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Hybrid neural network-heuristic model for forecasting the energy demand of livestock farms

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ABSTRACT

Relevance. The article is devoted to the development and investigation of neural network and hybrid neural network–heuristic models for forecasting the energy demand of livestock farms. **Purpose and objectives.** The study aims to develop a hybrid neural network–heuristic model for forecasting the energy demand of livestock farms based on the integration of recurrent neural networks and heuristic optimization algorithms, enabling improved short-term forecasting accuracy under variable production and external conditions. The study develops a neural network model for forecasting the energy demand of a livestock farm based on recurrent architectures of long short-term memory and gated recurrent units, capable of processing multifactor hourly time series that characterize the operating modes of farm equipment. **Methods.** The baseline forecasting model is based on recurrent neural network architectures, including long short-term memory and gated recurrent units, while hyperparameter adjustment is performed using an evolutionary genetic algorithm. Model implementation and computational experiments were carried out using the Python programming language in a cloud computing environment. **Results.** The baseline neural network model demonstrated an acceptable level of forecasting accuracy, confirming its ability to reproduce the overall dynamics of energy consumption and seasonal variations. A hybrid neural network–heuristic model for forecasting the energy demand of livestock farms is proposed and formalized, combining a recurrent neural network forecasting module with a heuristic hyperparameter optimization algorithm. The use of an evolutionary genetic algorithm for automated tuning of the neural network architecture and training parameters is substantiated. This approach increased the model's adaptability to changes in livestock farm operating regimes and reduced forecasting errors without a significant increase in computational complexity. As a result of the optimization procedure, an optimal neural network configuration was identified, characterized by an extended memory window, short-term forecasting horizon, and rational structure of hidden layers. The optimized model provided a noticeable reduction in forecasting errors compared to the baseline solution. To validate the effectiveness of the proposed hybrid model, computer experiments were conducted using data from a livestock farm. **Conclusions.** The obtained results confirmed stable forecasting performance both under average energy consumption regimes and peak load conditions, indicating the feasibility of applying the developed hybrid model as an analytical basis for decision support in the management of autonomous energy systems of livestock farms..

Keywords: Energy demand; livestock farms; neural networks; hybrid model; genetic algorithm; heuristic optimization

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INTRODUCTION

Modern livestock farms operate under conditions of constantly increasing energy loads, which is due to the introduction of automated systems for animal husbandry, climate control, feeding, milking, and waste processing. Under such conditions, energy consumption becomes an important factor in the economic efficiency and stability of production processes. The problem is further complicated by fluctuations in energy prices, instability of centralized power supply, and the need to integrate renewable and autonomous energy sources, which leads to increased requirements for the accuracy of energy demand forecasting [1], [2], [3].

Traditional approaches to energy consumption forecasting, based on statistical methods and classical regression models, have a limited ability to take into account the nonlinear nature and dynamic variability of energy processes. Energy demand on livestock farms is influenced by a complex set of factors, including seasonal fluctuations, meteorological conditions, animal biological cycles, equipment operating modes, and production process schedules. Under these conditions, classical methods often do not provide adequate forecast accuracy, especially in a changing or uncertain project environment [4], [5].

The development of computational intelligence methods has opened up new opportunities for predicting the energy consumption of complex systems. In particular, artificial neural networks are widely used for modeling nonlinear dependencies and analyzing time series in energy problems. Recurrent neural networks, in particular Long Short-Term Memory and Gated Recurrent Unit architectures, which are capable of storing and using information about long-term time dependencies [6], [7], [8], have proven to be particularly effective in such tasks. The above indicates their suitability for use in forecasting energy demand, which is characterized by both short-term changes and seasonal fluctuations.

At the same time, the effectiveness of neural network models largely depends on the correct choice of hyperparameters, such as the number of hidden layers, the number of neurons, the learning rate, and the length of time windows. The process of manually adjusting these parameters is laborious and does not guarantee optimal results. In this regard, scientific research increasingly uses heuristic and metaheuristic optimization methods, in particular genetic algorithms, which provide an effective search for optimal solutions for multidimensional parameters [9], [10], [11].

