

ENTERPRISE MULTI-LEVEL ENERGY EFFICIENCY MANAGEMENT SYSTEM DEVELOPMENT

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ABSTRACT

Improving the energy efficiency of the economy is a complex problem, the solution of which involves the development and implementation of a number of system solutions, at the level of both a country, a region and separate enterprises. Development of an enterprise multi-level energy efficiency management system is an important tool for improving the energy efficiency of an enterprise. The purpose of the study is to develop and improve models, methods and synthesis of data collection and processing tools of an enterprise multi-level energy efficiency management system with high technical and economic characteristics.

The theory of Petri nets and their expansion is used for building functional models of an enterprise multi-level energy efficiency management system, the theory of solving the problems of multi-criteria optimization — for selection of an element base, methods of neural network technologies — for synthesis of intellectual data processing tools, the theory of hardware and software design for synthesis of information technology elements, and the methods of object-oriented approach are used in the process of software development.

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The method of calculating the signal of postsynaptic excitation of neural elements in artificial neural networks has been improved, which is based on parallel tabular-algorithmic calculation of scalar product with the use of two or more tables and reduces the time of data processing. The results of the synthesis of a basic element consisting of a microcontroller, temperature sensor, heater and communication module are given. 284 alternatives were generated, from which a variant with a higher value of the target function was selected.

In conclusion, a simulation model of the system of automated synthesis of elements of the regional energy management system is developed, which uses the free Octave environment and allows to examine and check the operation of the method of selecting the element base and synthesis of components of the enterprise technological process energy efficiency management.

Keywords: energy efficiency; management system; neural network; algorithm; dynamic analysis

1. INTRODUCTION

The economy development of each country is closely linked to the improvement of its energy efficiency, which depends on a balanced and economical use of energy resources; energy supply technologies, equipment and schemes used; consumption patterns of fuel and energy resources; the level of energy efficiency management and energy consumption.

To assess the energy efficiency of a country economy, a number of indicators are used, in particular, gross domestic product (GDP), which characterizes the level of consumption of fuel and energy resources per unit of gross domestic product manufactured.

Improving the energy efficiency of the economy is a complex problem, the solution of which involves the development and implementation of a number of system solutions, at the level of both a country, a region and separate enterprises. An important tool for improving the energy efficiency of enterprises is the development of an enterprise multi-level energy efficiency management system (EMEMS). The basic objectives of EMEMS are: collection, storage and real-time processing of data on the technological process, energy consumption and output. Using the results of the processing of such information, EMEMS assesses energy efficiency indicators and generates management decisions to improve energy efficiency.

The main requirements for data collection, storage and processing are: bringing them closer to sensors, operating mechanisms and energy meters; intellectualization of the procedure of processing and decision-making; meeting the size, energy consumption, cost and development time constraints.

The creation of such tools requires the development and improvement of existing methods of data collection, storage and processing and their focusing on the widespread use of the current element base. In addition, it requires the development of methods for the synthesis of data collection, storage and processing tools and models for dynamic analysis of their operation in EMEMS.

Significant contribution to the theory and practice of enterprise energy efficiency research have been made by: Chen et al. (2018) - development of basic principles of energy management; Hamdaoui and Maach (2017) - regional energy planning and development of local energy systems; Hsiao 2017 - economy and energy industry of regions; Willem et al.

(2017) - methods and means of building automated energy efficiency management systems; Marchi and Zanoni (2017) - research on energy efficiency management issues at the state level and interstate cooperation; Fernando and Hor (2017) - use of energy efficiency management systems in the production sphere; Cooremans and Schönenberger (2019) - development of recommendations for improvement of energy efficiency in production; Li and Tao (2017) - solutions for improvement of energy efficiency in the IT field; Schimpe et al. (2018) - intellectualization of energy efficiency management systems; Tronchin et al. (2018) - engineering solutions to increase energy efficiency; Jia et al. (2017) - development of a generalized energy efficiency factor; Ge et al. 2017 - models of process control systems; la Cruz-Lovera et al. (2017) - development of models and tools for energy efficiency management; Marzband et al. (2017) - energy efficiency management models based on artificial neural networks.

For the successful operation of the enterprise it is necessary to take into account many factors and be able to control the system, analyze its operation and make effective decisions (Mahv et al. 2001, Cai et al. 2017). To achieve this goal, it is necessary to use the infrastructure (Ilin et al. 2017) making it possible to take into account business processes, production cycles and obtain information about the state of the system in real time.

The conducted analysis allows to state that the key elements of the management system at the enterprise are the planning of enterprise resources (Amxilatits et al. 2017), supply chains (Yin et al. 2017, Aminsharei et al. 2017), environment monitoring systems, security systems, resources and personnel of the enterprise.

For enterprise deployment, a variety of ready-made (basic) modules are used, each of which is focused on solving specialized problems. These modules come from different vendors and vary in both architecture and interface. This approach makes it possible to develop a business by using additional modules attached to the existing system.

As a result, the enterprise management system consists of many modules, which are formed into a single system. The whole enterprise system management strategy is based on the integration of business logic of the system and production in real time. The enterprise management system covers everything from sensors to decision making operators.

