Monitoring and Control of Energy Consumption Systems, using Neural Networks

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Abstract: Industries, cities, towns and households, around the world, need reliable, affordable and sustainable energy to meet their electricity demand. Renewable energy can make a significant contribution to the development of this area and satisfy this need of the population, both in private households and in the field of industry, transport and supply of entire settlements. This study examines the design of an intelligent energy management system for a residential building. The smart home energy management system must use new infrastructure based on modern technologies such as DSE (Deep Sea Electronics) controller, smart devices, advanced communications, electrothermal models of critical components and advanced optimization models. The main advantage of this energy management system is that it will allow real-time control and monitoring of a home that includes all the components connected to it (for example, a distribution transformer and household appliances). The control system should work without changing the customer's lifestyle. The article discusses topical issues of energy saving in accordance with the development program of the Republic of Kazakhstan until 2050, analyzes the trends in energy saving policies, in different countries. It is developed C# software, for monitoring and control.

Keywords: smart house; energy saving; neuronet; fuzzy logic; energy management

1 Modern Approaches to Energy Saving Policy: Trends in the World and in the Republic of Kazakhstan

1.1 Trends in Energy Saving Policy

The global response to energy security challenges is essentially a growth model that is based on the principles of energy efficiency and environmental sustainability.

Over the past two decades, the main focus has been on integrating energy efficiency with environmental policies, especially in relation to global climate change. Almost all national and regional energy efficiency strategies are directly linked to climate change policies. The global potential for energy savings is enormous. According to the International Energy Agency [1], successful implementation of energy efficiency measures would reduce greenhouse gas emissions by 80%, while significantly improving the security of supply. The International Energy Agency estimates that only improving the energy efficiency of electrical appliances through the use of the best available technologies, as part of a policy aimed at reducing the end-user costs of using electrical appliances, will save up to 1000 TWh by 2030, as compared to the current situation. The production of cars with lower fuel consumption will sharply reduce the demand for fuel resources. In rapidly growing developing economies, the transport sector is projected to account for 43% of energy demand by 2025, up from nearly 35% in 2008.

China, India, Brazil and other countries, where over the past two decades there has been a rapid economic growth and demand for energy, in the face of rising prices for hydrocarbons, are also beginning to switch to energy conservation policies. One of the most important recent trends is the improvement of energy-saving and energy-efficient technologies in construction. The potential for energy savings is high – the IEA estimates that buildings and appliances could account for one quarter of the potential CO_2 emissions reductions up to 2050 [1-4]. Energy saving in the transport sector is also a priority area. Increasing the share of new and renewable energy sources in developed countries is also integrated into energy efficiency policies. The ongoing development of new technologies makes the development of renewable energy sources such as solar energy, hydropower and biomass more affordable and efficient. The main limiting condition is the economic factor – as long as they are still expensive. However, continuous scientific and technical progress in the use of new and renewable energy sources (NRES) and the constant rise in the cost of traditional energy resources, primarily 6 liquid hydrocarbons, expand the scope of NRES mainly in areas without centralized energy supply.

There are very clear differences in approaches to energy saving in different countries associated with the peculiarities of the national mentality, cultural preferences and prevailing stereotypes of behavior. However, an important common feature of developed countries is the concentration of policy on achieving energy savings at the stage of energy use.

Let's consider approaches to energy saving in different countries.

1.2 United States of America

The US economy is 2.5 times more energy efficient than the Kazakhstani economy. According to some experts, 9 times less energy is spent on industrial production in America than in Kazakhstan. At present, the level of energy consumed in the country for the production of goods and services in the amount of $1, has decreased by more than 50% compared to 1970. The American achievements in energy efficiency are the result of years of energy conservation efforts. A feature of the US energy efficiency policy is the very widespread use of various measures of financial incentives and the evasion of the adoption of all kinds of codes and regulations.

As part of the Vision 2025 initiative, more than a half of all states have adopted their own energy efficiency programs and have established building codes that require new buildings to be energy efficient.

The main goals and directions for improving energy efficiency in the United States include the following key points:

1) Reduce US dependence on oil imports
2) Develop and introduce energy-saving technologies for public buildings, residential buildings, transport, energy, and industry.

The Energy Efficiency and Renewable Energy Authority has been established within the US Department of Energy with the following key objectives to support these goals [2] [3]:

- Strengthening the energy security of the United States
- Improving the quality of the environment
- Ensuring the economic viability of public-private partnerships, whose activities are aimed at increasing the efficiency and productivity of labor
- Introduction of environmentally friendly, reliable and affordable 12 energy technologies; introduction of alternative energy sources into everyday life, ensuring a higher quality of life.

There are federal programs in the United States for promotion energy conservation and ways to improve energy efficiency.

