Synthesis of intelligent power management system of food manufacturing processes with power consumption prediction

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Abstract

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Introduction. The study is done to justify the methods of intelligent power management system of food manufacturing processes (FMP) devoted to increase the effectiveness of electric power use.

Materials and methods. The study is based on intelligent control methods, power consumption prediction algorithm using artificial neural networks and active identification method of load static load characteristics.

Results and discussion. Based on the system analysis of FMP control it is determined control criteria and functions. To implement the control functions in intelligent power management system of FMP it is used: model of predicting power consumption, making decision algorithms of power management, procedure of forming the optimal list of consumers-regulators and calculating the rational modes of power consumption.

To predict the power consumption of food manufacturing process the multilayer perceptron is chosen from the set of artificial neural network architectures. It is shown that the optimal configuration of the neural network in the task is three layered perceptron with hidden layer where the number of elements equals to the half-sum of the elements of the input and output layers. Perceptron training is carried out by combined backpropagation/Cauchy machine method. The computational experiment with prediction of power consumption of food manufacturing process on the next year has the learning error in the range of 0.05-0.06.

The algorithm of determining the optimal voltage, which provides energy efficient operating modes of power system, uses static load characteristics. To make the algorithm more accurate and effective it is used procedure of static load characteristics identification in the interactive mode for the main modes of the technological process, taking into account the state of consumers-regulators and the degree of compensation of reactive power with the help of transformer equipped with the electronic switch.

Conclusions. The algorithms of intelligent power management system of FMP become more efficient with the use of power consumption prediction and static load characteristics identification algorithms.

Glossary

FMP – food manufacturing processes

SLC – static load characteristics

IACS PSC – intelligent automated control system of power supply and consumption

DMS – decision-making system

CIS – computer information system

DFD – data-flow diagram

SFS – shop floor substation

OLTC – on load tap changing

MS – main substation

LV – low voltage

HV – high voltage

Introduction

Efficient use of electric power in food manufacturing processes (FMP) is the main part of the problem of reducing electricity consumption that cannot be solved without control automation of transmission, distribution and consumption of electricity in FMP power system. The implementation of a new electricity market model, methods of managing electricity demand and renewable energy sources necessitates the use of methods for prediction of electricity consumption and power management. The main provisions for the synthesis of electric power measurement and control systems are presented in [1, 2, 3]. The issues of power consumption and load control with the use of consumers-regulators, their mathematical models and technological resources are covered in [4, 5]. Power supply control methods and tools are discussed in [6, 7, 8].

However, despite the large amount of researches, there is no single methodological approach to designing efficient power supply and distribution management systems based on system analysis and managed process predicting, as well as on the consideration of dynamic factors of production process. Moreover, there is no full use of the interconnected systems of mathematical models and methods of predicting, normalizing, planning and controlling the operating modes of FMP electric power system. Therefore, the development of methods for designing automated control systems for power consumption and supply of FMP that use sophisticated mathematical models, intelligent control algorithms, and software based on the latest information technologies that ensure the efficiency of transmission and consumption of electric power, is an urgent scientific and technical task [9].

Materials and methods

Materials

Object of the study is intelligent automated energy management system of FMP with power consumption prediction, designed to provide energy saving without losing performance.

In this study it is used:

- Methods of electric power consumption prediction;
- Control methods of electric power supply of manufacturing processes.

Methods

Plan of studies

The studies were conducted in the following order:

1. Choosing control criteria of FMP power control system;
2. Determining of control tasks of power supply and distribution of FMP;
3. Designing and justification the method for prediction of FMP power consumption;
4. Synthesizing the structure of the power consumption control system;
5. Developing and justification the control methods of FMP power supply using static load characteristics.

