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Araştırma Makalesi

FUTURE OF UNEMPLOYMENT IN JAPAN: AN ARTIFICIAL NEURAL NETWORK FORECAST UTILISING ARTIFICIAL INTELLIGENCE AND MACROECONOMIC DYNAMICS

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Abstract[1]

Since the unemployment rate is a critical factor that directly affects a country's economic performance and social health, reducing unemployment with effective policies is of great importance for sustainable development and prosperity. Therefore, precise forecasting of the unemployment rate is pivotal to effective policymaking and planning, especially in Japan, where unique demographic structures and economic challenges prevail. This study aims to estimate the unemployment rate in Japan using an Artificial Neural Network (ANN) model with the annual data for the period 1985-2017. Key factors shaping Japan's labour market dynamics, such as artificial intelligence-related technology patent applications, inflation rate, population growth rate, and labour productivity, are used to estimate the unemployment rate. The findings indicate that the Japanese unemployment rate is expected to increase gradually until 2030. This research provides significant insights to the Japanese government and policymakers through a non-linear forecasting model that includes the variable of artificial intelligence, which has not previously been used in the literature.

Keywords: *Artificial Neural Networks, Unemployment Forecasting, Artificial Intelligence, Japan.*

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[1] Ethics committee approval is not required for this study.

JAPONYA'DA İŞŞİZLİĞİN GELECEĞİ: YAPAY ZEKA VE MAKROEKONOMİK DİNAMİKLER İLE BİR YAPAY SİNİR AĞI TAHMİNİ

Öz

İşsizlik oranlarını azaltmak bir ülkenin hem ekonomik performansını hem de sosyal sağlığını doğrudan etkileyen kritik bir faktör olduğundan, etkili politikalarla işsizlikle mücadele etmek sürdürülebilir kalkınma ve refah için büyük önem taşımaktadır. Bu nedenle işsizlik oranını doğru bir şekilde tahmin etmek, özellikle benzersiz demografik yapıların ve ekonomik zorlukların hakim olduğu Japonya'da, etkili ekonomik planlama ve strateji geliştirmenin merkezinde yer almaktadır. Bu çalışma, 1985-2017 dönemine ait yıllık verilerle Yapay Sinir Ağı (YSA) modeli kullanarak Japonya'daki işsizlik oranını tahmin etmeyi amaçlamaktadır. Yapay zeka ile ilgili teknoloji patent başvuruları, , enflasyon oranı, nüfus artış hızı ve işgücü verimliliği gibi Japonya'nın işgücü piyasası dinamiklerini şekillendiren temel faktörler işsizlik oranını tahmin etmek için kullanılmıştır. Sonuçlar, işsizlik oranının 2030 yılına kadar kademeli olarak artacağının beklendiğini göstermektedir. Bu araştırma, literatürde daha önce kullanılmamış olan yapay zekayı değişkenini de içeren doğrusal olmayan bir tahmin modeli aracılığıyla hesaplandığından Japon hükümetine ve politika yapıcılara önemli bilgiler sağlamaktadır.

Anahtar kelimeler: *Yapay Sinir Ağları, İşsizlik Tahmini, Yapay Zeka, Japonya.*

INTRODUCTION

Unemployment is a socio-economic phenomenon illustrating some individuals who are able to and willing to work but cannot find suitable jobs. This phenomenon directly indicates a dysfunctionality in the labour market, where there is a maladjustment between labour supply and demand, leading to lower economic growth. In addition to this decline in total output, high levels of unemployment deepen economic inequality and distort the distribution of wealth in the long term. In addition, a persistent high level of unemployment might lead to a loss of skills (Darity Jr., 1999, p. 494). The adverse effects of unemployment are not limited to the social impacts. Sen (1997, p. 160) discussed that the impact of being unemployed on human psychology cannot be neglected as it causes social exclusion and loss of freedom.

Given the detrimental effects on the economy, societies and individuals, forecasting the unemployment rate plays a crucial role in policy-making and planning. Before the stagflation in 1973, the policymakers tended to rely on Okun's law, which shows the correlation between output and unemployment alterations to predict unemployment level. After the stagflation, different time series models were exercised to forecast the unemployment rate precisely in the literature. The autoregressive integrated moving average model (ARIMA), introduced by Box and Jenkins (1970), is one of the most common approaches that has been used in empirical studies such as for Germany (Funke, 1992), Spain (Vicente et al., 2015), Nigeria (Etuk et al., 2012), and for Romania (Dobre & Alexandru, 2008). The accuracy and efficacy of the model were proven by several studies focused on European countries (Edlund & Karlsson, 1993; Dumicic et al., 2015). However, Montgomery et al. (1998), De Long and Summers (1994) and Rothman (1998) report that the US unemployment shows cyclical asymmetries, which means unemployment rates show sheer rises, having sharp peaks at the end and alternate with much more steady and prolonged decreases having slight troughs at the end. Considering these asymmetric cyclicales, they discuss that univariate linear models fall short of representing these asymmetries in forecasting. Using a classical nonlinear time series model (Threshold Autoregressive model), they find that nonlinear regressions outperform the linear time series model for predicting the US unemployment rate. Congruent results are documented in the literature, and they suggest that non-linear time series estimations display better performance in capturing the asymmetric behaviour of unemployment rates than the linear time series models (Rothman, 1998; Proietti, 2003; Parker & Rothman, 2005).

