 2017 (Bersales, 2017). Our country's economic growth of 6.9 percent in this third quarter, performs even better than China again and also to its neighboring ASEAN countries (Tomacruz, 2017).

Despite rapid economic growth, unemployment is still a persistent problem in our country. Some of the reasons for these problem were rapid population growth, lack of quality education, and environmental factors ("Philippines: Factors Causing Unemployment," 2017). Labor force grows faster than its Gross Domestic Product (GDP) and our government highly invests in education but focuses less on the availability of jobs for future labor force participants resulting to the oversupply of potential workers that would not lead not only to more unemployment but underemployment as well (Daunoras et al., 2011). Moreover, job creation has struggled to keep pace with an ever-expanding population. The number of people entering the job market has been greater than the number of jobs created in three of the last five years. Another factor may be the low quality of jobs available (Salvosa, 2015). Unemployment being a prominent factor in economic growth, forecasting the path of the unemployment rate in the near term is necessary.

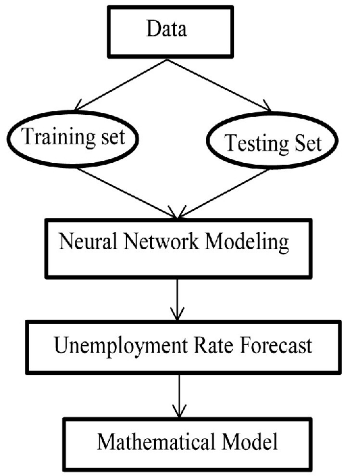
The proportion of the total number of unemployed to the total number of persons in the labor force which is in percent is called an unemployment rate ("Selected Philippine Economic Indicators," 2013). Unemployment rate data is an example of time series data. To analyze time series data, time series analysis is the method that is used and time series forecasting is the use of the model to predict future values based on previously observed values ("Time Series," n.d.).

Time series analysis is one of the applications of Artificial Neural Networks (Belavkin, n.d.). Artificial Neural Networks have been widely utilized as a promising alternative method to time series forecasting (Zhang et al., 2001). It is a new challenger to traditional statistical model (Hill, et al., 1996).

An artificial neural network (ANN) usually called Neural Network (NN) is a mathematical or computational model inspired by the structure and functional aspects of biological neural networks. This consists of interconnected group of artificial neurons, and it processes information using a connectionist approach to computation (central connectionist principle is that mental phenomena can be described by interconnected networks of simple and often uniform units) (Yang, 2018).

One of the types of architecture of ANN is a Feed-forward Artificial Neural Network (FANN). FANNs allow signals to travel one way only, from input to output. There is no feedback (loops) that is; the output of any layer does not affect that same layer. FANNs tend to be straight forward networks that associate inputs with outputs. This type of organization is also referred to as bottom-up or top-down (Pagariya, et al., 2013). This is the most suitable and appropriate ANN architecture in time series predictions. Thus this study uses FANN to forecast the trend of the Philippine unemployment rate.

FRAMEWORK



Data are divided into training set and testing set. Neural network model is trained on the training data set and its performance is tested on the testing data set. After training of the neural network, forecast of the trend of the unemployment rate are generated and the mathematical model of the forecast is derived.

OBJECTIVES OF THE STUDY

The main objective of the study was to forecast the trend of Philippine unemployment rate using a feed-forward artificial neural network. To achieve the main objective, the specific objectives were as follows: 1) consider potential economic indicators that affect unemployment; and 2) formulate the mathematical model for forecasting the trend unemployment rate.

METHODS

This section presents the methodology used to achieve the objectives of the study.

1. Potential economic indicators affecting unemployment

In this study, data were obtained from the PSA Region X that were lifted from the Philippine Statistics Yearbook which is on annual basis from 1991-2014. The input variables for the neural network model that are used in this study were selected based on previous researches, wherein these variables were commonly used as predictors that affect unemployment, such as in the works of Connoly (n.d), Subramaniam, et al.(2011), Resurreccion (2014), Urrutia, et al. (2017), Mahipan, et al. (2013) and Balli, et al. (2013). These variables are Population, Labor Force, Gross Domestic Product (GDP), Gross National Income (GNI), Inflation Rate, Education (Elementary Level Cohort Survival Rate, High School Level Cohort Survival Rate, and Higher Education Graduates) and Index values of production of key manufacturing enterprises by industry.

Intuitively, other economic indicators such as Foreign Trade and GDI are also included in this work because these variables tell us the economic condition, performance and development of our country for a particular period. Time series charts are also used for visual investigation of the data to better understand the relation between them (subjective inspection).