1.3 Japan

By setting a 30% increase in energy efficiency by 2030 over 2006, the Japanese government is committed to ensuring a modern energy supply / demand structure in a market with the high prices expected by the government in the medium to long term. Japan has pledged to provide funding in the amount of 1.6 trillion. yen to create a so-called "low-carbon society" – a society with low CO_2 emissions, including 3770 billion yen to replace old cars with new, more fuel efficient cars and 295 billion yen to help purchase energy-efficient household appliances. The stimulus package in Japan also includes the allocation of resources to subsidize businesses that introduce energy-efficient hardware and equipment, and to improve small and medium-sized enterprises by conducting energy diagnostics and investing in innovative energy-saving technologies [2].

Approaches to energy saving in Japan implies the introduction of 3 fundamentals into various spheres of society: solar energy, electric cars, energy-saving household appliances. The specific goal is to double the share of renewable sources in energy consumption and achieve the highest indicator in the world – 20%.

Germany, the United Kingdom and the United States are also implementing eco-driving programs based on the experience of Japan.

1.4 The European Union

The European Union is a major driving force in promoting energy efficiency strategies and combating global climate change, and its regulatory impact, extends far beyond its member states. Not all EU Member States give the same attention to energy efficiency, but there is now a requirement for some basic policy. A number of countries far exceed this minimum [2-4].

A number of countries have integrated renewable energy and energy efficiency policies, where this combination is often referred to as a sustainable energy strategy. Such measures have been in place for a long time, and the resulting benefits are undeniable. Since the 1990s, the EU's energy efficiency policy has been closely linked to tackling climate change and has also integrated many aspects of renewable energy and the improvement of technologies for the use of all fossil fuels.

Germany does not have a specific general energy conservation law, but there is a Federal Cogeneration Act and an Energy Saving Ordinance (to introduce a low energy housing standard). Much of the legal framework is based on the transposition of the EU Energy Efficiency Directives into national legislation. An important feature of the organization of energy saving in the country is the preferential financing of energy saving measures by banks and large corporations, and not by the state.

The energy saving management system provides for the delegation of basic functions to the regional and local levels. Energy efficiency issues are closely linked to climate change mitigation activities. When purchasing computers and other electronic devices, the administrative institutions of Berlin should opt for the products that consume the least amount of electricity. Germany is one of the recognized world leaders in energy efficiency in buildings.

Germany and the UK are leading the way in implementing building certification. Only in Germany there are energy efficiency requirements that ensure the optimal level of minimum costs over a 30-year life cycle of buildings.

There is no general energy efficiency law in the UK. Much of the legal framework is based on the transposition of the EU Energy Efficiency Directives into national legislation.

According to the National Energy Efficiency Action Plan, the state policy priority is to consistently promote energy efficiency in business, the public sector and in households. Achievement of targets for reduction of carbon dioxide emissions according to the plan to reduce emissions of carbon dioxide 1980-2050 suggests that total energy consumption in 2050 should not exceed 2011 levels.

The main goals of the UK in the field of improving energy efficiency and the transition to a "low carbon" economic model: development of a distributed power generation system, including “low carbon” heat generation; more active development of communal systems, including combined heat and power generation systems; active participation in the European carbon trading system; increasing the share of using renewable energy sources; support and development of alternative fuels for transport [2] [4].

A system of national, regional and local funds and agencies to support energy efficiency has been developed.

1.5 Kazakhstan

With the adoption by Kazakhstan of the "Strategy "Kazakhstan 2050"and the Concept of transition to a "green" economy, the country has chosen a fundamentally new way of development of society. According to the Concept, the key role will be played by the focus of state policy on reducing environmental impact, resource conservation and achieving a high level of quality of life of the population. Energy efficiency is one of the central points in a gradual transition to a green economy. At present, in terms of the energy intensity of GDP, Kazakhstan is among the countries with the highest values. According to the experts of the Charter, significant opportunities for improving energy efficiency in industry, energy, housing and communal services and transport are concentrated in Kazakhstan [5] [6].

Energy accounts for about 47% of the total consumption of primary energy resources. At the same time, in the energy sector, there is a high proportion of wear and tear of generating and power grid equipment, which, as a result, leads to low efficiency of power generation and a relatively high amount of losses in power grids. In the industrial sector, a high level of energy consumption is primarily due to the activities of such energy-intensive sectors of the economy as oil and gas, metallurgy and mining. At the same time, the technical condition of the equipment and the problem of reducing the workload of enterprises significantly affect the efficiency of the industry. A number of legislative restrictions adopted in terms of energy consumption in industry have not yet yielded positive results. An analysis of the approved norms of energy consumption in industry showed their inapplicability to the working conditions of some enterprises, especially in terms of the mining and metallurgical complex and coal mining. In terms of housing and communal services, most of the existing housing stock consists of apartment buildings with central heating based on boiler houses or CHP plants. With the current state of infrastructure, district heating networks are characterized by low efficiency and significant heat losses. On average, residential buildings in Kazakhstan consume three times more energy per unit area than in the Nordic countries. The high level of heat loss is mainly associated with outdated equipment, as well as the lack of proper repair. The transport sector accounts for up to 17% of the total consumption of the country's primary energy resources, while the technical condition of a part of the vehicle fleet and the quality of the fuel used have a significant impact on specific fuel consumption and emissions of harmful substances. The transition to new fuel quality standards, the introduction of modern navigation and information systems will improve the energy efficiency of the transport sector and increase the throughput of the transport system.

