Complex-valued open recurrent neural network for power transformer modeling

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Modeling of Electric Power Transformer with On-Load Tap Changer Voltage Control using Complex-Valued Neural Networks

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Abstract: - Use of Complex-Valued Neural Networks (CVNN) is proposed for modeling of power transformer. An advantage of this approach is possibility to build accurate and precise models, training the network with previously simulated or with measured real data (transformer's voltages and currents). Inherent capability of CVNN to handle complex values appears as an advantage in comparison with real-valued neural networks in power engineering. Due to neural networks' nature, it is possible to take into account of different spontaneous factors which hardly can be precisely considered in analytical models. The paper describes modeling of a transformer system with On-Load Tap Changer (OLTC) voltage control using analytical method and new CVNN-based method. In the first part of the paper analytical model is introduced. The model is based on conventional transformer's equations complemented with nonlinearities in magnetizing system, ambient temperature influence on windings and OLTC voltage stabilization. Typical day-long load curve is used for the simulation. The second part of the paper describes basics of CVNNs and the application of the approach for modeling of the transformer system. Data generated by analytical model is used for training and verification of derived CVNN-based model. Verification shows that CVNN is capable to track nonlinear dynamics of power equipment. Proposed method can be considered as basics for further developments of CVNN use in the field of electrical equipment modeling.

Key-Words: - Complex-valued neural network; CVNN; Transformer modeling; Power equipment modeling; On-load tap changer; OLTC, Continuous Time Modeling, Complex Valued Back Propagation.

1 Introduction

Detailed modeling of electrical power network elements is necessary for receiving accurate simulation data. In analytical models it is usually difficult to take into account all the factors that have influence on the power equipment. An approach which allows to build a model which may track a lot of real phenomena in dynamic regimes is modeling using neural networks. In [1],[2] modeling of a transformer with Real-Valued Neural Networks (RVNN) is described. Such networks are also applied for the task of differential protection and transformer insulation modeling [3],[4]. The approach generally consists of two parts: firstly one generates data with analytical model; then a neural network is trained and tested. Comparison with analytical results shows applicability of an approach.

In the present paper the modeling of a power transformer system with nonlinearities (due to On-Load Tap Changer) is proposed as an extension of [5], using the approach based on Complex-Valued Neural Networks (CVNN). As its name implies the difference from real-valued ones in capability to deal with intrinsic capability to deal with the complex numbers instead of the real ones. Taking into account the common representation of electrical values as rotating vectors, which can be treated as complex numbers, this feature is useful and promising in frame of power grid elements modeling.

Like in approaches using RVNN, on the basis of analytical model simulation data, CVNN-based model work is shown. Conventional method is described in the first part of the paper: temperature influence, on-load work, tap changer and result of the simulation by itself. The second part deals with CVNN principles. Then, having simulated data from the analytical model, the CVNN is trained and tested. The results are explained using various statistical measures.

2 Analytical Transformer Modeling

Well-known basic equations of a power transformer, supplemented by terms representing a nonlinear magnetizing system, influence of an ambient temperature and On-Load Tap Changer (OLTC) voltage stabilization system are considered to be an analytical model of a power transformer system in the paper. The system is considered to work on some changing load which corresponds to the evening load peak. Basic equations and nonlinear part are widely discussed in literature [5] and are omitted here. Remaining peculiarities are given below.

2.2 Influence of ambient temperature on the transformer

In order to get more realistic model, windings' resistance dependence from temperature have been introduced:

$$R = R_{nom}(1+\alpha(T-20)) \quad (1)$$

where R is calculated winding resistance

R_{nom} – nominal winding resistance

α – temperature coefficient

T – temperature

Transformer windings are assumed to be made from copper and corresponding temperature coefficient $\alpha = 3.8 \cdot 10^{-3}\ K^{-1}$ is used.

Temperature variation is assumed as in Fig. 1 within 12 hours time range from 12:00 till 24:00 (from 0:00 p. m. till 12:00 p. m.). Sun peak happens in the daytime, then the temperature decreases due to weather change for the worse.