The input variables (predictors) used in this paper are defined and presented in Table 1.

Table 1

Definition of the Input Variables

Variable	Definition
Population	This refers to the total number of persons in a territory at a specified time. It covers both nationals and aliens, native and foreign-born persons, internees, refugees and any other group physically present within the borders of a country at a specified time.

Table 1 Continued

Variable	Definition
Labor Force	The population 15 years old and over whether employed or unemployed who contribute to the production of goods and services in the country.
Gross Domestic Product (GDP)	This refers to the value of all goods and services produced domestically; the sum of gross value added of all resident institutional units engaged in production (plus any taxes, and minus any subsidies, on products not included in the values of their outputs).
Gross National Income (GNI)	This variable refers to the gross domestic product adjusted with the net primary income from/to the rest of the world. It refers to the primary income consisting of compensation and property income receivable from abroad less compensation and property income payable abroad.
Gross Domestic Investment (GDI)	Additions of capital stock in a country that does not include deductions for depreciation of capital that may have been produced previously.
Inflation Rate	The annual rate of change or the year-on-year change in the Consumer Price Index.
Elementary Level Cohort Survival Rate	This refers to the percentage of enrollees at the beginning grade or year in a given school year who reached the final grade or year of the elementary level.
High School Level Cohort Survival Rate	This refers to the percentage of enrollees at the beginning grade or year in a given school year who reached the final grade or year of the secondary level.
Higher Education Graduates	Number of persons who completed a course study at the third level of education.

Table 1 Continued

Variable	Definition
Index of value of production of key manufacturing enterprises by industry	The monthly change of production values in selected manufacturing enterprises
Foreign Trade	Relates to commerce between the Philippines and other countries by sea or air whether for private or government use or for commercial purposes, gifts or samples.

Time series charts:

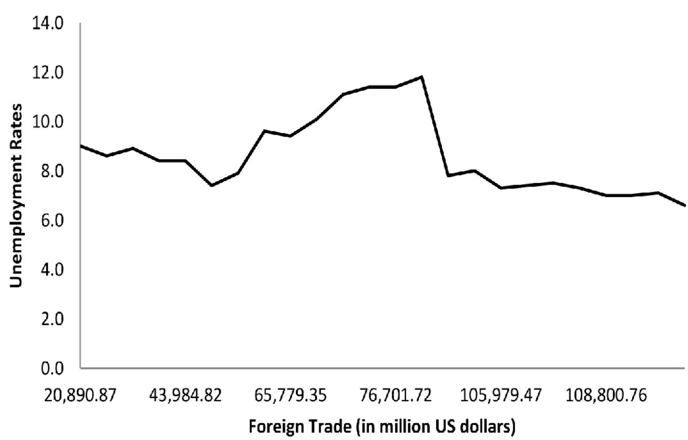


Figure 1. Graph of Unemployment Rates vs Foreign Trade.

The graph in Figure 1 shows the relation between Unemployment and Foreign Trade from 1991 to 2014. Unemployment is at the highest when Foreign Trade reaches 83719.73 (in a million US dollars). After this point, a decreasing trend is observed. From the graph, we can also observe that as Foreign Trade increases, Unemployment decreases.

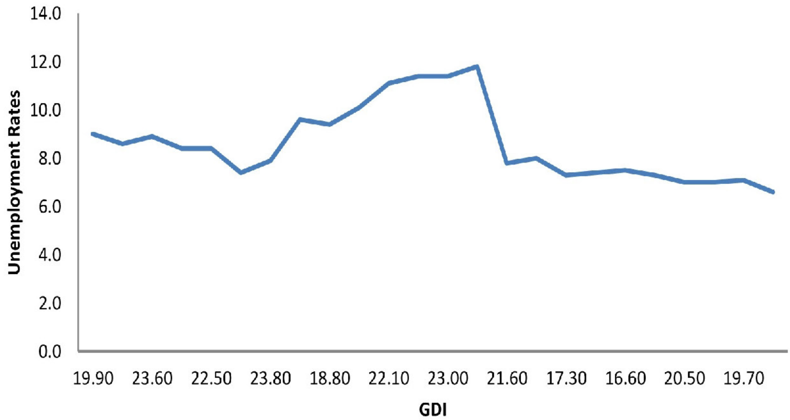


Figure 2. Graph of Unemployment Rates vs GDI.

