Increase in accuracy forecast for electrical energy consumption of the WEM subjects using fuzzy neural networks

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Abstract. This paper covers in depth functioning essence of the balancing electricity market in the Russian Federation in accordance with the current economic stimuli. Significant role of the prediction process for energy resources consumption has been noted, which has a direct influence on a pricing policy within the marked trade area. Analysis of different factors, that impact execution accuracy of the one day in advance model, was conducted. Problem of the weakly defined and unknown parameters, that influence the performance of the balancing electricity market, is suggested to resolve by means of fuzzy neural controller. The paper presents its structure and settings, and possibility to scale it to use not only as an analyzer but as an executive element in the subsystems of electric power systems. High accuracy performance of the fuzzy neural controller was shown - around (0,5-3) %, that is much higher than methods already in use (for instance, based on a coefficient of decline/growth of power consumption).
Keywords: wholesale electricity market; economic stimuli; electric energy consumption forecast; fuzzy neural networks; simulation modelling.

1. Introduction

Wholesale electricity market (WEM) in the Russian Federation is a technical and economic platform that stands for competitive environment for production, transportation and consumption of an energy resources within 75 federal subjects. Subjects of this system are sellers and buyers of electricity and power that meet requirements mentioned in the RF Government Regulation dated 27.10.2010 №1172 (changed 31.07.2019) «On the establishment of the Rules of Wholesale Electricity and Capacity Market».

WEM consists of the following elements (figure 1):

- electrical energy market (consists of three segments: regulated contracts (RC); «day-ahead market» (DAM); and also balancing market (BM)) - electrical power production and sale;
- capacity market – bidding process to deliver connected capacity reserve;

- system services market – provide qualitative and quantitative characteristics of the energy resources;
- system operator of the unified energy system (SO «UES») - technical market regulator;
- non-commercial partnership trading system administrator (NP «TSA») - economic governing organ;
- federal antimonopoly service (tariff regulation that concerns PC); Ministry of Energy of the Russian Federation (legislative support, supervisory responsibilities) - not shown on the picture.
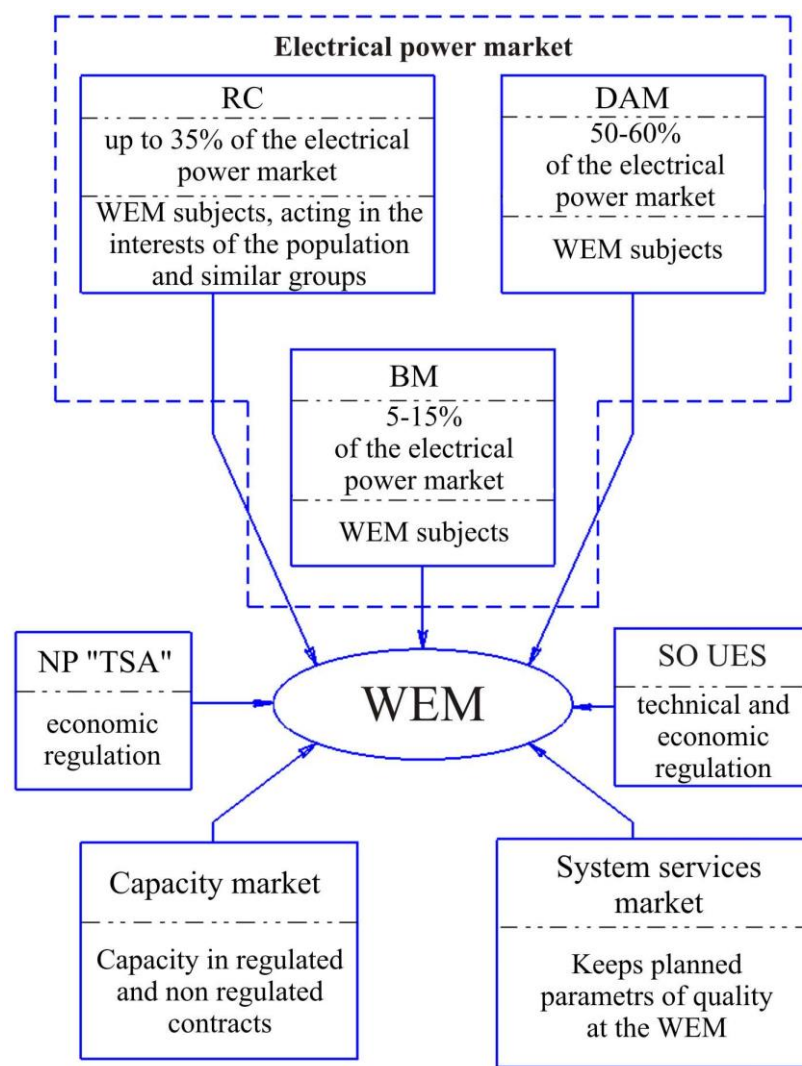

Figure 1. WEM function chart.