2 Review and Simulation

2.1 Literature Review

As smart homes have become a very active and well-established research topic, many publications on this topic can be found. This field is developing rapidly and is attracting synergy of several areas of science to improve the quality of life for people.

Richard Harper, who has researched the field of smart technology for private homes, wrote that the way a home is built or environmental considerations will not make it a smart home. But "what makes it smart, is the interactive technology it contains" that can help realize "the dream of a home that can actively help its inhabitants" [7-9].

Research on smart homes has mainly focused on hardware solutions for a long time. Currently, the term mainly refers to the integration of information technology into residential buildings. Safety, healthcare, energy efficiency and improving the comfort of residents are the main research topics in the field of smart homes. Interconnection between devices and advanced control of lighting, entertainment and multimedia devices to improve comfort is proposed in several publications [7] [10-13]. In addition, in the field of security, remote information and intervention systems have been developed to enhance control inside the house when the resident is absent. Another application of security systems mentioned in the literature is presence modeling [14] [15]. However, there is still room for more research in other areas.

Many approaches to energy conservation in buildings using smart technologies can be found in the literature.

Most of the approaches to energy conservation in smart buildings described in the literature aim to reduce the energy consumption of heating, ventilation and air conditioning (HVAC) devices such as a home heating system [16], air conditioning [17], or both [18] [19]. Others do not directly address the reduction in consumption of such devices, but provide improved monitoring and control [8]. Most of these projects use a wide variety of sensors to measure humidity and temperature and process data with a fuzzy controller [20] [21] for power distribution. Others, who also sought to "minimize household energy waste," identified two more areas for incorporating energy management functions: "lighting and appliances" [22] [23]. When simulating various scenarios using synthetic data, they found that the potential for energy savings in private homes is nearly 30 percent. They examined the presence sensors to turn on the lighting devices, that detected the person using infrared heat detection.

The new approach suggests that the controlled home is equipped with some energy efficient devices such as rooftop solar PV panels, energy storage, and controlled / uncontrolled appliances. There are many benefits to implementing this new approach. The main one is that it allows real-time control and monitoring of all the various components connected to a customer/utility-owned home. Thus, the burden of integrating new loads is reduced and further increases the integration of renewable energy sources into the distribution system. In addition, it allows you to implement various home optimization functions to maximize the benefits for both utilities and consumers. All this without any inconvenience to the end user and without overloading/overheating the distribution transformer.

Any system is influenced by external factors. The energy management system includes the use of alternative energy, for example, as in this work – the operation of solar panels. The efficiency of solar panels is directly dependent on the direction of the sun's rays. For best efficiency, the sun's rays should be directed perpendicular to the surface of the module. The illumination of the surface of solar panels with this arrangement will tend to maximum. The system for controlling the maximum illumination during the day must periodically change the position of the solar panels to maintain a right angle between the direction of the rays and its plane, i.e. ensure that solar panels rotate during the day to maximize the flow of solar radiation.

2.2 Data Processing

As a basis for calculating the power generated by the solar panel, we take the monthly electricity consumption. In order to calculate the required power for our solar panel, we need to know the monthly electricity consumption. We can determine the required amount of electricity consumed in kilowatts per hour, by looking at an electric meter (Figure 1).

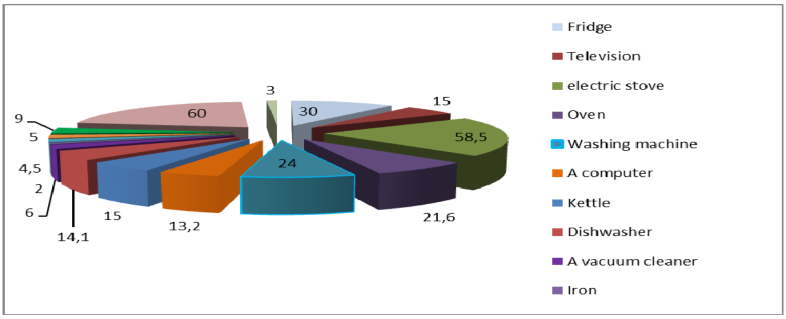

Figure 1
Electricity consumption by various devices

If the costs are, for example, 281 kWh, then the solar battery should generate about 10 kWh of electricity per day. Based on this, it can be calculated that to obtain 10 kWh of energy under ideal conditions, an array of panels with a capacity of at least 1 kW, the number of 15 panels, will be required. In the calculations, it should be borne in mind that solar panels generate electricity only during daylight hours, and their performance depends on both the angle of the sun above the horizon and weather conditions. On average, up to 70% of the total amount of energy is generated from 9am to 4pm, and in the presence of even slight cloudiness or haze, the power of the panels decreases 2-3 times. If the sky is covered with continuous clouds, then at best we can get 5-7% of the maximum capacity of the heliosystem.