The graph in Figure 2 shows the relation between Unemployment and GDI from 1991 to 2014 and the trend is either upward or downward. Unemployment is at the highest when GDI is 21.6% and has its lowest point when GDI is 20.9 % but constantly decreases when GDI starts to increase from 24.5% to 29.1%. Here, we observe that there is a tendency for unemployment to decrease as GDI increases.

2. Formulation of the mathematical model for forecasting the trend of the Philippine unemployment rate.

This section discusses how to obtain the mathematical model for predicting the trend of the unemployment rate. However, derivation of this mathematical model can only be done after forecasting has been made. Thus, a step by step forecasting procedure for forecasting is first presented.

The feed-forward neural network topology of the study and the interpretation of its structure are also presented in this section.

The schematic diagram of the forecasting procedure utilized in this study is illustrated in Figure 3.

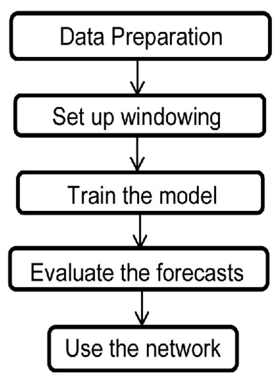


Figure 3. Flow Chart of the Forecasting Procedure.

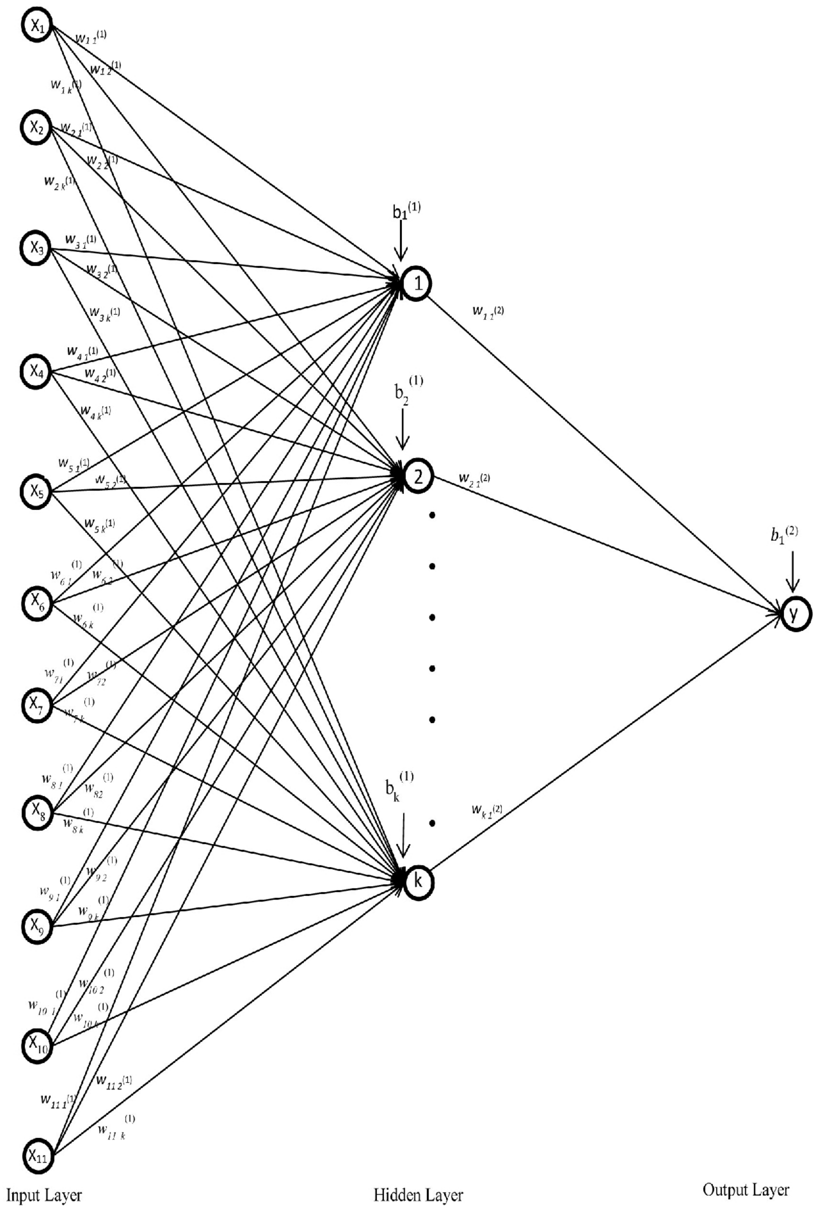


Figure 4. Feed forward neural network structure of the study.