Thus, an actual scientific task is to develop and improve models, methods and synthesis of data collection and processing tools for an enterprise multi-level energy efficiency management system with high technical and economic characteristics. Accordingly, the subject of the study is relevant.

The purpose of the study is to develop and improve models, methods and synthesis of data collection and processing tools of an enterprise multi-level energy efficiency management system with high technical and economic characteristics. This study was conducted in Bulgaria during 2017-2019.

2. MATERIALS AND METHODS

To solve the problems set in the study, we used the theory of Petri nets and their extension to build models of operation of EMEMS, the theory of solving multi-criteria optimization problems for the selection of element base, methods of neural network technologies for synthesis of intellectual data processing tools, the theory of designing

hardware and software tools for synthesis of information technology (IT) components, methods of object-oriented approach in the process of software development.

One of the ways to increase the energy efficiency of process control is the use of intelligent components (GhaffarianHoseini et al. 2017, Serale et al. 2018, Xia et al. 2018). In EMEMS, intelligent components are used for executing these tasks: recovery of lost data coming from sensors in the conditions of interference; dynamic filtering of data from sensors; compression and decompression of technological data; intellectualization of regulators of automatic control systems, including servos; intellectualization of control of operating mechanisms and complex objects; intellectual analysis; management decision making support systems; recognition of images and scenes in systems of artificial vision; traffic forecasting and autonomous control of vehicles; forecasting, control and management of technological processes; optimization of costs of resources and operating modes of technological process control systems; adjusting the parameters of the technical tools depending on the environment conditions; providing information security.

It is suggested to implement the intellectual components of EMEMS on the basis of artificial neural networks (Wang et al. 2017, Johansson et al. 2018). When developing intelligent components based on the use of artificial neural networks, the task of synthesis is reduced to selection of a neural network architecture that will meet the task being executed, the selection of the training algorithm, the generation of training and testing samples.

The next steps are to set up and train artificial neural networks, which in most cases is reduced to identifying neural network parameters (weighting factors, connectivity and offset values of neural element activation functions) using training sample and task features.

The purpose of setting up a neural network is to identify its parameters – the number of layers of neural elements and the number of neurons in each layer. For making settings, a training data sample is divided into three subsets: training, validation and testing ones. The process of setting the parameters of the neural network properly is performed through repeated training. Quality assessment and selection of the best structure option is based on validation sample data. The final test of the quality of the setting and training is done with the help of a testing data sample.

The criterion for selecting the optimal structure is the criterion of the optimal complexity model. Some neural networks, such as single-layer perceptrons, do not provide for setting procedure because their structure is defined by the structure of data vectors. The quality of setting and training neural networks directly depends on how well the tasks are executed.

The main components, on the basis of which neural-like systems are synthesized, are neuroelements, in which the weighting factors V_j are pre-calculated and do not change or very rarely change in the process of operation. In the general case, a neuroelement transforms in accordance with the formula:

$$F = f\left(\sum_{j=1}^n V_j Y_j\right) \quad (1)$$

where F – neuroelement output signal, f – activation function, n – input number.

From formula (1) it follows that the processing of data in the neuroelement is reduced to the operation of calculating the scalar product and the activation function f . Much of the intellectual components are synthesized on the basis of microcontrollers (microprocessors), the operating basis of which is simple arithmetic operations (adding, subtraction, inversion and offsets). Such intelligent components use multiplication algorithms with direct generation of partial products to calculate scalar product, since they are regular and well-structured. The most common of these are multiplication algorithms with single-digit analysis. The multiplication of binary numbers with analysis of a single digit of the multiplier is written as follows:

$$Z_j = W_j X_j = \sum_{i=0}^{n-1} 2^{-i} V_j y_i = \sum_{i=0}^{n-1} 2^{-i} R_{ji} \quad (2)$$

where n – multiplier digit capacity; y_i – value of i -th digit of multiplier; R_{ji} – i -th partial product.

This multiplication algorithm is executed in n steps, each of which is reduced to generation and accumulation of partial products in accordance with these formula:

$$R_{ji} = V_j y_{ji} \quad (3)$$

$$Z_{ji} = 2^{-1} Z_{j(i-1)} + R_{ji} \quad (4)$$

where Z_{ji} – sum of accumulated partial products, $Z_0 = 0$.

To calculate a scalar product $C = \sum_{j=1}^n V_j Y_j$ using multiplication algorithms (3 and 4), it

is necessary to perform n multiplication operations and $n-1$ addition operations. One can reduce the time of finding scalar product by using a multi-operand approach and a vertical computation model. When using a multi-operand approach and a vertical computation model, the process of calculating a scalar product is regarded as performing a single operation on operands that come in consecutive digit sections. The implementation of this calculation requires the generation of a macropartial product for each digit section R_{1i} . The calculation of a scalar product with the generation of a macropartial product is implemented by the following formula:

$$C = \sum_{j=1}^n V_j Y_j = \sum_{i=0}^{n-1} 2^{-i} R_{1i}, \quad (5)$$

where

$$R_{1_i} = \sum_{j=1}^n V_j \times j_i = \sum_{j=1}^n R_{j_i} \quad (6)$$

In neural-like systems, the weighting factors V_j are pre-calculated, they can be considered as constants. To calculate a scalar product, we improve a vertical tabular-algorithmic method of calculation that involves calculation and storage in memory of macropartial products R_{1_i} with their subsequent summation. The calculation of the values of macropartial products R_{1_i} is performed using the following formula:

