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The Remaining Life of Distribution Transformer Prediction by Using Neuro-Wavelet Method

Abstract: *The distribution transformer is one of the important equipment in delivering electricity to consumers. Apart from the normal use, fault conditions in the transformer can cause the life of the transformer to decrease being not optimal performance up to operating life limit. Therefore, it is very important to calculate the remaining life of the transformer. The steps taken are calculating the remaining life of the transformer using IEC 60076-7 and predicting the remaining life of the transformer using wavelet transform and back propagation neural network. The parameters required for this study are transformer current signal, loading, and transformer age. Measurement of current and temperature of distribution transformers in North Surabaya was conducted with a rating of 20 KV/ 380-220 V. Transformer current measurement has been processed using wavelet transforms to obtain detailed coefficients used to calculate energy values and power spectral density (PSD). Energy values, PSD, and transformer loading are training and testing data on the back propagation neural network. The expected output method is the prediction of the remaining life of the transformer.*

Streszczenie. *Transformator rozdzielczy jest jednym z ważnych urządzeń w dostarczaniu energii elektrycznej do odbiorców. Poza normalnym użytkowaniem, warunki awaryjne w transformatorze mogą spowodować skrócenie żywotności transformatora, co nie jest optymalną wydajnością aż do granicy żywotności. Dlatego bardzo ważne jest obliczenie pozostałej żywotności transformatora. Podjęte kroki polegają na obliczeniu pozostałego okresu eksploatacji transformatora przy użyciu normy IEC 60076-7 i prognozowaniu pozostałego okresu eksploatacji transformatora przy użyciu transformaty falkowej i sieci neuronowej z propagacją wsteczną. Parametry wymagane do tego badania to sygnał prądowy transformatora, obciążenie i wiek transformatora. Pomiar prądu i temperatury transformatorów rozdzielczych w Północnym Surabaya został przeprowadzony z wartością znamionową 20 KV/380-220 V. Pomiar prądu transformatora został przetworzony za pomocą transformacji falkowej w celu uzyskania szczegółowych współczynników służących do obliczania wartości energii i gęstości widmowej mocy (PSD) . Wartości energii, PSD i obciążenie transformatora to dane uczące i testujące w sieci neuronowej wstecznej propagacji. Oczekiwaną metodą wyjściową jest przewidywanie pozostałego czasu życia transformatora (**Przewidywanie pozostałego okresu eksploatacji transformatora dystrybucyjnego za pomocą metody Neuro-Wavelet**)*

Keywords: distribution transformer; IEC 60076-7; wavelet transform; Energy; Back propagation neural network.
Słowa kluczowe: transformator rozdzielczy; IEC 60076-7; transformacja falkowa; Energia; Sieć neuronowa wstecznej propagacji.

Introduction

Transformer is one of the main components in the process of distributing electricity to consumers to guarantee the continuity of electric power service to consumers. However, the process of distributing electricity to consumers is interruptedunder certain conditionsdue to several factors. They are short-circuit faults, harmonic effects, load increasing, the influence of chemical mechanisms, and transformer isolation degradation. Those factors result in reduced transformer life and not optimal transformer performance until maximum operating time limit. Several studies have been conducted to monitor and evaluate the condition of the transformer, including predicting and monitoring the power transformer. They are for determining the load capacity and the remaining life of the transformer. Bicen et al. [1] proposed two methods for monitoring and evaluating the condition of the transformer, high measurement-time resolution and functional algorithm. This method contains the durability and life of the transformer which depends on the heat generated by the transformer internal. The first method is to observe the thermal behavior of the transformer under normal conditions to overload conditions, and then calculated using the hot spot temperature formula, the second method is equations relating to predictions of the leading demand and a realistic life-loss. The second method is about the lifetime of the power transformer which depends on the characteristics of the load conditions and the load factor bygrouping the daily load in 1 year. The results of this study showed that the remaining isolation period depended on the load conditions on the transformer. Besides the factor of transformer isolation, it is necessary to vary the load and age shrinkage in the previous year to determine the short and long term life of the power transformer.

Jardini et al. [2] evaluated the remaining transformer life based on the daily load profile. A number of transformersand load profiles were used as database patterns to determine the remaining transformer life [2]. The calculation of the remaining life of the transformer took into account the daily load curve, ambient temperature, possibility related to load, temperature values and transformer life. Then the classification was carried out using the classification through cluster analysis method, classification using Euclidean distance, classification using the ANN model LVQ, and interpolation using ANN model MLP (Multi-Layer Perceptron). The results of this study can classify transformer life by using various methods. Apart from the daily to annual load conditions, the harmonic effect is also one of the causes of the shrinkage of the transformer life. As in research [3] which carried out measurement of harmonic data with non-linear loads on distribution transformers to investigate transformer losses and the remaining life of the transformer due to harmonization. The steps taken include calculating the harmonic loss factor, calculating the remaining transformer life, and explaining the harmonic data logging. The results of this study showed that the greater the load and the THD value the longer the transformer life was due to the increase in transformer losses and hot spot temperature. Similarly with the previous study, this study [4] monitors the condition of the transformer by considering harmonic currents by using a combination of wavelet transform and probabilistic neural network (PNN) to classify the transformer life. The harmonic currents obtained through the measurements have been filtered using a wavelet transform. The energy value and PSD of the wavelet transform process will be used as input to PNN to classify the transformer life. Before being used as input to PNN, the energy and PSD values need to be normalized so that these values are the same. However, the results of this study showed an accuracy value of 80% due to data limitations. Also, the rotary autotransformer used as object for the research [16] and power transformer [17].

Another study compared the top oil temperature and hot spot temperature in conditions with and without harmonics [5]. This study used a dynamic thermal model under linear and non-linear load conditions by considering the hot spot temperature, top oil, and the remaining life of the transformer. The results of this study showed that temperature reduced transformer life. While studying [6] conducted experiments with the input parameters of the dissolved gas analysis factor (DGAF), percent water in insulation, acidity, aging acceleration factor, dissipation factor, and breakdown voltage. After getting all the input parameters, the transformer health index was determined using the ANFIS method. Since the research did not discuss the prediction of the transformer remaining life, this study was conducted to predict the remaining life of the transformer. It was conducted by using wavelet transform method and back propagation neural network. Support vector machine (SVM) also used by other researchers to analyse the transformer condition [15].