The combination of neural network models with heuristic optimization algorithms forms a hybrid approach to forecasting, which improves the accuracy and stability of models under variable operating conditions. In recent studies, such hybrid approaches have proven effective in forecasting the energy consumption of buildings, industrial facilities, and local power systems, but their application in the agricultural sector, particularly for livestock farms, remains understudied [12], [13], [14].

These conditions highlight the need for accurate short-term energy demand forecasting tools that can operate under nonlinear, dynamic, and uncertain environments typical for livestock farms. The development of such tools is a prerequisite for effective energy planning and further implementation of intelligent energy management solutions in agricultural production systems.

LITERATURE ANALYSIS

In recent years, there has been a significant increase in the number of scientific studies devoted to energy consumption forecasting using artificial intelligence methods. The main focus of these studies is on solving short- and medium-term electrical load forecasting problems for buildings, microgrids, and hybrid energy systems. Generalized reviews show that traditional statistical models are gradually being replaced by intelligent approaches capable of taking into account the nonlinearity of processes, the stochastic nature of data, and the influence of external factors [15], [16], [17]. These studies demonstrate that the transition from classical statistical models to machine learning and neural network–based approaches has led to a reduction in forecasting errors due to the ability of such models to capture nonlinear relationships and the influence of exogenous factors. However, most of the reviewed approaches remain limited by their dependence on predefined model structures and assumptions regarding data stationarity, which restricts their adaptability to highly dynamic energy consumption patterns.

Much of the current research focuses on the application of recurrent neural networks for the analysis of energy consumption time series. In particular, Long Short-Term Memory and Gated Recurrent Unit architectures are used to forecast electrical loads due to their ability to store information about long-term time dependencies. Comparative studies show that LSTM and GRU models are more accurate than classical methods and shallow neural networks in terms of accuracy, especially in the presence of seasonal and daily fluctuations [18], [19], [20]. These advantages indicate that recurrent networks are a promising tool for use in energy demand forecasting tasks for complex production systems.

The improvement in forecasting accuracy is primarily achieved through the ability of LSTM and GRU architectures to model long-term temporal dependencies and mitigate the vanishing gradient problem. At the same time, their performance strongly depends on the selection of architectural parameters and input sequence length, which may lead to overfitting or unstable predictions if not properly configured.

A separate area of modern research is related to the application of deep learning. Such models are directly used in the agricultural sector and, in particular, in animal husbandry. In works [21], [22], [23], the effectiveness of using neural network models for forecasting electricity consumption on industrial livestock farms with a forecast of up to 24 hours, taking into account meteorological parameters and production conditions [24], was investigated. In addition, predictive models can be integrated into farm management systems, in particular ventilation and microclimate, in order to reduce energy consumption without compromising animal welfare [25]. At the same time, the authors of these works focus on specific technological subsystems and do not consider the task of optimally configuring the predictive models themselves.

Despite the positive results reported in these studies, most approaches focus on specific technological subsystems and apply fixed neural network architectures without systematic optimization of their hyperparameters. This limits the scalability and transferability of such models to different livestock farms operating under varying production and environmental conditions.

A significant limitation of neural network models, which researchers point out, is the dependence of prediction results on the choice of hyperparameters and architectural solutions. Incorrect selection of the input window length, number of layers, or learning rate leads to overfitting, unstable predictions, or high computational costs. In this regard, recent studies have increasingly used automated tuning methods, among which metaheuristic algorithms occupy a special place [26], [27], [28].

Genetic algorithms have proven to be an effective tool for optimizing the hyperparameters of neural network models in time series forecasting tasks. In some studies [29], [30], [31], it has been shown that using a genetic algorithm to tune LSTM models allows for a better balance between prediction accuracy and model generalization compared to classical search methods or manual parameter selection. Such approaches are quite relevant for applied tasks where data has a complex structure and contains noise and gaps, which is typical for real energy systems on farms. Nevertheless, the effectiveness of genetic algorithms depends on the choice of population size, mutation and crossover rates, and may involve increased computational effort, which necessitates their careful adaptation to the specific characteristics of the forecasting task.