After calculating how much energy the solar panel produces in one day, the annual output of the solar panel can be determined (Figure 2) [21].

For example, consider the average daily insolation by months from one of the meteorological servers for Ust-Kamenogorsk. The data are indicated taking into account atmospheric phenomena and are averaged over several years.

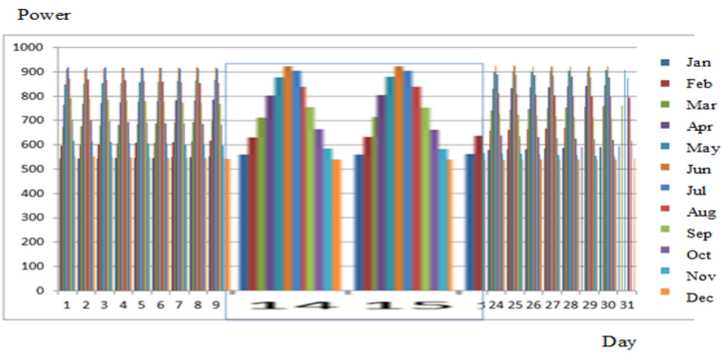

Figure 2
Annual power of the solar panel (2019)

The unit of measurement of insolation in the table is kWh / m^2 / day (kilowatt-hours per square meter per day).

The angle of inclination of the plane, degrees in relation to the ground (0 degrees – insolation on the horizontal plane and 90 degrees – insolation on the vertical plane, etc.), with the plane oriented to the South.

As we can see, the most unfavorable month for this region is December, the daily average insolation on the horizontal surface of the earth is 0.5 kWh / m^2 / day and on the vertical – 1.22 kWh / m^2 / day. With an angle of inclination of the plane relative to the ground of 70 degrees, the insolation will be 1.26 kWh / m^2 / day, the optimal angle for December is 74 degrees. The most favorable month is June and the insolation on the horizontal surface will be 5.27 kWh / m^2 / day, the optimal tilt angle for June is 11 degrees [21].

The angle of inclination of the solar panel, with year-round use in a system that consumes on average the same power regardless of the season, must coincide with the optimal angle of inclination of the most unfavorable month in terms of the amount of solar radiation.

The optimal tilt angle for December in Ust-Kamenogorsk is 74 degrees, so it is worth installing a solar panel, since in other months the insolation is noticeably greater, and as a result, the generation of electricity will be more than enough. Moreover, in winter at tilt angles of 70-90 degrees, precipitation in the form of snow will not accumulate on the solar panel. If the task is to obtain maximum power from solar panels throughout the year, then it is required to constantly orient the solar panel as perpendicular to the sun as possible. Average daily insolation by months is presented in Table 1.

Table 1
Average daily insolation by months

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average annual insolation kW * h / m2 / day
0°	0.75	1.56	2.81	3.87	5.13	5.27	5.14	4.30	2.63	1.49	0.81	0.50	2.86
40°	1.51	2.55	3.78	4.34	5.12	4.97	5.00	4.57	3.22	2.20	1.46	1.08	3.32
55°	1.66	2.70	3.82	4.16	4.70	4.51	4.53	4.31	3.17	2.27	1.58	1.20	3.22
70°	1.72	2.71	3.67	3.79	4.18	3.95	4.00	3.85	2.97	2.24	1.62	1.26	3.00
90°	1.65	2.50	3.19	3.07	3.21	2.99	3.05	3.08	2.51	2.02	1.53	1.22	2.50
Optimal angle	72.0	63.0	50.0	34.0	20.0	11.0	16.0	27.0	43.0	58.0	69.0	74.0	44.6

The choice of a suitable neural network for modeling depends on the specific task, as well as on the type of data and their volume. There are many classifications of networks, but for solving problems typical for the electricity market, it is best to use a multilayer perceptron (the problem of predicting energy consumption) and Kohonen networks (the problem of constructing a client profile of electricity consumption).

In the real world, there are many parameters that affect power consumption and determine the dimension of the vector of input signals X, and not all of them have the same effect on power consumption. For example, it can be assumed that the electrical load in the forecast period depends on the following parameters (predictors): load in the last week; day of the week; number of working days; the duration of daylight hours; air temperature; cloudy; the end of the month; customer equipment maintenance schedule; duration of the heating period; client type; branch of the economy. How can we single out the most significant among the many parameters?

Most of the significant parameters for forecasting consumption relate to the so-called cyclical parameters: daily, weekly dependencies; monthly, quarterly, annual; weekends / working days, etc. And another significant group of parameters is determined by functional characteristics: meteorological conditions; client type; branch of the economy; characteristics of premises, etc. In addition, today it is customary to single out the factors of the market environment (www.gkhprofi.ru/news.php?id=69) that affect consumption: volumes and prices of the “day ahead market”; volumes and prices of the "balancing market"; market supply and demand, etc.