Another issue in forecasting is deciding which non-linear approach is more suitable. The recent advancements in modern statistics and machine learning help forecasting analysts by improving nonlinear forecasting methodologies like support vector machines (SVM), artificial neural networks (ANN) and deep learning (Katris, 2020, p. 674). Amongst these models, Pelaez (2006) and Wang and Zheng (2009) find that the ANN models provide the most accurate results.

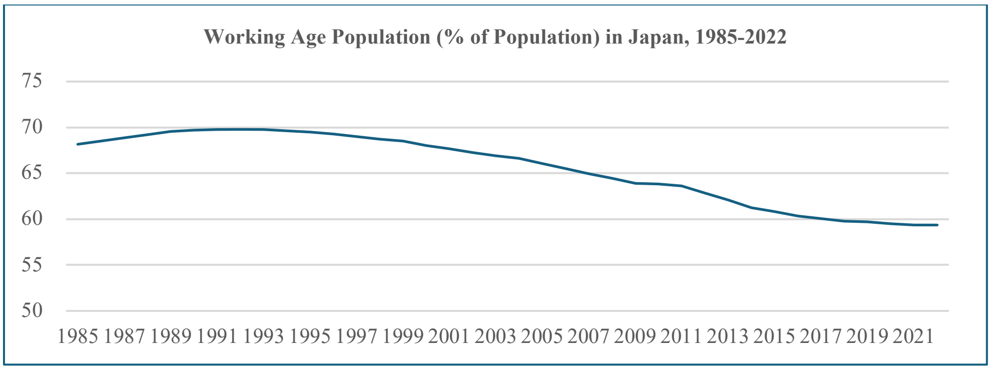
Artificial neural networks are modelled on the biological principles of the human brain. Similar to the human brain, the model inductively learns new associations, patterns and functional relationships by analysing the provided data (Aiken, 1996, p.38). Aiken (1996) discusses the advantages of using the ANN model over time-series techniques and statistical modelling. First, ANN is not programmed like other traditional software programs; instead, it is trained. The training process entails repeatedly exposing the network to individual data examples used for predictions or groupings until the network discerns the underlying patterns between the independent variables (inputs) and dependent variables (outputs). Secondly, the ANN method does not demand any assumptions for the underlying data like other linear or non-linear regressions to be predicted. Finally, ANN does not require a complete and perfect dataset, meaning the model can be developed with missing data.

Johnes (1999) compares the outcomes of non-linear time series models, classical linear time series models, and artificial neural network (ANN) models using the monthly unemployment rate data of the United Kingdom. The findings present that ANN provides more accurate predictions where the data display non-linear characteristics (Chiu & Su, 1998; Freisleben & Ripper, 1995; Tufaner & Sözen, 2021; Yamacli & Yamacli, 2023). In the same vein, Moshiri and Brown (2004) report that the ANN method provides better estimations for the US, Canada, France and Japan. They discuss that the classical non-linear forecasting techniques are not improved for all models; however, the ANN models can be used for all types of non-linear mapping issues as they are universal approximators. Hence, he states that the use of the ANN can be the solution to the model specification issue.

Considering the advantages of the model, we apply the ANN method to forecast the unemployment rate in Japan using annual data from 1985 to 2017. The estimation of the unemployment rate has become progressively more important for policymakers and the government in Japan due to its unique demographic challenges and the structure of the labour market. The Japanese economy has been witnessing a tight labour market as labour supply nearly reached its limits. The traditional Japanese labour market has been determined by a lifelong employment system, seniority-based wages, working for long hours and loyalty. Although the system helped to strengthen economic growth after the post-war period, it resulted in restricted labour mobility and labour shortage. In the early 1990s, the outburst of the asset bubble crisis led to a decrease in job growth. This reduction incentivised firms to hire non-regular workers, and this arising duality in the labour market caused crucial negative impacts on labour productivity (Aoyagi and Ganelli, 2015, p. 107).

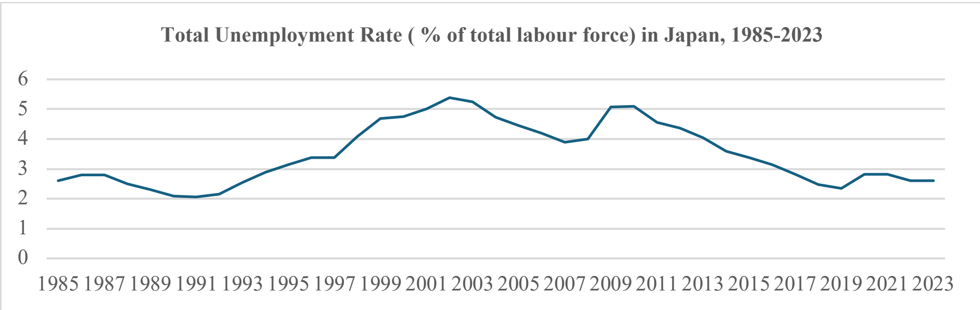
The problems in the Japanese labour market are not limited to the duality and traditional system. Figure 1 shows that the working-age population, representing the share of 15 to 64 years in the total population, has been gradually declining after reaching its peak in 1993. This substantial decrease in the working-age population leads to a severe labour shortage and eventually puts pressure on wages in Japan. The pressure on wages might lead to alterations in wage- and price-setting behaviours and contribute to ending decades of deflation in Japan. Figure 3 indicates that the battle of the Japanese economy with deflation has nearly come to an end.