$$R_{1_i} = \begin{cases} 0 \rightarrow y_{1_i} = y_{2_i} = y_{3_i} = \dots = y_{n_i} = 0 \\ V_1 \rightarrow y_{1_i} = 1, y_{2_i} = y_{3_i} = \dots = y_{n_i} = 0 \\ V_2 \rightarrow y_{1_i} = 0, y_{2_i} = y_{3_i} = \dots = y_{n_i} = 0 \\ V_1 + V_2 \rightarrow y_{1_i} = 1, y_{2_i} = 1, y_{3_i} = \dots = y_{n_i} = 0 \\ \vdots \\ V_2 + \dots + V_n, \dots \rightarrow y_{1_i} = 0, y_{2_i} = y_{3_i} = \dots = y_{n_i} = 1 \\ V_1 + V_2 + \dots + V_n \rightarrow y_{1_i} = y_{2_i} = y_{3_i} = \dots = y_{n_i} = 1 \end{cases} \quad (7)$$

The calculated values R_{1_i} are stored in memory at an address that is a combination of values of digit sections of n multipliers y_{j_i} . The structure of the memory table for storage of macropartial products R_{1_i} is given in Figure 1.

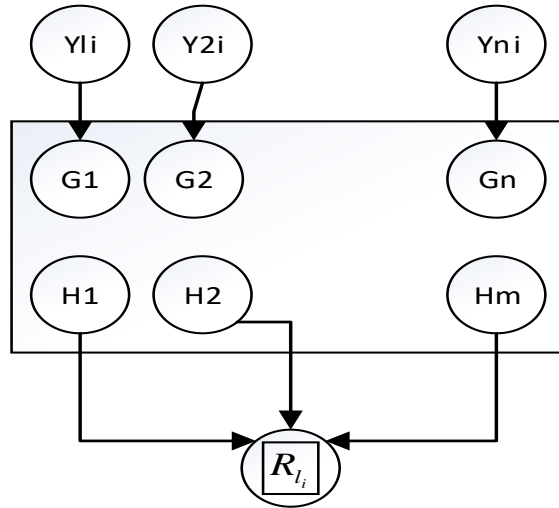


Figure 1. Memory table structure for storage of macropartial products.

The memory space for storage of macropartial products R_{1i} is determined by the formula:

$$H = 2^n \times m \quad (8)$$

where m – digit capacity of macropartial products R_{1i} .

In each operating cycle, at the memory address, which is a digit section of multipliers y_{ji} , a macropartial product R_{1i} is read, which is added up according to the formula (5).

The calculation of the scalar product using the tabular-algorithmic method is carried out in 'n' iterations. Reducing the time for calculation of a scalar product with this method can be achieved by paralleling the calculation process by using two or more memory tables. The improved tabular-algorithmic method using two memory tables for calculation of a scalar product is written as follows:

$$C = \sum_{j=1}^n V_j Y_j = \sum_{t=0}^{\frac{n}{2}-1} 2^t R_{1i} + 2^{\frac{-n}{2}} \sum_{h=\frac{n}{2}}^{n-1} 2^{-(h-\frac{n}{2})} R_{1i} \quad (9)$$

The calculation of a scalar product with this method is performed in $n/2$ iterations (Perera et al. 2017). The improved tabular-algorithmic method for calculation of a scalar product is designed for multi-core microprocessors.

Neural network training can be performed using both an iterative and non-iterative method. The iterative training process is a step-by-step process, in which each time new values of sample vectors are fed to the input of the neural network. The training can be performed both with a supervisor and without a supervisor (self-training). When using the training with a supervisor it is required that sample vectors have output components, i.e., known feedback. The training without a supervisor does not provide for division of vectors into input and output components. The main characteristics of neural network training are the quality of selection of weighting factors and training time. These characteristics are interrelated and their selection is made on the basis of the requirements that result from the statement of the problem. Comparisons of iterative neural network training methods are performed by the number of steps required to find the correct solution and the number of additional variables required to organize the computational process. In this case, the best iterative training methods are those, in which the training is performed in fewer steps and with fewer additional variables.

3. RESULTS

For automated synthesis of components of EMEMS on the basis of the developed methods for selection of element base and synthesis of components of a enterprise multi-level

management system software is being developed. The algorithm for the operation of these tools consists of the following steps:

- Step 1: System startup and initialization.
- Step 2: Database connection initialization.
- Step 3: Read input data on the element base.
- Step 4: Read data on search criteria and restrictions.
- Step 5: Read information on required system structure (number and type of sensors, actuators and communication modules).
- Step 6: Search and filter element base according to min/max values of element criteria.
- Step 7: Normalization of weighting factors for each of the criteria.
- Step 8: Normalization of partial criteria for each of the filtered elements.
- Step 9: Computation of an integrated efficiency value for each of the elements.
- Step 10: Element sorting in the descending order of the integrated efficiency value.
- Step 11: Synthesis of an alternative of combining a subset of elements into a module.
Validation of component interfaces and selection of alternatives that satisfy the interoperability of interfaces.
- Step 12: Calculation of the integrated efficiency value for each of the synthesized modules.
- Step 13: Element sorting in the descending order of the integrated efficiency value.
- Step 14: Output of results for the user.