2.3 Simulation

Let's consider a simplified model for solving problems typical for the electric power industry.

Description of the model. A multilayer perceptron is a network of several layers of neurons connected in series. At the lowest level of the hierarchy is the input layer of sensory elements $x_1, \ldots, x_L$, whose task is only to receive and distribute the input information over the network. Further, there is one or (less often) several hidden layers (Figure 3).

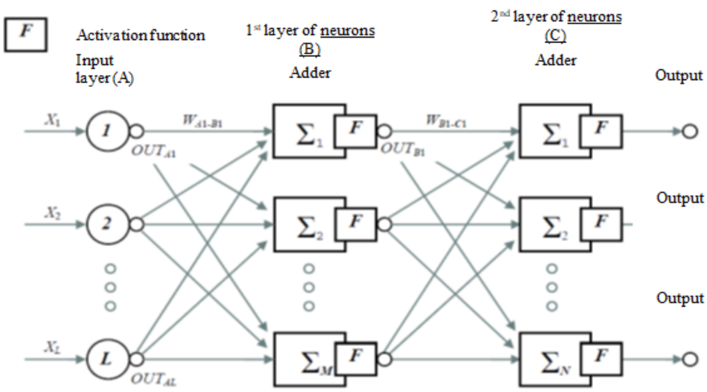

Figure 3
The structure of the neural network

Each neuron on the hidden layer has several inputs connected to the outputs of the neurons of the previous layer or directly to the input sensors $x_1, \ldots, x_L$, and one output. The outputs of the neurons of the last, output layer describe the result processed by the network. The neurons of each layer are not connected with each other and only interact with the neurons of the previous and subsequent layers. Each neuron sums up the signals coming to it from the neurons of the previous hierarchy level with weights, and then, using the activation function, transforms the summation result. The activation function F (ξ) provides the nonlinearity required for the convergence of the learning process. The neuron output signal is given by the expression:

$$OUT = F(\xi) = 1/(1 + \exp(-\xi)) \qquad (1)$$

where $\xi = \sum_{k-1}^{L} x_k w_k$; x_k — neuron inputs; w_k — synaptic weights of inputs; L — is the number of neuron inputs. The sigmoid is selected as the activation function. The structure of the neural network used in this work is shown in Figure 3.

The following designations are used: - each layer of the neural network has its own letter (for example, the letter A corresponds to the input layer, the output to C; - the neurons of each layer are numbered with Arabic numerals; - W_{A1-B1} - synaptic weight between neurons A1 and B1; - OUT_{A1} - output neuron A1. Before using a neural network to obtain a forecast, it must be trained, that is, to determine the synaptic weights. The deterministic method of back propagation of the error is often used to train perceptrons [15] [20]. This method assumes a priori knowledge of the set of required outputs of the neurons of the last layer networks, called target, for a given set of inputs of the initial (zero) layer. For brevity, these sets of inputs and outputs will be called vectors. During training, it is assumed that for each input vector there is a target vector that parallels it, specifying the required output. These vectors are called a training pair The network learns on many pairs. The optical weights are initialized to random numbers ranging from 0 to 0.1. The learning process consists in calculating the output vector of the network and correcting the weight matrices for each training pair at each iteration according to the formulas below [6] [19]. The formula for correcting the weights for the output layer is $w_{p-k}(i + 1) = w_{p-k}(i) + \eta\delta_k OUT_p$, where i is the number of the current training iteration;

$$\delta_k = OUT_k(1 - OUT_k)(T_k - OUT_k) \quad (2)$$

- w_{p-k} : is the value of the synaptic weight connecting the neuron p of the hidden layer with the neuron k of the output layer
- η : coefficient of "learning rate", which allows you to control the average value of the change in the weights
- OUT_p : output of neuron p of the hidden layer
- T_k : is the target value of the output of the neuron k of the output layer
- OUT_k : output of neuron k of the output layer

The formula for correcting the weights for the hidden layer is written as:

$w_{p-q}(i + 1) = w_{p-q}(i) + \eta\delta_q OUT_p$, where i is the number of the current training iteration;

$$\delta_q = OUT_q(1 - OUT_q)(T_k - OUT_k) \quad (3)$$

$$\delta_q = OUT_q(1 - OUT_q)\sum_{k=1}^{N} \delta_k w_{q-k};\ w_{p-q} \quad (4)$$

w_{p-q} — is the value of the synaptic weight connecting neuron p of the previous (in this case, input) layer with neuron q of the hidden layer

η — is the coefficient of “learning rate”, which allows to control the average value of the change in the weights

OUT_p — output of neuron p of the previous (in this case, input) layer

OUT_q — output of neuron q of the hidden layer

N — is the number of neurons of the next (in this case, output) layer. The iteration includes enumerating all training pairs and summing the mean square errors of predictions over all network outputs of all training pairs E(i). The learning process ends when the difference between the total errors of the current and previous iterations E(i)−E(i−1) is less than a given threshold.

