Technical and economic optimization of fuel facilities – energy complex using elements of fuzzy logic and artificial neural networks

A L Rutskov¹, Ya P Fedorov² and L V Volkov³

¹Branch of JSC "UK EFKO" in Voronezh, Taranchenko St., 40, Voronezh, 394018, Russia
²Department of corporate Finance and corporate governance Financial University under the government of the Russian Federation, M. Zlatoustinsky lane, 7, Moscow, 101000, Russia
³Department of management Financial University under the government of the Russian Federation, M. Zlatoustinsky lane, 7, Moscow, 101000, Russia

E-mail: alex_8_90@mail.ru

Abstract. This article discusses the possibilities of optimizing the fuel and energy complex by improving the accuracy of the forecast of the state in both the operational and medium-term periods: from an hour to several years. The model used to implement the mentioned energy efficiency improvement is based on the use of fuzzy neural networks together with the function of minimizing power losses in the elements of electric power systems. The Mamdani modification is used, which takes into account the database of previous periods of the system state, represented as static load characteristics. The organization of this approach allows you to take into account weakly formalized factors, thereby improving the quality of forecasting and dispatching management. At the same time, it is possible to use models for a wide class of objects, which is achieved due to its scalability. The estimation of forecasting accuracy of the proposed approach exceeds similar indicators of currently used statistical methods and regression implementations. These factors are direct economic drivers of reducing production costs.

1. Introduction

The functioning of modern facilities of the fuel and energy complex (FECF): resource extraction, supply complexes and end users is associated with the need to optimize the technological processes of using electric energy.

The time variations inherent in the functioning of the FECF are significantly indistinct, which is expressed in the multi-factor dependence of finding the optimum of electric energy losses. To solve this problem, the primary factor is the creation of a model of energy consumption dynamics that has the function of forecasting and developing control actions.

The main disadvantages of most of the developed models are the actual non-accounting (or weak accounting) of weakly formalized factors due to the lack of accuracy in implementing the forecast of energy consumption. At the same time, the corresponding fluctuations in the FECF are represented by linear approximations, which in principle does not allow optimizing the modes with an accuracy exceeding the error of the noted forecasting process.
The functioning of the model considered in this article is organized using combined fuzzy neural networks (FNN), which make it possible to increase the accuracy of indicators for estimating future periods (for solving optimization problems) in comparison with existing classical implementations (regression models).

2. Purpose and objectives of the work
The aim of the work is to increase the competitiveness of the FECF, which is achievable by optimizing the indicator of electric power losses during transmission in local power grid elements (power lines, power transformers, elements of distribution networks).

To achieve this goal, a number of tasks have been solved:
- the basic optimization model is defined for the subsequent development of algorithms for predicting energy resources in the FECF;
- developed variations of algorithms for the FNN-based model;
- evaluation of the effectiveness of the developed algorithms in relation to simulation models of FECF functioning for short-term, medium-term and long-term forecasting is obtained.

3. Materials and methods
There are two basic optimization approaches for the considered class of problems [1 - 5]:
- Lagrange equations;
- gradient models (Newton-Raphson algorithm).

For the purpose of practical use of optimization algorithms, the characteristics of the active and reactive components of FECF are presented as static load characteristics (SLC):

\[ P(U) = P_{nom}(U) a_0 U + a_1 U + a_2 U^2 + \ldots + a_n U^n + \varepsilon_P(U); \]
\[ Q(U) = Q_{nom}(U) b_0 U + b_1 U + b_2 U^2 + \ldots + b_n U^n + \varepsilon_Q(U); \]

where:
- \( P(U), Q(U) \) – is the active and reactive power;
- \( P_{nom}(U), Q_{nom}(U), U_{nom} \) – nominal values of active and reactive power and voltages under normal conditions;
- \( \varepsilon_P(U), \varepsilon_Q(U) \) – dependences of the distribution of active and reactive power on weakly formalized factors;
- \( a_0, a_1, a_2, \ldots, a_n, b_0, b_1, b_2, \ldots, b_n \) – parameters of the characteristic technological process of FECF functioning;
- \( U \) – current measured voltage value.

