

P. D. Lezhniuk, Dr. Sc. (Eng.), Prof.; O. O. Rubanenko

CALCULATION OF CURRENT PARAMETERS OF POWER SYSTEM MODE WITH INCOMPLETE INITIAL DATA USING NEURAL MODELLING

A mathematical model is offered which allows to find load power in a node at telemetry devices failure, using hybrid neural network and Sugeno algorithm of fuzzy conclusion.

Keywords: power losses, Sugeno algorithm of fuzzy conclusion, power in a node, membership function.

Actuality

Power industry structure replacement and transition to the other level of functioning resulted to the advent of new and sharpening of existing problems of transmission and distribution of electric power. One of such problems is power losses increase. For a long time they did not exceed 10% in power systems (PS) [1, 2], and last years it grew to the level which almost twice exceeds the same figures in foreign countries [2, 3]. One of the reasons is moral and physical ageing of power network equipment on all levels of Ukraine power system (UPS) and the impossibility of its upgrade as a result of difficult financial state in the industry [4, 5, 6]. Prospective direction of energy loss saving is introduction of modern automatic and computer-based system of UPS control to provide of optimal mode of operation [7]. Efficiency of their operation is determined by algorithms, which are the basis of their work.

Optimum control efficiency is determined by accuracy and adequacy of mathematical models. On the whole mathematical models of automation process for dynamic systems optimal control are characterized by partial approach. The creation of complete picture of the simulated phenomenon allows to attain sufficient generalization of research results and to apply the later to the similar phenomena.

To increase optimal control efficiency it is reasonable to apply the same methodological basis and system approach on all the stages of optimal control task solving from mathematical model formation to practical realization of optimum solution.

Therefore the tasks of creation of mathematical models for normal mode optimal parameters changes are urged nowadays. They will allow to define such changes of voltage on substations which would provide the minimum total losses in networks. It is necessary to develop models, which allow to calculate those initial parameters necessary for the calculation of the normal mode, but were not received for some reasons.

The purpose of this work is to develop a mathematical model which allows to find power loads with the help of fuzzy modeling telemetry devices.

Unknown parameters calculation for normal mode

In the process of exploitation there are situations, when as a result of damage of telemetry system or telemetering channels failure and some other reasons initial data are not enough for the high-quality of normal mode of PS optimal parameters calculation. Let's consider such situation on the example of 330-750 kV SWPS (South-west power system) networks (Fig.1).

In the process of implementation of such management principles a part of informative functions is possible to segregate without the loss of principles of the variable-ratio transformers centralized control. Thus, on a certain interval of load change a transformer control can be carried out only taking into account the parameters of correction area. On leaving parameters off the given interval a control law is automatically corrected. As the correction is carried out, taking into account a general-system optimal criterion as a result of optimization calculations taking into account all technical limitations, then the system approach is the same for all situations [8, 9].

Implementation of optimal control law is carried out taking into account sensitivity. The task of optimal control is formulated in such a way, that the adjustable parameter, in our case it is power in a node, is in the optimal area. Such range is determined real-time for every separate transformer on the basis of information, received by telemetry channels from nodes, which are included into its area of correction. Voltage is made optimum by the automatic control system (ACS) voltage regulator devices in the optimum area [10].

As result of equipment failure on substation (node 830) a dispatcher can not view loading information in node 830. Information about nodes 710, 756, 824, 837 continues to be available.

The results of the previous measurements are saved on the server of SWPS, the fragment of this information is given in Table 1.