In Figure 4, circles are used to denote the units of the neural network. The leftmost layer of the network is called the input layer. The units in this layer represent the input variables. Since there are eleven independent variables used in this paper, which are Population, Labor Force, Gross Domestic Product (GDP), Gross National Income (GNI), Gross Domestic Investment (GDI), Inflation Rate, Elementary Level Cohort Survival Rate, High School Level Cohort Survival Rate, Higher Education Graduates, Index of value of production of key manufacturing enterprises by Industry and Foreign Trade, then there are also eleven input units in the network wherein one input unit corresponds to one independent variable.

The middle layer of the network is called the hidden layer because its values are not observed in the training set. This study uses one hidden layer and the number of hidden units at this point is assumed to be *k* (where *k* = 1,2,3,4,5,6,7,8,9,10 and *k* is the number of independent variables) because the optimum number of hidden units is still to be verified via experimentation.

The rightmost layer of the network is called the output layer. The unit in the output layer corresponds to the target or the dependent variable which is the variable Unemployment Rate.

The pattern that is sought by the neural network in the data through the mapping between inputs and desired outputs is translated into a computational model.

The computation that the neural network represents in Figure 4 is:

$$y = denormalized\,[f_{output}\big(a_1{}^{(1)}w_{11}{}^{(2)} + a_2{}^{(1)}w_{21}{}^{(2)} + a_3{}^{(1)}w_{31}{}^{(2)} + a_4{}^{(1)}w_{41}{}^{(2)} + \dots\dots\dots\dots\dots + a_n{}^{(1)}w_{k1}{}^{(2)} + b_1{}^{(2)}\big)] + \varepsilon \quad (1)$$

where:

$$a_1{}^{(1)} = f_{hidden}(x_1w_{11}{}^{(1)} + x_2w_{21}{}^{(1)} + x_3w_{31}{}^{(1)} + x_4w_{41}{}^{(1)} + x_5w_{51}{}^{(1)} + x_6w_{61}{}^{(1)} + x_7w_{71}{}^{(1)} + x_8w_{81}{}^{(1)} + x_9w_{91}{}^{(1)} + x_{10}w_{10\,1}{}^{(1)} + x_{11}w_{11\,1}{}^{(1)} + b_1{}^{(1)})$$

$$a_2{}^{(1)} = f_{hidden}(x_1w_{12}{}^{(1)} + x_2w_{22}{}^{(1)} + x_3w_{32}{}^{(1)} + x_4w_{42}{}^{(1)} + x_5w_{52}{}^{(1)} + x_6w_{62}{}^{(1)} + x_7w_{72}{}^{(1)} + x_8w_{82}{}^{(1)} + x_9w_{92}{}^{(1)} + x_{10}w_{10\,2}{}^{(1)} + x_{11}w_{11\,2}{}^{(1)} + b_2{}^{(1)})$$

$$a_3{}^{(1)} = f_{hidden}(x_1w_{13}{}^{(1)} + x_2w_{23}{}^{(1)} + x_3w_{33}{}^{(1)} + x_4w_{43}{}^{(1)} + x_5w_{53}{}^{(1)} + x_6w_{63}{}^{(1)} + x_7w_{73}{}^{(1)} + x_8w_{83}{}^{(1)} + x_9w_{93}{}^{(1)} + x_{10}w_{10\,3}{}^{(1)} + x_{11}w_{11\,3}{}^{(1)} + b_3{}^{(1)})$$

$a_4^{(1)} = f_{hidden}(x_1 w_{14}^{(1)} + x_2 w_{24}^{(1)} + x_3 w_{34}^{(1)} + x_4 w_{44}^{(1)} + x_5 w_{54}^{(1)} + x_6 w_{64}^{(1)} + x_7 w_{74}^{(1)} + x_8 w_{84}^{(1)} + x_9 w_{94}^{(1)} + x_{10} w_{10\,4}^{(1)} + x_{11} w_{11\,4}^{(1)} + b_4^{(1)})$

. .

. .