At the same time, research is being conducted on intelligent energy management of hybrid and autonomous energy systems. Some researchers emphasize that effective management of such systems is impossible without accurate load forecasts, which are used as input data for decision-making algorithms and optimization of equipment and energy storage modes [32], [33], [34]. At the same time, it is advisable to combine predictive models with optimization algorithms within a single intelligent tool.

A review of the literature indicates that existing approaches to energy consumption forecasting have achieved significant improvements through the use of recurrent neural networks and metaheuristic optimization techniques. However, most models are either designed for urban or industrial energy systems or apply isolated forecasting and optimization procedures without their integration into a unified framework. In addition, the specific operational conditions of livestock farms, including variability in production processes and partial autonomy of energy supply, are often insufficiently considered. These limitations highlight the need for developing a hybrid neural network–heuristic model tailored to livestock farm conditions, which can provide accurate load forecasting as a basis for intelligent energy management.

FORMULATION OF THE PROBLEM

The current state of energy supply for livestock farms is characterized by significant variability of energy demand caused by seasonal, daily, and technological factors. These conditions complicate energy planning and increase the risk of inefficient use of generation and storage resources, especially in autonomous and hybrid energy systems.

Existing energy demand forecasting approaches for livestock farms are predominantly based on simplified statistical models or fixed-structure neural networks, which do not sufficiently account for nonlinear dynamics and changing operating regimes. As a result, such approaches provide limited forecasting accuracy and lack adaptability to real operational conditions.

Therefore, the problem addressed in this study is the development of an energy demand forecasting approach capable of processing multifactor time series and adapting to variable operating conditions of livestock farms.

THE PURPOSE AND THE OBJECTIVES OF THE STUDY

The aim of the work is to develop a hybrid neural network-heuristic model for forecasting energy demand for livestock farms, which is based on a combination of recurrent neural networks and heuristic optimization algorithms, which, unlike

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existing ones, provides increased forecasting accuracy, adaptability to changes in production and external conditions, as well as the possibility of practical use in energy planning tasks for autonomous and hybrid energy systems.

In this study, forecasting accuracy is quantitatively evaluated using MAE, RMSE, and MAPE metrics, while adaptability and stability are assessed based on the model's ability to preserve prediction accuracy under changing operating regimes, including peak load periods and abrupt variations in energy consumption observed in the experimental data.

To achieve this goal, the following tasks should be solved in the work:

– develop a neural network model for forecasting energy demand based on LSTM/GRU recurrent architectures, capable of effectively analyzing multifactorial time series;

– develop and formalize a hybrid neural network-heuristic model for forecasting energy demand, combining a neural network forecasting module with a heuristic optimization algorithm;

– to form and implement a heuristic algorithm for optimizing the hyperparameters of the neural network component of the hybrid model in order to improve the accuracy and stability of forecasts;

– to conduct an experimental verification of the proposed hybrid model on data from real livestock farms and evaluate its effectiveness in terms of forecasting accuracy.

RESEARCH METHODS

The study employs methods of time series analysis, recurrent neural networks, and heuristic optimization to address the task of short-term energy demand forecasting for livestock farms. Multifactor hourly time series of energy consumption, meteorological parameters, and production indicators are used as input data.

In this study, the term energy demand refers to the instantaneous electrical power demand of a livestock farm, expressed in kilowatts (kW), rather than cumulative energy consumption measured in kilowatt-hours (kWh). The forecasting task is formulated as short-term prediction of power demand time series, which are subsequently used for energy planning and management purposes.

The input dataset used for training and testing the hybrid forecasting model consists of multifactor time series representing the operational conditions of a livestock farm. The input data include hourly energy consumption measurements, meteorological parameters, and production-related indicators. All data streams are synchronized in time and aggregated to a uniform hourly resolution to ensure consistency of the input sequences.

To construct the input samples for the neural network models, a sliding window approach was applied. Each input vector is formed by a sequence of historical observations over a fixed time window, while the target output corresponds to the forecasted energy demand for the subsequent prediction horizon. This approach enables the model to capture short-term and seasonal temporal dependencies inherent in energy consumption data.

Recurrent neural network architectures, specifically Long Short-Term Memory and Gated Recurrent Unit models, are applied to capture temporal dependencies in energy consumption data. A heuristic optimization algorithm is used to tune the hyperparameters of the neural network models. Forecasting accuracy is evaluated using standard statistical error metrics.