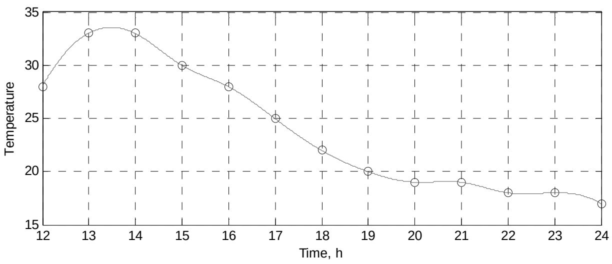

Fig. 1. Temperature variation

2.3 Load curve

Implemented transformer model works on some specified load which should be treated as equivalent impedance of some power system, supplied by the transformer. Peak on the load curve (Fig. 2) corresponds to evening peak of a typical household load. For being more realistic, small noise to the load profile is added.

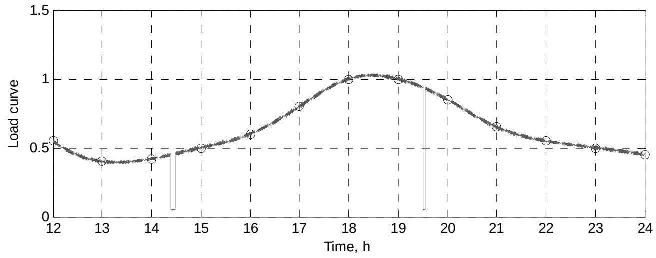

Fig. 2. Load variation [7, p. 47]

Moreover, in some points of simulation models of short circuits are added. Introduced extreme regimes help to test OLTC stabilization system and ability of CVNN to handle with such nonlinear data.

2.4 On-load tap changer

The transformer under consideration is equipped with On-Load Tap Changer (OLTC) mechanism on the primary winding. Range of voltage variation is equal to $\pm 15\%$ with 2.5% step.

2.5 Transformer's parameters

Given transformer model is based on the real transformer data of Russian transformer OMP-10/10 [6].

Table 1. Transformer Parameters

Parameter	Symbol	Value	Unit
Nominal power	S	10	κVA
Primary winding voltage	U_1, U_{hv}	10	κV
Frequency	f	50	Hz
Secondary winding voltage	U_2, U_{lv}	230	V
No-load current	I_{nl}	4.2	%
No-load power	P_{nl}	60	W
Short circuit power	P_{sc}	280	W
Short circuit voltage	U_{sc}	3.8	%

The detailed calculation of the equivalent circuit parameters is given in [5].

2.6 Simulation results

Analytical modeling is carried out in MATLAB, where all mentioned above peculiarities are implemented.

Transformer is assumed to work with nominal input AC voltage, having voltage output equals to 230 V (RMS) consequently.

Simple voltage control algorithm with OLTC is applied. The aim is to keep secondary voltage on the nominal level in spite of load and temperature fluctuations. During the simulation RMS value of secondary voltage $U_{2\mathrm{RMS}}$ is calculated over each electrical cycle using integral formula. Then it is compared with predefined quality margins (220 and 240 V) and corresponding control action (OLTC switching) is undertaken.

Results, obtained from the simulation are presented in Fig. 3, where all voltages, currents, temperature, load and OLTC position are presented. Fig. 4 shows $U_{2\mathrm{RMS}}$ voltage value during the simulation.

As it can be seen, temperature variation has low influence on the secondary current. At the same time, load variation has significant influence on the results being the main reason for OLTC switchings.