2. Materials and Methods

Specific nature of energy resources doesn`t allow to accumulate it (at least for now), therefore, balance between production and consumption must be mantained in real time mode. Last named circumstance is a major technical factor which is the necessity of ensuring electricity consumption forecast error minimization. It can be explained in a way that electricity production is a complicated technological

process during which all of the generated product must be consumed (under conditions of trasportation losses optimization).

Therefore, setting up WEM creates an economic stimuli to icrease forecast accuracy, meaning that all electricity consumption deviations from planed values (preliminarily requests submitted by subjects during forming of DAM) are purchased or sold using BM prices. Specifics of the balancing market makes dynamics of pricing policy for purchase/sale unsufficient/excessive energy resources volume multidirectional.

$$C_{BM\_pur} = \max (C_{DAM}; C_{BM}) \tag{1}$$

$$C_{BM\_sale} = \min (C_{DAM}; C_{BM}) \tag{2}$$

where C_{DAM} – electrical power cost by volume at DAM;

   C_{BM} – electrical power cost by volume at the BM.

Way of forming DAM assumes finding an equilibrium price (figure 2) and volumes of delivery (consumption) - chosen bids, that has been taken into account for this electrical power market segment the day before billing period starts. Volumes that are not collected should be traded at BM or should be excluded by the subject of market on its own initiative (cancellation of production/consumption of electrical power).
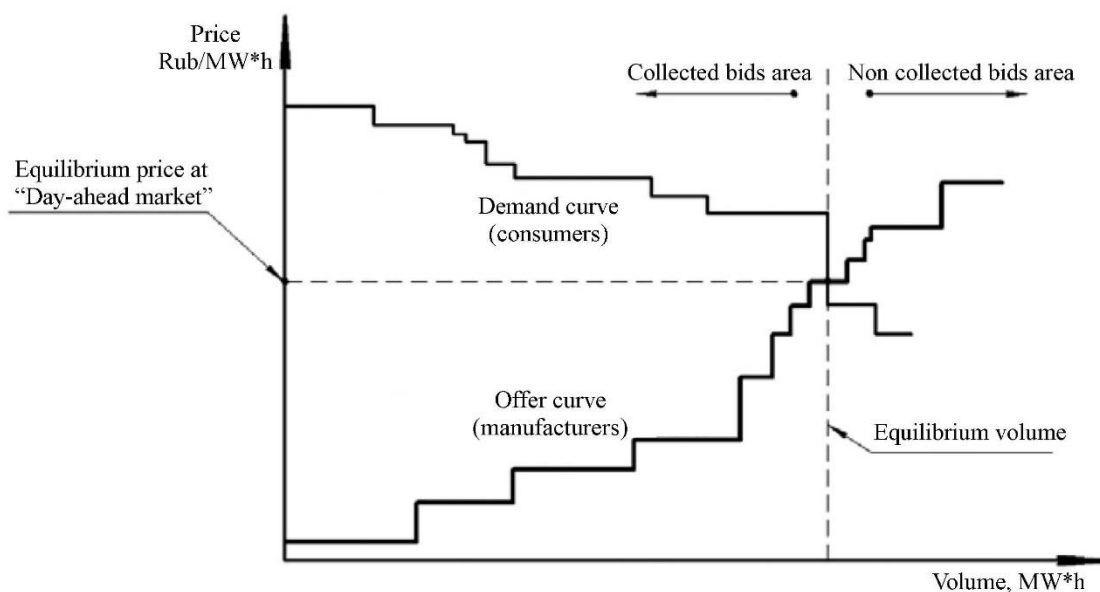

Figure 2. Bids selection mechanism at DAM.