Method for prediction of FMP electric power consumption. The value of electricity consumption of FMP consists of the power consumption w_i of all N currently operating power loads and electricity losses ΔW in the network elements:

$$W = \sum_{i=1}^N w_i + \Delta W \quad (1)$$

Electricity losses, in its turn, in the main elements of power supply systems: lines and transformers, will depend on the electrical parameters of these elements (their active and reactive resistances) and the power transmitted through them:

$$\Delta W = f(W_a, W_p, R, X) \quad (2)$$

During the operation of the power supply system, the support of its elements can be considered almost unchanged. Thus, the change in the current power loss in the power network will occur due to changes in the total capacity of electrical receivers when they are turned on, off or change the mode of operation.

The power consumption w_i of each receiver, or group of receivers, in turn, can be presented as follows:

$$w_i = f(\lambda_1, \lambda_2, \dots, \lambda_n) \quad (3)$$

where $\lambda_1, \lambda_2, \dots, \lambda_n$ – the parameters that affect electricity consumption.

The number of power-consuming units (primarily asynchronous and synchronous motors) in FMP can reach hundreds and thousands. For each unit, the parameters that affect its power consumption may be different. Development of a forecasting model of FMP power consumption, which takes into account the parameters that affect the power consumption of each unit, is not possible due to the large number of correlated input parameters in such a model. The most optimal way to create such a model is the combination of power-consuming units to groups on any grounds (technological, electrical), followed by the identification of parameters that affect the power consumption of each group. In turn, the set of affecting parameters of each group will be a set of input parameters for the forecasting model of electricity consumption of the enterprise as a whole.

The multilayer perceptron was chosen from the set of artificial neural network architectures to predict the power consumption of FMP.

Method of determining the static load characteristics. The determining of static load characteristics (SLC) is carried out using the regression equation of SLC for active and reactive power in the form of second-order polynomials:

$$P^* = a_0 + a_1 U^* + a_2 (U^*)^2 \quad (4)$$

$$Q^* = b_0 + b_1 U^* + b_2 (U^*)^2 \quad (5)$$

where a_0, a_1, a_2 and b_0, b_1, b_2 are the coefficients of SLC polynomials of voltage, by active and reactive powers, respectively, and also, $a_0 + a_1 + a_2 = 1$ and $b_0 + b_1 + b_2 = 1$.

By the method of least squares [14] the system of equations of the form (4), for example, for active power has the following form

$$\begin{bmatrix} P_{*0} \\ P_{*1} \\ \dots \\ P_{*Mp+1} \end{bmatrix} = \begin{bmatrix} 1 & U_{*0} & U_{*0}^2 \\ 1 & U_{*1} & U_{*1}^2 \\ \bullet & \bullet & \bullet \\ 1 & U_{*Mp+1} & U_{*Mp+1}^2 \end{bmatrix} \cdot \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} \quad (6)$$

The system of equations (6) refers to overdetermined systems of linear algebraic equations. Testing the hypothesis of the adequacy of regression models is carried out using Fisher's test, for which the residual variance is calculated.

$$D_{res}^2 = \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n - p - 1} \quad (7)$$

where D_{res}^2 is the residual variance; Y_i – experimental data of power consumption (active or reactive); $\hat{Y}_i$ – experimental data of power consumption (active or reactive); n – the number of experiments; p – the number of factors of the regression equation.

The resulting values of the coefficients of polynomials a_0, a_1, a_2 and b_0, b_1, b_2 are the first approximation.

Results and discussion

System analysis and methods of the FMP control process

The task of managing power supply and power consumption is to minimize the set of technical and economic criteria: the losses from disconnecting or switching to the reduced operating mode of active power consumers-regulators; the number of commutations of consumers-regulators; the power losses in the electric power system due to leakage reactance; under following restrictions: the active load; the voltage of the electricity consumers; the parameters of electrical power quality.

To develop the intelligent control system the authors performed system analysis of control process of electric power transmission, distribution and consumption, which consists in the following. At the set-theoretic level, the process of managing organizational and technical objects is represented as a mapping of separate stages:

$$F_n : \{L \times K \times Z \times P_{in}\} \rightarrow P_{out}, n = 1, 2, \dots, N \quad (8)$$

where L – the stage of forming basic control functions; K and Z – accordingly, the forming stages of possible combinations of basic conditions and mechanisms of control functions

implementation; $P = P_{in} \cup P_{out}$ – the forming stage of possible combinations of the main data flows; P_{in} and P_{out} – sets of input and output data flows.