$a_k^{(1)} = f_{hidden}(x_1 w_{1k}^{(1)} + x_2 w_{2k}^{(1)} + x_3 w_{3k}^{(1)} + x_4 w_{4k}^{(1)} + x_5 w_{5k}^{(1)} + x_6 w_{6k}^{(1)} + x_7 w_{7k}^{(1)} + x_8 w_{8k}^{(1)} + x_9 w_{9k}^{(1)} + x_{10} w_{10\,k}^{(1)} + x_{11} w_{11\,k}^{(1)} + b_k^{(1)})$

k = 1,2,3,4,5,6,7,8,9,10

x_1 = Population

x_2 = Labor force

x_3 = Inflation

x_4 = GDP

x_5 = GNI

x_6 = GDI

x_7 = Foreign Trade

x_8 = Index of value of production of key manufacturing enterprises by Industry

x_9 = Cohort survival rate at the Elementary Level

x_{10} = Cohort survival rate at the High School Level

x_{11} = Higher Education Graduates

$w_{11}^{(1)}$ = is the weight associated with the connection between unit 1 in the input layer and unit 1 in the hidden layer

$w_{21}^{(1)}$ = is the weight associated with the connection between unit 2 in the input layer and unit 1 in the hidden layer

$w_{31}^{(1)}$ = is the weight associated with the connection between unit 3 in the input layer and unit 1 in the hidden layer

$w_{11\,1}^{(1)}$ = is the weight associated with the connection between unit 11 in the input layer and unit 1in the hidden layer

$w_{12}^{(1)}$ = is the weight associated with the connection between unit 1 in the input layer and unit 2 in the hidden layer

$w_{22}^{(1)}$ = is the weight associated with the connection between unit 2 in the input layer and unit 2 in the hidden layer

${w_{32}}^{(1)}$ = is the weight associated with the connection between unit 3 in the input layer and unit 2 in the hidden layer

${w_{11\,2}}^{(1)}$ = is the weight associated with the connection between unit 1 in the input layer and unit 2 in the hidden layer

${w_{1k}}^{(1)}$ = is the weight associated with the connection between unit 1 in the input layer and unit *k* in the hidden layer

${w_{2k}}^{(1)}$ = is the weight associated with the connection between unit 2 in the input layer and unit *k* in the hidden layer

${w_{3n}}^{(1)}$ = is the weight associated with the connection between unit 3 in the input layer and unit *k* in the hidden layer

${w_{11\,k}}^{(1)}$ = is the weight associated with the connection between unit 11 in the input layer and unit *k* in the hidden layer

${w_{11}}^{(2)}$ = is the weight associated with the connection between unit 1 in the hidden layer and the unit in the output layer

${w_{21}}^{(2)}$ = is the weight associated with the connection between unit 2 in the hidden layer and the unit in the output layer

${w_{31}}^{(2)}$ = is the weight associated with the connection between unit 3in the hidden layer and the unit in the output layer

${w_{k1}}^{(2)}$ = is the weight associated with the connection between unit *k* in the hidden layer and the unit in the output layer

${b_1}^{(1)}$ = is the bias associated with unit 1 in the hidden layer

${b_2}^{(1)}$ = is the bias associated with unit 2 in the hidden layer

${b_3}^{(1)}$ = is the bias associated with unit 3 in the hidden layer

${b_k}^{(1)}$ = is the bias associated with the unit *k* in the hidden layer

${b_1}^{(2)}$ = is the bias associated with the unit in the output layer

${a_k}^{(1)}$ = is the activation of unit *k* in the hidden layer

ε = is the random error

y = is the predicted unemployment rate

$f_{hidden}(x) = \frac{1}{1+\ e^{-x}}$, x is any real number. This is the sigmoid activation function of the units in the hidden layer.

$f_{output}(x) = x$, x is any real number. This is the linear activation function of the unit in the output layer.

To compute for the final output (y), the initial output is denormalized first (to convert it into its raw value) and added to a random error because the input values were normalized initially using the equation

$$x_{new} = \frac{x - \mu}{s}$$

where x_{new} is the standard score of a raw score x, μ is the population mean and s is sample standard deviation before it was used for training and testing. So therefore the initial output value is also in normalized form. To denormalize the initial output the following equation is applied:

$$f_{denorm} = fs + \mu \qquad (2)$$

where f_{denorm} is the denormalized value of f, s is the sample standard deviation and μ is the population mean of the variable unemployment.

RESULTS AND DISCUSSION

1. Forecasting the Philippine Unemployment Rate

Figure 5 shows the model building process for the development of the algorithm. The algorithm was implemented using RapidMiner Studio Free Edition 8.1.001, a widely known and used software tool for data mining and predictive analytics. The process required two stages, namely - training the model and testing the model.