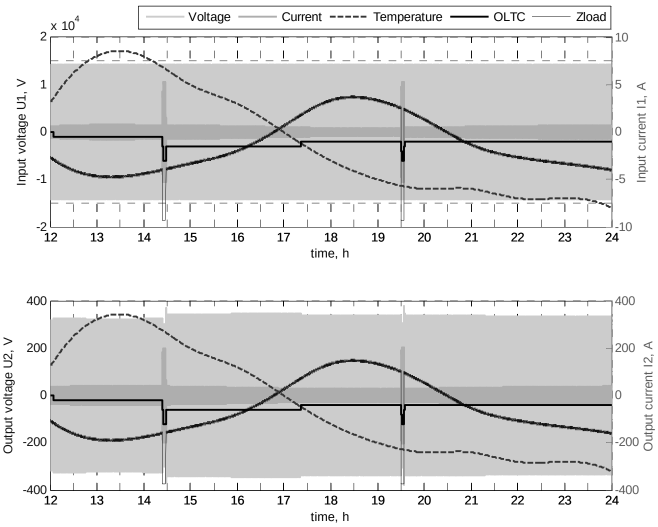

Fig. 3. Results of the simulation. Because of introduced variation of load, temperature and OLTC control currents and secondary voltage vary in time.

The main aim of the conducted analytical modeling is to generate data of the transformer with nonlinearities in order to train and test complex-valued neural network in the next section. Time scaling has been used (12 hours is represented by 60 seconds of power device simulation). Such an assumption makes the task of CVNN even harder since the change of loads and temperature happens slower in reality. See next sections for details.

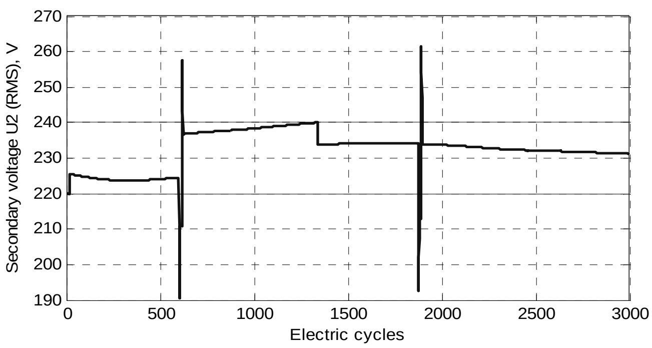

Fig. 4. Modeled OLTC voltage control increases quality of supply facilitating to keep secondary voltage in defined margins (220 and 240 V). Margins violation happens in case of heavy faults because of limited OLTC switching range.

3 Complex-Valued Neural Networks

Complex-Valued Neural Network (CVNN, see [8] and [9]), an essential extension of a traditional real-valued neural network, is a universal approximator of data, where inputs of network, weights and transition functions are from the complex values domain.

The basics of CVNN are briefly discussed in the paper. The task for the NN is to find the mapping from inputs into outputs ($\mathbb{C} \to \mathbb{C}$) so that the selected inputs propagated through the neural network can lead to the set of expected values (targets). The CVNN can be trained with absolutely the same methods which are used for the Real Valued NN but with some minor modifications which we will discuss below.

Feed Forward Path. The feed forward path is the same for the CVNN as it is discussed in many papers for the Real-Valued Neural Network (RVNN). It is shown with gray arrows at the Fig. 5. Network inputs propagate through the input layer (*netin*$_0$ in Fig. 5) of the network, then go to the first hidden layer as its inputs (*netout*$_0$). Then the inputs are to be multiplied with the weights matrix W_1 which consists of complex numbers. After this linear algebra operation a transition function f should be applied. The procedure is repeated iteratively. After the information goes out of the network (*netout*$_2$) it should be compared to the teacher signal *target* (see Fig. 5) using the error function. The so called feed forward path is absolutely the same for the CVNN as it is normally considered for the RVNN. The difference starts when one is trying to calculate the approximation error. The approximation error is defined as follows (see [12]):

$$E = \frac{1}{T}\sum_{t=1}^{T}\left(y_t - y_t^d\right)\overline{\left(y_t - y_t^d\right)} \to \min_{w} \qquad (2)$$

where the bar above the values means conjunction. This error is a non analytical function, which means that there is no derivative defined in the normal sense. Fortunately, one can calculate the derivatives using the so called Wirtinger calculus by considering the special class of functions which maps its complex arguments to a real space. A more detailed discussion of this problem was done in [8]. Presented error function (see eq. 2) is universal since it optimizes not only the length of the complex value, but also its angle (or phase). Utilization of this error function allows calculating the Taylor expansion and using it for the gradient descent weights optimization.