The step taken in this study was to calculate the remaining life of the transformer using the IEC 60076-7 standard. The parameters required for this study were current signal of transformer, loading and transformer life. Transformer current measurement has been processed using wavelet transform to obtain detailed coefficients used to calculate the energy value and PSD. Energy value, PSD and transformer loading were training and testing data on back propagation neural networks. The expected output method was the prediction of the remaining life of the transformer.

Neuro-Wavelet Method

Wavelet Transform

Wavelet transformation is a transformation method that transforms signals in the time domain into signals in the time and frequency domains. This transformation method adopts the Fourier Transform and Short Time Fourier Transform methods. In general, the wavelet transform consists of 2, Continue Wavelet Transform and Discrete Wavelet Transform [7]. Continue Wavelet Transform (CWT) calculates the convolution of a signal with a modulation window any time with any desired scale. This modulation window which has a flexible scale is commonly called the main wavelet or the basic wavelet function. While Discrete Wavelet Transform $(\Delta\theta_{hr})$ (DWT) is a simpler discrete form. The basic principle of DWT is to get a time and scale representation of a signal using $(\Delta\theta_{omr})$ digital filtering techniques and sampling operations. Implementation of discrete wavelet is described by following equation.

$$(1)\qquad x[n]=\sum_{k}a_{j0,k}\phi_{j0}[n]+\sum_{j=j0}^{J-1}\sum_{k}d_{j,k}\varphi_{j,k}[n]$$

where $\phi[n]$ is the scaling function, and $\varphi[n]$ is the mother wavelet, $\phi_{j0,k}[n]=2^{j0/2}\phi(2^{j0}n-k)$ is the scaling function at a scale of $s=2^{j0}$ shifted by $k, a_{j0,k}$ are the approximation coefficients at a scale of $s=2^{j0}$ and N = 2 , where N is the number of $x[n]$ samples.

The way DWT works in detail is to convert the input signal into two signal classifications, high frequency (detail coefficient) with high time resolution and low frequency (approximation coefficient) [8] with low time resolution. This decomposition process is carried out repeatedly to produce the desired signal. This theory is called the wavelet decomposition tree. Figure 1 shows an example of a wavelet decomposition tree. First, the signal is passed through the high and low pass filter. Half of each result is sampled by means of a sub-sampling operation known as the one-stage decomposition process. The output from the low pass filter is used as input in the next level decomposition process. This process is repeated until the level of the decomposition process desired. The wavelet coefficient obtained will be in the form of transformed signal information that has been compressed.

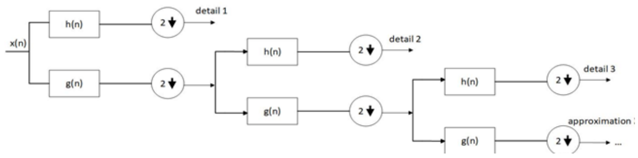


Fig. 1. Wavelet decomposition tree

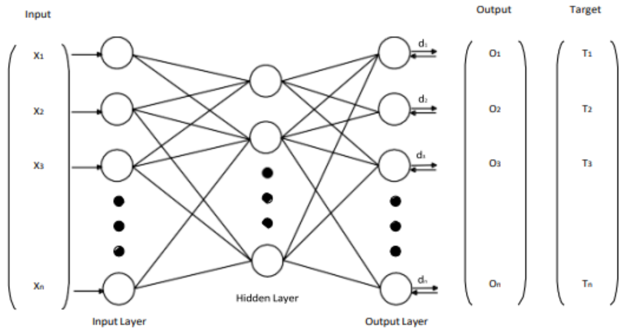


Fig. 2. Backpropagation network architecture[12]

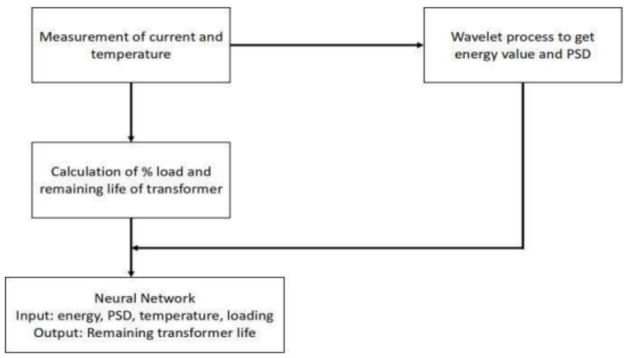


Fig. 3. Block diagram of research stages

Back Propagation Neural Network

Back propagation neural network is a supervised training method. Its function is to reduce errors by adjusting weights based on differences in output and the desired target. The back-propagation neural network architecture is shown in Figure 2.

The back-propagation neural network algorithm consists of two stages, feed-forward and back-propagation. The back-propagation neural network consists of an input layer, a hidden layer, and an output layer. The back-propagation neural network layer is a development of a single layer network that has two layers, an input layer and an output layer. The output layer in the back-propagation neural network has a smaller error value than the error value in a single layer network because the hidden layer functions to update the weights. Neural network back-propagation process, the input layer network, is forwarded to the hidden layer. Each hidden layer and output layer are multiplied by weight and summed with bias. If there is a different pattern with the target, then the value of each weight for each layer unit will be corrected in the reverse direction.

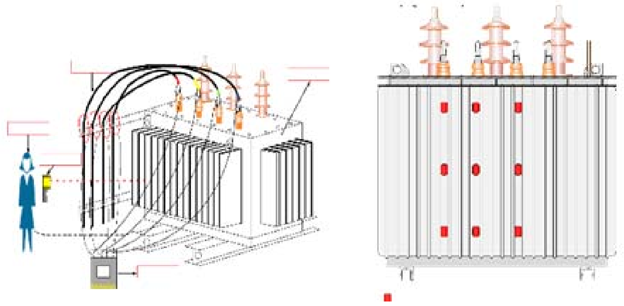
Remaining Life of Distribution Transformer Prediction Using Neuro-Wavelet Method

In this paper, the prediction of the remaining life of the transformer will be carried out using the neuro-wavelet method consisting of several steps, such as measuring the current and temperature of the transformer, calculating the load data and the remaining life of the transformer, processing the transformer current data using daubechies wavelet transform, determining of the value of the power spectral density (PSD) and energy using the wavelet method, normalization and denormalization, and transformer life prediction using neuro-wavelet. In general, the stages of the study carried out can be seen in Figure 3.