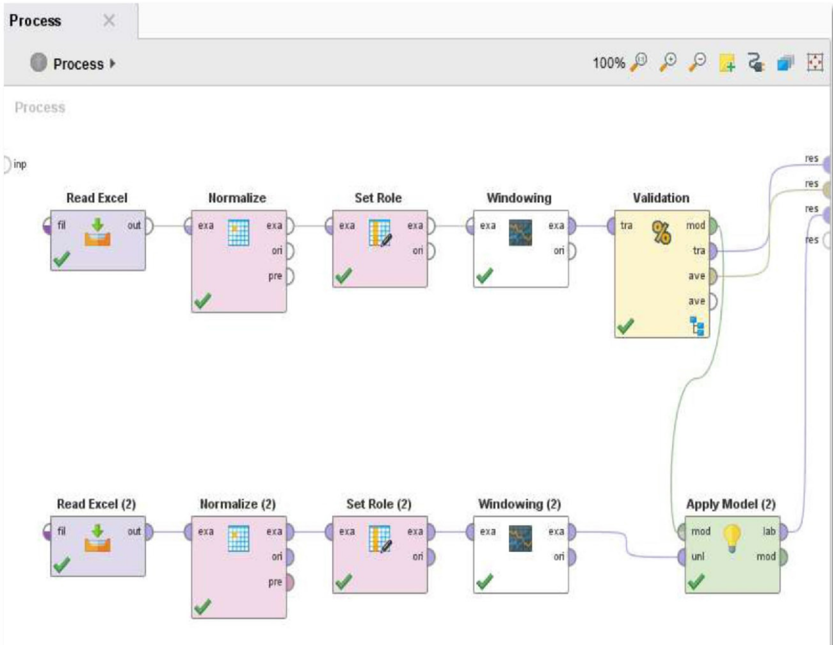
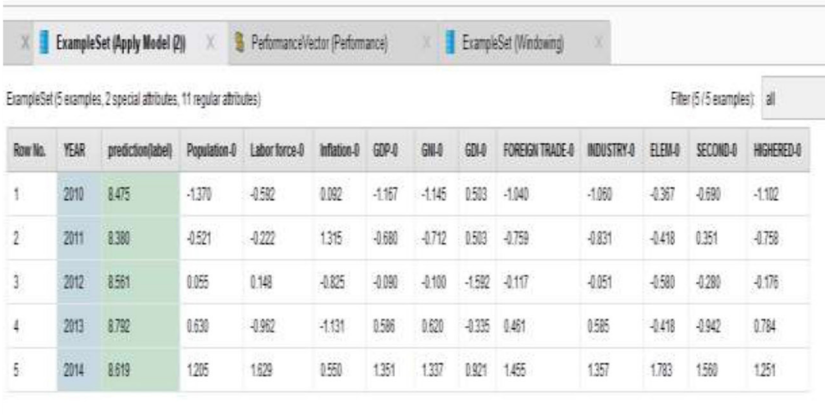


Figure 5. Overall process of the time series forecasting.

Eighty percent (80%) of the data set which is from 1991 to 2009 was imported to the Rapidminer database. This data set was used for training the model while twenty percent (20%) of the data set which covers data from 2010 to 2014 was used to test the performance of the model. The neural network learned the pattern existing between the input and target variables using backpropagation technique with a learning rate of 0.74 and a momentum of 0.58. After running the process, forecasting results generated are the prediction trend accuracy of the model, prediction on the test set and the neural network structure.



ExampleSet (Apply Model (2)) | PerformanceVector (Performance) | ExampleSet (Windowing)

ExampleSet (5 examples, 2 special attributes, 11 regular attributes)   Filter (5 / 5 examples): all

Row No.	YEAR	prediction(label)	Population-0	Labor force-0	Inflation-0	GDP-0	GNI-0	GDI-0	FOREIGN TRADE-0	INDUSTRY-0	ELEM-0	SECOND-0	HIGHERED-0
1	2010	8.475	-1.370	-0.592	0.092	-1.167	-1.145	0.503	-1.040	-1.060	-0.367	-0.690	-1.102
2	2011	8.380	-0.521	-0.222	1.315	-0.680	-0.712	0.503	-0.759	-0.831	-0.418	0.351	-0.758
3	2012	8.561	0.055	0.148	-0.825	-0.090	-0.100	-1.592	-0.117	-0.051	-0.580	-0.280	-0.176
4	2013	8.792	0.630	-0.962	-1.131	0.586	0.620	-0.335	0.461	0.585	-0.418	-0.942	0.784
5	2014	8.619	1.205	1.629	0.550	1.351	1.337	0.921	1.455	1.357	1.783	1.560	1.251

Figure 6. Screen shot of the Predicted Values of Unemployment Rates on the Testing Set.