Figure 1: Working-Age Population, 1985-2022



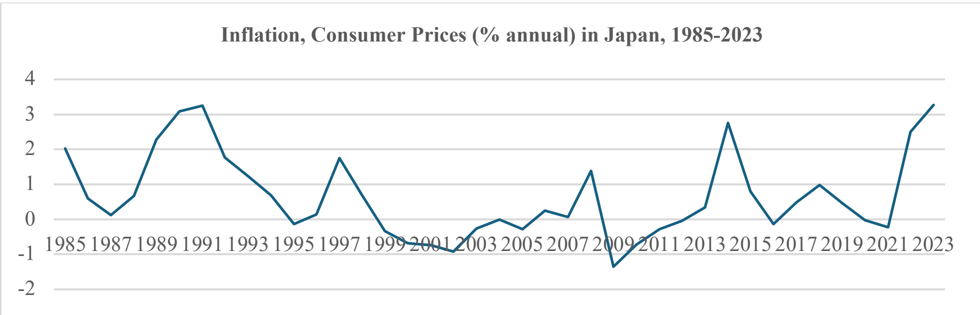
Source: OECD. (2024a). Working-age population: Japan. OECD. Retrieved May 28, 2024, https://www.oecd.org/en/data/indicators/working-age-population.html?oecdcontrol-d6804ae080-var1=JPN.

Figure 2: Total Unemployment Rate, 1985-2023



Source: Worldbank. (2024a). World Development Indicators. Retrieved May 19, 2024, from https://data.worldbank.org/indicator/SL.UEM.TOTL.NE.ZS?locations=JP

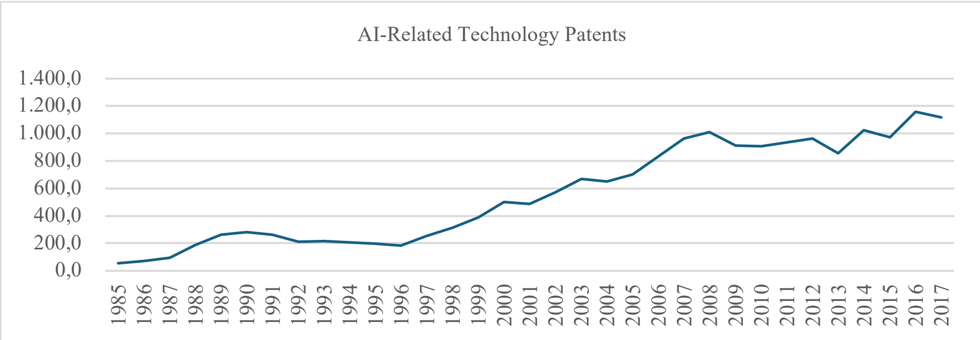
Figure 3: Inflation of Consumer Prices, 1985-2023



Source: Worldbank. (2024b). World Development Indicators. Retrieved May 19, 2024, from https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG?end=2023&locations=JP&start=1985

Another reason highlighting the importance of forecasting Japanese unemployment is the recent advancements in artificial intelligence. Japan Patent Office reported that the number of domestic applications for AI-related inventions has rocketed during the last decade after the Japanese Cabinet announced Society 5.0, as shown in Figure 4. (Japan Patent Office, 2023). With this plan, the government aim to create a super-smart society where advanced technologies like AI, robotics, big data and the Internet of Things are integrated into all facets of human life (Huang et al., 2022, p. 425). Although there is no certain consensus on the impacts of AI on unemployment in the literature, several findings show that AI (with automation) results in the direct substitution of jobs and tasks that workers currently perform. Hence, AI is expected to cause the displacement effect, which can diminish the labour demand, wages and employment (Frey & Osborne, 2017, p. 265; Nedelkoska & Quintini, 2018, p. 115).

Figure 4: AI-Related Technology Patents



Source: OECD. (2024b). OECD Patent Statistics. Retrieved May 28, 2024, from https://www.oecd-ilibrary.org/science-and-technology/data/oecd-patent-statistics_patent-data-en

Given the challenges in both the labour market and economic structure above, predicting the unemployment rate is essential for the Japanese government and policymakers. This study, aims to estimate the Japanese unemployment rate using artificial intelligence, makes an important contribution to the literature as it is one of the limited number of studies in the literature. Also, as Japan is home to one of the highest domestic AI-related patent applications, this study can make significant contributions to the future planning studies of politicians who are in a position to make decisions regarding combating unemployment. Moreover, the fact that the ANN architecture, which was put forward by considering four input variables in the case of Japan, can be used as a role model in estimating unemployment rates in other countries increases the importance of the study.

The rest of the paper consists of four sections. The next section explains the data processing and the input variables used in the model. Then, the paper includes the methodology and the results, respectively. Finally, the conclusion is included.

INPUT VARIABLES AND DATA PROCESSING

This research predicts the Japanese unemployment rates with the help of population, a number of artificial intelligence patents, inflation, and labour productivity input data, which are the most crucial indicators that shape the unemployment rate in Japan, taking into account Japan's annual data for 1985-2017. In the study, future predictions are made about the unemployment rates of the Japanese economy using the artificial neural networks (ANN) method. The variables used, their explanations, and the databases from which the variables are obtained are listed in Table 1. MATLAB (R2015b) program is used to estimate the unemployment model in Japan.