Presentation of this algorithm, in the form of a flow diagram, is given in Figure 2.

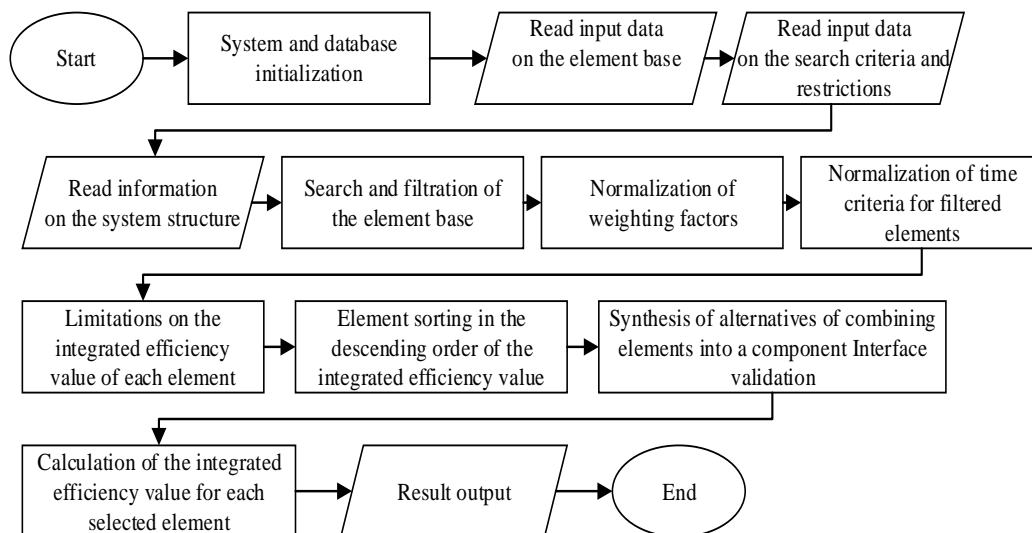


Figure 2. Algorithm for generation of components of an enterprise multi-level management system based on the principle of energy efficiency.

This algorithm has a linear structure and consists of 2 consecutive blocks. In the process of practical implementation, the blocks are designed as subprograms:

- subprogram for selection of element base for synthesis of components of enterprise management systems responsible for downloading variants of components from the database, their pre-filtering according to the set technical-economic indicators, calculating the integrated efficiency value for each component and sorting the results in the descending order of the integrated efficiency value.
- subprogram for synthesis of structure of components of enterprise energy efficiency management systems, which inputs receive variants of components from the first subprogram. Then, the generation of variants of combining the elements into a single component is carried out. These variants are filtered by the interoperability of interfaces. The variants, which were validated, are saved and an integrated efficiency value is calculated for them. The variants are sorted in the descending order of an integrated efficiency value.

So, the developed algorithm makes it possible to automate the process of synthesis of the structure of components of EMEMS taking into account the interfaces of basic components, and makes it possible to improve the quality of the designed modules of EMEMS.

In order to improve the efficiency of the synthesis system, the dynamics of the system operation was studied depending on various input parameters. The main parameter of the study is the efficiency of the system operation depending on the number of synthesis parameters.

A series of simulations of the synthesis system operation has been carried out in the study. For the study, different variants of data collection and processing tools with a various number of elements ranging from 2 to 12 basic elements were generated. During each of the simulations of the synthesis system, one microcontroller was selected, which was the main element of the system. The auxiliary elements were selected from a list of sensors, actuators and expansion modules. In particular, for one of the synthesis variants there were selected sensors of temperature, lighting, and smoke; actuators of lighting and heating, as well as Bluetooth communication modules and LCD screens.

During each synthesis generation, they calculate the total number of element combination variants, the number of variants that are filtered by the interoperability of interfaces, and measure the operation time of the synthesis system. The simulation was performed on a macbook Pro 2015 computer with a Core processor and 7 and 16 GB of RAM. The example of obtained data is presented in Table 1.

One of the important parameters of the synthesis system operation is the dependence of the number of combinations of basic elements on the number of search parameters. The synthesis system has an additional filter that allows to exclude those variants, which are not compatible by the number of available interfaces. For the purpose, in the paper the emphasis was placed on the study of the effectiveness of this particular method.

According to the obtained results, it is apparent that the method of element filtering by the compatibility of interfaces begins to have an effect when the number of system synthesis parameters increases. Accordingly, the larger the number of elements the system must consist of, the more ports of the microcontroller will be involved. As a result, in many variants, there are no free ports and the system cannot be connected to a single microcontroller. Accordingly, the percentage of variants that are filtered out is growing with the increase in the number of elements.