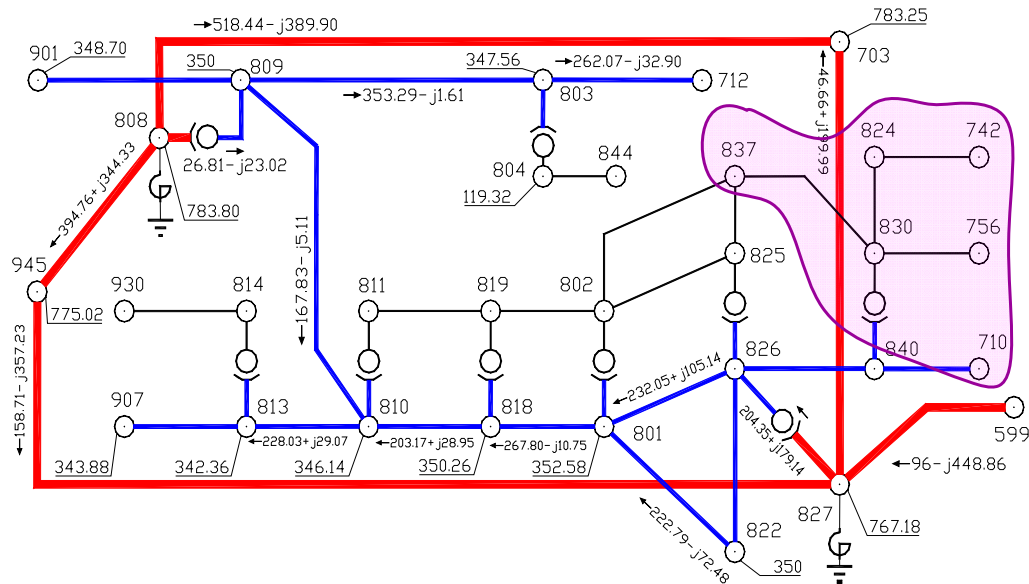


Fig. 1. Fragment of 110-750kV SWPS networks

It is important to define results of measurements in a node necessary for the calculation of optimum parameters for the normal mode. Let's consider the determination of load power on the following example.

Sugeno algorithm of fuzzy conclusion

For this purpose we will take advantage of Sugeno algorithm of fuzzy conclusion. This algorithm involves the following stages [10].

1. Rulebase system creation for fuzzy conclusion. Only fuzzy rules are used in a rulebase in the form of:

Rule: IF " β_1 is α " And " β_2 is α " THAT " $w = \varepsilon_1 \cdot a_1 + \varepsilon_2 \cdot a_2$ ".

Here $\varepsilon_1, \varepsilon_2$ are weighting coefficients. Thus initial variable w is determined as a real number.

2. Fuzzification of input variables.

3. Aggregation of subconditions in fuzzy rules. For the calculation of terms truth degree of all fuzzy rules, the boolean operation of min-conjunction is usually utilized. Rules are considered active and utilized for the next calculations, if terms truth degree of them is different from zero.

4. Activation of subconclusions in fuzzy rules. First, there are values of truth degrees for all fuzzy rules conclusions. Second, the calculation of ordinary (not fuzzy) values of output variables of every rule is carried out. It is executed with the use of formula for a conclusion, in which the values of input variables are put to the stage of fuzzification in place of a_1 and a_2 . A great number of

values $S=\{c_1, c_2, c_3, c_4 \dots c_n\}$ and a great number of values of initial variables of $W=\{w_1, w_2, w_3, w_4 \dots w_{cn}\}$, is determined with the help of this algorithm.

5. Accumulation of fuzzy rules conclusion. An accumulation is actually absent, as calculations are carried out with ordinary real numbers.

6. Defuzzification of output variables. The modified variant is utilized in the form of centre-of-gravity method for one-point sets.

Model creation

Modelling is performed in MATLAB medium. Editor of hybrid networks *Anfis* is used for this purpose.

We load data from Table 1 for the creation of hybrid network. Powers for nodes 710, 756, 824, 837 and power for node 830 are indicated as input data.

Table 1

Part of SWPS substations telemetry data				
$P_{load710}$	$P_{load756}$	$P_{load824}$	$P_{load837}$	$P_{load830}$
13.23	3.00	11.04	7.28	8.01
8.10	3.01	6.8	4.68	6.23
10.80	3.00	8.92	5.88	8.01
13.50	3.002	11.04	7.28	9.78
14.58	3.005	11.04	7.28	8.01
16.2	3.01	13.81	9.1	12.10
17.55	3.02	13.81	9.10	11.56
22.95	3.00	16.99	11.20	14.23
22.41	3.00	16.99	11.20	15.12
..			...	..
16.47	3.1	12.96	8.54	11.58

Before application of *Generate Fis*, we choose three terms for each input value, and also a type of membership function, for example *gauss2mf*. Choose the type of function of linear initial function. After the generation we will get the next hybrid network structure in Fig.2.

