OPTIMIZATION OF ELECTRIC POWER SYSTEMS USING FUZZY NEURAL NETWORK ALGORITHMS

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Abstract

The article addresses optimization of power supply systems by using fuzzy neural networks to increase the accuracy of operational forecasts and implement active control systems in the power supply grids. As a practical example, the article considers the optimization of parameters of the 220 kV Yuzhnaya Substation operated by the Regional Dispatching Office of the Voronezh Region Electric Power System (Voronezh, Russia). The obtained results indicate an increase in the energy efficiency of the studied equipment by 4.38% (in terms of real power loss), as compared to the existing control mode, through the use of fuzzy neural controllers that improve the accuracy of forecasts of the relevant technological parameters. The developed solutions can be used in electrical power systems and load nodes as a part of control modules. The economic effect is achieved by taking into account the poorly for malizable factors and compensating for their impact on real power loss in the transformer equipment.

Keywords: Optimization of power supply systems, energy efficiency, simulation, distributed objects, fuzzy neural networks, adaptive control systems

I. Introduction

The main elements of electric power systems (EPS) are 110–220 kV AC substations. The energy efficiency of transmission and distribution networks depends on the optimum performance of substations. For this reason, they are the paramount

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facilities for the implementation of the Smart Grid concept (or the Flexible AC Transmission System concepts).
This paper discusses how to optimize real power losses, which is a basic parameter of substation operation, while observing the reliability requirements for power grid facilities.

II. Materials and Methods

The main indicator of normal operation that is used to evaluate the energy efficiency of transmission facilities, is real power loss:

\[ \Delta P_\Sigma = \Delta P_{ld} + \Delta P_{cc} + \Delta P_{cr}, \]  
(1)

where \( \Delta P_\Sigma \) is the total real power losses; \( \Delta P_{ld} \) is the real power losses under load; \( \Delta P_{cc} \) is the conditional constant real power losses (except for corona losses); and \( \Delta P_{cr} \) is the corona loss.

Then,

\[ \Delta P_{ld\%} = \frac{1}{(1 - \frac{\Delta U_{\%}}{100})^2} - 1 = \frac{S^2}{U^2} \left( 1 - \frac{1}{(1 - \frac{\Delta U_{\%}}{100})^2} \right) R_{eq} \]  
(2)

\[ \Delta P_{cc\%} = \left( 1 + \frac{\Delta U_{\%}}{100} \right)^2 - 1 = \Delta P_{xx} \cdot \sum_{i=1}^{m} T_{pt} \left( \frac{U}{U_n} \right)^2 \]  
(3)

\[ \Delta P_{cr\%} = 6.88 \left( 1 + \frac{\Delta U_{\%}}{100} \right)^2 - 5.88 \left( 1 + \frac{\Delta U_{\%}}{100} \right) - 1 = \Delta P_{cr} \cdot L \cdot k_{cr} \]  
(4)

where \( \Delta U_{\%} \) is the change in the magnitude of supply voltage in percentage terms; \( S \) is the value of total power transmitted by the transmission facilities; \( U \) is the current value of supply voltage; \( R_{eq} \) is the equivalent resistance of the transmission facilities; \( \Delta P_{xx} \) is the no load power of transformers; \( T_{pt} \) is the number of operating hours of the transformer in \( i \)-th mode; \( U_n \) is the nominal voltage of the transformer; \( \Delta P_{cr} \) is the average specific corona loss; \( L \) is the length of the line; and \( k_{cr} \) is corona loss factor equal to:

\[ k_{cr} = 6.88 \left( \frac{U}{U_n} \right)^2 - 5.88 \left( \frac{U}{U_n} \right) \]  
(5)

The share of load losses in regional EPSs is significantly greater than the share of conditional constant losses. Therefore, in order to reduce total real power losses \( \Delta P_\Sigma \), the voltage in the transmission facilities is usually maintained at the maximum permissible level. However, this does not take into account the actual static load characteristics (SLC) of the power consumption nodes. The problem of EPS optimization becomes much more complicated if SLC are taken into account, and, in general, it is solved using Lagrange-type and Newton-Raphson-type methods.

Given the above, the optimization model, based on the criterion of minimum power loss in the distribution facilities of EPS, can be implemented as the following objective function:

\[ \text{objective function} \]
\[ F_j = \sum_{i=1}^{k} W_i(P_0) = \sum_{i=1}^{k} \left[ \left( \frac{\sqrt{(P_i(D)^2+Q_i(D)^2)} R_{eqi}}{U_i} \right)^2 \left( \frac{1}{1 - \frac{\Delta P_{xxl}}{T_{pi}}} - 1 \right) + \Delta P_{xxl} \cdot \frac{U_i}{U_{nl}} \right]^2 + \Delta P_{cri} \cdot \]

\[ L_1 \cdot k_{u_{cri}} \rightarrow \min \]

where \( W(P_0) \) is the real power loss in EPS facilities.