Table 1: Description of Target and Input Variables

Variables	Explanation	Source
Target- Unemployment	Unemployment, total (% of total labor force) (national estimate)	World Development Indicators
Input 1- Population	Population growth (annual %)	World Development Indicators
Input 2- Artificial intelligence	Technologies related to artificial intelligence	OECD online database—Patent statistics
Input 3-Inflation	Inflation consumer price (annual %)	World Development Indicators
Input 4-Labour productivity	GDP per hour worked	OECD (2024)

Source: World Bank. (2024). World Development Indicators. Retrieved May 19, 2024, from https://databank.worldbank.org/reports.aspx?source=world-development-indicators; OECD. (2024b). OECD Patent Statistics. Retrieved May 28, 2024, from https://www.oecd-ilibrary.org/science-and-technology/data/oecd-patent-statistics_patent-data-en; OECD. (2024c). GDP per hour worked. Retrieved May 28, 2024, from https://www.oecd.org/en/data/indicators/gdp-per-hour-worked.html

While the unemployment rate is determined as the output variable with annual data for the period 1985-2017, population growth (annual %), number of artificial intelligence-related technology patents, inflation consumer price (annual %), and GDP per hour worked, which is an indicator of labour productivity, are used as input variables. Due to limited access to data on the number of artificial intelligence-related technology patents variable, the end year of the series is 2017. Descriptive statistics of the variables are given in Table 2.

Table 2: Descriptive Statistics

Variables	Mean	Median	Minimum	Maximum	Std. Deviation
Target:					
Unemployment rate (%)	3.6701	3.589	2.059	5.386	1.0285
Inputs:					
Population (%)	0.1690	0.2139	-0.1852	0.6259	0.2149
Artificial intelligence	558.0756	498.8311	55	1158.5505	357.8557
Inflation (%)	0.5594	0.2493	-1.3528	3.2514	1.1677
Labor productivity	82.5363	85.8	54.6	101	13.8117

Table 2 represents the mean values, median, minimum and maximum values, and standard deviations of the variables used in the study. As can be seen from the statistical explanation, the highest value for the unemployment rate, with an average of 3.67% and used as the dependent variable in the study, is 5.38%, and the lowest value is only 2.05%. Observations regarding the population growth rate variable range between -0.18% and 0.62%, but its average value is 0.16%. While the average value of artificial intelligence-related technology patents is 558.07, the minimum and maximum values are 55 and 1158.55, respectively. The inflation rate, another important variable in this article, varies between -1.35% and 3.2%, but its average is 0.55%. The labour productivity reaches its maximum value at 101, while the minimum value is 54.6, and the average is 82.53.

After the required data was determined, the input and output data were normalised between -1 and 1 to eliminate the possibility of outliers, that is, data with extremely small and large values, misleading the network. This process is carried out with the help of the *premnmx* command in the Neural Network Toolbox. Normalised values for each raw input/output dataset are calculated using the formula used in Equation 1.

$$p_n = 2 \text{ x} \left(\frac{p - min_p}{max_p - min_p}\right) - 1 \quad (1)$$

Where p is the value of the variable p_n is the normalised value ranging from -1 to 1. min_p refers to the lowest value of the variable in the series examined and max_p refers to the highest value (Uliana et al., 2024, p. 4; Wang, 2023, p. 800).

After training the normalised data with the newff (feedforward backpropagation algorithm) command, the validation and test data are normalised. While these data are normalised, they are normalised at the same rate as the training data. In this way, an identical data table is obtained. Then, the prediction process is carried out. Since these estimated values are between -1 and 1, the real values of the data obtained are revealed by reverse normalisation with the help of the postmnmx command and the formula in Equation 2.

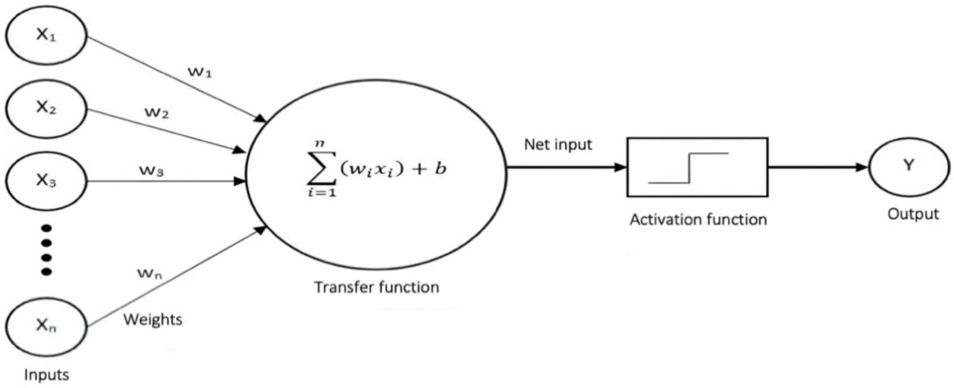
$$p = 0.5(p_n + 1)*(max_p - min_p) + min_p \quad (2)$$

Here, p_n refers to the normalised value, min_p and max_p refer to the smallest and largest values of the series, respectively (Demuth et al., 1998, p. 13-178).

METHODOLOGY

Artificial neural networks, which are the core names of deep learning dating back to the 1940s, are systems designed inspired by the biological brain (human brain or the brain of another animal) (Goodfellow et al., 2016, p. 13). The way artificial neural networks and the human brain work is similar in two respects. First, knowledge is received by the network via a process of learning. Secondly, the links called synaptic weights between nerve cells are used to store information (Haykin, 1999, p. 23). In artificial neural networks that mimic the human neuron, the inputs represented by X are multiplied by the relevant connection weights denoted by W after entering the neuron and then combined with a combination function (sum function). In this way, the net input of the neuron is obtained. The net input is processed by the activation function. The output of the activation function determines the net output of the neuron. (Hamzaçebi, 2021, p. 24 - 40) An illustration of an artificial nerve cell is shown in Figure 5.