Weights Optimization. In order to minimize the error (which is the point of the neural network training) the gradient descent (GD) algorithm, which uses its Taylor expansion to adjust the network weights, is used:

$$E(w+\Delta w) = E(w) - \eta g^T \overline{g} + \frac{\eta^2}{2} g^T G \overline{g} \qquad (3)$$

After the Taylor expansion is calculated the training rule can be represented as follows:

$$\Delta w = -\eta \cdot \overline{g},\ \overline{g} = \overline{\frac{dE}{dw}} \qquad (4)$$

where η is the so called learning rate – a real valued constant, which serves the following needs. Taking it relatively small we can ignore all the members of the Taylor expansion of the order different from one. Note that gradients conjunction is very important due to the need in the existence of the Taylor expansion for the network training. Calculation of the gradients can be efficiently utilized with the error back propagation algorithm presented at the Fig.5. Doing the iterative changes of the weights according to the eq.4 one can train the CVNN to reproduce the desired output values having only the input information.

Backward Path. Here, in order to calculate all partial derivatives of the error with respect to the weight one have to propagate the derivative of the error back through the network till the input layer (first proposed in [13]). In case of CVNN, the back propagation algorithm remains nearly the same as it is typically used in real-valued neural networks (for details refer to [11]). The back propagation calculations are marked with black arrows at Fig. 5.

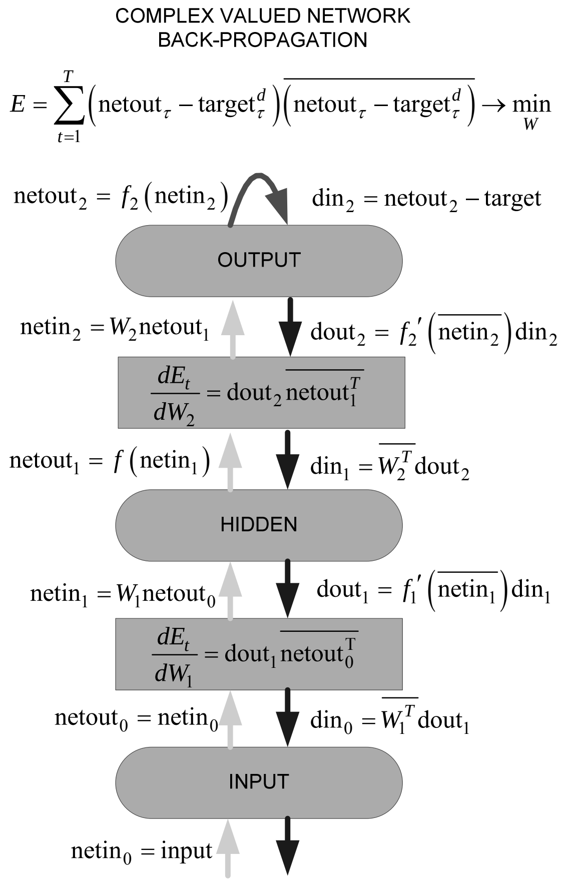

Fig. 5. Complex Valued Back-Propagation. Notations: *netin* - layer inputs, *netout* - layer outputs, *din* -layer derivative input, *dout* -layer derivative output, W_i are network weights, arrows show the information flow. The figure depicts the locality of the BP algorithm and independence of the BP from the network architecture.

One can see from the Fig. 5 that the back propagation for the CVNN has changes related to values conjunctions. These conjunctions appear due to the Wirtinger calculus used to calculate the derivatives of the errors (see [11] and [12]).