Table 1. Dependence of the operation time of the synthesis system on the number of simulation parameters

Quantity	Exhaustive search	Excluded variants	Difference	Computational time savings	Time (milliseconds)
2	49	49	0	0	1
3	196	196	0	0	2
4	588	588	0	0	3
5	1,764	1,764	0	0	7
6	12,348	12,348	0	0	28
7	24,696	24,696	0	0	42
8	49,392	49,392	0	0	63
9	148,176	148,176	0	0	217
10	296,352	260,064	36,288	12,24489796	454
11	2,074,464	1,312,416	762,048	36,73469388	6,546
12	6,223,392	3,701,376	2,522,016	40,52478134	20,797

One of the important parameters of the synthesis system is the complexity of calculations during its operation. In this case, an important parameter is the operating time of the system, depending on the number of variants for combining elements.

Based on the obtained data, we can conclude that the logarithm of system operating time is linearly dependent on the volume of input data.

As the operating time of the system increases exponentially, then an important issue is the possibility to reduce the total number of calculations by cutting off the worst-case variants (according to the value of the objective function).

To achieve the goal, one can use an elitist strategy when the main positions in the synthesis are occupied by elements that were better during the operation of the element selection system.

To examine this hypothesis, a series of computational experiments were conducted when there were compared the results of the synthesis system operation based on a complete set of input data and a reduced set of data when there were used the sample elements that had better values of objective function.

Different compression values were selected to assess the sample compression factor, which showed how much % of the original sample would be used (Table 2).

Table 2. Dependence of search results matching on percentage of application of better elements

Cutting percentage	Parameter number				
	8	9	10	11	12
90	100	100	100	100	100
80	100	100	100	100	100
70	100	100	100	0	0
60	100	100	100	0	0
50	54	54	54	0	0
40	8	8	8	0	0

Accordingly, to save resources, it is possible to reduce the initial sample of elements to speed up calculations.

The method of filtering of synthesis variants by the compatibility of interfaces in combination with Pareto method approaches can improve the efficiency of the synthesis system. Since total (value of the objective function) is calculated by using an additive and multiplicative function, elements with the best parameters generate variants with a larger value of the generalized objective function.

If you cut parameters according to the compatibility of interfaces, one can get good variants using a small number of calculations. Accordingly, this approach allows to use fewer calculations and increase the number of parameters that the synthesized system must consist of.

During the processing of data from EMEMS sensors, it is quite often necessary to deal with data loss, the need to implement approximation of data at the next moments in time, the need to process fuzzy data, etc. In such situations it is advisable to use special tools. For example, in this paper we suggest to process data using a microcontroller with software-based neural network. It is clear that for most technical tasks such combination is sufficient in terms of speed, and for real-time systems neural network can be implemented at the hardware level.

As an example, a typical intellectual data processing tool using the example of a smart greenhouse management system will be considered (D'Agostino et al. 2017). The smart greenhouse is responsible for maintaining the microclimate and lighting regime for growing plants under specified conditions. The corresponding subsystem is implemented in the form of a neurocontroller.

The following structure of the control system is developed, which includes the following components (Figure 3) a microcontroller that includes a control program and a ported neural network for data analysis and making management decisions.

The management system includes these sensors: air temperature sensor for monitoring the temperature regime in the system; air humidity sensor for monitoring the water vapor content in the air; soil moisture sensor for soil moisture monitoring; lighting sensor for monitoring ambient light levels and system timer for monitoring the time of day.

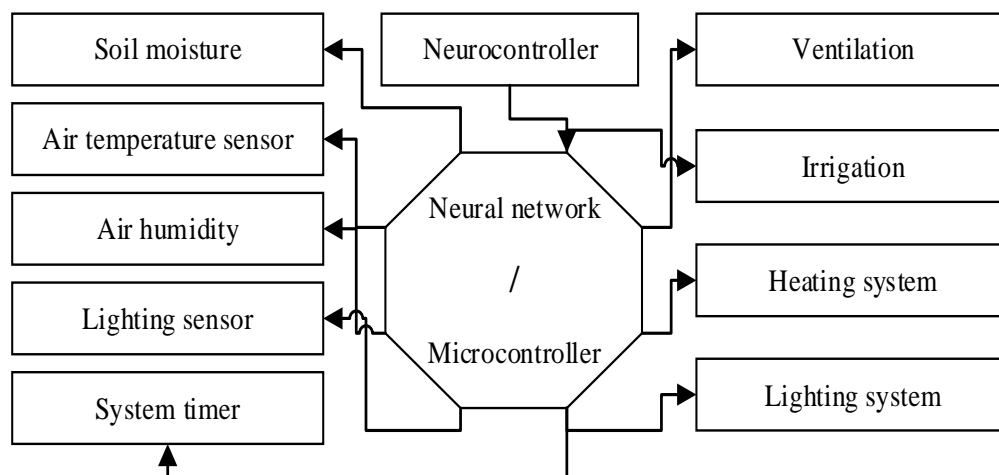


Figure 3. Smart greenhouse management subsystem structure.

The above sensors allow to detect changes in the greenhouse environment. Actuators were used to influence the greenhouse environment. In particular, in the developed smart greenhouse management system such actuators (actuating systems) were used: soil irrigation subsystem; ventilation system for reducing temperature and humidity within the management system and air filtration; system for heating air within the system; lighting system that switches on in the case of insufficient external lighting.