Figure 5: Artificial Nerve Cell Structure

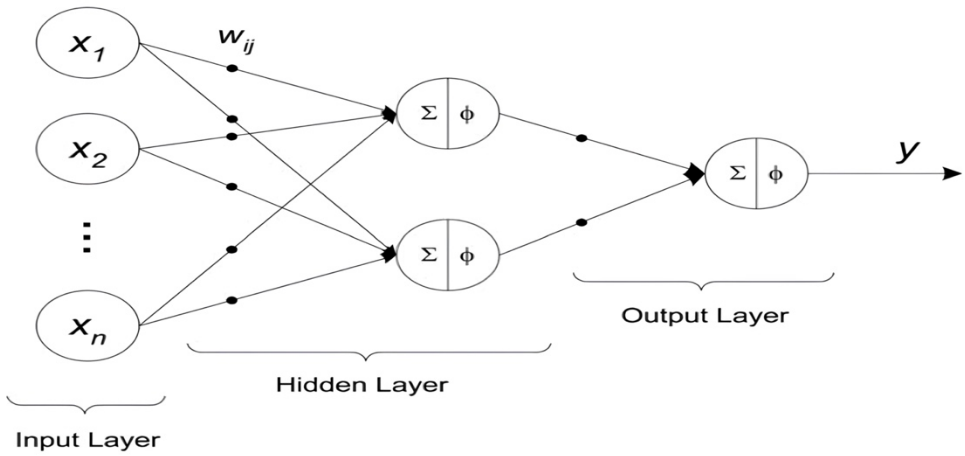


Source: Chang, Y. H., & Chung, C. Y., 2020, p.46.

In the structure shown in Figure 5, x_i refers to the value of the ith input, w_i refers to the connection weight of the ith input, and net input refers to the net input of the artificial neuron. The activation function has values between [0, 1] or [−1, 1], depending on which function is used, such as logistic, hyperbolic tangent, or Gaussian. Learning algorithms are used to correct synaptic weight. The most popular one is the backpropagation algorithm, which is based on the logic of re-adjusting the connection weights by minimising the mean square error. The algorithm corrects the synaptic weights based on the error output (Gue et al., 2020, p. 1451; Haykin, 2009, p. 139).

An artificial neural network refers to a structure in which many processing elements are interconnected, as shown in Figure 6. The figure shows a three-layer network structure containing n inputs, two hidden layers, and one output. Processing elements are arranged in sequential layers, from the input layer to the output layer, and connections are established between neighbouring layers. The input layer receives the information, and the output layer transmits it out. All other layers, referred to as hidden layers, acquire and disseminate information within the network (Kavaklıoğlu et al., 2009, p. 2720-2721). The reason why the layer is described as hidden is that the ANN is closed to any external influence, and the operations carried out here cannot be seen by the user (Aamodt, 2010, p. 39). It further denotes that this segment of the neural network remains obscured from direct observation at both the input and output layers of the network. The role of hidden neurons is to effectively mediate between external input and network output. By including one or more hidden layers, the network gains the capability to extract higher-level statistics from its input (Haykin, 2009, p. 22).

Figure 6: Architecture of ANN



Source: Kavaklioglu, K., Ceylan, H., Ozturk, H. K., & Canyurt, O. E., (2009)

Determination of ANN Structure

Hidden layers and neurons: Multilayer networks involve three layers: input, output, and at least one hidden layer. When creating a prediction model with ANN, many parameters, such as the number of layers in the network structure, the number of neurons in the layers, and network training parameters, need to be determined. Determining the number of hidden layers and neurons from the ANN model is usually done by trial and error (Palani et al., 2008, p. 1588). The selection of the hidden layer and the number of neurons to be included in this hidden layer(s) is important for the performance of the established network. If the number of hidden layers is low, the network cannot learn; if it is large, the network resorts to memorisation and cannot achieve the desired result. Increasing the number of cells also increases the learning period and adaptation process (Elmas, 2003, p. 114). In the literature, "n" and "m" define the number of input and output neurons, respectively. Tang and Fishwick (1993) define the number of hidden neurons as "n", Wong (1991) as "2n", Lippman (1987) as "2n+1", Masters (1993) as "$\sqrt{n*m}$", Bailey and Thompson (1990) as "0.75*n" (Sönmez Çakır, 2024, p. 61; Hamzaçebi, 2021, p. 119).

Learning rate (η) and momentum (α): The purpose of these parameters is to accelerate the training process while minimising the errors of the model. There are no special rules for selecting values for these parameters. Nevertheless, the training process is initiated by selecting a set of values. For example, η = 0.2 can be chosen for the learning rate ranging from 0 to 1, and α = 0.5 can be chosen for the momentum coefficient ranging from 0 to 0.9 (Palani et al., 2008, p. 1588).

Activation function: Activation functions are important elements that influence the network's performance. Tangent-sigmoid (tansig), logarithmic-sigmoid (logsig), and purelin transfer functions are frequently used in the latent layer of ANNs. The equations of these transfer functions are given below (Lertworasirikul and Tipsuwan, 2008, p. 69):

$$\text{logsig}(x) = \frac{1}{(1+e^{-x})} \tag{3}$$

$$\text{tansig}(x) = \frac{2}{(1+e^{-2x})} - 1 \tag{4}$$

$$\text{purelin}(x) = x \tag{5}$$

Training Algorithm: For ANN to work optimally and produce results, it must be well-trained. It is extremely important to choose the algorithms and functions to be used during this training to provide the best results. Algorithms frequently used in model development are given below. (Pandey et al., 2012, p. 1217)

1. Levenberg–Marquardt: Trainbr, Trainlm,
2. Steepest descent: Traingdm, Traingd, Trained, Traingda, Trainer
3. Conjugate gradient: Traincgp, Tracing, Traincgb
4. Newton's method: Trainoss, Trainbfg.