Therefore, deviation from forecasted numbers of bids, chosen for DAM, as part of the actual energy resources consumption within design day, creates losses for the subject who allowed such deviations, if it leads to breaking planed schedule [1, 2]. For instance, during supply shortage (produced volumes less than current requests from energy receiving devices) any WEM participant, that needs to increase purchases, according to expression (1), will purchase electricity at BM. That is the way to implement a kind of extra charge penalty which compensates expenses of manufacturers and infrastructure participants for unexpected operating modes (characterized by increasing expenses). Note that in case of supply shortage, during sale of energy resources to WEM consumers, this initiative is

put into action for the price $-C_{DAM}$ (because it helps to restore balance, moving it closer to equilibrium volume).

Data analysis at the WEM website [3] demonstrates that mean value of absolute deviations C_{DAM} from C_{BM} over the period 6 months in 2019 for the first pricing zone of the RF is in range $\pm$ (17-35) %; averaged volume of balancing market over the same period - 47,468 billion KWh (or 12,25 % of the electrical power market).

Decrease of the BM portion is possible by increasing accuracy of the forecast for electricity consumption. For this purpose, proved way is to use methods based on fuzzy neural network (FNN) [2, 4] and fuzzy neural controller (FNC).

Figure 3 presents a generalized function chart for FNC that use assignment vector current value at the i-th moment of time $-g_{a.}(i)$ - input data to evaluate electricity consumption forecast for deferred expenses; and also exit of the object`s reference model $-y_2(i+k)$ - forecasted value. Reference model based on ANN (which is the reference model for the subject to control (SC), in this case – WEM electrical power market) describes dynamics of the mentioned system within corresponding timeframes, trained on forecasted error $e_2(i+k) = y_2(i+k) - y_{SC}(i)$, and control signal $- y_1(i+k)$. Setting vectors W_1, W_2 give the ability to exercise parameterization of the input terms (for FNN) and activation functions (for ANN).
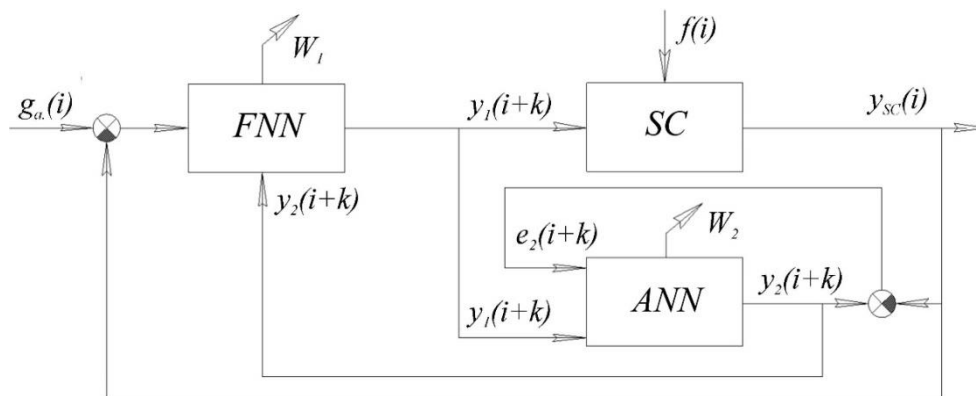

Figure 3. FNC function chart for electricity consumption of the WEM subjects forecast.

Vectors $g_{a.}(i)$ and $y_2(i+k)$ take the following data bases (DB) as an input value:

- consumption volume distribution of the WEM subject in the prior period $P(i)$;
- cyclic and random factors (environmental influence, modes of operation that connected with the calendar cycles) $- M(i)$;
- planned structure of the energy receiving devices $- S(i)$.

3. Results

By applying settings mentioned above, FNC uses inverse model SC and becomes the process controller with high adaptive characteristics, driven by undetermined factors that are fully taken into consideration.

Specifics of such an arrangement should be noted:

- fuzzy neural network (FNN), as part of the fuzzy controller, has freely scalable structure, and therefore, possibility to use it on unstructured subjects of WEM;
- artificial neural network (ANN), by using reference model SC, increases the effectiveness of decision making for current status assessment of the energy receiving devices.

Best results within the framework of studies [15] demonstrated P-shaped and Gaussian membership functions of terms for input variables. Exit of FNC is executed as linearized value.

Structure of the reference model (ANN) is presented with the help of the multilayered perceptron, trained on fast backpropagation of error algorithm. Structure of the network is variable and depends on SC. Type of the activation function – sigmoid.