1.1 Currents and temperatures measurement in transformers

The object of study in this article is the distribution transformer. Current and temperature measurements were carried out on several distribution transformers in North Surabaya, East Java, Indonesia. The distribution transformer to be measured was a distribution transformer with a voltage level of 20 KV/220-380 V. The selected distribution transformer has a remaining lifespan of 14 years, 19 years, 21 years, 22 years, 23 years, 24 years, 25 years, 26 years. Measurement of transformer current data uses the FLUKE 435 Series II power quality analyzer. Measurements are made by attaching the probe contained in the measuring instrument to each phase channel, the R, S, T, N phases and a current clamp to each of the R, S, T, N phases as shown in Figure 4. a).

Measurement and data collection of transformer currents is carried out for 24 hours. Measuring the temperature of the transformer using a FLUKE Ti125 infrared thermal camera is carried out by pointing the thermal camera towards the distribution transformer body [9], a sketch of transformer temperature measurement can be seen in Figure 4 (b). The temperature data was collected by aiming the cursor on the transformer tank. When shooting the transformer, the temperature appears at the point pointed to by the cursor in the image called the spot temperature. This spot temperature is useful for knowing the temperature at the intended point.



a b

Fig. 4. (a) Sketch of transformer current measurement (b) Sketch of transformer temperature measurement

1.2 Calculating loading data and remaining life of the transformer

The parameter needed to determine the remaining life of the transformer is loading data. The loading data is a percentage of the measured current ratio in each phase with the nominal current. In this study, the load measurement has been carried out in a day so it is assumed that the daily load pattern is the same throughout the year.

The phases to calculate the remaining life of the transformer are to calculate the temperature of the top oil and the difference between the temperature of the hot spot and the top oil. Top oil temperature depends on ambient temperature conditions which can be calculated using the following equation [10].

$$\theta_o = \left[\frac{1 + K^2 R}{1 + R}\right]^x x\ \Delta\theta_{or} \quad (2)$$

Where K is a load factor, R is a losses ratio, $\Delta\theta_{or}$ is increasing in top oil temperature.

The following equation is used to determine the difference between the hot spot temperature and the top oil temperature:

$$\Delta\theta_{h1} = k_{21}\, x\, K^y\, x\, \Delta\theta_{hr} \quad (3)$$

$$\Delta\theta_{h2} = (k_{21} - 1) x\, K^y\, x\, \Delta\theta_{hr} \quad (4)$$

$$\Delta\theta_h = \Delta\theta_{h1} - \Delta\theta_{h2} \quad (5)$$

a new equation is obtained to determine the hot spot temperature value by combining equations (2) and (4),

$$\theta_h = \theta_o + \Delta\theta_h \quad (6)$$

Where θ_o is top oil temperature, $\Delta\theta_h$ is the difference in temperature of hot spots and top oil.

The unequal temperature distribution in the distribution transformer causes the highest temperature to experience the greatest reduction in insulation so that it will affect the aging rate. The relative aging rate (V) is determined in equation (7):

$$v = 2^{(\theta_h - 98)}/6 \quad (7)$$

Where θ_h is hot spot temperature.

The effect of decreasing winding insulation can lead to a reduction of transformer life so that equation (8) can be used to measure the remaining life of the transformer.

$$L = \sum_{n=1}^{N} V_n\ x\ t_n \quad (8)$$

Where V_n is relative aging rate during the nth interval, t_n is the Nth time interval, n is number in each nth time interval, and N is the number of numbers over the intervalperiod.

The remaining life of the transformer in equation (8) is the value of the remaining life in hours per day. This valueis multiplied by 365 days to get the remaining life in years. Based on the IEEE standards, this calculation uses a base age of 180,000 hours or more. While, based on IEC 60076-7 standard the basic life of a distribution transformer of 30 years are used [11]. The calculation uses equation (8). As a guideline for calculating hot spot and top oil temperatures, the thermal characteristics of thedistribution transformer with the ONAN type of coolant aregiven in Table 1.

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$$Remaining\ life = \frac{8760-(L \times 365)}{8760} \times (30 - number\ of\ operation\ year) \qquad (9)$$

Table 1. Thermal Characteristics For Loading Calculation of "ONAN" Distribution Transformers

Description	ONAN
Oil Exponent (x)	0.8
Exponential Windings (y)	1.6
Losses Ratio (R)	5
Hot Spot Factor (H)	1.1
Oil Constants (τ_o τ_o)	180
Turning Constants (τ_w τ_w)	4
Ambient Temperature (θ_a) (θ_a)	20
Hot Spot Temperature (θ_h) (θ_h)	98
Gradien Hot Spot to Top Oil (in tank) ($\Delta\theta_{hr}$) ($\Delta\theta_{hr}$)	23*
Average Increase of Oil Temperature ($\Delta\theta_{omr}$) ($\Delta\theta_{omr}$)	44
Increase of Top Oil Temperature ($\Delta\theta_{or}$) ($\Delta\theta_{or}$)	55*
Increase of Bottom Oil Temperature ($\Delta\theta_{br}$) ($\Delta\theta_{br}$)	33
k11	1
k21	1
k22	2

Processing of current sample data

Current sample data obtained from the measurement results of the transformer current are in the form of a current signal that has been distorted by the harmonics that appear in the system as shown in Figure 5. The current sample that has been obtained will then be processed using daubechies wavelet transform using MATLAB software. This method is used to break the current signal into several frequency groups. The use of the daubechies method was chosen based on the results of previous studies which showed that daubechies gave better MSE results [12]. Current samples that have been sampled are separated into several signal decompositions. Each decomposition has two parts, the approximation coefficient and the detail coefficient. At the first 1.8 Prediction of the remaining life of the transformer The back propagation method is used to predict the remaining life of the transformer. The first way is that the back propagation network initializes the weights randomly without using a scale factor [14]. Back propagation neural network consists of two layers, a hidden layer and an output decomposition level, the signal is divided into 2, the approximation coefficient and the detail coefficient. At the second decomposition level, the approximation coefficient at the first level is used to produce the approximation coefficient and the second coefficient detail. The wavelet decomposition process can be seen in Figure 6.