Arrangement of Data Sets: Data partitioning must be done when presenting the data to the artificial neural network. At this stage, independent (input) and dependent (target-output) variable definitions, as well as how much of the data will be allocated for training, verification, and testing, must be introduced to the network. Generally, in the literature, 70% of the data is training, 15% testing and 15% validation, or 80% training, 10% testing and 10% validation. Zhang et al. (1998) stated that in the case of binary splitting, 90% of the data can be used for training, 10% for testing, or 70% for training and 30% for testing.

Measures of Performance: MAPE (mean absolute percentage error), RMSE (square root of the mean square error), and R^2 (coefficient of determination) are used to determine the applicability of the resulting models.

$$\text{MAPE}\ (\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_p(i)-y_a(i)|}{y_a(i)} \times 100 \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_p(i)-y_a(i))^2} \quad (7)$$

Here, N is the total number of observations, $y_p(i)$ is the predicted observation value, $y_a(i)$ is the actual observation value (Shetty and Pai: 2021). The R^2 formula to express $\overline{y_a}$ the average of actual observation values is given below.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_a(i)-y_p(i))^2}{\sum_{i=1}^{n}(y_a(i)-\overline{y_a})^2} \quad (8)$$

Lewis (1982) evaluates models with a MAPE value below 10% as "very good", models with a MAPE value between 10% and 20% as "good", and models with a MAPE value between 20% and 50% as "acceptable". Models with MAPE values over 50% are classified as "incorrect and faulty". RMSE and R^2 values being at the lowest (close to zero) and highest (close to 1) levels, respectively, enable a good ANN calibration in terms of prediction accuracy (Mutascu ve Hegerty, 2023, p. 409).

RESULTS

In this study, unemployment is estimated using annual data from Japan between 1985 and 2017. The input variables considered in the study are population, number of artificial intelligence patents, inflation, and labour productivity. 70% of the data was used for training, 15% for verification, and 15% for testing. While considering these ratios, the values in the literature are taken into account, and adjustments are made to increase the model performance of the ANN through trial and error. In the study, first of all, the most successful artificial neural network parameters that predict unemployment with the least error are determined. For this purpose, the data is tested in different network structures, and the network structure with the best prediction result is preferred. The function expression of the model, which has 4 input variables and 1 output variable, is as follows.

Unemp= f (Pop, AI, Inf, LabPro)

Different learning algorithms may produce different prediction performances due to the unique structure of the data. In this study, "Levenberg-Marquardt" (trainlm), "Bayesian regularisation backpropagation" (trainbr) and "The one-step secant" (trainoss) algorithms, which are frequently used in the literature, were selected as training algorithms and tested separately. The trial and error method is used to find the best ANN architecture. For this reason, first, the number of hidden layers is accepted as 1, then the number of neurons is increased, and then the activation function is changed. Then, the same process is repeated by changing the number of hidden layers. In line with the recommendations in the literature, Tang and Fishwick (1993) state that the number of neurons should be determined as "n", Wong (1991) as "2n", and Lippman (1987) as "2n+1". Since there are 4 input variables in our study, the number of neurons to be included in the hidden layer is determined as 4, 8 and 9. In this context, 18 models are created RMSE, MAPE, and R^2 statistical information are used to evaluate the success of the models. Trials and training performances showing the ANN architecture of the models are given in Table 3.