The system analysis results of control of power transmission, distribution and consumption processes are presented in the form of mappings for individual actions:

- Registration of power consumption, status of the electric grid, and power quality indices, as well as verification of measurement data reliability;
- Model selection and prediction of electricity consumption: forming a list of consumers-regulators and their optimal combination;
- Deciding on electricity costs: deciding on changing the configuration and operating modes optimization, normalizing of power quality indices;
- Recording and up-to-date maintenance of electric power cost management database.

The results of the system analysis have become the basis for the design of automated control system of FMP power supply and consumption.

The purpose of management is the efficient (reliable and conservative) supply and use of electricity in FMP. The control criterion that optimizes payment for electricity under existing relationships with the power supply company can be taken as

$$J = \lambda_w W + \lambda_w \Delta W + k_w \lambda_w W + Y_p (\Delta P, t_{ml}) + Y_{TR} (y_{UO}, M) \rightarrow \min \quad (9)$$

where λ_w and W – respectively, the tariff for electricity and its consumption volume by FMP (including losses in the grid); λ_w and ΔW – respectively, the tariff for electricity consumed above the contract and its consumption volume; k_w – the factor of payment for the consumed (or generated) reactive energy in excess of the values stipulated in the contract (to be approved by the tariff regulator); Y_p – costs for regulation of active power in hours of maximum load of the power system; Y_{TR} – losses from unreliable operation of electrical equipment y_{UO} and unscheduled maintenance of the equipment M .

The functional structure of the intelligent automated control system of power supply and consumption of FMP (IACS PSC) has been developed (Figure 1).

Figure 1. Functional structure of IACS PSC

As design stage of IACS PSC the authors have performed the decomposition of the main control goal into partial control goals, which made it possible to create a reasonable choice and implementation of individual components of the task and is carried out using the method of ensuring compatibility and integration. Synthesis is based on the presentation of individual subsystems in the form of a set of interconnected structures: decision-making system (DMS), functional, organizational, technical and informational structures.

I was developed methods and tools for power consumption management in FMP with the use of DMS. The DMS of FMP power management solves the following tasks: establishment of restrictions on the power consumption mode; planning of electricity consumption indicators of FMP; ensuring reliable functioning of the electrical equipment of FMP. Meeting the requirements of the power system in terms of electricity consumption with the minimum cost for FMP is achieved by changing the operating mode of power consuming equipment of consumers-regulators (taking off-line or switching to reduced operating mode) [4]. The following algorithm for controlling the mode of FMP power consumption is proposed [10]. In the normal operating mode, scanning of electricity meters every fixed time interval is initiated by the computer information system (CIS) at the upper level of the consumption mode control subsystem, and then it is performed determination and calculation of actual electricity consumption at the current moment by the elements of the lower level of consumption mode control subsystem. Decisions are made depending on the predicted value of power consumption. As follows from the above procedure, power management consists of:

- Solving the problems of predicting power consumption and selecting the optimal configuration of consumers for its regulation (the upper level of consumption mode control subsystem);
- Solving the problem of supporting the consumption of selected objects within the specified time limits during the billing period (the lower level of the consumption mode control subsystem).

To implement the control functions it is used: model of predicting power consumption, algorithms of making decisions on power management, forming the optimal list of consumers-regulators and calculating the rational modes of power consumption.

The choice of the composition of electrical equipment for regulating power consumption is made using the vector criterion $F(x)$ with components

$$F_1(x) = \sum_{j=1}^n \sum_{i=1}^{m_j} y_{ij} k_{ij}, F_2(x) = \sum_{j=1}^n \sum_{i=1}^{m_j} k_{ij} \quad (10)$$

where y_{ij} is the loss from the use for regulating i -th consumer at the j -th level of FMP power system; y_{ij} – a Boolean variable that takes a value equal to 1 if i -th consumer is used at j -th level to adjust the load and 0 otherwise; m_j – the number of consumers allocated for regulation at j -th level.