FNC functional diagram in the ANFIS system is presented on the figure 4. Implementation method – Sugeno.
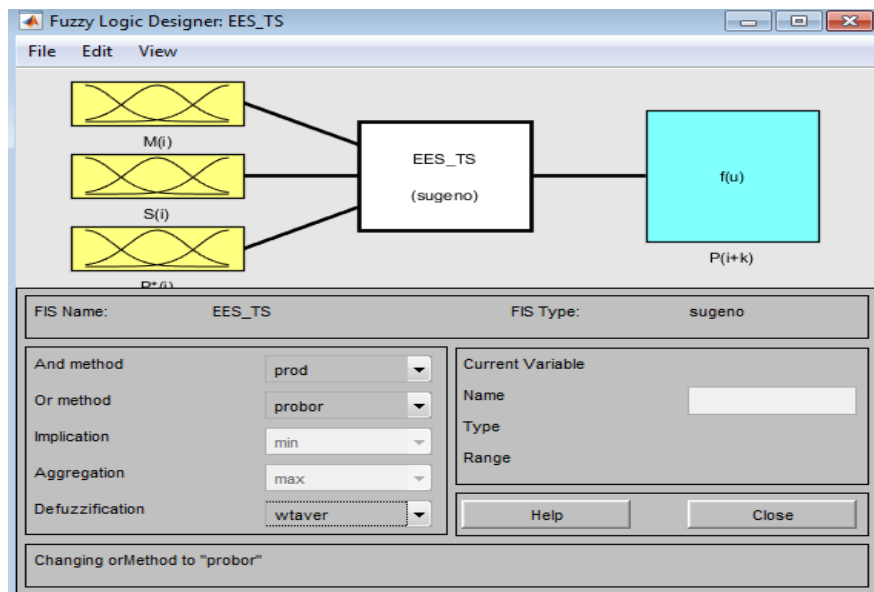

Figure 4. Functional diagram of FNC implementation in ANFIS system.

General structure of FNC implemented for the process control of the forecasted WEM subject's electricity consumption dynamics for short-term and medium-term periods (for the case of input terms assignment – $9 \times 3 \times 3 : P(i) \times M(i) \times S(i)$) presented on figure 5.
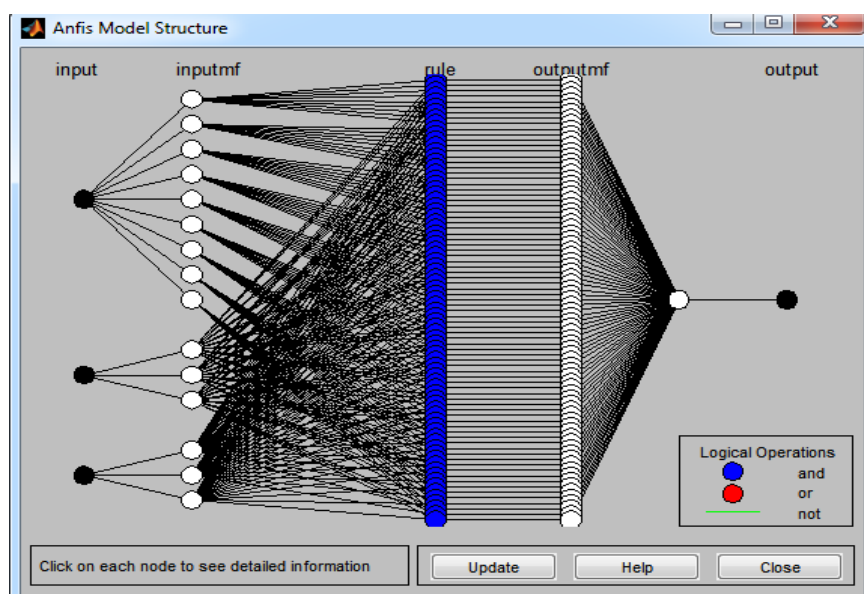

Figure 5. Basic FNN structure within the framework of the developed FNC.

Combination of the least squares method and reverse gradient descent method (hybrid) was utilized as the learning algorithm.

Table 1 presents settings for FNN, training by the combination of the least squares method and reverse gradient descent method along with variations of structure types of membership functions of input membership terms for implementation of Sugeno.