Before network training choose the hybrid method of training, which is the combination of least-squares method and reverse gradient reduction method.

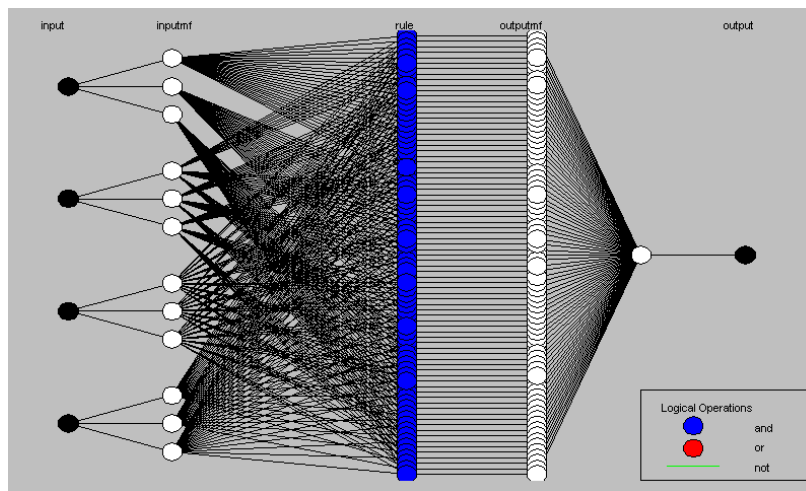


Fig.2 Hybrid network structure

Set the level of training error - 0. Set the amount of training epochs - 10 (Fig.3).

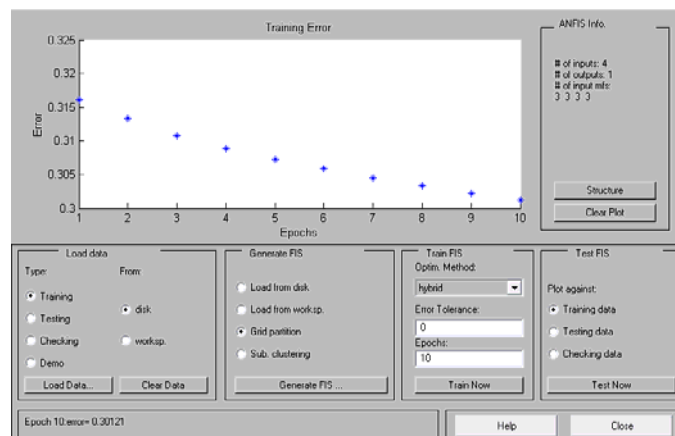
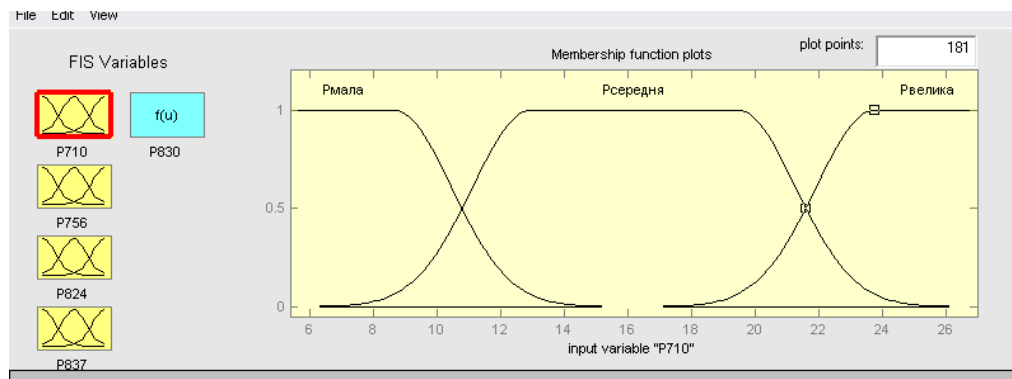


Fig. 3 Network training error

The membership function for the terms of P_{830} variable loading of are given in a Fig. 4.