NeurophStudio environment was used to design, train and test the neural network. This is a free software for designing neural networks of different types. This software allows to monitor the training process, modify the structure of the neural network, determine the set of training values, visualize training results, etc. A multi-layer perceptron was selected as the neural network.

In NeurophStudio environment there were designed a neural network consisting of 4 input neurons and one balancing neuron, 6 internal neurons and one balancing neuron (Hossain et al. 2017, Katchasuwanmanee et al. 2017). The output layer contains 4 neurons (Figure 4).

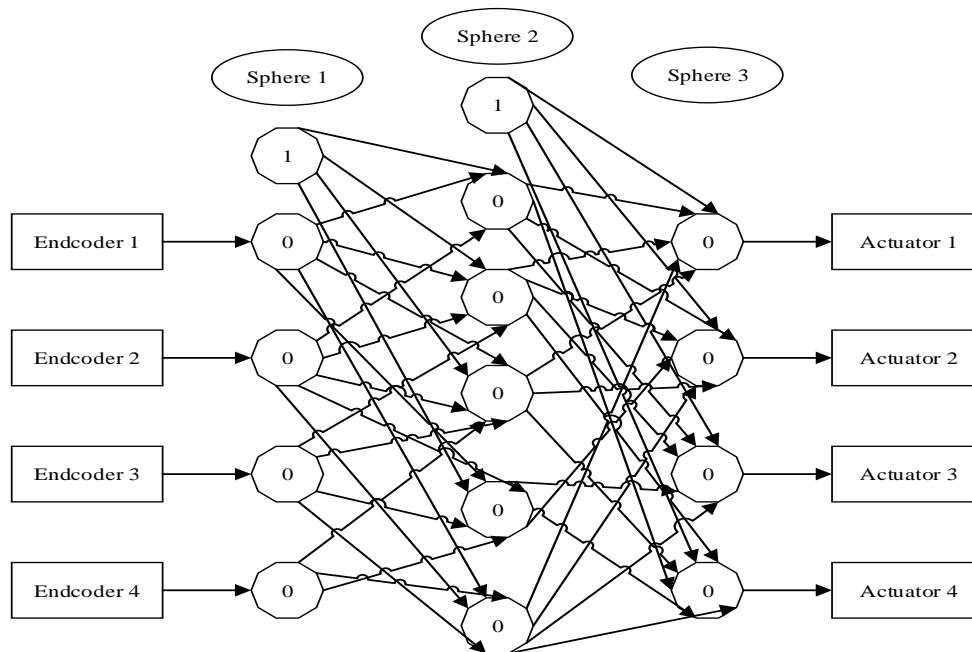


Figure 4. Suggested multi-layer perceptron neural network system.

Multi-layer perceptron neural network training is performed using the method of inverse error propagation. The operation of the neural network is checked for 20 % of the data that was not included during the training process. An example of the dependency of a neural network training error on the number of iterations is given in Figure 5 and Figure 6.

This means that the neural network was not specifically trained, and the results of work with this sample allow to check how the neural network works based on independent data. As a result of the neural network checking, the following results were obtained: the mean square error is 0.032. After that, it is possible to export a trained neural network to implement the neurocontroller.

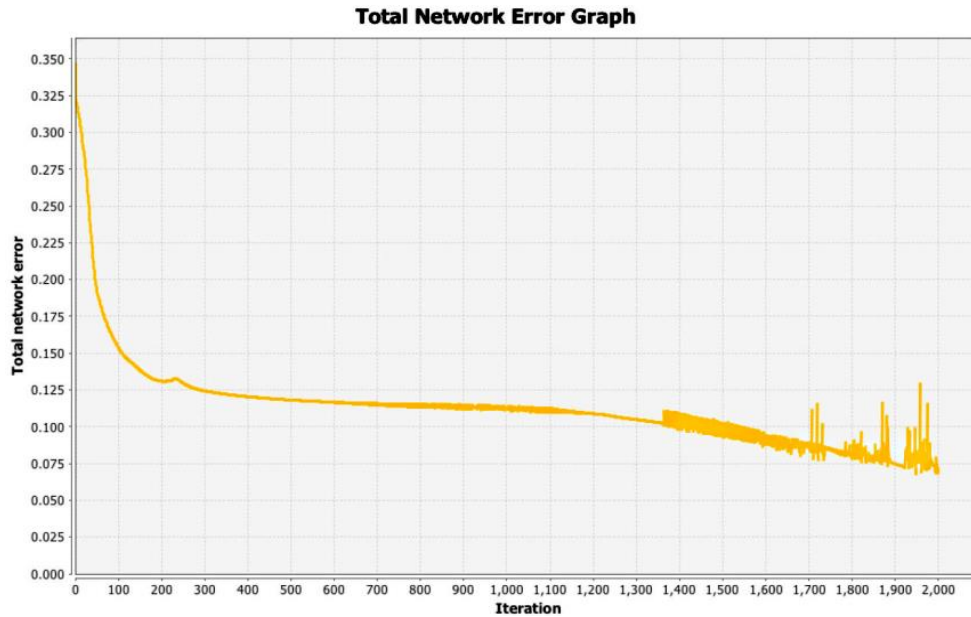


Figure 5. Neural network learning results, iteration 1-2000.