III. Results

Let us consider the 220 kV Yuzhnaya Substation as a typical facility operated in normal mode by the Regional Dispatching Office of the Voronezh Region Electric Power System (Russia). The operational diagram of the substation is presented in Figure 1.

The main functional elements of the 220 kV Yuzhnaya Substation, which provide the transmission of power flows from 1,2 and 220 kV transfer bus bars (intake points 1–3) to 4,5 and 110 kV transfer bus bars (output points 1–4), are three auto-type transformers AT-1-200, AT-2-135, and AT-3-135.

The operation modes of the substation are controlled by:

- on-load tap-changer AT-1,
- residual current operated circuit-breakers AT-2-135 and AT-3-135,
- static capacitor batteries BSK-110-1 and BSK-110-2.
Tables 1 and 2 summarize the data of operating days for the period from 2014 through 2016.

Table 1: Values of $\tan \phi$, $\cos \phi$ and $W(t)$ operating days for the period from 2014 through 2016 the 220 kV Yuzhnaya Substation at points 1–3.

| Date (dd/mm/yy) | Hours of extreme values | $P$ (kW) | $Q$ (kWAr) | $\tan \phi$ | $\cos \phi$ | Average capacity (MW) |
|-----------------|-------------------------|----------|------------|-------------|-------------|-----------------------|
| 11.06.2014      | 05:00                   | 103950   | 86100      | 0.828       | 0.77       | 113.333               |
|                 | 19:00                   | 194250   | 79800      | 0.411       | 0.925      |                      |
| 17.12.2014      | 05:00                   | 97650    | 71400      | 0.731       | 0.807      | 121.688               |
|                 | 15:00                   | 158550   | 53550      | 0.338       | 0.947      |                      |
| 17.06.2015      | 05:00                   | 112350   | 87150      | 0.776       | 0.79       | 155.000               |
|                 | 11:00                   | 207900   | 11235      | 0.054       | 0.999      |                      |
| 16.12.2015      | 06:00                   | 67200    | 80850      | 1.203       | 0.639      | 105.000               |
|                 | 16:00                   | 133350   | 102900     | 0.772       | 0.792      |                      |
| 15.06.2016      | 04:00                   | 106050   | 76650      | 0.723       | 0.81       | 163.333               |

Fig. 1: Generalized operational diagram of the 220 kV Yuzhnaya Substation
IV. Discussion

A simulation based on a fuzzy neuron controller (FNC) that controls transformers was developed as an alternative control system. Figure 2 shows the simulated operational diagram of the 220 kV Yuzhnaya Substation built in Matlab. The detailed description and the calculation of parameters of the transformers and the simulation are beyond the scope of this article.

The simulation was created in order to accurately describe the controlled facility (transformers) for the purpose of subsequent implementation of the reference simulation and optimization of the power consumption node by the criterion of minimum power loss using a FNC.
Figure 3 shows the generalized block diagram of the FNC, which is the core of the control system in the simulation (Figure 2). The FNC uses the current change of the reproduced vector of the control function at the $i$-th instant of time $g_3(i)$ and the output of the reference simulation $y_2(i+k)$. The reference simulation is based on an artificial neural network (ANN), which describes the dynamics of the controlled facility in the corresponding ‘time slices’ of the continuous process of power flow and learns from the prediction of error $e_2(i+k) = y_2(i+k) - y_{o2}(i)$ and the control signal $y_1(i+k)$. Setup vectors $W_1, W_2$ make it possible to adjust the parameters of input terms (for FNC) and activation functions (for ANN).

Fig. 3: Generalized block diagram of the FNC and the ANN-based reference simulation for distribution facilities at different hierarchy levels
As a result of such setup, the ATC network implements an inverse model of the controlled facility and as a controller with high adaptive properties due to the full consideration of undetermined factors and impacts affecting the controlled facility.

It should be noted that the block diagram of the FNC, shown in Figure 3, can be applied to implement voltage regulation both in components of the regional power transmission facilities and in local control systems of the power consumption nodes. It is possible due to the following features:

- the neutron-fuzzy network, which is a part of the FNC, has a structure that has the property of free scaling, and, consequently, a possibility of applying an arbitrary structure to the elements of the Power Supply Monitoring and Control System;
- the ANN, which implements the reference simulation of the controlled facility, allows enhancing the efficiency of decisions made within the control unit of the local technological objects in the Power Supply Monitoring and Control System.