Forming a list of consumers-regulators to control the active load is based on the solution of the integer programming problem with Boolean variables using a heuristic algorithm. The choice of consumers for load regulation is made from the top level which contains at least one consumer with the load that is less than load to be switch off. Optimization at j -th level is performed according to criterion (11)

$$\sum_{i=1}^{m_j} (y_{ij} / W_{ij}) k_{ij} \rightarrow \min \quad (11)$$

where W_{ij} – electric power consumption of i -th consumer at j -th level of power system.

Justification of algorithm for prediction of FMP electricity consumption

As was mentioned in the Methods it was chosen the multilayer perceptron to predict the FMP power consumption.

The basis for determining the dimensions of the input and output layers of the perceptron is based on the following considerations:

- The input layer contains the number of neurons corresponding to the total amount of retrospective data, including daily electricity consumption, average daily temperature, illuminance and humidity during the working days of the year before the day when the prediction is computed, as well as the coefficient of change of the FMP production volume with respect to previous year;
- The output layer should contain neurons that determine the predicted values of electricity consumption for the next year.

The coefficient of FMP production volume change is calculated by the ratio

$$K_{npi} = \frac{V_l}{V_{l+1}} \quad (12)$$

where V_l – production volume that is produced on l -th year.

Selection of the number of hidden layers and its elements was carried out experimentally so that for different input and output data sets a minimum prediction error was achieved.

It is established that to predict power consumption it is advisable to use one hidden layer with the number of elements equal to the half-sum of the elements of the input and output layers of the perceptron.

$$n_H = \left[(n_X + n_Y) / 2 \right] \quad (13)$$

where n_H is the number of elements in the hidden layer, and n_X, n_Y – the number of elements in the input and output layers of the perceptron.

Thus, the perceptron for predicting power consumption contains three layers, while the input layer contains 529 neurons, hidden – 392, and the output – 264 neurons.

The set of weighting coefficients of the perceptron is presented by a synoptic map W , the weight of the connection between each neuron of adjacent layers is denoted as w_{ij}^1, w_{ij}^2 , where i, j – index numbers of neurons in the initial and final layer, respectively; $W_1, \dots, W_N$ and $T_1, \dots, T_N$ – input values of daily electricity consumption and last year's daily average ambient temperature; K_{npi} – coefficient of change of production volumes; $Y'_1, \dots, Y'_{N'}$ – output signals of neural network, the corresponding forecasted values of power consumption.

The accuracy of forecasting electricity consumption of FMP largely depends on the size of the retrospective sample used to train the perceptron. Studies have shown that a retrospective sample of FMP consumption and meteorological data for a period of four years is sufficient to obtain the required accuracy of forecasts.

A retrospective sampling of power consumption values includes a sequence of training pairs

$$L^m (\mathbf{K}^m, \mathbf{Y}_b^m) \quad (14)$$

where $\mathbf{K}^m = [W_1^j, \dots, W_k^j, T_1^j, \dots, T_k^j]$ – the input data vector (input signal); $\mathbf{Y}_b^m$ – the vector of expected output values for $L^m, m = 1, 2, \dots, N$, (N – the number of learning data sets).

When constructing the input vector I of the retrospective data sample, it's taken into account all values of daily power consumption, average daily temperature and light for each working day preceding the forecast year.

At the output of the perceptron, the predicted value W^I for the I -th input vector of signals determines the predicted values of power consumption of FMP for the next year.

The following formula is used to normalize the input data

$$P_m^H = (P_m - P_{\min}) / (P_{\max} - P_{\min}) \quad (15)$$

where $P_{\min}$ and $P_{\max}$ are the minimum and maximum value of the input data in this sample, P_m and P_m^H – non-normalized and normalized values of the perceptron m -th input.