The main forecasting tool is recurrent neural networks of Long Short-Term Memory and Gated Recurrent Unit architectures, selected for their ability to take into account long-term time dependencies and adapt to nonlinear changes in data. Neural network models were trained based on historical data using a procedure of dividing the sample into training, validation, and test subsets to ensure the generalizability of the models.

A genetic algorithm is used for automated tuning of the hyperparameters of the neural network component, which ensures effective search for optimal configurations in a multidimensional parameter space. Optimization is performed using the forecast quality function as an adaptability criterion, which allows to increase the accuracy and stability of forecast results under various conditions of livestock farm operation.

Experimental verification of the proposed hybrid neural network-heuristic model was performed on data from a real livestock farm. Standard statistical error indicators were used to evaluate the accuracy of the forecast, and the results obtained were compared with the basic forecasting models. This approach allows for an objective assessment of the effectiveness of the proposed model and justifies its use in practical energy planning tasks.

The described data collection and preprocessing pipeline corresponds to the input data and defines the structure of the input samples supplied to the forecasting module of the hybrid model.

NEURAL NETWORK MODEL FOR ENERGY DEMAND FORECASTING BASED ON RECURRENT LSTM/GRU ARCHITECTURES

Forecasting energy demand for livestock farms involves analyzing multifactorial time series, in which load values are determined both by previous system states and by external factors. These factors include the operating modes of technological equipment, microclimatic parameters, seasonal fluctuations, and daily cycles of production activity. Given these characteristics, it is advisable to use recurrent neural networks capable of storing information about time dependencies and adapting to the nonlinear dynamics of processes to build a predictive model.

The input data for the neural network model is formed as a multidimensional time series, which is presented as a sequence of vectors:

$$X = \{x_1, x_2, \ldots, x_T\}\ , \tag{1}$$

where $x_t = [P_t, z_t]$ is the vector of features at time t; P_t is the actual energy consumption; z_t is a set of external factors, including air temperature, humidity, ventilation modes, and other equipment.

The forecasting task is to determine the forecast value of energy demand $\bar{P}_{t+\Delta}$ at a given horizon based on previous observations. To model such dependencies, a long short-term memory (LSTM) recurrent neural network is used in the work. The main feature of LSTM is the presence of information flow control mechanisms implemented using input, forget, and output valves. Mathematically, the operation of an LSTM cell can be described by a system of equations:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)\ , \tag{2}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)\ , \tag{3}$$

$$\bar{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)\ , \tag{4}$$

$$c_t = f_t e c_{t-1} + i_t e \bar{c}_t\ , \tag{5}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)\ , \tag{6}$$

$$h_t = o_t \bullet \tanh(c_t)\ , \tag{7}$$

where h_t is hidden state; c_t is memory state; $\sigma(\cdot)$ is sigmoid activation function; e is the candidate cell state (candidate memory content) computed in equation (4) using the hyperbolic tangent activation function; $\bullet$ is componentwise multiplication.

This structure allows storing important information about previous states of the system and effectively reproducing long-term dependencies in energy consumption time series.

Along with LSTM, the study considers the use of the Gated Recurrent Unit architecture, which is a simplified version of a recurrent network and is characterized by fewer parameters. The GRU mechanism is based on the use of update and reset gates, which are described by the following relationships:

$$z_t = \sigma(W_z[h_{t-1}, x_t])\ , \tag{8}$$

$$r_t = \sigma(W_r[h_{t-1}, x_t])\ , \tag{9}$$

$$h_t = \tanh(W_h[r_t e h_{t-1}, x_t])\ , \tag{10}$$

$$h_t = (1 - z_t) e h_{t-1} + z_t e h_t\ , \tag{11}$$

In equations (2)–(11), the following notation is used. The symbols W_i with different indices denote weight matrices and weight vectors of the recurrent neural network, where superscripts indicate the corresponding network layer and subscripts define the connections between input, hidden, and output units. Bias terms are denoted by b_i with appropriate indices. The symbol e in equation (5) represents the element-wise activation error (residual) associated with the corresponding gate computation. The activation functions $\sigma(\cdot)$ and $tanh(\cdot)$ denote the logistic sigmoid and hyperbolic tangent functions, respectively. All vector and matrix operations are performed in accordance with standard recurrent neural network formulations.