Fig.4. Membership function for the terms of P_{830} variable load

The choice of optimum membership function (in respect to training error) and optimum method of training was carried out by comparison sixteen types of plots.

The network training lasts 30 minutes (with processor Sempron 2,8 +). Training error is 0,3 MW

(Fig.3).

It is possible use *Rule Viever* for the research of the developed model of hybrid network.

The target value of the unknown variable (power of node 830) is determined for known loads of nodes 710,756,824,837 by the developed model (Fig.5).

So, for example, for load power in nodes 710,756,824,837:

$P_{710}=22,41\text{MW}$; $P_{756}=3,00\text{ MW}$; $P_{834}=22,41\text{MW}$; $P_{837}=22,41\text{MW}$.

The predicted value of load power in node P_{830} is 14,6 MW.

Error $15,12-14,6=0,52\text{ MW}$.

For example, for load power in nodes 710,756,824,837:

$P_{710}=13,23\text{ MW}$; $P_{756}=3,00\text{ MW}$; $P_{834}=11,04\text{ MW}$; $P_{837}=7,28\text{ MW}$.

The predicated value of load power in node P_{830} is 8,01 MW.

Error $8,01-8,01=0\text{ MW}$.

A multiple approach was used for the construction of the network, namely variants with *trimf*, *trapmf*, *gbellmf*, *gaussmf*, *pimf*, *dsigmf*, *psigmf* membership function were examined. We also used an alternative approach for the hybrid method of training, that is a method of reverse distribution of errors *backpropo*.

The developed model is a system of logical equaltions (Fig. 6).

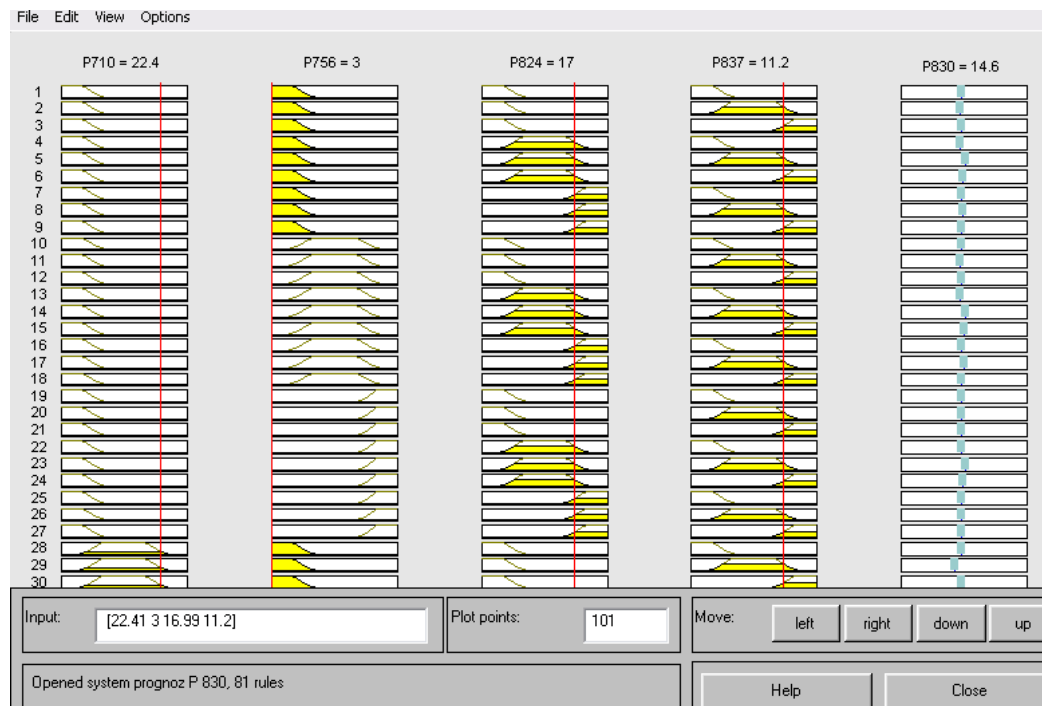


Fig.5. Results of power load calculation in node 830 by the developed model.