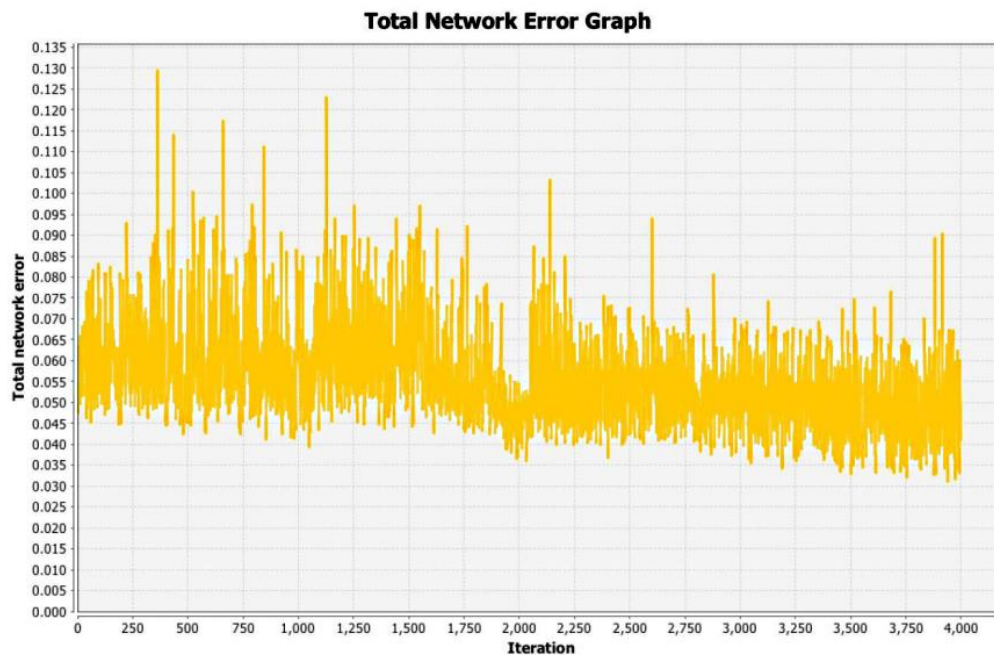


Figure 6. Neural network learning results, iteration 2001-6000.

Each of the neurons has connections to adjacent levels. Within the environment, one can examine the structure and connections between neurons. For correct neural network training, it is recommended to divide the set in 2 parts. The first part is used to train the neural network, while the second part is a control set, with the help of which the neural network can be tested based on new data.

In this case, the neural network learning is performed based on 80 % of the data set.

The software neurocontroller implementation includes several modules, each of which is responsible for a particular aspect of the neurocontroller operation. The software consists of the following modules:

System initialization module responsible for: preliminary system initialization; initialization of ports for operation with sensors, actuators and a system timer; loading the initial data.

Module for interaction with peripherals responsible for: interaction with sensors, which consists of periodic reading the data from the sensors; interaction with the system timer, which consists of setting the start time and periodic reading of the current time of day; interaction with actuators, which consists of transmitting control signals to relays to change the status of actuators.

Neural network-based data processing module responsible for: initialization of the neural network, which consists of loading the dimensions of the neural network, the type of neuron function, and matrices of weighting factors; input of input data into the neural network; simulation of neural network operation; output of output data for generation of control commands for actuator control.

4. DISCUSSION

The main tasks of this module is to simulate the operation of a neural network. For the purpose, a subprogram was implemented, which performs sequential calculations of the value of each neuron taking into account the type of neuron function and the connections between the neurons. The generated values of each element are at the end of the subprogram.

The algorithm of the neurocontroller operation is as follows:

- Step 1: System initialization.
- Step 2: Port initialization.
- Step 3: Initial data loading.
- Step 4: Wait for the interrupt command to start the main loop. Is the interrupt command started? Yes - go to Step 5. No – go to Step 4.
- Step 5: Read temperature sensor data.
- Step 6: Read moisture sensor data.
- Step 7: Read lighting sensor data.
- Step 8: Read time of day data.
- Step 9: Enter input data into the neural network.
- Step 10: Start the subprogram for calculation of neural network values.
- Step 11: Retrieve output data from the neural network.
- Step 12: Generate control signals.
- Step 13: Send the control signals to the relay.
- Step 14: Set the interrupt command to 1 second, go to step 4.