NN Training for the Given Problem. The inputs for the network are the following parameters: input current, input voltage, load and temperature, the outputs (desired values) we are interested here are the output current (I2) and the output voltage (U2). According to the transformer model described above a set of 50000 patterns is generated. 30000 patterns are used for network training and the rest 20000 are used to test the network and to provide the results. For this experiment the network had 10 neurons at two hidden layers, at which the transition functions are *sin*. The network is trained for each output. Learning rate equals to $\eta = 0.01$. It is taken small so that we can neglect all terms of the order above 1 at the Taylor expansion (see eq. 3-4). The amount of epochs for training is equal to 100, i. e. the 100 steps of the back propagation algorithm.

During the training process the error for the outputs is exponentially decreasing to 3.685e-003 for I2 is, and to 4.944e-003 for U2.

Some noise can also be added in order to check the approximation.

The following statistics for the training set are used to check the quality of data approximation:

- Root mean squared error (RMSE)
- Correlation coefficient (R)
- Determination coefficient (R2)

The results of modeling are shown in Fig. 6 and Table 2, where *time* characterizes time steps at which measurements are made. Here one can see that the network approximation is quite good, which also can be verified by testing the network on the test set (see Fig. 7-8 and Table 3). The output values almost coincide with the target ones and only differ slightly at the bump area; and the statistical coefficients are also close to their corresponding best values.

Table 2. Quality of training

Real part	RMSE	R	R2
I2	0.0033	0.9997	0.9995
U2	0.0058	0.9999	0.9999

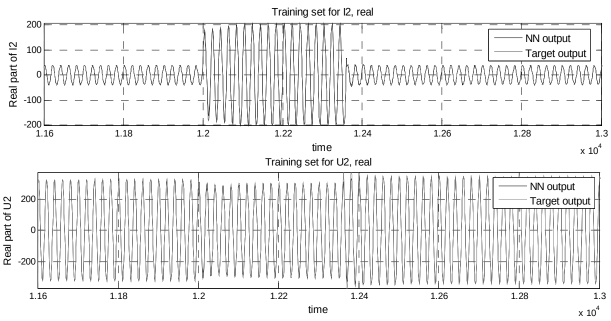

Fig. 6. Results of the transformer modeling for the subset of data containing bumps. One can see the real part of the network outputs and the actual values of I2, U2 on the training set.

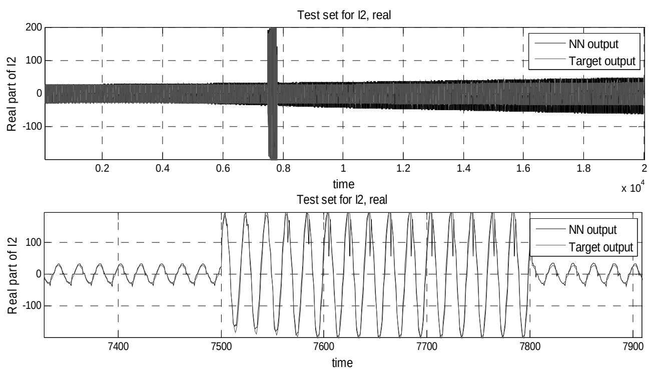

Fig. 7. Results of the transformer modeling for I2. One can see the real part of I2. The difference between the outputs and target is small.

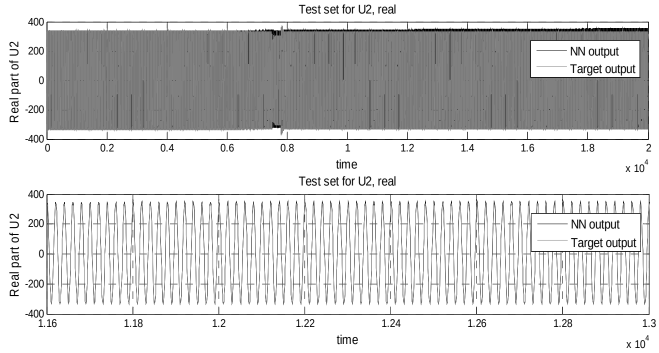

Fig. 8. Results of the transformer modeling for U2. One can see the real part of U2 on the test set. The difference between the outputs and target is small.