Due to its lower computational complexity, GRU can be an effective alternative to LSTM in cases of limited computational resources or the need for faster model training.

The architecture of the neural network model for forecasting energy demand is shown in Fig. 1. It includes an input layer for feeding multi-factor time series data, one or more LSTM/GRU recurrent layers, and an output linear layer that generates the forecast value of energy demand. This structure allows the model to be adapted to different time window lengths and data complexity.

The neural network model is trained by minimizing the loss function, which reflects the difference between actual and predicted energy consumption values. The work uses the root mean square error:

$$L = \frac{1}{N}\sum_{t=1}^{N}(P_t - \bar{P}_t)^2\ , \tag{12}$$

where N is the number of observations in the training sample.

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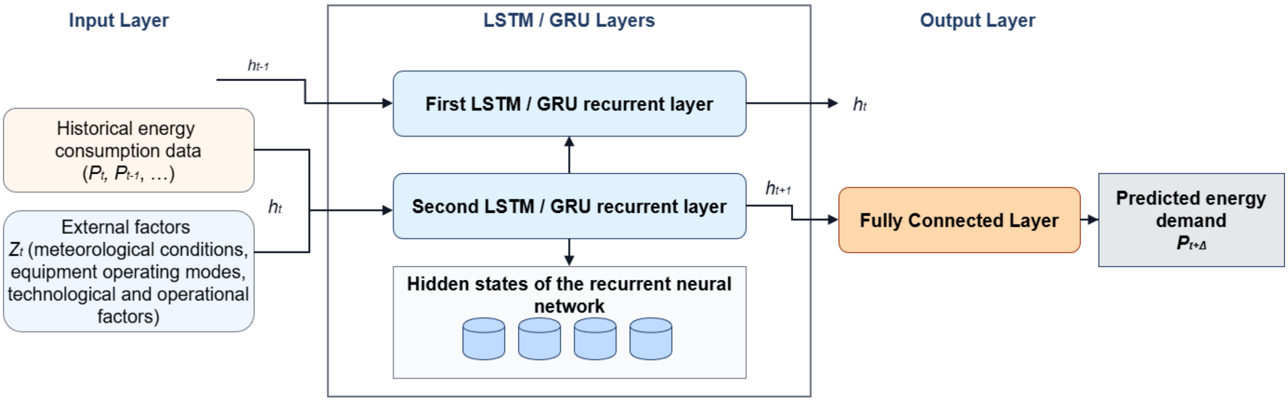

Fig.1. **Architecture of a neural network model for forecasting energy demand based on LSTM/GRU**
***Source*: compiled by the authors**

The root mean square error L is used to quantitatively assess the difference between actual and predicted energy consumption values and is used as an objective function during model training. Model parameter optimization is performed using gradient methods, which ensures the convergence of the training process [36].

The main hyperparameters of the neural network model, which are subject to adjustment within the hybrid approach, are shown in Table 1. Their selection significantly affects the accuracy of forecasting and the generalizing ability of the model, which justifies the feasibility of further heuristic optimization.

Table 1. **Basic hyperparameters of the neural network prediction model**

Parameter	Description
Time window length	Number of previous observations
Number of recurrent layers	LSTM/GRU depth
Number of neurons	Hidden state size
Learning rate	Optimization step
Activation function	Type of nonlinear transformation

***Source*: compiled by the authors**

Thus, the developed neural network model based on LSTM/GRU recurrent architectures provides accurate forecasts of energy demand for livestock farms, taking into account the multifactorial nature of data and time dependencies. The resulting model is a basic component of a hybrid neural network-heuristic model, which is further supplemented by a heuristic algorithm for optimizing hyperparameters to improve forecasting efficiency.

HYBRID NEURAL NETWORK-HEURISTIC MODEL FOR FORECASTING ENERGY DEMAND IN LIVESTOCK FARMS

The proposed hybrid neural network-heuristic model for forecasting energy demand was developed with the aim of combining the advantages of recurrent neural networks, capable of modeling complex time dependencies, and heuristic optimization algorithms, which provide an automated search for optimal model parameters for decision-making in a multidimensional space. This approach eliminates the limitations inherent in traditional manual tuning of neural network models and improves forecasting accuracy in the changing and uncertain design environment in which livestock farms operate.