The U-shaped membership function and the Gaussian type membership function of the terms of input variables have been previously found to be the most optimal. The FNC output is implemented in the form of a linearized value.

The structure of the ANN-based reference simulation is a multilayer perceptron with an algorithm for the rapid back propagation of error. The network structure is variable and depends on the controlled facility; the number of learning cycles is determined using heuristic methods; the activation function is sigmoid.

The available SLCs of the considered energy consumption node include data that the Regional Dispatching Office of the Voronezh Region Electric Power System takes as forecast information when regulating the voltage at AT-1, AT-2, and AT-3 at the 220 kV Yuzhnaya Substation:

- for AT-1:

\[
\begin{align*}
    P_1(U) &= P_{1n}(U) \left[ 2.17 - 1.55 \cdot \left( \frac{u}{u_n} \right) + 3.57 \cdot \left( \frac{u}{u_n} \right)^2 \right]; \\
    Q_1(U) &= Q_{1n}(U) \left[ 6.25 - 3.8 \cdot \left( \frac{u}{u_n} \right) + 4.9 \cdot \left( \frac{u}{u_n} \right)^2 \right];
\end{align*}
\]  

(7)

- for AT-2:

\[
\begin{align*}
    P_2(U) &= P_{2n}(U) \left[ 3.51 - 2.9 \cdot \left( \frac{u}{u_n} \right) + 1.15 \cdot \left( \frac{u}{u_n} \right)^2 \right]; \\
    Q_2(U) &= Q_{2n}(U) \left[ 2.87 - 2.5 \cdot \left( \frac{u}{u_n} \right) + 5.1 \cdot \left( \frac{u}{u_n} \right)^2 \right];
\end{align*}
\]  

(8)

- for AT-3:

\[
\begin{align*}
    P_3(U) &= P_{3n}(U) \left[ 2.47 - 5.17 \cdot \left( \frac{u}{u_n} \right) + 1.03 \cdot \left( \frac{u}{u_n} \right)^2 \right]; \\
    Q_3(U) &= Q_{3n}(U) \left[ 2.17 - 4.02 \cdot \left( \frac{u}{u_n} \right) + 9.4 \cdot \left( \frac{u}{u_n} \right)^2 \right];
\end{align*}
\]  

(9)
In order to determine the capabilities of FNC as applied to the transformers of the 220 kV Yuzhnaya Substation, let us calculate the planned SLC value to select the optimal voltage level according to Expression 6 and, thus, minimize real power losses.

For this, we use the ANN, trained on the basis of the simulation of the transformer in no load operation, as a reference simulation in the FHC structure (built as shown in Figure 3).

The identification parameter block of the reference simulation is implemented in Matlab ANFIS (similar to AT-1, AT-2, AT-3): the structure is a multi-layer perceptron; the number of neurons in the hidden layer is 250; the sampling interval is 0.35 sec.; the number of delay elements at the input and output is 2; the training sample is 5,000; the number of training epochs is 500; the training algorithm is train br.

The input data of the training sample are the line-to-line power supply voltages of the three-phase system: \(u_{AB}, u_{BC}, u_{CA}\). For the output signal of the reference simulation, we obtain the predicted values: the \(u_{AB}^{\text{ref}}, u_{BC}^{\text{ref}}, u_{CA}^{\text{ref}}\) states of the controlled facility for the subsequent periods of time. Each of them has its own learning channel, the structure of which is shown in Figure 4.

![Fig. 4: Simulation of the FNC part in the transformer control system of the 220 kV Yuzhnaya Substation](image)

The settings of the fuzzy neuron network (FNN) in accordance with the Mamdani implementation are given in Table 3. Vectors \(M(i), S(i), U^*(i)\) are used as input variables. Two former ones are similar to those used for the power flow dynamics control model; the latter is contained in the redundant \(P^*(i)\). The output vector is \(U_{\text{ref}}(i + k)\), which is the magnitude of the voltage parameter adjustment to achieve the optimal value by the real power loss criterion.

| Table 3: FNN settings in accordance with the Mamdani implementation |
|---------------------------------------------------------------|
| **Network type** – FNN (Mamdani) |  |

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2. Typology and implementation of fuzzy data input/output

| Distribution of membership terms $M(i) \times S(i) \times U^*(i)$ | Quantity of training rules (pcs) | Types of transfer functions of input terms | Types of transfer function of output term $U_{reg}(i+k)$ |
|---------------------------------------------------------------|---------------------------------|-------------------------------------------|-----------------------------------------------------|
| $9 \times 3 \times 3$                                          | 184                             | psigmf                                    | linear                                              |