The same system of equations, but written in another form is:

IF $P_{710} = \text{«large»}$ AND $P_{756} = \text{«middle»}$ AND $P_{824} = \text{«middle»}$ AND $P_{837} = \text{«large»}$
 $P_{830} = \text{«middle»}$
 IF $P_{710} = \text{«large»}$ AND $P_{756} = \text{«middle»}$ AND $P_{824} = \text{«large»}$ AND $P_{837} = \text{«little»}$ THAT
 $P_{830} = \text{«middle»}$

 IF $P_{710} = \text{«large»}$ AND $P_{756} = \text{«large»}$ AND $P_{837} = \text{«large»}$ AND $P_{824} = \text{«large»}$ THAT
 $P_{830} = \text{«large»}$

69. If (P710 is in1mf3) and (P756 is in2mf2) and (P824 is in3mf2) and (P837 is in4mf3) then (P830 is out1mf69) (1)
 70. If (P710 is in1mf3) and (P756 is in2mf2) and (P824 is in3mf3) and (P837 is in4mf1) then (P830 is out1mf70) (1)
 71. If (P710 is in1mf3) and (P756 is in2mf2) and (P824 is in3mf3) and (P837 is in4mf2) then (P830 is out1mf71) (1)
 72. If (P710 is in1mf3) and (P756 is in2mf2) and (P824 is in3mf3) and (P837 is in4mf3) then (P830 is out1mf72) (1)
 73. If (P710 is in1mf3) and (P756 is in2mf3) and (P824 is in3mf1) and (P837 is in4mf1) then (P830 is out1mf73) (1)
 74. If (P710 is in1mf3) and (P756 is in2mf3) and (P824 is in3mf1) and (P837 is in4mf2) then (P830 is out1mf74) (1)
 75. If (P710 is in1mf3) and (P756 is in2mf3) and (P824 is in3mf1) and (P837 is in4mf3) then (P830 is out1mf75) (1)
 76. If (P710 is in1mf3) and (P756 is in2mf3) and (P824 is in3mf2) and (P837 is in4mf1) then (P830 is out1mf76) (1)
 77. If (P710 is in1mf3) and (P756 is in2mf3) and (P824 is in3mf2) and (P837 is in4mf2) then (P830 is out1mf77) (1)
 78. If (P710 is in1mf3) and (P756 is in2mf3) and (P824 is in3mf2) and (P837 is in4mf3) then (P830 is out1mf78) (1)
 79. If (P710 is in1mf3) and (P756 is in2mf3) and (P824 is in3mf3) and (P837 is in4mf1) then (P830 is out1mf79) (1)
 80. If (P710 is in1mf3) and (P756 is in2mf3) and (P824 is in3mf3) and (P837 is in4mf2) then (P830 is out1mf80) (1)
 81. If (P710 is in1mf3) and (P756 is in2mf3) and (P824 is in3mf3) and (P837 is in4mf3) then (P830 is out1mf81) (1)

If P710 is and P756 is and P824 is and P837 is Then P830 is

in1mf1
in1mf2
in1mf3
none

in2mf1
in2mf2
in2mf3
none

in3mf1
in3mf2
in3mf3
none

in4mf1
in4mf2
in4mf3
none

out1mf1
out1mf2
out1mf3
out1mf4
out1mf5
out1mf6
out1mf7
out1mf8

☐ not ☐ not ☐ not ☐ not ☐ not

Connection: ☐ or ☒ and

Weight: 1

Delete rule Add rule Change rule

<< >>

Fig.6. System of logical equations

So, 16 types were considered. Choosing the best model the optimization criterion is a minimum of training error. It is 0,30727 for a select decision. The dependence of the predicted value of node 830 from load of 710,756,824,837 nodes is difficult. The surface of the predicted values of loads in node 830, is given in Fig. 7-10.