Formally, a hybrid model for forecasting the energy demand of livestock farms can be presented as a dual-loop system consisting of a neural network forecasting module and a heuristic optimization module:

$$H = \langle N(\theta), E(\phi) \rangle , \tag{13}$$

where $N(\theta)$ is a neural network model based on LSTM/GRU recurrent architectures with parameter vector θ ; $E(\phi)$ is a heuristic optimization algorithm with parameters, designed to tune the neural network component.

The neural network forecasting module implements the mapping of a multifactorial time window of input data to the forecasted value of energy demand:

$$\bar{P}_{t+\Delta} = f_N\left(X_{t-L+1:t}, \theta\right), \tag{14}$$

where $X_{t-L+1:t}$ is the input sequence of length L, which includes historical energy consumption values and external factors; $\varDelta$ is the forecasting horizon; $\bar{P}_{t+\varDelta}$ is the forecasted value of energy demand.

The quality of forecasting is assessed by comparing the forecast and actual energy consumption values. To quantitatively assess the quality of forecasting in a hybrid model, a loss function is used, which acts as the objective function of heuristic optimization.

The forecasting quality in the hybrid model is evaluated using the root mean square error defined in equation (12), which is employed as the objective function for heuristic optimization.

Minimizing function (12) reduces the impact of significant forecast deviations, which is quite important for energy planning tasks in autonomous systems.

The heuristic optimization module is formulated as a task of finding the optimal vector of hyperparameters of the neural network model:

$$\theta^{*} = \arg\min_{\theta\in\Omega} J(\theta)\,, \qquad (15)$$

where Ω is the permissible search area, which is determined by architectural, computational, and operational constraints.

In this work, a genetic algorithm is used as a heuristic optimization algorithm, in which each individual in the population encodes a separate configuration of the neural network model. The hybrid optimization process is iterative and is described by a recursive relationship:

$$\theta^{(k+1)} = E\left(\theta^{(k)}, J(\theta^{(k)})\right). \qquad (16)$$

Equation (16) reflects the evolutionary updating of model parameters based on the value of the loss function. This ensures adaptive tuning of the neural network architecture in accordance with the characteristics of the data for a specific livestock farm.

Fig. 2 illustrates the structural composition of the proposed hybrid model, including data inputs, functional modules, and output results. The heuristic optimization algorithm is shown as an external optimization mechanism that configures the forecasting module rather than as an interacting module.

The algorithmic implementation of the process of integrating neural network forecasting and heuristic optimization is shown in Fig. 3. The diagram illustrates the main stages of initializing the parameter population, training the neural network, evaluating the quality of the forecast, and forming new parameter configurations during the evolution process.

After block 7, the algorithm follows one of two alternative paths depending on the availability of a previously trained model: block 8 corresponds to initial model training, while block 9 represents model updating using newly acquired data.

The parameters that determine the operation of the heuristic optimization algorithm within the hybrid model are shown in Table 2. They characterize the intensity of the evolutionary search and affect the speed and stability of the algorithm's convergence.