The behavior of the perceptron, in addition to the weight coefficients, also significantly depends on the type of activation function that converts the input signal of the neuron into the output.

Sigmoid function is accepted as activation function

$$f(u) = 1 / (1 + e^{-au}) \quad (16)$$

where a – the neuron's parameter.

The selection of the sigmoid activation function is due to the fact that this function has continuous derivatives that are required for the operation of the inverse error backpropagation algorithm and amplifies weak signals to a greater extent than strong ones, which is important for high prediction accuracy.

The evaluation of perceptron quality is performed by the following expression:

$$\varepsilon = \sum_{i=1}^R \varepsilon^i; \quad \varepsilon^j = |Y_{np}^j - Y^j|^2 \quad (17)$$

where ε is the learning error, Y_{np}^j and Y^j – the values of the predicted and actual outputs of the perceptron.

Perceptron training is carried out by one of the fastest algorithms – the error backpropagation algorithm based on the gradient descent method.

The expression is used to adjust the weights

$$\Delta w_{lm}^{(k)} = -\zeta \partial \varepsilon / \partial w_{lm} \quad (18)$$

where w_{lm} is the weight coefficient of synaptic connection between l -th neuron of the k -1-th layer and m -th neuron of the k -th layer; ζ – learning speed ratio.

To increase the efficiency of the algorithm, the order of observations in the training samples of different iterations is varied (in order to reduce the probability of hitting the local minimum and eliminate the effect of retraining); it is performed linear variation of learning speed from 0.25 to 0.01.

Despite the fact that the method of error back propagation is widely used in the artificial neural network learning, it has a significant drawback – it does not cope well with local minima [15, 16], which can lead to deterioration of their work. To get out of the local minima, a statistical method of training is used – the Cauchy machine [15, 16], in which a random change of the neural network weighting factors is performed. However, this method is not effective due to slow convergence, as many steps of its implementation are performed in the wrong direction.

Combining the above algorithm of error backpropagation with the Cauchy machine method [11] allows obtaining a combined learning algorithm, which quickly finds the global minimum of learning error.

Figure 2 shows the generalized scheme for power consumption predicting using the perceptron and Figure 3 presents the results of prediction using a perceptron.

Figure 2. Generalized diagram for predicting power consumption using a perceptron

Figure 3. The result of prediction using a perceptron

The learning error is in the range of 0.05-0.06. The maximum relative error is 0.702-0.951%, and the root mean square error is 0.304-0.433%.

Synthesis of structure of the power consumption control system

The subsystem for FMP power consumption is developed (Figure 4), which is a set of interacting units – forecasting, rationing and planning of electricity consumption, selecting of the optimal composition of consumers and the dialog subsystem for decision-making to manage electricity consumption [10].

Figure 4. Structure of the control subsystem of FMP power consumption

Consider the features and purpose of individual functional units.

Unit of power consumption forecasting. On the basis of the data arriving from the database of management of FMP expenses, by means of the three-layer perceptron, forecasting of power consumption of production divisions and FMP as a whole is carried out. Predicted values of electricity consumption for these objects are included in the block of rationing and planning of electricity consumption.

Power consumption rationing and planning unit. On the basis of the received forecast values the total rate of expense and total planned electricity expenses of production divisions, and also a rate of expense and planned electricity expense in FMP as a whole are defined.

The obtained data are contained in the database of electricity flow management. It also contains calculated on their basis the total planned costs of electricity for non-production units of FMP.

Control system gives the chance to make automatically and operatively annual, quarterly and monthly electric balances in FMP and on the most energy-consuming units and production divisions.

On the basis of these balances the analysis of electricity use is carried out, directions of economy are defined, possibilities of reduction of unproductive expenses and electrical energy losses are revealed and actions for improvement of its use are defined.