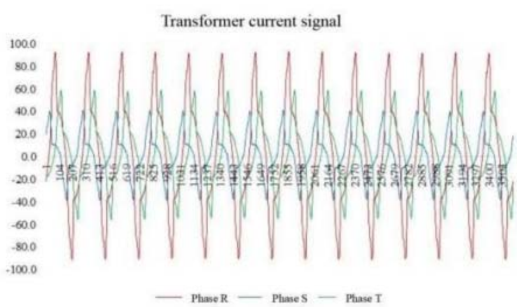

Fig. 5. Transformer current signa

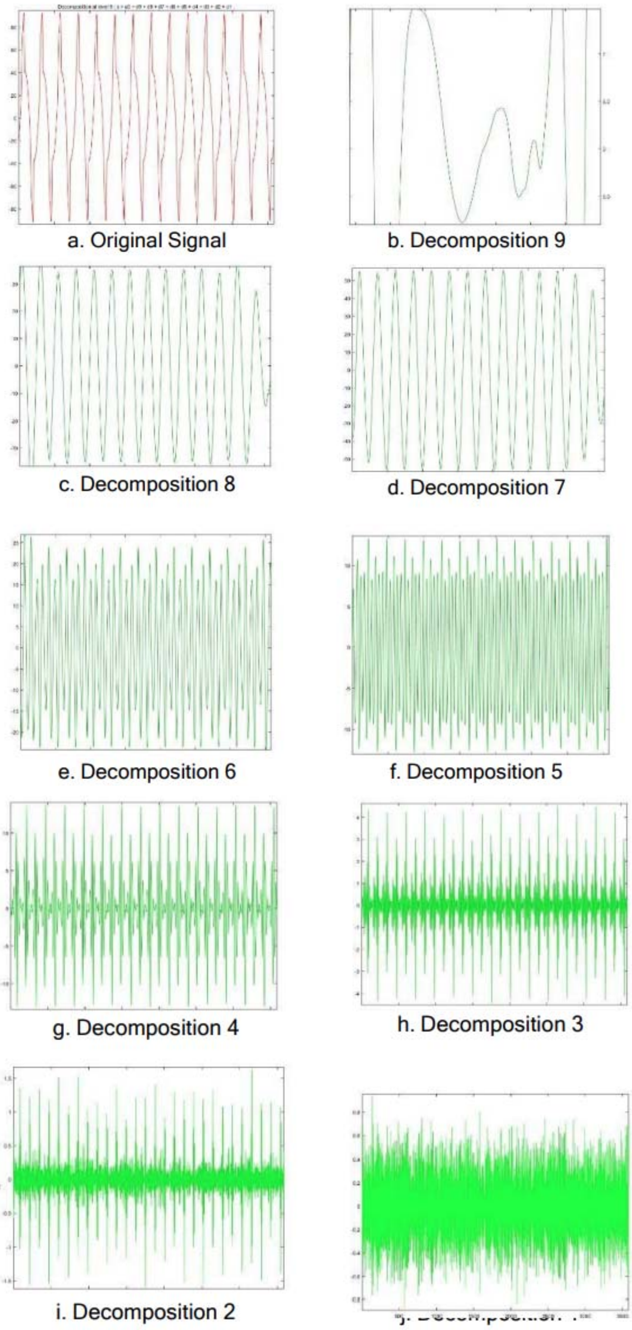

Fig. 6. The result of wavelet decomposition on transformer TR-1

Table 2. Capacity and Operating Year of Distribution Transformer

No.	Transformer Label	Capacity (KVA)	Operation Year (years)
1	TR-1	160	6
2	TR-2	100	4
3	TR-3	100	4
4	TR-4	400	6
5	TR-5	100	5
6	TR-6	100	5
7	TR-7	315	7
8	TR-8	100	6
9	TR-9	200	5
10	TR-10	200	5
11	TR-11	200	4
12	TR-12	100	5
13	TR-13	315	7
14	TR-14	315	7

15	TR-15	160	6
16	TR-16	250	6
17	TR-17	100	4
18	TR-18	200	5
19	TR-19	315	7
20	TR-20	200	5
21	TR-21	200	5
22	TR-22	250	7
23	TR-23	250	7
24	TR-24	500	7

Table 3. Measurement Result Data of TR-1 Current and Temperature for 24 Hours

Time	R (A)	S (A)	T (A)	Temperature (^{O}C)
01.00	34.3	46.8	58.3	44.85
02.00	38.4	52.5	65.3	46.41
03.00	38.4	52.5	65.3	46.41
04.00	38.4	52.5	65.3	46.41
05.00	32.3	44.2	55.0	41.75
06.00	21.9	30.0	37.3	41.75
07.00	11.5	15.8	19.7	37.08
08.00	13.7	18.7	23.3	37.08
09.00	13.7	18.7	23.3	37.08
10.00	13.7	18.7	23.3	37.08
11.00	13.7	18.7	23.3	37.08
12.00	13.7	18.7	23.3	37.08
13.00	13.7	18.7	23.3	37.08
14.00	13.7	18.7	23.3	36.83
15.00	13.7	18.7	23.3	38.12
16.00	19.2	26.2	32.7	38.38
17.00	19.2	26.2	32.7	39.16
18.00	53.5	73.1	91.0	52.11
19.00	56.9	77.8	96.9	53.14
20.00	56.2	76.8	95.7	53.4
21.00	56.2	76.8	95.7	53.14
22.00	53.5	73.1	91.0	52.11
23.00	50.0	68.4	85.2	50.81

Determination of energy and power spectraldensity

After splitting the signal based on the frequency band, the next process is feature extraction. The selected feature extraction is energy from a signal obtained by neutralizing the power spectral density (PSD). Whereas in the wavelet transform, PSD is obtained from the quotient between the energy and the frequency of each level of high pass filter. The energy generated from this transformation is the sumof the squares of the data values at each frequency level of the high pass filter signal [13] so that it can be presented mathematically as follows:

$$Energy = \sum_{d0}^{d1} f(HPF)_n^2 \quad (10)$$

$$PSD = \frac{energy}{f(HPF)_n} \quad (11($$

Where d_0 is the final range of the number of data, d_n is the initial range of the amount of data, $f(HPF)_n$ is high pass filter frequency or detail signal, and *n* is a level of detail signal.

Normalization and denormalization

Theresults of the energy values and PSD that have been done before must be normalized first. Normalization is the scaling of values that fall into a range of activation functions used in the network. In this study, the backpropagation algorithm uses the binary sigmoid activation function meaning that the data must be transformed first because the output range of the sigmoid function is [0,1]. The data can also be transformed into intervals [0,1]. To normalize the data, you can use the formula in equation (12):

$$Normalization\ (\acute{x}) = \frac{x-Min(x)}{Max(x)-Min(x)} \quad (12)$$

where x is the initial data, $\acute{x}$ is the output data, $Min(x)$ is the minimum value of initial data, and $Max(x)$ is the maximum value of the initial data.
Data that has previously been normalized also need to be denormalized to find out the actual data using the formula in equation (13).

$$X = \acute{x}\,(Max(x) - Min(x)) + Min(x) \quad (13)$$

where x is the initial data, $\acute{x}$ is the output data,is $Min(x)$ the minimum value of initial data, and $Max(x)$ is the maximum value of the initial data.