Figure 6 shows the predicted values from 2010 to 2014 with a prediction trend accuracy of.875 or 87.5% shown in Figure 7. This means that the model is 87.5% accurate in predicting the trend of unemployment.

Figure 7. Screen shot of the prediction trend accuracy of the model.

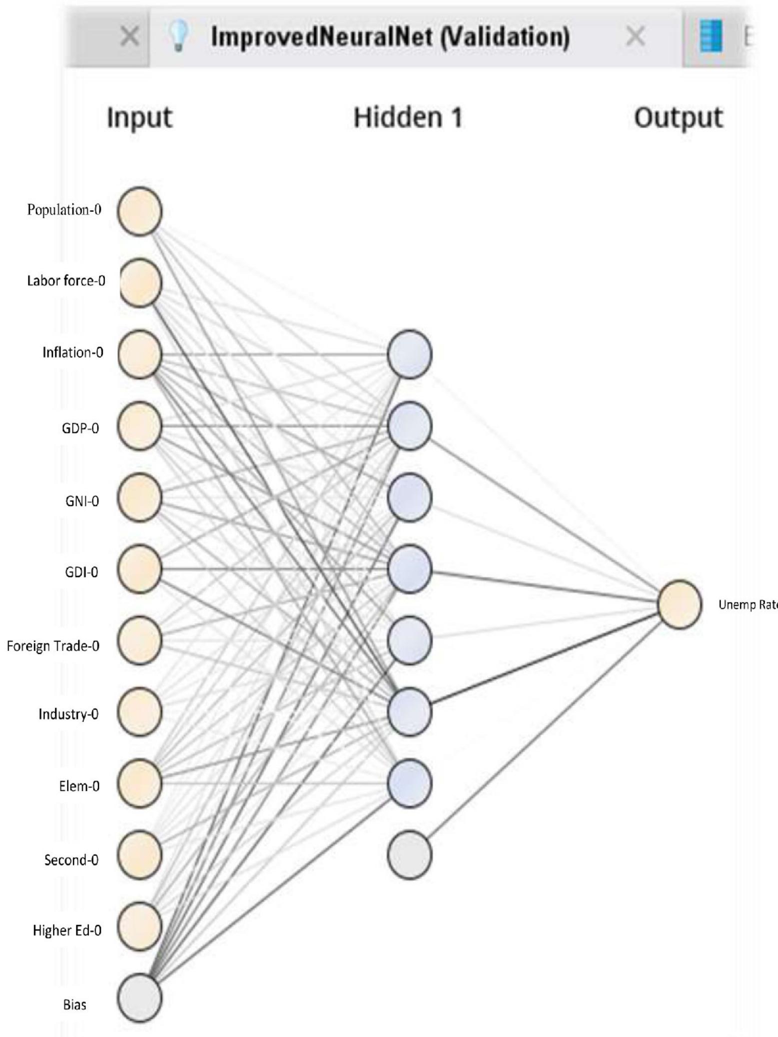


Figure 8. Screen shot of the neural network output with a single hidden layer and eleven attributes.

Figure 8 shows the neural network structure of the model. The input layer has eleven plus one unit where the eleven units represent the eleven input variables and the additional unit is the bias unit (note that a bias unit is a unit with a constant value of 1). The structure has a single hidden layer with seven units plus one bias unit and the output layer has one unit which corresponds to the output or target variable.

Table 2

Weights and biases of the network

Input variable	Hidden (sigmoid)							Bias
	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6	Node 7	
Population	-0.069	0.309	-0.131	0.508	-0.093	-0.750	-0.028	
Labor Force	-0.259	-0.289	0.223	-0.315	-0.243	-1.317	-0.290	
Inflation	0.647	0.504	0.681	0.533	0.662	1.053	0.649	
GDP	0.267	0.712	0.225	0.800	0.209	-0.397	0.321	
GNI	0.183	0.645	0.156	0.728	0.196	-0.575	0.331	
GDI	-0.162	-0.678	-0.057	-0.843	-0.029	-0.957	-0.220	
Foreign Trade	-0.105	0.417	-0.134	0.618	-0.184	-0.445	-0.039	
Industry	0.195	-0.059	0.236	-0.158	0.244	-0.065	0.156	
Elementary	0.419	0.354	0.502	0.416	0.493	-0.814	0.400	
Secondary	-0.142	0.119	-0.211	0.198	-0.217	0.592	-0.208	
Higher Educ.	0.197	0.495	0.171	0.604	0.159	-0.326	0.239	
Bias	-1.217	-0.963	-1.194	-0.936	-1.200	-0.413	-1.178	
Output(linear)	0.089	-0.849	0.246	-1.198	0.271	-1.746	-0.034	1.095

Tables 2 shows the weights (links of the input nodes and output nodes) and biases of the network with sigmoid function as the hidden layer activation function and linear function as the output layer activation function.