3. Topology and training of ANN (multilayer perceptron)

| Quantity of layers (pcs) | Quantity of hidden layers (pcs) | Quantity of elements in training sample (pcs) | Quantity of elements in test sample (pcs) |
|--------------------------|---------------------------------|-----------------------------------------------|------------------------------------------|
| 4                        | 2                               | 18 970                                        | 376                                      |

Stopping condition – RMS growth

ANN weights updating method – epoch (free-scaled time period)

Figure 5 shows the evaluation of the integral indicator of the power conversion and consumption process on the example of AT-1 at the 220 kV Yuzhnaya Substation, both for the existing control solution (the considered SLC values) and the use of FNC. A similar situation is observed at AT-2 and TA-3.

![Figure 5: Control of AT-1 at the 220 kV Yuzhnaya Substation by the real power loss criterion: (a) existing solution; (b) FNC](image)

V. Conclusion

The analysis of the curves in Figure 5 and the data obtained for AT-2 and AT-3 allows for the following conclusions:

– the existing algorithm applied to optimize the operation of a local facility in the Power Supply Monitoring and Control System (the 220 kV Yuzhnaya Substation) fails to fully take into account the actual SLC, which is the reason for excessive real power losses;

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the FNC used in the control system of the auto-type transformer and the voltage booster reduce the voltage level (by more accurate accounting of SLC) and hence brought the magnitude of real power loss in the given power consumption node to an optimized value;

- with the FNC, real power losses of the equipment of the 220 kV Yuzhnaya Substation (AT-1,2,3) were reduced by 0.439 MW (4.38%) as compared to the existing solution (10.0063 MW). At the same time, the power supply voltage values remain within the regulatory limits as per GOST 32144-2013.

It should be noted that currently in the existing EPSs, insufficient attention is paid to the analysis and subsequent use of the findings related to such uncertain and poorly formalizable factors as the cyclical fluctuations in consumer load, changes in climatic and economic factors, and state of distributed objects in the EPSs. At that, the focus is maintained on resolving local issues of the optimization of individual facilities in the energy distribution systems, while the interaction of adjacent transmission and consumption structures is insufficiently considered, causing the excessive energy intensity of the power supply complex.

The solution of this task can be found in the systematic introduction of adaptive power distribution control systems as applied to the regional distribution facilities based on the Smart Grid concept. The FNCs have been found efficient and hence can be recommend for use in R&D and innovative transformation of the power supple industry.

The proposed optimization method can significantly reduce the real power losses in transmission and distribution of power and, therefore, can facilitate of the EPS development.
References

I. Aiolfi, M., Capistran C., Timmermann, A. (2010). Forecast combinations. Working Papers 2010-04, Banco de México.

II. Al Rashidi, M. R., El-Hawary, M. E. (2009). A survey of particle swarm optimization applications in electric power systems. IEEE Transactions on Evolutionary Computation, 13(4), 913–918.

III. Antoniadis, A., Brossat, X., Cugliari, J., Poggi, J. (2013). Clustering functional data using wavelets. International Journal of Wavelets, Multiresolution and Information Processing, 11(01).

IV. Burkovsky, V.L., Gusev, K.Yu. (2010). Neyrosetevaya model prognozirovaniyadynamikiekonomicheskikhkhpokazateley [Neural network simulation for forecasting the dynamics of economic indicators]. VestnikVoronezhskogosudarstvennogotekhnicheskogouniversiteta = Bulletin of the Voronezh State Technical University, 6(4), 80–82.

V. Burkovsky, V.L., Krysanov, V.N., Rutskov, A.L. (2014). Prognozirovaniyepotrebeniyaelekstroenergipromyshlennympredpriyatiya mi s ispolzovaniyemmetodoviskusstvennykhneyronnykh i neyro-nechotkikhsetey [Forecasting power consumption by industrial enterprises using artificial neural and neuro-fuzzy networks]. Proceeding of the International (19th All-Russian) Conference on Automated Electric Drive (AEP-2014), Saransk, Russia.

VI. Burkovsky, V.L., Krysanov, V.N., Rutskov, A.L. (2016). Realizatsiaprogrammnogokompleksaprognozirovaniyuavrovnynaregionalnogoenergopotrebeniya [Sales program complex: Prediction of the regional level of energy consumption]. VestnikVoronezhskogosudarstvennogotekhnicheskogouniversiteta = Bulletin of the Voronezh State Technical University, 12(3), 41–47.