In this paper, we propose a model consisting of two similar perceptrons, one of which is applicable for predicting the hourly load profile of a working day, the other for a weekend or holiday. In the proposed model, the learning processes for workdays and weekends (or holidays) were separated, i.e., four matrices of synaptic weights were calculated (two for each perceptron). When training one neural network, the actual data of only working days were selected, and the resulting weight matrices were used only when predicting the load profile of working days. The second neural network was used to predict the load profile of weekends (or holidays). In the case under consideration, the output layer, which is an hourly load profile for a day, contains 24 neurons, the hidden layer contains 15 neurons, and the input layer contains 30 neurons. The input vector contains the characteristics of electricity consumption for the previous day (3 neurons), the average daily air temperatures of the previous day and the forecast of the air temperature of the forecast day (2 neurons). When training the perceptron, the known actual temperature was used as a temperature prediction. To account for seasonality, 12 neurons are used by the number of months in a year and three by the number of decades L. A. Delegodin 69 per month, and to account for the type of day - 10 neurons (seven days of the week, holidays, pre-holiday and post-holiday days). The number 10 is supplied to three of these inputs, corresponding to the month, decade in the month and the type of the predicted day, and the number 1 is supplied to the other inputs. the value of the maximum and minimum hourly costs for the previous day, in the calculation of which it is taken into account whether the forecast day is a working day or a day off (or a holiday). The learning process for each network includes two stages. First, the network is trained on the entire set of training pairs (a time interval of up to 1.5 years, depending on the actual data available in the database), and then it is retrained on a minimum time interval (a month preceding the predicted day). The training pair is the input vector and the target vector (known actual hourly load profile for the day represented by the input vector). The values of the input and target vectors are normalized, that is, they are converted to relative values in the range from 0 to 1. The forecast accuracy based on the use of artificial intelligence methods depends on the available input data that determine the network architecture, the degree of data reliability and the required forecast period. For short-term forecasting of the enterprise load, the necessary initial data are statistical reporting data on daily power consumption. For high reliability of the data used at the enterprise under study, a high-precision multifunctional automated system for monitoring and accounting for consumption should be initially implemented. Such a system was created, for example, in 2005 at the Novosibirsk Scientific Center within the framework of the Energy Saving SB RAS program [18] [24] [25]. The system contains a central server with an integrated database and 26 peripheral data collection centers with their own local databases in the institutes of the center. An important result of the creation of this system is the receipt of a large array of sufficiently detailed information about the flows of various energy resources and the technological parameters of these resources.

Confidence intervals were calculated using a sample of 100 items. The average forecast error is 0.65%. Profiles of daily actual and predicted loads of consumption of active electricity for two decades of April: 1 - actual load; 2 - the predicted load is 0.87, the value of the confidence interval is 0.27 kWh, the minimum is 0.01 kWh, the average error of the hourly forecast is 1.87%. The average forecast error is 0.65%. Let's consider in detail the construction of a fragment of a neural network. The LVQ (Learning Vector Quantization) network – learning vector quantization – or the input vector classification network, which is a development of Kohonen's self-organizing map (SOM) [7] [14], was chosen as a neural network (NS) (Figure 4).

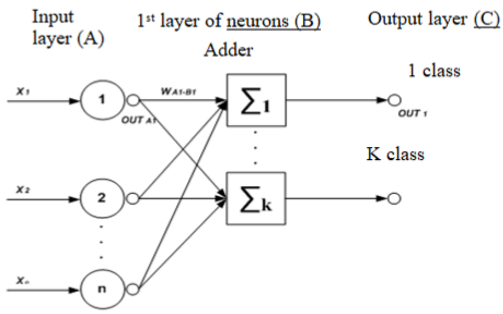

Figure 4

Block diagram of a neural network

Let's consider the description of the main actions of the developed algorithm.

The neural network analysis 1… .k of the states of the energy consumption system of the house is carried out simultaneously by parallel analysis of the registered signal by each neural network, as a result of the analysis, an array of data is obtained from the outputs of the neural networks. Let's make an amendment: we are talking about the energy consumption system – energy supply. Further in the text, we will use one of the components of the system for brevity.

Then the post-processing of the neural network results is carried out, and the data from the outputs of the neural networks is sent to logical blocks designed to identify the corresponding state of each block of the energy consumption system of the house, and then to the priority encoder designed to highlight the corresponding state of the energy consumption of the house as a whole. Then the output of the neural network analysis result is carried out. Logic blocks are based on decision rules for each state of the home's energy system.

The construction of decision rules for analyzing the outputs of neural networks is based on the fact that deviations at each of the MI localizations are not manifested in all leads. To construct the decision rules for choosing one of the k states of the energy consumption system of a house, Table 2 is compiled. Table 2 presents combinations of the presence and absence of signs of excess power consumption in various localizations [15] [20].