2. Mathematical Model of the Philippine Unemployment Rate Trend Forecast

The mathematical model of the trend forecast of the Philippine unemployment rate was derived using the weights and biases displayed in Table 2 and these values are substituted in equation (1).

The mathematical model is as follows:

$$y = denormalized\ [f_{output}(\ 0.089a_1{}^{(1)} - 0.849\ a_2{}^{(1)} + 0.246a_3{}^{(1)} - 1.198a_4{}^{(1)} + \ 0.271a_5{}^{(1)} - 1.746a_6{}^{(1)} - 0.034a_7{}^{(1)} + 1.095\ )] + \ \varepsilon$$

where:

$a_1{}^{(1)} = f_{hidden}(-0.069x_1 - 0.259\, x_2 + 0.647\, x_3 + 0.267x_4 + 0.183x_5 - 0.162x_6 - 0.105x_7 + 0.195x_8 + 0.419x_9 - 0.142x_{10} + 0.197x_{11} - 1.217)$

$a_2{}^{(1)} = f_{hidden}\,(0.309x_1 - 0.289\, x_2 + 0.504\, x_3 + 0.712x_4 + 0.645x_5 - 0.678x_6 + 0.417x_7 - 0.059x_8 + 0.354x_9 + 0.119x_{10} + 0.495x_{11} - 0.963)$

$a_3{}^{(1)} = f_{hidden}\,(-0.131x_1 - 0.223\, x_2 + 0.681\, x_3 + 0.225x_4 + 0.156x_5 - 0.057x_6 - 0.134x_7 + 0.236x_8 + 0.502x_9 - 0.211x_{10} + 0.171x_{11} - 1.194)$

$a_4{}^{(1)} = f_{hidden}\,(0.508x_1 - 0.315\, x_2 + 0.533\, x_3 + 0.800x_4 + 0.728x_5 - 0.843x_6 + 0.618x_7 - 0.158x_8 + 0.416x_9 + 0.198x_{10} + 0.604x_{11} - 0.936)$

$a_5{}^{(1)} = f_{hidden}\,(-0.093x_1 - 0.243\, x_2 + 0.662\, x_3 + 0.209x_4 + 0.196x_5 - 0.029x_6 - 0.184x_7 + 0.244x_8 + 0.493x_9 - 0.217x_{10} + 0.159x_{11} - 1.200)$

$a_6{}^{(1)} = f_{hidden}\,(-0.750x_1 - 1.317\, x_2 + 1.053\, x_3 - 0.397x_4 - 0.575x_5 - 0.957x_6 - 0.445x_7 - 0.065x_8 - 0.814x_9 + 0.592x_{10} - 0.326x_{11} - 0.413)$

$a_7{}^{(1)} = f_{hidden}\,(-0.028x_1 - 0.290\, x_2 + 0.649\, x_3 + 0.321x_4 + 0.331x_5 - 0.220x_6 - 0.039x_7 + 0.156x_8 + 0.400x_9 - 0.208x_{10} + 0.239x_{11} - 1.178)$

$f_{hidden}(x) = \frac{1}{1+ e^{-x}}$ and $f_{output}(x) = x$ (x is any real number) are the activation functions of the hidden and output layers respectively.

CONCLUSIONS

This paper aimed to forecast the trend of Philippine unemployment rate using Feed-forward Artificial Neural Network. Potential economic indicators such as Population, Labor Force, Gross Domestic Product (GDP), Gross National Income (GNI), Inflation Rate, Education (Elementary Level Cohort Survival Rate, High School Level Cohort Survival Rate, and Higher Education Graduates) and Index values of production of key manufacturing enterprises by industry that affect unemployment were considered. Forecasting model obtained in this study showed a prediction trend accuracy of 87.5% on the testing set. This means that the model can be an effective tool for analyzing and predicting the behavior of the dynamics of the unemployment rate.

Furthermore, a mathematical model was formulated based on the forecasting obtained.

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