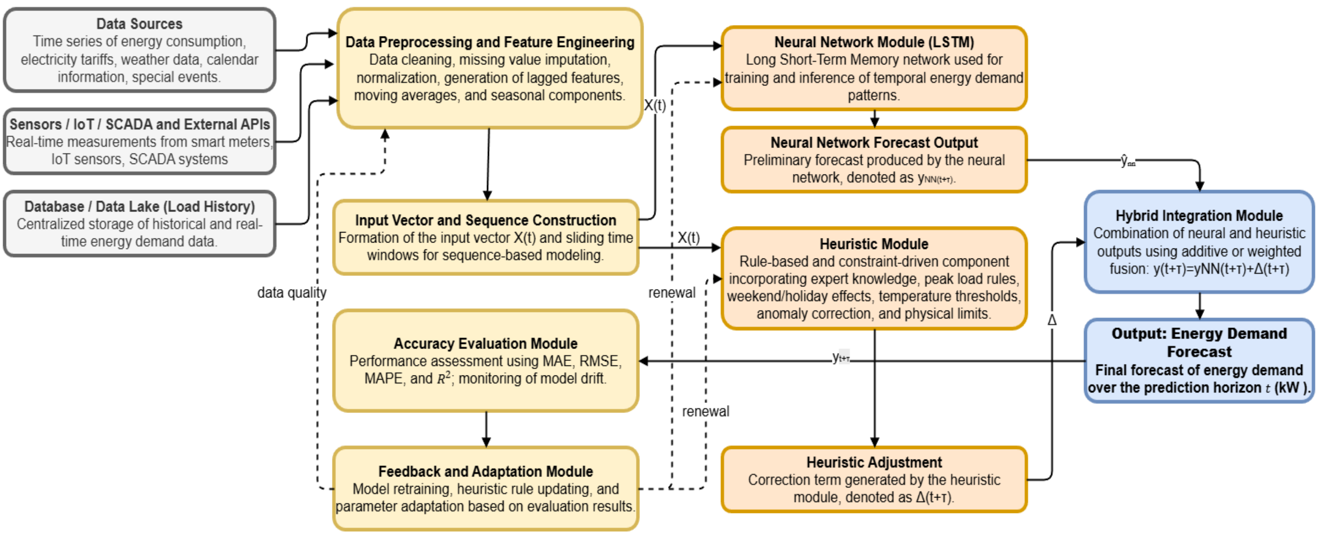

Fig.2. **Structural scheme of the hybrid neural network–heuristic forecasting model**