Table 2

Household Energy System - Possible Scenarios

Scenario	**Appliances consuming electricity**														
	Ref	TV	Est	Ov	WsM	PC	Pot	DsM	Vac	Ir	McW	MCo	bulb	Ht	Led
Sc 1	+	-	+	-	+	-	-	+	+	+	-	-	-	-	+
Sc 2	+	-	-	-	+	+	-	+	-	-	-	-	+	+	-
Sc 3	+	+	-	-	+	+	+	+	+	+	+	+	-	-	+
Sc 4	+	+	-	+	-	+	+	+	-	-	+	+	-	+	+
Sc 5	+	-	+	-	-	+	+	+	-	-	-	-	+	-	-
Sc 6	+	+	-	+	-	-	-	+	+	+	+	-	-	-	-
Sc 7	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Sc 8	+	-	-	-	-	-	-	-	-	-	-	-	-	+	+

Logic blocks are used to analyze data from the outputs of each NS. One logical block is used for each state of the home energy system. The inputs of the block receive the data obtained as a result of the NSA of those leads, which, in accordance with Table 1, "signal" the presence of excess power consumption and the data obtained as a result of the neural network analysis of the leads that do not "signal" the presence of a critical excess, i.e. correspond to the norm.

Decision rules for eight situations are constructed in accordance with Table 2:

1) The energy generated by solar panels is sufficient, you can use the energy storage mode:

$$F_1 = Ref\&\overline{TV}\&Est\&\overline{Ov}\&WsM\&\overline{PC}\&\overline{Pot}\&DsM\&Vac\&Ir\&\overline{McW}\&\overline{MCo}\&\overline{bulb}\&\overline{Ht}\&Led$$

2) The energy generated by solar panels is sufficient:

$$F_2 = Ref\&\overline{TV}\&\overline{Est}\&\overline{Ov}\&WsM\&PC\&\overline{Pot}\&DsM\&\overline{Vac}\&\overline{Ir}\&\overline{McW}\&\overline{MCo}\&bulb\&Ht\&\overline{Led}$$

3) The energy generated by solar panels is enough for the operation of devices, connect an alternative source or battery for insurance:

$$F_3 = Ref\&TV\&\overline{Est}\&\overline{Ov}\&WsM\&PC\&Pot\&DsM\&Vac\&Ir\&McW\&MCo\&\overline{bulb}\&\overline{Ht}\&Led$$

4) The energy generated by the solar panels is enough for the operation of

the included devices, for insurance, connect an alternative source or battery:

$$F_4 = Ref\&TV\&\overline{Est}\&Ov\&\overline{WsM}\&PC\&Pot\&DsM\&\overline{Vac}\&\overline{Ir}\&McW\&MCo\&\overline{bulb}\&Ht\&Led$$

5) The energy generated by the solar panels is enough for the operation of the included devices:

$$F_5 = Ref\&\overline{TV}\&Est\&\overline{Ov}\&\overline{WsM}\&PC\&Pot\&DsM\&\overline{Vac}\&\overline{Ir}\&\overline{McW}\&\overline{MCo}\&bulb\&\overline{Ht}\&\overline{Led}$$

6) The energy generated by solar panels is sufficient, you can use the energy storage mode:

$$F_6 = Ref\&TV\&\overline{Est}\&Ov\&\overline{WsM}\&\overline{PC}\&\overline{Pot}\&DsM\&Vac\&Ir\&McW\&\overline{MCo}\&\overline{bulb}\&\overline{Ht}\&\overline{Led}$$

7) The energy generated by solar panels is barely enough to operate the devices, connect an alternative source or battery for insurance:

$$F_7 = Ref\&TV\&Est\&Ov\&WsM\&PC\&Pot\&DsM\&Vac\&Ir\&McW\&MCo\&bulb\&Ht\&Led$$

8) The energy generated by solar panels is surplus, you can use the energy storage mode:

$$F_8 = Ref\&\overline{TV}\&\overline{Est}\&\overline{Ov}\&\overline{WsM}\&\overline{PC}\&\overline{Pot}\&\overline{DsM}\&\overline{Vac}\&\overline{Ir}\&\overline{McW}\&\overline{MCo}\&\overline{bulb}\&Ht\&Led,$$

Here,

Ref, TV, Est, Ov, WsM, PC, Pot, DsM, Vac, Ir, McW, MCo, bulb, Ht, Led, $\overline{TV}, \overline{Est}, \overline{Ov}, \overline{WsM}, \overline{PC}, \overline{Pot}, \overline{DsM}, \overline{Vac}, \overline{Ir}, \overline{McW}, \overline{MCo}, \overline{bulb}$

are data from the outputs of the neural network.