The optimization model based on the minimum power loss criterion in FECF is implemented as an objective function [2]:

\[ F_j = \frac{1}{W} \sum_{i=1}^{k} \left( \frac{P_i^2 + Q_i^2}{U_i^4} \right) R_{3i} \left( 1 + \frac{\Delta U_{qli}}{100} \right)^{-1} \]
\[ + \Delta P_{xli} \cdot T_{pi} \left( \frac{U_i}{U_{nom}} \right)^2 + \Delta P_{kopi} \cdot L_k \cdot U_{kopi} \rightarrow \min, \]

where:
- \( W \) – is the sum of power losses in FECF elements;
\( R, L \) – equivalent resistance values and the length of the FECF elements;
\( \Delta U_{b} \) – supply voltage as a percentage;
\( \Delta P_{\text{xxi}} \) – idling loss power in FECF elements;
\( T_{\text{Di}} \) – number of operating hours of FECF equipment;
\( \Delta P_{\text{loopi}} \) – the average specific losses to the crown;
\( k_{\text{Ucori}} \) – loss factor for the crown.

At the same time, it is mandatory to fulfill the balance restrictions:

\[
\begin{align*}
P_{\text{anti}} + P_{ci} & > 0; \\
Q_{\text{anti}} + Q_{cl} & > 0; \\
i = 1, \ldots, k;
\end{align*}
\]

where \( P_{\text{anti}}, Q_{\text{anti}}, P_{ci}, Q_{cl} \) – are the values of internal and external flows of active and reactive power in FECF elements.

Equations (1) - (3) form a universal free-scale model for the redistribution of power flows in the FECF, which will allow optimization by the criterion of minimum losses, taking into account weakly formalized and uncertain factors [5].

In [4-7], due to the simplicity of the organization and high accuracy indicators, Mamdani was implemented together with the modified Newton-Raphson algorithm:

\[
R^U : \text{If } x(t-1) \text{ is } X^u_1 \text{ and, ..., and } x(t-r) \text{ is } X^u_r \text{ then } y(t) = a^u, u = 1, u
\]

where:

- \( R^U \) – is a set of expert rules for forming the FNN;
- \( x(t) = (x_1(t), \ldots, x_r(t)) \) – vector of input variables;
- \( y(t) \) – vector of the output value;
- \( M^u_1, M^u_r, y^u \) – areas of input and output effects of FNN;
- \( a^u \) – output constant containing a weighted estimate of the input values and the network operation process.

4. Results

For the developed modification of the forecasting model and further optimization of FECF production indicators based on FNN (4), together with criteria (1)-(3), the accuracy indicators of the process of managing the dynamics of power flows in the short, medium and long-term periods were studied. The results were evaluated using Matlab software [4, 5].

When implementing the FNN model based on the Mamdani algorithm, ANFIS, a block of the Matlab simulation modeling software package, was used. The accuracy of optimization of FECF production indicators [4, 5] was studied through the forecasting process as a function of:

- variation of the membership function of input terms;
- implementations of the training set;
- changes to the ins architecture along with training time.

For numerical evaluation of the forecasting process and subsequent

The best results from the sample were shown by the implementation of the FNN with the architecture of input terms \((6 \times 3 \times 3)\), as well as the psigmf function [4, 5].

The results of training the model based on the FNN are shown in figures 1, 2.
Figures 3 - 5 show the results of the model functioning in comparison with similar results for the regression model.

**Figure 1.** Forecast of FECF production parameters.

**Figure 2.** Results of training the FNN model (psigmf: $6 \times 3 \times 3$).

**Figure 3.** Forecasting the dynamics of energy consumption of the FECF (June 2018): the fact is, the standard (regression), FNN – thousand MW; and an error in the functioning of forecast systems based on the normative method and the application of the FNN - %.
Figure 4. Forecasting the dynamics of energy consumption of the FECF (December 2018): the fact is, the standard (regression), FNN – thousand MW; and an error in the functioning of forecast systems based on the normative method and the application of the FNN - %.

Figure 5. Forecasting the dynamics of FECF energy consumption (20.06.18 – business day/weekdays): the fact is, the standard (regression), FNN – thousand MW; and an error in the functioning of forecast systems based on the normative method and the application of the FNN - %.

The analysis of the functioning of the model [4, 5], built on the basis of FNN, allows us to speak about its high accuracy characteristics, significantly exceeding the accuracy of existing regression (classical) implementations, as follows from figures 3 - 5.

5. Discussion

Thus, the following results were obtained [4, 5], confirmed by the graphs in figures 1, 2:

- the use of classical / normative (based on regression dependencies) implementation of the process of forecasting and subsequent optimization of FECF modes is justified in the case of a high degree of constancy of factors affecting the functioning of groups of energy consumers;
- also, regression models are useful as idealized (target) structures, while the forecast error in them is fundamentally not lower than the level (3-6) %;
the use of models for optimizing the production indicators of FECF (in particular, the process of redistributing power flows) makes it possible to achieve forecast errors of no more than (1.5-2.8) % with full consideration of the distribution trend of weakly formalized (including uncertain) factors [2, 4, 5].