Table 3. Quality of testing

Real part	RMSE	R	R2
I2	0.04	0.95	0.90
U2	0.02	0.99	0.99

4 Conclusions

The work of a transformer is modeled with a complex-valued neural network. The described approach enhances the preliminary simulation results derived in the previous research [5]. Injection of nonlinearities and adding noise in the analytical model for generating data made the model more realistic.

From obtained results the following conclusions can be formulated:

- Use of CVNN is justified for tasks of modeling power transoformer with high degree of nonlinearity (OLTC). Moreover, the described neural network can also be used for dynamics forecasting of the transformer.
- Capabitlity to deal with complex numbers instead real ones gives the benefit to CVNN approach in comparison with RVNN.
- Described new method (CVNN) can be used for power equipment modeling.

The following step for new method development is implementing of tests with data from real devices. The attractive feature is that it is possible to model each grid device individually, just teaching the CVNN with measured data from particular device.

Significant end-use of the approach consists in integration of obtained CVNN-based transformer model in power engineering simulation software packages.

References:

[1] Minchev, S.V., Neural networks for modeling of dynamic systems with hysteresis. В Proceedings First International IEEE Symposium Intelligent Systems. *IS'02: First International IEEE Symposium "Intelligent Systems"*. Varna, Bulgaria, с. 42-47.

[2] Minchev, S.V., & Venkov, G.I., Modeling of nonlinear dynamic systems via discrete-time recurrent neural networks and variational training algorithm. *2004 2nd International IEEE Conference on "Intelligent Systems"*. Proceedings. Varna, Bulgaria, с. 105-108.

[3] M. Tripathy, R-P Maheshwari, H. K. Verma *"Power Transformer Differential Protection Based On Optimal Probabilistic Neural Network"*, IEEE Transactions on Power Delivery, 2010

[4] K. Shaban, A. El-Hag, A. Matveev *"A cascade of artificial neural networks to predict transformers oil parameters"*, IEEE Transactions on Dielectrics and Electrical Insulation, 2009

[5] Yury S. Chistyakov, Elena V. Kholodova, Alexey S. Minin, Hans-Georg Zimmermann, Alois Knoll "Modeling of electric power transformer using complex-valued neural networks" at the *2011 IEEE International Conference on Smart Grid and Clean Energy Technologies*, China, 2011, in press.

[6] *Orion OMP transformers catalog* [Online]. Available: http://www.orion-nt.ru/cat/transf/tr-hmel/tr_omp1.htm

[7] A. Lykin, "*Elektricheskie sistemy i seti*", Moscow, Logos, 2008.

[8] H. Leung, S. Haykin, "*The complex back propagation*", IEEE Transactions on Signal Processing., Vol.39, No.9, September 1991., pp. 2101 – 2104.

[9] T. Kim, T. Adali, "Fully complex multi-layered perceptron network for nonlinear signal processing", *VLSI Signal Processing 32*, pp. 29-43, 2002.

[10] Zimmermann H.-G., Minin A., Kusherbaeva V., "Historical consistent complex valued recurrent neural network", *ICANN 2011*, Part I, LNCS 6791, pp. 185–192, 2011.

[11] Zimmermann H.-G., Minin A., Kusherbaeva V., "Comparison of the complex valued and real valued neural networks trained with gradient descent and random search algorithms", *Proc. of ESANN 2011*, pp. 216-222, 2011.

[12] D. H. Brandwood, "A complex gradient operator and its application in adaptive array theory". *IEEE Proceedings, F: Communications, Radar and Signal Processing*, 130(1):1116, 1983.

[13] R. Neuneier, H.G. Zimmermann, "How to train neural networks, neural networks: tricks of the trade", *Springer*, pp. 373-423, 1998