The unit for forming the optimal composition of power consumers. Based on the data received from the database for the electricity cost management, as well as the requirements of the power system, a list of consumers-regulators is formed, which will ensure compliance with the requirements of the power system for electricity consumption. The list of consumers-regulators and volumes of electricity consumption is transferred to the decision support subsystem.

Power consumption decision support subsystem. From the database of the electricity consumption management it is received data on the actual and planned electricity consumption by production units and FMP as a whole, as well as the optimal composition of electrical energy consumers.

Relevant options for decisions (management effects of control actions), which are a set of organizational and technical measures aimed at adjusting the plans for electrical energy

consumption in FMP and production units during the period that appeared before the end of the year, are transferred to the decision maker.

Application of methods of power consumption forecasting, decision-making procedures and algorithm of formation of power consumption rational modes allows adjusting technological process, to form optimum structure of consumers-regulators and to provide standard levels of power consumption.

The general diagram of the decision-making process using the dialog subsystem of decision-making support is presented in Figure 5.

Figure 5. Power consumption decision-making process using the dialog subsystem

The general scheme of the power management decision-making process can be represented as follows:

$$J(t_0) \rightarrow (F, V) \rightarrow E \rightarrow ERP \rightarrow v^*(t_k) \quad (19)$$

where V is the set of alternative solutions generated using predicted power consumption values; F – objective function (optimality criterion), in our case, the criterion of optimality is the minimum electricity consumption in the production process; E – expertise of alternative production plans generated; ERP – expertise results processing using the predicted values of electricity consumption; v^* – the optimal solution.

At the stage of forming the goals of FMP it is determined the desired state of the management object, i.e. what should be achieved as a result of management decisions. When forming a system of goals, it is necessary to ensure their appropriate subordination, completeness, interconnectedness, certainty and actuality. Usually the global (strategic) goals of FMP are developed first, and then their ranking according to the degree of importance and terms of realization is carried out. The main purpose of short-term (tactical) management

decisions on production is the organization of production activities of FMP, which ensures the rational use of available resources and maximizing profits.

The usage of methods of forecasting electricity consumption and the formation of the optimal composition of electricity consumers in the process of preparing management decisions to form a production program on the criterion of minimizing electricity consumption is necessary and justified for the following reasons:

- A huge number of alternatives that require comprehensive assessment;
- The difficulty of taking into account random factors in the process of decision preparation and implementation;
- The need to operate with large amounts of information about the functioning of FMP.

In Figure 6 presents the consolidated graphs of actual and planned electricity consumption, obtained as a result of the implementation of the proposed decision-making algorithm for power consumption management of FMP.

Figure 6. Planned and actual electricity consumption of FMP

On the basis of the system analysis, the data structure of the power management subsystem was synthesized using the presented methods. In Figure 7 the data structure is represented in the form of data-flow diagram (DFD). This structure is the base of a single information space, which is required for designing of the hardware and software system and forming a database for managing power consumption.

Application of power consumption prediction methods, decision-making procedure and algorithm of calculating power consumption optimal modes allows adjusting the technological process, forming the optimal configuration of consumers-regulators and providing standard levels of power consumption.

Control methods of FMP power supply using static load characteristics

The power management subsystem provides the solution to the problems of choosing optimal configuration, energy efficient operating modes, reactive power compensation, maintaining the standard values of electricity quality indices. Methods and tools have been developed to control the power supply of FMP. The objective function of the power management to provide energy-efficient modes is:

$$J = \frac{M}{T} \int_0^T \left\{ \sum_{j=1}^{nm} P_j + K_Q \sum_{j=1}^m Q_j + \sum_{i=1}^n \Delta P_s + K_Q \sum_{i=1}^n \Delta Q_s \right\} dt \quad (20)$$

$$J \rightarrow \min_{X(t) \in \Omega}$$

where M – expected value of active and reactive power losses; T – estimate time interval; P_s and Q_s – loss of active and reactive power at the main substation level; P_j and Q_j – the loss of active and reactive power in the j -th load node; K_Q is the ratio of reactive power loss to active power loss.