6. Conclusion
The article notes the work on the implementation of the model of optimization of FECF production indicators based on the FNN. At the same time:

1) the objective optimization function for the minimum of active power losses \( F_j = \frac{k}{i=1} W_i \rightarrow \min \) is defined together with the restrictions typical for the FECF. The dependence of the distribution of active and reactive power on undefined and poorly formalized factors: \( \xi_p(U), \xi_q(U) \), that affect the quality of the realized process of optimization of FECF is taken into account.

2) the development of a modified Newton – Raphson algorithm based on the FNN (with the possibility of implementing variations) in order to improve the efficiency of functioning is Noted. This algorithm allows us to fully take into account uncertain and weakly formalized factors: \( \xi_p(U), \xi_q(U) \).

3) estimation of the accuracy of the most optimal variant of the model implementation has the following characteristics: number of layers / structure of layers (number of neurons): 4 / (3/10/25/1); type of optimization algorithm: Mamdani; distribution of terms of belonging to 1 layer: ; activation function of the first layer: psigmf.

At the same time, the following quality indicators were obtained: relative learning error-1.624 %; network learning time – 2.57 s (for the case of short – term / medium-term forecast). The simulation is based on the Intel Core i5-7400k – Core Processor (3.0 GHz). The freely configurable structure of network settings is noted, which allows using it equally effectively for tasks of short-term/medium-term and long-term forecasting and optimization of FECF production indicators.

References
[1] Zhelezko Yu S 2009 Poteri elektroenergii. Reaktivnaya moshchnost’. Kachestvo elektroenergii: Rukovodstvo dlya prakticheskih raschetov [Power losses. Reactive power. Power quality: a Guide for practical calculations] (Moscow: ENAS) [In Russian]
[2] Nikolenko S I, Kadurin A A and Arhangelskaya E O 2019 Glubokoe obuchenie [Deep learning] (St. Petersburg: Piter)
[3] Kudinov Yu I, Kudinov I Yu and Suslova S A 2007 Nechetkie modeli dinamicheskikh processov [Fuzzy models of dynamic processes] (Moscow: Nauchnaya Kniga)
[4] Rutskov A L, Burkovsky V L, Sidorenko E V and Krysanov V N 2020 Implementation of a SMART GRID in industrial and residential complexes based on fuzzy neural networks J. of Mechanics of Continua and Mathematical Sciences: Special Issue 8 251-63
[5] Rutskov A L, Burkovsky V L and Sidorenko E V 2020 Optimization of electric power systems using fuzzy neural network algorithms J. of Mechanics of Continua and Mathematical Sciences: Special Issue 8 264-76.
[6] Çevik H H and Çunkaş M 2015 Short-term load forecasting using fuzzy logic and ANFIS Neural Computing and Applications 26(6) 1355-67
[7] Shi B, Yu-Xia L I and Xin-Hua Y U 2009 Short-term load forecast based on modified particle swarm optimizer and back propagation neural network model J. of Computer Applications 29(4) 1036-9
[8] Monteleoni C, Schmidt G A, Saroha S and Asplund E 2011 Tracking climate models Statistical Analysis and Data Mining 4(4) 372-92
[9] Li P, Li Y, Xiong Q, Chai Y and Zhang Y 2014 Application of a hybrid quantized elman neural network in short-term load forecasting Int. J. of Electrical Power and Energy Systems 55 749-59
[10] Nedellec R, Cugliari J and Goude Y 2014 Gefcom2012: Electric load forecasting and backcasting with semi-parametric models *Int. J. of Forecasting* 30(2) 375-81

[11] Devaine M, Gaillard P, Goude Y and Stoltz G Forecasting electricity consumption by aggregating specialized experts *Machine Learning* 90(2) 231-60

[12] Migliore M et al. 2006 Parallel network simulations with NEURON *J. of Computational Neuroscience* 21(2) 119-29

[13] Berenji H R 1992 A Reinforcement Learning- Based Architecture for Fuzzy Logic Control *Int. J. of Approximate Reasoning* 6 267-92

[14] Davison A P, Brüderle D, Eppler J, Kremkow J, Muller E, Pecevski D, Perrinet L and Yger P 2008 PyNN: A Common Interface for Neuronal Network Simulators *Frontiers in Neuroinformatics* 2 11

[15] Alneyadi S, Sithirasenan E and Muthukumarasamy V 2016 A survey on data leakage prevention systems *J. of Network and Computer Appl.* 6(62) 137-52