Prediction of the remaining life of the transformer

The back propagation method is used to predict the remaining life of the transformer. The first way is that the back propagation network initializes the weights randomly without using a scale factor [14]. Back propagation neural network consists of two layers, a hidden layer and an output layer. The data needed to simulate back propagation is input data in the form of energy density data and PSD. Energy density data and PSD were selected based on the results of previous studies which showed that these data have been used to predict the remaining life of the transformer [4]. The performance results of the method used need to calculate the MSE (Mean Square Error) valueof equation (14) and the level of accuracy (%) of equation (15

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Na_i - Np_i)^2 \quad (14)$$

$$Accuracy\ (\%) = 100\% - (\frac{Na_i - Np_i}{Na_i} \times 100) \quad (15)$$

Where N is the the amount of data, Na_i is the actual value, Np_i is the predicted value

Number of iterations 10000

Minimum number of errors : 10^{-7}

Learning rate value : 0.4

Result And Discussion

Current and temperature measurement results

The distribution transformer measured is a distribution transformer with varying capacities with a voltage level of20 KV / 220-380 V in Table II. The selected distribution transformers have a remaining lifespan of 14 years, 19 years, 21 years, 22 years, 23 years, 24 years, 25 years, 26 years. Measurement of transformer current data uses the FLUKE 435 Series II power quality analyzer, while measuring temperature data uses the FLUKE Ti125 infrared thermal camera. This study uses 24 transformers, data from the measurements of current and temperature of TR-1 and TR-2 can be seen in Table III and IV.

1.3 The results of calculating the loading data and the remaining life of the transformer

One of the parameters needed in determining the remaining life of the transformer is the loading data that has been obtained. Table V shows loading data of distribution transformator for two hours.

The results of the calculation of the remaining life of the transformer are presented in Table VI and VII. The remaining life calculation shows that the greater the loading value on the transformer, the higher the hot spot temperature. High hot spot temperatures will shrink the life of the transformer.

According to the IEC 60076-7 standard, distribution transformers operate with continuous loading at a temperature of 20 ° C and an increase in winding temperature of 98 ° C in order to operate until they reach their normal life. However, most transformers in Indonesia operate at room temperature around 30 ° C. The high ambient temperature where the transformer is operated greatly affects the thermal characteristics and hot spot temperature. The higher the ambient temperature, the higher the hot spot temperature on the transformer resulting in a decrease in transformer life.

Table VIII is an example of a TR-24 distribution transformer, which shows that the predicted age loss of hot spot temperature obtained from the loading variation for 24 hours is 0.83 hours / day so that the remaining age is 22.20 years. This value is smaller than the calculation of the hot spot temperature data from the measurement results, the age loss of 2.19 hours / day so that the remaining age is 20.89 years. This shows that the actual remaining life of the transformer as calculated is higher than the measurement result.

Table 4. Measurement Result Data of TR-2 Current and Temperature for 24 Hours

Time	R (A)	S (A)	T (A)	Temperature (^{O}C)
01.00	3.3	1.2	1.8	33.7
02.00	3.3	1.2	1.8	33.7
03.00	3.3	1.2	1.8	33.7
04.00	3.3	1.2	1.8	33.7
05.00	3.3	1.2	1.8	33.7
06.00	3.3	1.2	1.8	33.7
07.00	3.3	1.2	1.8	33.7
08.00	8.2	2.9	4.5	35.3
09.00	8.2	2.9	4.5	35.3
10.00	9.0	3.2	5.1	35.7
11.00	9.0	3.2	5.1	35.7
12.00	9.0	3.2	5.1	35.7
13.00	9.0	3.2	5.1	35.7
14.00	11.9	4.2	6.6	36.6
15.00	12.7	4.5	7.1	36.9
16.00	12.7	4.5	7.1	36.9
17.00	13.4	4.7	7.5	37.1
18.00	13.4	4.7	7.5	37.1
19.00	13.5	4.8	7.5	37.2
20.00	4.6	1.6	2.5	34.1
21.00	4.6	1.6	2.5	34.1
22.00	3.3	1.2	1.8	33.7
23.00	3.3	1.2	1.8	33.7
24.00	3.3	1.2	1.8	33.7

Table 5. Loading Data of Distribution Transformer for 24Hours

Time	Transformer Label				
	TR-1	*TR-2*	*TR-3*	*TR-4*	*TR-5*
01.00	0.483	0.027	0.043	0.754	0.051
02.00	0.541	0.027	0.043	0.754	0.051
03.00	0.541	0.027	0.043	0.754	0.051
04.00	0.541	0.027	0.043	0.754	0.051
05.00	0.456	0.027	0.043	0.754	0.051
06.00	0.309	0.027	0.043	0.754	0.051
07.00	0.163	0.027	0.043	0.754	0.051
08.00	0.193	0.068	0.060	0.336	0.129
09.00	0.193	0.068	0.060	0.336	0.129
10.00	0.193	0.076	0.149	0.336	0.144
11.00	0.193	0.076	0.149	0.336	0.144
12.00	0.193	0.076	0.149	0.336	0.144
13.00	0.193	0.076	0.149	0.336	0.144
14.00	0.193	0.099	0.149	0.336	0.188
15.00	0.193	0.105	0.156	1.012	0.188
16.00	0.271	0.105	0.167	1.012	0.188
17.00	0.271	0.111	0.167	1.012	0.188
18.00	0.754	0.111	0.120	1.012	0.188
19.00	0.802	0.112	0.120	1.012	0.188
20.00	0.792	0.038	0.120	1.012	0.092
21.00	0.792	0.038	0.120	1.012	0.092
22.00	0.754	0.027	0.043	1.012	0.092
23.00	0.705	0.027	0.043	1.012	0.071