The controlled object in the management system of power supply and distribution of FMP is a multilevel system of transmission, distribution and consumption of electric energy. On the basis of the system analysis, the functional diagram and data structure (Figure 8) of the power supply subsystem was synthesized using the presented methods.

On the basis of mathematical model of power system it is calculated the power supply system operating modes for the main modes of the technological process, taking into account the state of consumers-regulators. The method of determination of the optimal voltage on 0.4 kV buses of shop floor substation (SFS) is developed, which provides energy efficient operating modes of power system, using static load characteristics.

Identification of SLC is carried out in the interactive mode for the main modes of the technological process, taking into account the state of consumers-regulators and the degree of compensation of reactive power with the help of SFS transformer equipped with the electronic switch.

Given the normal law of distribution of a random variable, it is used the least squares method to determine SLC [14] as it is described in the Methods.

Graphs of voltage and active power changes during the active experiment on the 0.4 kV bus-bars of 1000 kVA shop floor transformer are presented in Figure 9.

Maintenance of energy efficient voltage in the power system is provided by a two-level voltage regulation subsystem with fuzzy controllers. At the upper level, fuzzy regulators determine the farthest and closest connection and maintain the given voltage level in the distribution 6-10kV network using the on load tap changing (OLTC) transformer of main substation (MS) by a fuzzy controller based on Mamdani algorithm depending on the electrical distance SFS from MS, the load on the transformers and the voltage on the HV side of MS transformer. Using the Mamdani algorithm [12], the connection modes are determined, and the Sugeno algorithm [12] selects substations that have the electrically closest and most distant location from the power source (MS). Input signals of the controller: the voltage on HV buses of SFSs, electrically farthest and closest to MS; the value of the current tap of the MS transformer; the number of switches of OLTC system since the beginning of the current day. Output signals: movement direction of the tap changer and delay of actuation. At the lower level, a fuzzy controller and the SFS transformer with electronic switch maintains energy efficient voltage in the shop floor network. Fuzzy controller input signals: difference of rational voltage and current voltage values; is derived from the voltage value on the SFS LV buses. Output signals: transformer output voltage and time value after which the tap switching should be carried out. In order to ensure efficient operation, it is advisable to perform the construction of IACS PSC on the basis of a digital transformer substation [13]. The authors performed computer simulation of IACS PSC with the classical tap changer and fuzzy controllers for power system of meat-processing plant with two 25MVA transformers using MATLAB Simulink. The results of simulation showed that the use of a fuzzy controller allows reducing electricity losses by 4-6% compared to the classical voltage control algorithm.

Figure 7. DFD diagram of power consumption control subsystem

Figure 8. DFD diagram of power supply control subsystem

Figure 9. Graphs of voltage and active power change during the active experiment on the 0.4 kV bus-bars of 1000 kVA shop floor transformer

Based on the results of calculations performed according to the method described above, the coefficients of SLC on active and reactive power are determined and conclusions are made about the adequacy of both the coefficients themselves and the model as a whole. For the performed active experiment the SLC of active power (Figure 10) and the coefficients $a_0 = 1.458$, $a_1 = -2.233$ and $a_2 = 1.775$ are determined.

Figure 10. Static load characteristic: the dependence of active power of the voltage

Conclusion

In the paper the authors have developed the structure, the algorithms and the methods of the intelligent automated control system built on the basis of system analysis of the control process to provide energy efficient modes of power supply and consumption control of FMP as well as reduce electricity losses. The single information space of developed system allows implementing its efficient hardware and software design. The subsystem of power consumption control is based on the decision-making system, which uses heuristic methods of choosing consumers-regulators and power consumption prediction by artificial neural networks. The power supply control subsystem is able to maintain energy-efficient operating modes by means of fuzzy regulators that control rational voltage levels determined for the main process modes, the state of the consumers-regulators, and the degree of reactive power compensation. The results of computer simulation have proved efficiency of designed system comparing with classical approach.

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