VII. Çevik, H.H., Çunkaş, M. (2015). Short-term load forecasting using fuzzy logic and ANFIS. Neural Computing and Applications, 26(6), 1355–1367.

VIII. Cheng, Z., Juncheng, T. (2015). Adaptive combination forecasting model for china's logistics freight volume based on an improved PSO-BP neural network. Kybernetes, 44(4), 646.

IX. Cho, H., Goude, Y., Brossat, X., Yao, Q. (2013). Modeling and forecasting daily electricity load curves: a hybrid approach. Journal of the American Statistical Association, 108, 7–21.
X. Danilov, A.D., Shukur, O.M., Rutskov, A.L. (2016). Analiz primeneniyanechotkikhnevronnykhseteydlyaprognozirovaniyaenergi opotrebleniya [Analysis of the use of fuzzy neural networks for predicting energy consumption]. Aktualnyye naukomye issledovaniya XXI veka = Theory and practice, 4(6), 59–63.

XI. Devaine, M., Gaillard, P., Goude, Y., Stoltz, G. (2013). Forecasting electricity consumption by aggregating specialized experts. Machine Learning, 90(2), 231–260.

XII. Devaine, M., Gaillard, P., Goude, Y., Stoltz, G. (2013). Forecasting electricity consumption by aggregating specialized experts. Machine Learning, 90(2), 231–260.

XIII. Eban, E., Birnbaum, A., Shalev-Shwartz, S., Globerson, A. (2012). Learning the experts for online sequence prediction. Proceedings of the 29th International Conference on Machine Learning, Edinburgh, Scotland, UK.

XIV. Gamm, A.Z., Gerasimov, L.N., Golub, I.I., et al. (1983). Otsevaniyesostoyaniya v elektroenergetike = State estimation in power generation industry. Moscow, Nauka.

XV. Krysanov, V.N., Rutskov, A.L., Myazin, D.S. (2015). Optimizatsiyaparametrovtsikladiffuziisveklosakharnogoproizvodstva s primeneniyem nevronnychprintsipov = Optimization of diffusion cycle parameters in beet-sugar production using neural principles. Elektrotekhnicheskikompleksy i sistemy upravleniya = Electrotechnical Complexes and Control Systems, 2, 65–70.

XVI. Li, P., Li, Y., Xiong, Q., Chai, Y., Zhang, Y. (2014). Application of a hybrid quantized elman neural network in short-term load forecasting. International Journal of Electrical Power & Energy Systems, 55, 749–759.

XVII. Monteleoni, C., Schmidt, G.A., Saroha, S., Asplund, E. (2011). Tracking climate models. Statistical Analysis and Data Mining, 4(4), 372–392.

XVIII. Nedellec, R., Cugliari, J., Goude, Y. (2014). Gefcom2012: Electric load forecasting and backcasting with semi-parametric models. International Journal of Forecasting, 30(2), 375–381.

XIX. Order of the Ministry of Industry and Energy of the Russian Federation No. 380 of June 23, 2015 “On the procedure for calculating the ratio of the consumption of real and reactive power for certain power receiver (groups of power receivers) of electrical energy consumers.” Available at: https://normativ.kontur.ru/document?moduleId=1&documentId=256534
XX. Rosenblatt, R. (1961). Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms. Spartan Book, Washington D.C.

XXI. Russian National Standard GOST 32144-2013 (2013). Electric energy. Electromagnetic compatibility of technical equipment. Power quality limits in the public power supply systems.

XXII. Shi, B., Yu-Xia, L.I., Xin-Hua, Y.U. (2009). Short-term load forecast based on modified particle swarm optimizer and back propagation neural network model. Journal of Computer Applications, 29(4), 1036–1039.

XXIII. Taylor, J. (2003). Short-Term Electricity Demand Forecasting Using Double Seasonal Exponential Smoothing. Journal of Operational Research Society, 54, 799–805.

XXIV. Vorotnitsky, V.E., ZaslonoV, S.V., Kalinkina, M.A., Parinov, I.A., Turkina, O.V. (2006). Metody i sredstvarascheta, analiza i srezheniyapoterelektricheskoyenergiipriyeyeperedachepoelektricheskisnimset yam [Methods and means of calculating, analyzing and reducing electric power losses when it is transmitted through electrical networks]. Moscow.

XXV. Zadeh, L.A. (1974). Outline to a new approach to the analysis complex systems and decision processes. IEEE Trans. on Systems, Man, and Cybernetics, 3, 28–44.