At the stage of analyzing the outputs of neural networks (1 ... k)., Based on the decision rules (1 ÷ 8), a decision is made on the state of the power supply of the house. With the help of a priority encoder, one of the particular solutions obtained as a result of the analysis of the value of k by neural networks is selected. At the output of the priority encoder, a code of the input line number is formed, to which a positive input signal comes (a signal of a logical unit from the output of one of the k neural networks participating in the analysis). When several input signals arrive simultaneously, an output code is generated that corresponds to the input with the highest number, i.e. the higher inputs have priority over the lower ones. Therefore, the scrambler has priority. The result of performing the work of this stage is the number of the conclusion on the state of the energy consumption system. Then the resulting number is assigned a verbal description of the conclusion on the state of energy consumption, which is reported to the user.

The influence of the following parameters was investigated to assess the quality of training: the redundancy of the training sample, the amount of noise, the magnitude of the shift, the number of neurons in the hidden layer, the number of learning epochs. One of the reasons for the identified drawback is the problem of "dead" neurons, the essence of which is that in the process of learning the neural network, in reality, the weights of only a limited number of neurons are updated.

As a result of the research carried out, the following numerical indicators of the quality of teaching NS LVQ were obtained: specificity: 80%; sensitivity: 70%; generalization error: 0.25; learning error: 0.08. After training the neural network, the structure of the constructed fuzzy model will contain 252 rules. The two response surfaces of the system, obtained as a result of training, are shown in the Figure 5.

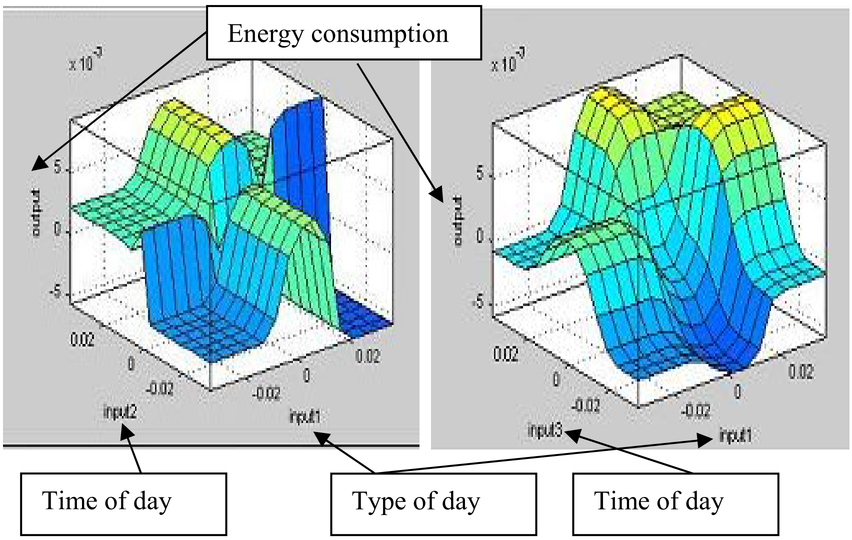

Figure 5

System response surfaces obtained as a result of training

The defuzzification stage allows to get a non-fuzzy value for each of the output variables, using the results of the accumulation of all output linguistic variables. The resulting surface allows to analyze the dependence of the values of the output variable on individual input variables. Combinations of input variables are set in accordance with their placement on the axes of the coordinate system. On the graph on the left, the dependence of energy consumption on the time of day and type of day, on the right, on the season and type of day.

The results obtained indicate the possibility of using the proposed approach to predict the electrical load. Neural networks are a suitable tool for solving energy consumption forecasting problems, alternative to traditional statistical methods.

Further improvement of the forecast accuracy is possible due to more accurate and fine tuning of the network structure and changing the number of input parameters.

The software is implemented in the C# environment in accordance with the developed schemes and requirements. Certificate of authorship for software #16772 on 14.04.2021 "Residential building intelligent energy management system "Smarthouse".

Development of the experimental installation and software will be discussed in details on AIS2022 and in the next publications.

Conclusions

The modern advanced approaches to the energy saving policy of such developed countries as the USA, Japan, Great Britain and some countries of the European Union are considered. Energy efficiency development trends in the world and the Republic of Kazakhstan.

The analysis of studies on smart home automation systems is carried out, their methods and their potential in the field of issuing recommendations for energy saving are discussed. We suppose that unpredicted situations, such as a pandemic, for example, will not significantly affect the accuracy of the system.

After analyzing the resulting fuzzy inference surface, we can conclude that it corresponds to expert ideas in the subject area under consideration. So, for example, it can be said that with the approach of the winter months and the simultaneous increase in load in the morning and evening hours, the situation becomes more complicated and more energy is required from the AC network. Accordingly, during the night hours in the summer, the battery power from solar panels is sufficient. Thus, the power of the selected solar panels is sufficient for the warm season at night and daytime, provided there are working days without the use of an alternating current network. At the same time, it is impossible to refuse to connect to the general AC network during peak loads in the morning and evening, as well as, in the cold season due to the connection of heating.

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