Table 3: ANN Alternative Architectures and Accuracy Tests

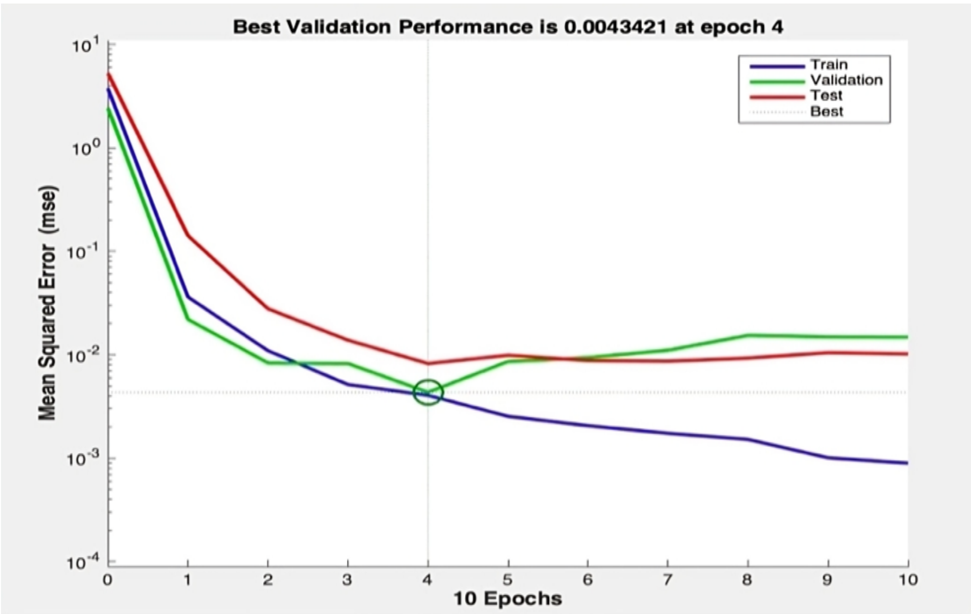
Number of Layers & Neurons	**Lrate**	**MC**	**Transfer Function**	**Training Algorithm**	R^2	**MAPE**	**RMSE**
1 layer 4 neurons	0.01	0.8	logsig	trainbr	0.9903	0.0208	0.1057
1 layer 4 neurons	0.5	0.8	tansig	trainlm	0.9890	0.0221	0.1130
1 layer 4 neurons	**0.4**	**0.6**	**tansig**	**trainbr**	**0.9940**	**0.0177**	**0.0835**
1 layer 8 neurons	0.3	0.6	logsig	trainlm	0.9869	0.0308	0.1232
1 layer 8 neurons	0.4	0.6	logsig	trainlm	0.9859	0.0135	0.1279
1 layer 8 neurons	0.4	0.7	logsig	trainoss	0.9812	0.0330	0.1475
1 layer 9 neurons	0.1	0.5	tansig	trainlm	0.9898	0.0183	0.1089
1 layer 9 neurons	0.7	0.7	logsig	trainlm	0.9846	0.0251	0.1338
1 layer 9 neurons	0.3	0.8	tansig	trainbr	0.9925	0.0147	0.0929
2 layers 4-4 neurons	0.2	0.8	Tansig-purelin	trainoss	0.9330	0.0654	0.2791
2 layers 4-8 neurons	0.2	0.8	Purelin-logsig	trainlm	0.9300	0.0385	0.2853
2 layers 4-9 neurons	0.6	0.9	Tansig-logsig	trainbr	0.9785	0.0161	0.1580
2 layers 8-4 neurons	0.7	0.9	Tansig-tansig	trainoss	0.9561	0.0536	0.2259
2 layers 8-8 neurons	0.01	0.9	Purelin-logsig	trainlm	0.9684	0.0397	0.1916
2 layers 8-9 neurons	0.6	0.8	Tansig-logsig	trainlm	0.9818	0.0237	0.1453
2 layers 9-4 neurons	0.7	0.8	Logsig-purelin	trainoss	0.9187	0.0737	0.3075
2 layers 9-8 neurons	0.3	0.8	Tansig-purelin	trainlm	0.9219	0.0564	0.3013

2 layers 9-9 neurons	0.1	0.9	Logsig-purelin	trainlm	0.9690	0.0463	0.1899

RMSE, MAPE, and R^2 values are identified by comparing the estimated values generated during the training phase of the model with the real values. When the artificial neural network models in Table 3, where the estimation performances of the training data set are compared, are examined, it is observed that the model with the number of latent layers 1, the number of neurons 4, the transfer function and the learning algorithm respectively, tansig-trainbr, has the best performance. The learning rate of this model is 0.4, and the momentum coefficient is 0.6.

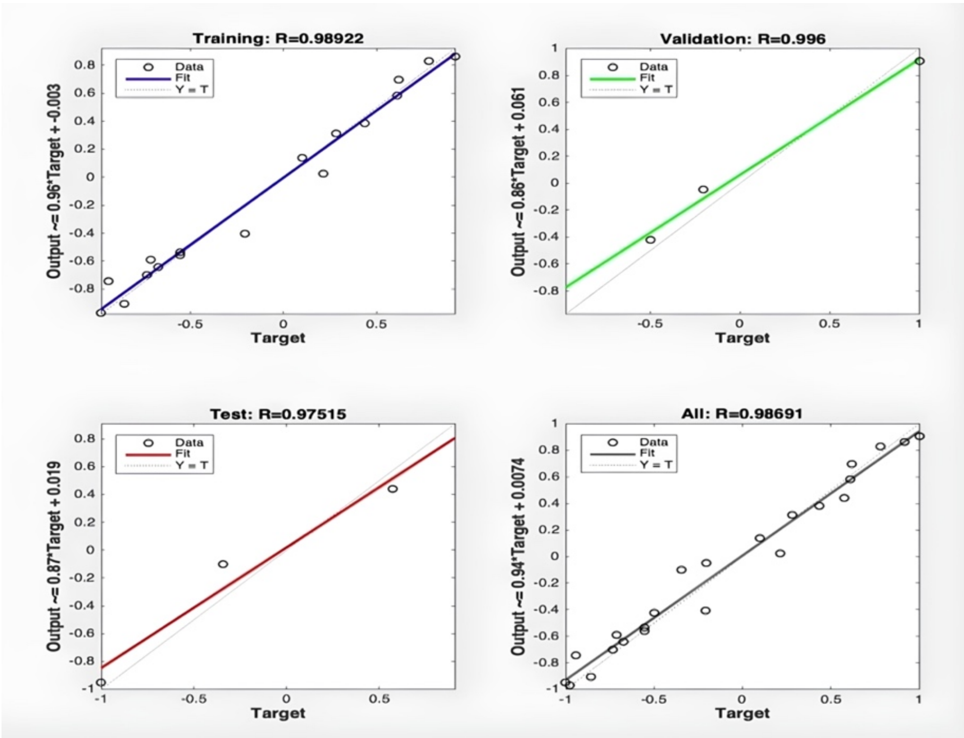
The fact that the RMSE value is close to 0 (0.0835), the R^2 is near to 1 (0.994), and the MAPE value is below 10% (0.0177) shows that the model produces predictions with high accuracy.