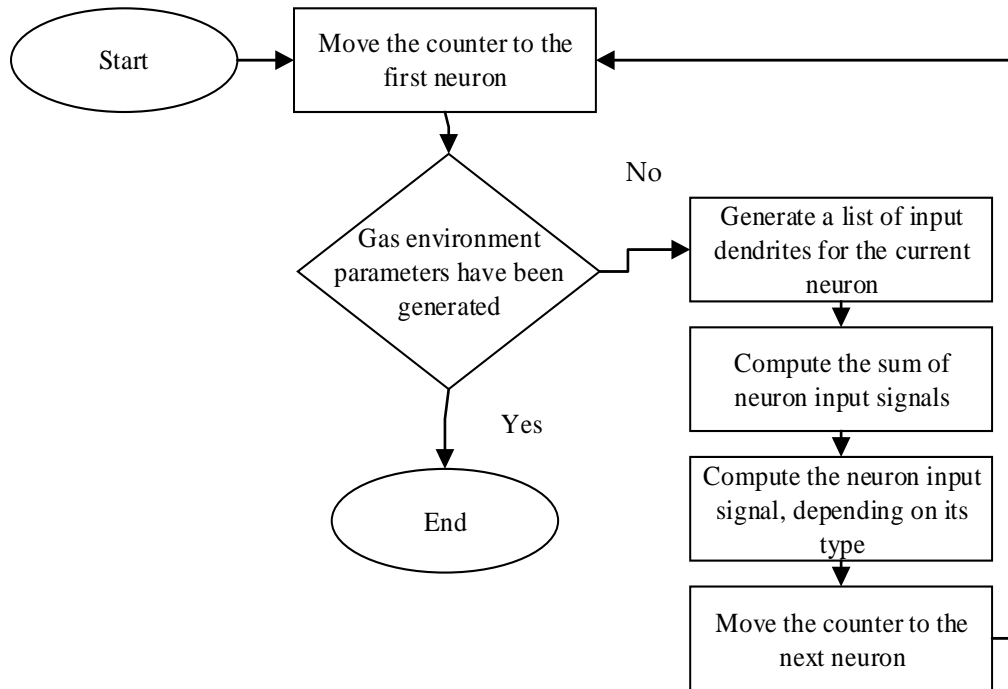


Figure 7. Simulation subprogram algorithm.

The main feature of a neurocontroller is its cyclical operation. Since there is no need to frequently query and update the system status, an interrupt command is used, which stops the main program run cycle and limits the main cycle run frequency.

During the main cycle run, a subprogram is called to simulate the operation of the neural network. Based on its response, commands are generated for actuator control. The algorithm of the subprogram for simulation of the operation of a neural network is given in Figure 7.

- Step 1: Move the counter to the first neuron.
- Step 2: Is the end of neural network reached? Yes — go to Step 7, No — go to Step 3.
- Step 3: Generate a list of input dendrites.
- Step 4: Compute the sum of neuron input signals.
- Step 5: Compute the neuron output signal, depending on its type.
- Step 6: Move the counter to the next neuron. Go to Step 2.
- Step 7: End subprogram.

The subprogram is responsible for calculating the values of each of the system neurons. As input data, the subprogram receives the readings of the sensors and system timer. As output data, the subprogram issues the status to which each actuator is to be switched (on/off).

Enterprise energy efficiency management at the level of technological processes requires extensive use of smart technologies and creation of a single information space with reliable, complete and latest information on the enterprise technological processes. One way to reduce the volumes of information is to bring processing tools (microcontroller systems) closer to sources of information (sensors) and actuators. Accumulated data are processed using computational intelligence technologies.

The obtained results are used to generate effective management decisions. It is possible to increase the level of enterprise technological process energy efficiency management by developing EMEMS, which integrates the functions of monitoring and control into a single system. Such system must become a convenient tool to support making management decisions at all management levels. When using such system, operators directly focus on managing the energy efficiency of technological processes.

CONCLUSION

In the paper, on the basis of theoretical and experimental studies, there was solved an actual scientific problem of developing and improving models, methods and synthesis of tools for collection and processing of data of an enterprise multi-level energy efficiency management system with high technical-economic characteristics.

Information technologies of data collection and processing in enterprise multi-level energy efficiency management systems were analyzed, and the basic areas of development of hardware and software tools for synthesis of systems of data collection and processing at the enterprise were determined, which allowed to formulate the objectives of the study.

Models of dynamic analysis of operation of information technology tools of data collection and processing in enterprise multi-level energy efficiency management systems were developed, which, through the use of the theory of simple, color and hierarchical Petri nets, provide for making a decision on the conformity of the operation of the system to the requirements of the specification.

The method of calculating the signal of postsynaptic excitation of neural elements in artificial neural networks was improved, which is based on parallel tabular-algorithmic calculation of a scalar product using two or more tables and provides a reduction of processing data of two or more times.

The structure, software and information support of the system of synthesis of the tools of data collection and processing in EMEMS were developed, which makes it possible to automate the synthesis process. A three-tier basic architecture of EMEMS with a variable equipment configuration, which has a permanent core and replaceable modules, with the help of which the system is adapted to the requirements of a specific enterprise, was built. The structure and operation algorithm of an intellectual EMEMS for greenhouse cultivation of plants were built.

The structure, operation algorithm of the basic intellectual component for data collection and processing, which is based on the use of artificial neural networks with the use, in the course of its software-hardware implementation, of parallel tabular-algorithmic calculation of a scalar product with the use of two or more tables, were developed, which makes it possible to process data in real time and parallel the process of fuzzy data handling.

AUTHOR CONTRIBUTIONS

V. M. organized the collection of empirical data and participated in the preparation of the manuscript. A. D. took part in the data processing. Y. K. helped with the review and literature. O. B. helped with providing the Internet connection for downloading corresponding

journals and was involved in the preparation of the manuscript. I. N. drafted the manuscript in accordance with the requirements of the journal.

CONFLICT OF INTEREST

The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

Informed consent was obtained from each individual participant involved in this study.

Source of Funding: This research received no external funding.

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