Table 2 presents simulation modeling qualitative results based on [4-13] in relation to the accuracy of functioning FNC forecast for electricity consumption of WEM subjects [14].

Table 1. Settings for FNN in compliance with implementation of Sugeno.

1. Netork type – FNN (Sugeno)			
2. Topology and implementation of fuzzy input-output data			
Membership terms assignment $(M(i) \times S(i) \times P^*(i))$	Number of learning rules, ea.	Transfer function types for input terms	Transfer function types for output terms
$3 \times 3 \times 3$; $6 \times 3 \times 3$; $9 \times 3 \times 3$	**176**	**trapmf; dsigmf; psigmf**	**constant**
3. Topology and ANN learning (multilayered perceptron)			
Total number of layers, ea.	Number of hidden layers, ea.	Number of elements in training data set, ea.	Number of elements in test data set, ea.
4	**2**	**17 850**	**324**
Stopping conditions of learning **– increase of root mean square error**			
Method of weight renewal in an artificial neural network – **epoch** (scale free time period)			

Table 2. Comparative analysis of models implementation based on FNC.

FNN learning algorithm – Sugeno (hybrid). Processor type - Intel Core i3-7350				
Input membership terms type (configuration $3 \times 3 \times 3$)				
	Term	trapmf	psigmf	dsigmf
Estimated parameters	ε_n	0,271	0,228	0,228
	r	0,981	0,989	0,987
	$\varepsilon_\%$	3,145	2,012	2,005
Number of training epochs		500,0	6,0	6,0
Learning time, sec		67,46	1,03	1,05
FNN learning algorithm – Sugeno (hybrid). Processor type - Intel Core i3-7350				
Input membership terms type (configuration $6 \times 3 \times 3$)				
Estimated parameters	ε_n	0,090	0,053	0,061
	r	0,980	0,987	0,988
	$\varepsilon_\%$	2,954	1,903	1,985
Number of training epochs		500,0	16,0	17,0
Learning time, sec		68,74	2,33	2,48
FNN learning algorithm – Sugeno (hybrid). Processor type - Intel Core i3-7350				
input membership terms type (configuration $9 \times 3 \times 3$)				
Estimated parameters	ε_n	0,021	0,012	0,012
	r	0,983	0,991	0,993
	$\varepsilon_\%$	2,901	1,853	1,751
Number of training epochs		500,0	51,0	53,0
Learning time, sec		69,41	7,03	7,36

Best results in the analyzed data set demonstrated the implementation of FNC based on Sugeno algorithm using input terms configuration such as ($9 \times 3 \times 3$) and membership function – dsigmf. Final results of the training, marked by FNC implementation on test data set, presented on the figure 6.

Figure 6. Results of FNC training on test data set.

Analysis of the functioning FNC forecast for electricity consumption in WEM allows to mention that its characteristics has high accuracy. Based on evaluation of the test data set, error is no more than 3,2%. With that in mind, and also using evaluation of the BM volumes and weighted mean value of deviation P_{DAM} from P_{BM} over a period of 6 month in 2019, one can observe qualitative estimation of potential savings, from utilization of FNC by WEM subjects, which is about 4,231 billion KWh.

As an expert recommended guideline, authors [1] point out that it is worthwhile to correct the consumption forecast graph by a value that doesn`t exceed forecast error on technology factors. However, in reality, due to lack of (significant lacking) data on competitive companies, it is more beneficial to increase accuracy of its own consumption volume with ability to correct this value after receiving high degree of confidence information about adjacent consumers.

4. Conclusion

1. Usage of models that control dynamic of power flow distribution as part of ADCS based on FNN (FNC) allows to obtain error within (0,5-3) %, which is vastly superior to already used in existing systems method of coefficient of decline/growth of power consumption with error (3-6) %.

2. Pointed out decrease in error control of power flow dynamic in operational and mid-term periods in models based on FNN (FNC) is possible as a result of complex use of both outside (weather conditions, cyclical pattern, factory operation) and inside (change of operating mode) undefined factors that influence elements of EPS.

3. Developed model of control power dynamic based on FNN (FNC) is easily scalable which allows to apply it both for operational usage within planner and for mid-term analysis of energy resources distribution.

4. It should be noted that possibility of development of optimal strategy in accordance with approaches, mentioned in this paper, is useful for generating companies and energy resources market as a whole.

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