Table 6. Calculation of The Remaining Life of The Transformer TR-1

Time	Load Factor	Θ_o	$\Delta\theta_h$	Θ_h	V	L	Remaining Life (Years)
01.00	0.48	24.35	7.18	31.53	0.0005	0.0456	23.95
02.00	0.54	26.98	8.61	35.59	0.00074		
03.00	0.54	26.98	8.61	35.59	0.00074		
04.00	0.54	26.98	8.61	35.59	0.00074		
05.00	0.46	23.18	6.54	29.72	0.000375		
06.00	0.31	17.92	3.52	21.45	0.000144		
07.00	0.16	14.48	1.26	15.75	7.47E-05		
08.00	0.19	15.04	1.66	16.70	8.34E-05		
09.00	0.19	15.04	1.66	16.70	8.34E-05		
10.00	0.19	15.04	1.66	16.70	8.34E-05		
11.00	0.19	15.04	1.66	16.70	8.34E-05		
12.00	0.19	15.04	1.66	16.70	8.34E-05		
13.00	0.19	15.04	1.66	16.70	8.34E-05		
14.00	0.19	15.04	1.66	16.70	8.34E-05		
15.00	0.19	15.04	1.66	1.66	8.34E-05		
16.00	0.27	16.83	2.84	19.67	0.000118		
17.00	0.27	16.83	2.84	19.67	0.000118		
18.00	0.75	38.48	14.63	53.11	0.005597		
19.00	0.80	41.46	16.16	57.63	0.009428		
20.00	0.79	40.86	15.85	56.71	0.00848		
21.00	0.79	40.86	15.85	56.71	0.00848		
22.00	0.75	38.48	14.63	53.11	0.005597		
23.00	0.71	35.63	13.16	48.79	0.003396		
24.00	0.48	24.35	7.18	31.53	0.000463		

Table 7. Calculation of The Remaining Life of The Transformer TR-12

Time	Load Factor	Θ_o	$\Delta\,\theta_h$	Θ_h	V	L	Remaining Life (Years)
01.00	0.027	13.1	0.07	13.23	5.58E-05	0.0014	25.99
02.00	0.027	13.1	0.07	13.23	5.58E-05		
03.00	0.027	13.16	0.07	13.23	5.58E-05		
04.00	0.027	13.16	0.07	13.23	5.58E-05		
05.00	0.027	13.16	0.07	13.23	5.58E-05		
06.00	0.027	13.16	0.07	13.23	5.58E-05		
07.00	0.027	13.16	0.07	13.23	5.58E-05		
08.00	0.068	13.36	0.31	13.66	5.87E-05		
09.00	0.068	13.36	0.31	13.66	5.87E-05		
10.00	0.076	13.42	0.37	13.79	5.95E-05		
11.00	0.076	13.42	0.37	13.79	5.95E-05		
12.00	0.076	13.42	0.37	13.79	5.95E-05		
13.00	0.076	13.42	0.37	13.79	5.95E-05		
14.00	0.99	13.62	0.56	14.19	6.23E-05		
15.00	0.105	13.70	0.63	14.32	6.33E-05		
16.00	0.105	13.70	0.63	14.32	6.33E-05		
17.00	0.111	13.76	0.68	14.44	6.41E-05		
18.00	0.111	13.76	0.68	14.44	6.41E-05		
19.00	0.112	13.77	0.69	14.47	6.44E-05		
20.00	0.038	13.19	0.12	13.31	5.63E-05		
21.00	0.038	13.19	0.12	13.31	5.63E-05		
22.00	0.027	13.16	0.07	13.23	5.58E-05		
23.00	0.027	13.16	0.07	13.23	5.58E-05		
24.00	0.027	13.16	0.07	13.23	5.58E-05		

Psrocessing results of current sample data

Current samples that have been obtained will be processed using daubechies wavelet transform using MATLAB software. The signal decomposition has two parts, the approximation coefficient and the detail coefficient. In the first decomposition the signal is divided into 2, the approximation coefficient and the detail coefficient. At the second decomposition level, the approximation coefficient at the first level is used to produce the second approximation coefficient and detail coefficient until it reaches the ninth decomposition with a smaller frequency range.

The signal is transformed into d1-d9 and a9 forms. The signal labelled s is the initial signal to be processed. The signal marked d1-d9 is the detailed coefficient or signal resulting from each decomposition level. While the a9 signal is the approximation coefficient at the ninth level aswell as the residual signal from several decompositions that have been done previously. Based on Figure 7, it canbe seen that the lower the decomposition, the denser the signal contained in d1 with a signal amplitude value of about 1. While the signal that has the greatest amplitude is the signal in the eighth decomposition because it is a fundamental signal.

Table 8. IEC 60076-7 Calculation Results vs. Hot SpotTemperature Measurement Results for TR-24

Calculation Result of IEC 60076-7				Measuremen t Resultof Hot Spot Temperature	
Time	LF	θ_{h_est}	V	θ_{h_meas}	V
01.00	0.8096	58.358	0.01025	69.65	0.037792
02.00	0.9067	68.042	0.03140	73.89	0.061714
03.00	0.9067	68.042	0.03140	73.89	0.061714
04.00	0.9067	68.042	0.03140	73.89	0.061714
05.00	0.3832	25.333	0.00022	51.01	0.004391
06.00	0.3832	25.333	0.00022	51.01	0.004391
07.00	0.3832	25.333	0.00022	51.01	0.004391
08.00	0.3832	25.333	0.00022	51.01	0.004391
09.00	0.3832	25.333	0.00022	51.01	0.004391
10.00	0.3832	25.333	0.00022	51.01	0.004391
11.00	0.3832	25.333	0.00022	51.01	0.004391
12.00	0.3832	25.333	0.00022	51.01	0.004391
13.00	0.3832	25.333	0.00022	51.01	0.004391
14.00	0.3832	25.333	0.00022	51.01	0.004391
15.00	0.3832	25.333	0.00022	51.01	0.004391
16.00	0.8568	62.976	0.01748	71.71	0.047966
17.00	0.8568	62.976	0.01748	71.71	0.047966
18.00	0.8568	62.976	0.01748	71.71	0.047966
19.00	0.8568	62.976	0.01748	71.71	0.047966
20.00	1.0439	82.905	0.17485	92.99	0.560854
21.00	1.063	85.074	0.22462	89.46	0.372698
22.00	1.0277	81.081	0.14162	92.29	0.516834
23.00	1.002	78.221	0.10177	85.92	0.247664
24.00	0.8096	58.358	0.01025	69.65	0.037792

2.3 Yield of energy and power spectral density (PSD)

The results of processing current sample data will be processed to obtain yield of energy and power spectral density as shown in Tables IX and X.