Figure 7: Best Performance-MSE Chart



The unemployment rate prediction model for Japan is trained in 1000 iterations, and as a result of this training, the graph of the MSE (Mean Squared Error) function of the model that best predicts the unemployment rate is shown in Figure 7. It is determined that the best validation performance was seen in the 4th iteration. Since the error rate did not increase in the validation and test sets after this iteration, there was no sign of memorisation. Since the validation and test set errors are similar and no significant memorisation occurs, the performance of the network is at an acceptable level. However, the MSE result of the model is 0.0043421. As a result, the acceptable performance target is achieved with the obtained MSE.

Figure 8: Regression Plot of Unemployment Rate Forecast Model



The regression graphs in Figure 8 show the link between the outputs and targets of the training, validation and test data sets, respectively. While the R value was 0.98 for the training data set, it was calculated as 0.99 and 0.97 for the validation and test data set. The fact that this value is very close to 1 indicates that the model has a good fit.

Table 4: Actual Values and Predicted Values of The Validation Dataset

Years	Actual Values	Predicted Values
2008	4.0020	4.0026
2009	5.0680	5.1310
2010	5.1030	5.1024
2011	4.5500	4.3873
2012	4.3580	4.4191
MAPE = 0.0125; R^2 = 0.9615; RMSE = 0.0826		

In the model in which Japan's unemployment rate is estimated with population growth (annual %), technologies related to artificial intelligence, inflation rate (annual %), and labour productivity variables, the actual and predicted values of the validation data set are given in Table 4. MAPE and RMSE values obtained in the validation set show that the unemployment rate prediction model is capable of making successful predictions. Because in the established unemployment rate prediction model, the margin of error between the actual values of the validation set and the obtained prediction values is quite low. The R^2 value of the validation dataset is found to be quite high (0.9615). Therefore, it is once again supported that the network learns rather than memorises.

Table 5: Unemployment Rate Forecast Until 2030

Years	Actual Values	Predicted Values
2019	2.351	2.328
2020	2.809	2.799
2021	2.828	2.803
2022	2.600	2.640
2023	2.649	2.631
2024		**3.018**
2025		**3.315**
2026		**3.418**
2027		**3.605**
2028		**3.907**
2029		**4.415**
2030		**4.850**

When prediction based on time series is made using artificial neural networks, future prediction is made with the data set of the past period of the series. Here, the number of input neurons varies depending on how many past observation values the serial value will be associated with. The past values of the variable constitute the inputs, and the predicted value constitutes the outputs. For example, the number of input neurons being 2 means that the value of the series at time t depends on the observation values at time t-1 and t-2 (Hamzaçebi, 2021, p. 203). In our model, the number of input artificial neurons is determined by trial and error, and it is revealed that the most suitable unemployment rate prediction model has 2 input artificial neurons. Table 5 shows the actual values and predicted values of Japan's unemployment rates for the years 2019-2023 and the unemployment rate forecast until 2024-2030. According to the results in the table, Japan's unemployment rates are expected to rise until 2030.

CONCLUSION

The unemployment rate is one of the critical indicators of a country's economic health and social stability, and it directly affects the effectiveness of policies and the welfare level of society. In this study, unemployment rates are estimated using the artificial neural network method, considering Japan's annual data for 1985-2017. The input variables determined by considering the studies in the literature are population growth (%), number of artificial intelligence-related technology patents, consumer price inflation (%) and labour productivity. Due to the limitation in obtaining data on the number of technology patents related to artificial intelligence, the dataset was selected until 2017. In creating the artificial neural network, normalisation is first applied to the data, and then the data set is split into three separate sections: 70% training, 15% validation and 15% test data set. When the models created using the trial and error method with the help of the Matlab2015b program are examined, it is determined that the best artificial neural network model is a structure with a single latent layer, the number of neurons is 4. It has been revealed that this model has a structure with Bayesian learning algorithm-trainbr and hyperbolic tangent-tansig activation function. After determining the structure with the best performance, unemployment rate data for 2024-2030 is estimated using data from 1985-2017. When the performance evaluation criteria are examined, it is concluded that the artificial neural network model successfully predicts. In the model estimated with the help of the input variables considered, Japan's estimated unemployment rates are expected to increase until 2030.

This predicted increment coincides with the literature. Regarding the fact that a lower population growth rate causes a decline in economic growth and demand for a labour force in the long term, Fukao et al. (2003) state that low population growth rates in Japan slow down economic growth, causing contractions in the labour market; therefore, this situation can increase the unemployment rate. The low population growth, as well as the aging population, is one of the reasons behind persistent downward pressure on prices in Japan (Katagiri et al., 2020; Braun & Ikeda, 2022), and deflation is expected to raise the unemployment rate through the downward spiral mechanism: the continuous decrease in prices causes diminishing profit margins, business failures, and higher unemployment, which lowers purchasing power, prices and output (Brooks & Quising, 2002, p. 1). Since policies against low population growth rates tend to have longer-term effects, policymakers can find a shorter-term solution to this problem by loosing strict immigration policies.

The integration of artificial intelligence and industrial robots in Japanese industries can alleviate the burden of the labour shortage; nonetheless, the rapid automation of tasks previously performed by the workforce raises concerns about potential job redundancy for the existing workforce (Ni & Obashi, 2021, p.1) Therefore, it is important for Japan to comprehensively update its education system with a focus on artificial intelligence and digital skills to enhance workforce proficiency and enable the current workforce to adapt to rapidly changing technology. These updates will help the workforce cope with the challenges created by technological advances by enabling it to adapt to new technologies and remain competitive.

In addition to these factors discussed above, future studies can predict the unemployment rate by increasing the input variables such as government size, foreign direct investments, labour market flexibility and the number of data to be used, which are not included in this research.

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