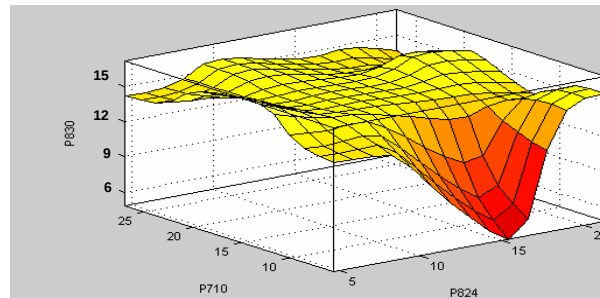


Fig. 7. Surface of the predicted values in node 830 depending on load in nodes 824 and 710

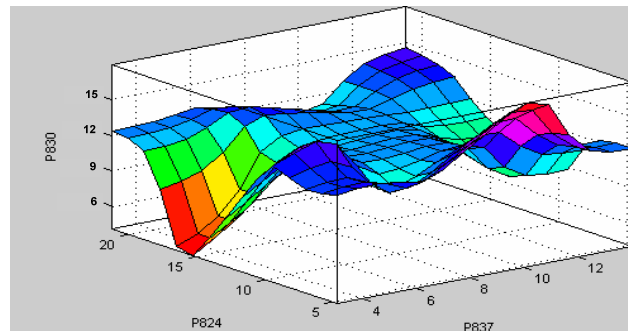


Fig. 8. Surface of the predicted values in 830 node depending on load in nodes 824 and 837

Verification of the developed model was conducted on MATLAB.

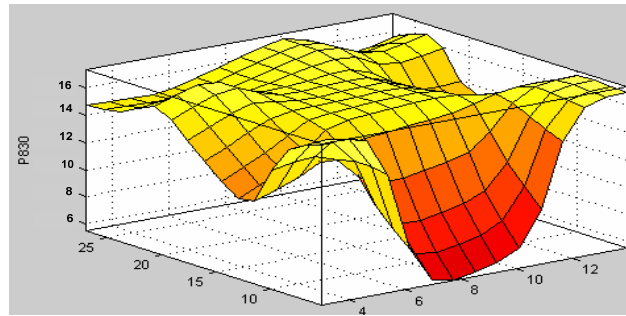


Fig.9. Surface of the predicted values in node 830 depending on load in nodes 837 and 710

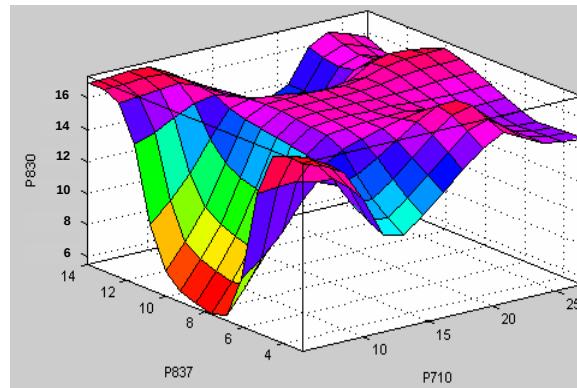


Fig.10. Surface of the predicted values in node 830 depending on load in nodes 710 and 837

An efficiency estimation of the developed model for unknown power value calculation in a node

For the network in Fig.1 losses (in the absence of the predicted data about load power in a node 830 $P_{830}=11,56$ MW) of the nonoptimum mode are 30,8 MW, and for optimum mode - 28,3 MW. Optimum mode introduction efficiency is 2,5 MW. Using predicted value of load power in node 830 $P_{830}=14,23$ MW, we get the value of losses for the optimum mode - 25,7 MW, and for nonoptimum – 29,2 MW. Optimum mode introduction efficiency is 3,5 MW. The use of the predicted value of load power in node 830 allows to decrease losses of power by 1 MW that is by 3,42%.

Conclusions

The implementation of the proposed method using of neural models allows to define necessary data for optimum parameters calculation of PS normal modes when input data are incomplete. Computation of such dependences in an analytical form is an intricate problem which is easily solved using neural modelling. A mathematical model was developed, which allows to find load power for the nodes at the refuse of telemetry devices, using hybrid neural network and Sugeno algorithm of fuzzy conclusion.

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Lezhnjuk Petro – Head of the Department of Electric Power Stations and Systems;

Rubanenko Olena – Graduate student of the Department of Electric Power Stations and Systems.

Vinnitsa National Technical University.