2.4 The results of the prediction of the remaining life of the transformer using back propagation

Testing the prediction of the remaining life of the transformer using a backpropagation neural network was carried out in several scenarios:

1) Case study 1

This scenario consists of 100% training data and testing data. The results of the simulations carried out to predict the remaining life of the transformer are shown in table XI and Figure 7. The average accuracy value is 93.92% and MSE is 4.68. Due to the small error value, it can be concluded that the input parameters used can be used to determine the remaining life of the transformer while the greatest error value is found in TR-23 of about 73.63.

Table 9. Energy Density and PSD on Transformer TR-1

ENERGY			PSD	
R	*S*	*T*	*R*	*S*
4005.3	1264	2896.9	40	12.6
73839.4	5919.3	34064.3	1476.7	118.3

Table 10. Energy Density and PSD on Transformer TR-2

TR-2	ENERGY			PSD		
	R	*S*	*T*	*R*	*S*	*T*
D7	25.8	26.2	21.8	0.2	0.2	0.2
D8	13.5	72.4	12.1	0.2	1.4	0.2

2) 2. *Case study 2*

This scenario consists of 50% training data and 50% testing data. The results of the simulations carried out to predict the remaining life of the transformer are shown in table XII and Figure 8. In case study 2, the selection of training data and testing data was carried out randomly so that an average accuracy value was obtained of 93.92% and MSE of 4.68. Due to the small error value, it can be concluded that the input parameters used can be used to determine the remaining life of the transformer, while the greatest error value is found in TR-14 at 22.31.

3) 3. *Case Study 3*

This scenario consists of 75% training data and 25% testing data. The results of the simulations carried out to predict the remaining life of the transformer are shown in Table XIII and Figure 9. In case study 3, the selection of training data and data testing was carried out randomly so that an average accuracy value was 88.23% and MSE was 11.03. The result of the biggest error is found in TR-20 of about 48.29.

Table 11. Prediction Simulation Results of Remaining Life vs.\ Original Remaining Life Composition I

No	Transformer Label	Remaining Life of Transformer (years)		Accuracy (%)	MSE
		IEC 60076-7 (years)	Prediction of Remaining Life (years)		
1	TR-1	24	23.9636	99.85	0.00
2	TR-2	26	25.634	98.59	0.13
3	TR-3	26	25.49	98.04	0.26
4	TR-4	23	22.9748	99.89	0.00
5	TR-5	25	25.4036	98.39	0.16
6	TR-6	25	25.3736	98.51	0.14
7	TR-7	21	21.0212	99.90	0.00
8	TR-8	24	24.0152	99.94	0.00
9	TR-9	24	23.8952	99.56	0.01
10	TR-10	25	23.846	95.38	1.33
11	TR-11	26	23.696	91.14	5.31
12	TR-12	25	23.6024	94.41	1.95
13	TR-13	23	23.1224	99.47	0.01
14	TR-14	23	23.0624	99.73	0.00
15	TR-15	24	24.1796	99.25	0.03
16	TR-16	24	22.4672	93.61	2.35
17	TR-17	26	24.9524	95.97	1.10
18	TR-18	25	21.6728	86.69	11.07
19	TR-19	22	22.9976	95.47	1.00
20	TR-20	23	22.3424	97.14	0.43
21	TR-21	21	22.3424	93.61	1.80
22	TR-22	19	22.2632	82.83	10.65
23	TR-23	14	22.6388	38.29	74.63
24	TR-24	22	21.6608	98.46	0.12
Average				93.92	4.68

The remaining life of the transformer in Table XIV shows that the accuracy between the remaining life using the measured temperature data (Hot Spot) is compared with the remaining age of the calculated temperature data (Hot $Spot_{count}$) of 75% of the data has an accuracy of 100%, while the rest has an accuracy of between 63 % -95%, the mean accuracy for the whole sample is 96.64%. This accuracy value is almost the same or with a very small difference of 96.723% in the remaining life of the prediction results of backpropagation. The difference is the number of samples that have perfect accuracy (100%) totalling 18 samples with the remaining life calculated based on the calculated hot spots (Hot $Spot_{count}$). So the prediction results of the remaining life of the transformer are almost the same as the remaining life of the measurement results (Hot $Spot_{count}$).

Table 12. Simulation Results Prediction of Remaining Life vs. Original Remaining Life Case Study 2

No	Transformer Label	Remaining Life of Transformer (years)		Accuracy (%)	MSE
		IEC 60076-7 (years)	Prediction of remaining life (years)		
1	TR-9	26	22.9977	88.45	9.01
2	TR-19	21	19.2247	91.55	3.15
3	TR-20	19	21.5879	86.38	6.70
4	TR-10	25	23.7229	94.89	1.63
5	TR-15	23	20.5029	89.14	6.24
6	TR-12	23	23.5017	97.82	0.25
7	TR-13	24	22.4328	93.47	2.46
8	TR-14	24	19.2765	80.32	22.31
9	TR-5	26	25.9475	99.80	0.00
10	TR-22	21	23.2889	89.10	5.24
11	TR-16	25	25.6717	97.31	0.45
12	TR-23	22	20.7507	94.32	1.56
Average				91.87	4.91

Table 13. Simulation Results Prediction of Remaining Life vs. Original Remaining Life Case Study 3

No	Transformer Label	Remaining Life of Transformer (years)		Accuracy (%)	MSE
		IEC 60076-7 (years)	Prediction of remaining life (years)		
1	TR-9	26	25.923	99.70	0.01
2	TR-19	21	19.8316	94.44	1.37
3	TR-20	19	25.9489	63.43	48.29
4	TR-10	25	25.9783	96.09	0.96
5	TR-15	23	25.5926	88.73	6.72
6	TR-12	23	25.979	87.05	8.87
Average				88.23	11.03

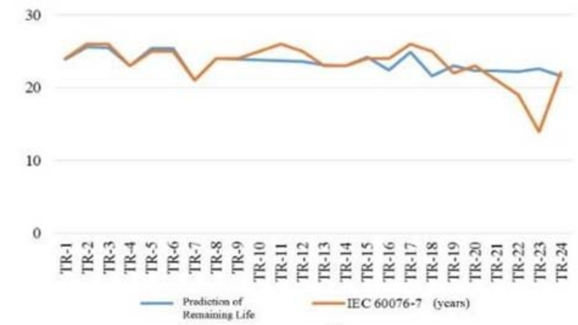

Fig. 7. Prediction of remaining life vs original remaining life in case study 1

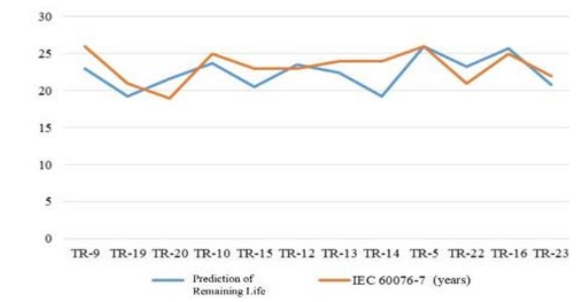

Fig. 8. Prediction of remaining life vs. original remaininglife in case study 2

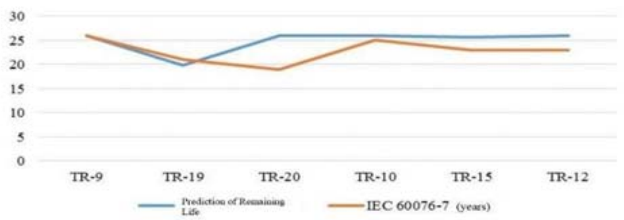

Fig. 9. Prediction of remaining life vs. original remaining life composition III

Conclusion

Prediction of the remaining life of the transformer using the neuro-wavelet method has been described in this paper. It was carried out based on the measurement of thecurrent and temperature of the transformer top oil. The object of this study was a distribution transformer with a voltage level of 20 kV/220 - 380 V located in North Surabaya, East Java, Indonesia. Current measurementdata was processed using doubechies wavelet transform which produced energy density and PSD. Back- propagation neural network was used to predict the remaining life of the transformer based on the PSD, energy density and loading transformer. Prediction of the remaining life of the transformer using the data of hotspot temperature measurement had an accuracy of 96.64%.

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REFERENCES

[1] Y. Biçen, F. Aras, dan H. Kirkici, "Lifetime estimation and monitoring of power transformer considering annual load factors," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 21, no. 3, hlm. 1360– 1367, June 2014.

[2] J. A. Jardini, H. P. Schmidt, C. M. V. Tahan, C. C. B. D. Oliveira, dan S. U. Ahn, "Distribution transformer loss of life evaluation: a novel approach based on daily load profiles," *IEEE Transactions on Power Delivery*, vol. 15, no. 1, hlm. 361–366, Jan 2000.

[3] M. Said, K. M. Nor, dan M. S. Majid, "Analysis of distribution transformer losses and life expectancy using measured harmonic data," dalam *Proceedings of 14th International Conference on Harmonics and Quality of Power - ICHQP 2010*, 2010, hlm. 1–6.

[4] W. F, W. K. Adi, A. Priyadi, M. Pujiantara, dan M. H. P, "Transformer monitoring using harmonic current based on wavelet transformation and probabilistic neural network (PNN)," dalam *2014 The 1st International Conference on Information Technology, Computer, and Electrical Engineering*, 2014, hlm. 419–423.

[5] O. E. Gouda, G. M. Amer, dan W. A. A. Salem, "Predicting transformer temperature rise and loss of life in the presence of harmonic load currents," *Ain Shams Engineering Journal*, vol. 3, no. 2, hlm. 113– 121, June 2012.

[6] H. Zeinoddini-Meymand dan B. Vahidi, "Health index calculation for power transformers using technical and economical parameters," *IET Science, Measurement Technology*, vol. 10, no. 7, hlm. 823– 830, 2016.

[7] H. Monsef dan S. Lotfifard, "Internal fault current identification based on wavelet transform in power transformers," *Electric Power Systems Research*, vol. 77, no. 12, hlm. 1637–1645, Okt 2007.

[8] J. CusidÓCusido, L. Romeral, J. A. Ortega, J. A. Rosero, dan A. G. Espinosa, "Fault Detection in Induction Machines Using Power Spectral Density in Wavelet Decomposition," *IEEE Transactions on Industrial Electronics*, vol. 55, no. 2, hlm. 633–643, Feb 2008.

[9] Faria, R. Salustiano, dan M. Martinez, "A prediction of distribution transformers aging based on tank infrared temperature measurements," dalam *22nd International Conference and Exhibition on Electricity Distribution (CIRED 2013)*, 2013, hlm. 1–4.

[10] IEC 60076-7:2018, "Power Transformer- Part 7 : Loading Guide for Oil-Immersed Power Transformers." .

[11] F. Husnayain, M. Latif, dan I. Garniwa, "Transformer oil lifetime prediction using the Arrhenius law based on physical and electrical characteristics," dalam *2015 International Conference on Quality in Research (QiR)*, 2015, hlm. 115–120.

[12] Rosmaliati, "Nguyen-Widrow Neural Network for Distribution Transformer Lifetime Prediction," *The International Conference on Computer ENgineering, Network and Intelligent Multimedia 2018*.

[13] Hafidz, P. E. Nofi, D. O. Anggriawan, A. Priyadi, dan M. H. Pumomo, "Neuro wavelet algortihm for detecting high impedance faults in extra high voltage transmission systems," dalam *2017 2nd International Conference Sustainable and Renewable Energy Engineering (ICSREE)*, 2017, hlm. 97–100.

[14] M. Purnomo Hery, *Supervised Neural Networks dan aplikasinya*, Pertama. Yogyakarta: Graha Ilmu, 2006.

[15] Hassane Ezziane , Hamza Houassine , Samir Moulahoum and Moustafa Chaouche, 2022, "Classifying Transformer Winding Fault Type, Location and Extent using FRA based on Support Vector Machine," *Przegląd Elektrotechniczny*, vol. 01, no. 23. doi: 10.15199/48.2022.01.04

[16] Viktor Kaplun, Roman Chuenko, and Svitlana Makarevych, 2022, "Modelling of Asynchronous Motor with Split Stator Windings on the Principle of a Rotary Autotransformer," *Przegląd Elektrotechniczny*, vol. 03, no. 39. Pp 39-43. doi: 10.15199/48.2022.03.10

[17] Dominika Szcześniak and Piotr Przybyłek, 2022, "Application of nanoparticles for modification of electro-insulating liquids used in power transformers," *Przegląd Elektrotechniczny*, vol. 06, no. 62. Pp 62-65.doi: 10.15199/48.2022.06.11