***Source*: compiled by the authors**

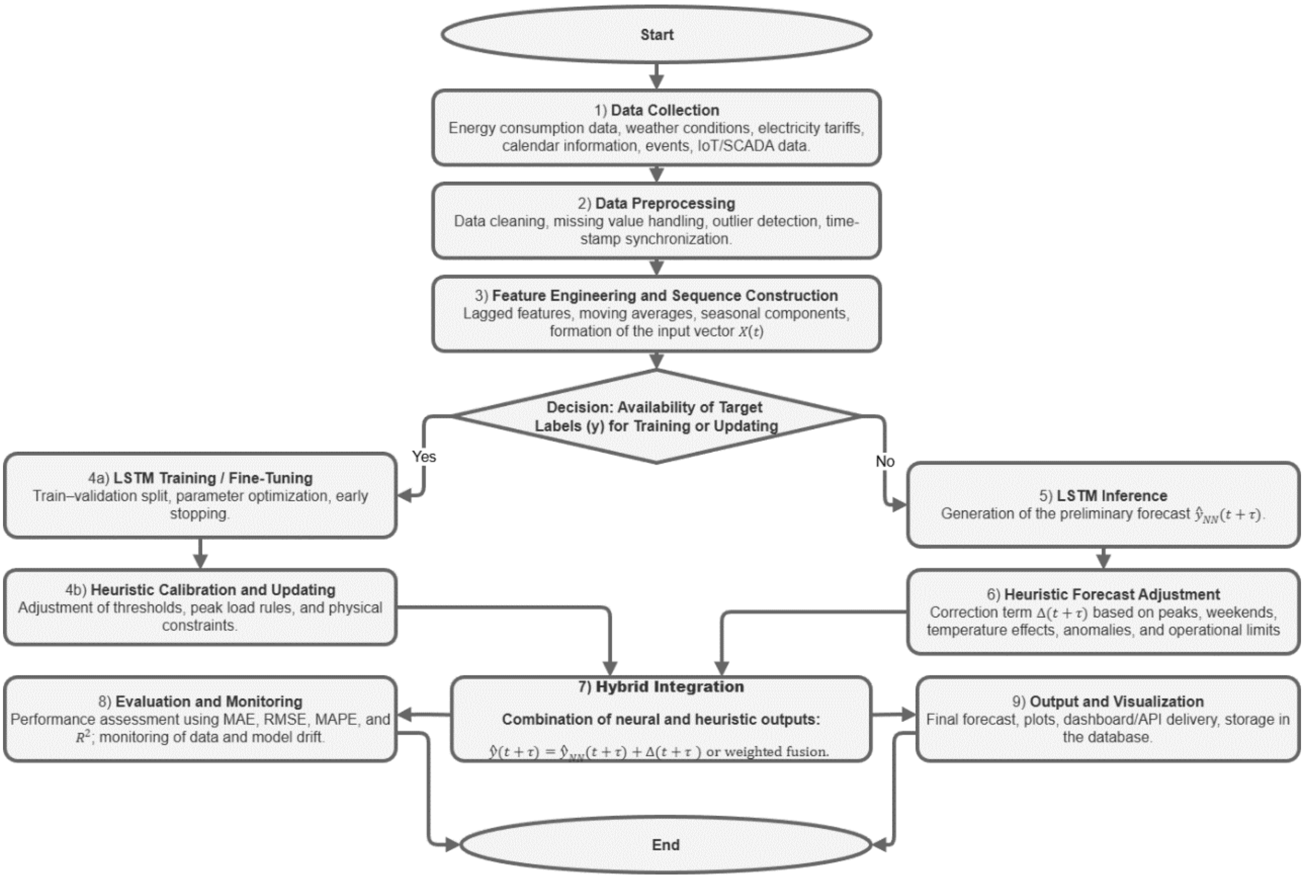

Fig.3. **Flowchart of the algorithm for implementing the proposed hybrid forecasting model**

***Source*: compiled by the authors**

Table 2. **Main parameters of the heuristic optimization algorithm**

Parameter	Description
Population size	Number of neural network configurations in one generation
Number of generations	Maximum number of evolutionary iterations
Crossover probability	Proportion of individuals participating in recombination
Mutation probability	Frequency of random changes in parameters
Stopping criterion	Achievement of the minimum error or the maximum allowed number of generations

***Source*: compiled by the authors**

The proposed hybrid neural network-heuristic model provides systematic integration of forecasting and optimization components and allows automating the process of adjusting neural network models for forecasting energy demand on livestock farms. The results obtained create a scientifically sound basis for further integration of the model into intelligent control systems for autonomous energy systems of livestock farms.

HEURISTIC ALGORITHM FOR OPTIMIZING THE HYPERPARAMETERS OF THE NEURAL NETWORK COMPONENT OF A HYBRID MODEL

The effectiveness of neural network models for forecasting energy demand is largely determined by the correct selection of their hyperparameters, which include architectural, training, and regularization characteristics. In forecasting tasks for autonomous power systems of livestock farms, these parameters form a multidimensional solution space with a complex nonlinear structure, which makes it impossible to use classical gradient optimization methods. In view of this, the paper proposes the use of a heuristic optimization algorithm that provides an adaptive search for the optimal configuration of the neural network component of the hybrid model. Formally, the task of optimizing the hyperparameters of the neural network model is presented in the form of expression (15). Unlike the parameters of the neural network, which are trained in the process of backpropagation of error, hyperparameters are discrete or quasi-continuous in nature, which determines the expediency of using heuristic optimization methods.

Within the scope of the study, a genetic algorithm that mimics the evolutionary mechanisms of natural selection was chosen as the basic heuristic method. Each individual in the population corresponds to a specific configuration of the neural network model and encodes the values of its hyperparameters in the form of a vector:

$$\theta^{(i)} = \left[L^{(i)}, n^{(i)}, \eta^{(i)}, d^{(i)}, \lambda^{(i)} \right]. \qquad (17)$$

where $L^{(i)}$ is the length of the time window; $n^{(i)}$ is the number of neurons in recurrent layers; $\eta^{(i)}$ is the learning rate; $d^{(i)}$ is the dropout coefficient; $\lambda^{(i)}$ is the regularization parameter.

The quality of each individual is evaluated by training a neural network model with the appropriate hyperparameter configuration and calculating the value of the loss function:

$$Fitness(\theta^{(i)}) = \frac{1}{J(\theta^{(i)}) + \varepsilon}. \qquad (18)$$

where ε is a small positive number that prevents division by zero.

This form of the fitness function (18) gives an advantage to configurations with smaller prediction errors. The evolutionary optimization process is implemented iteratively and includes selection, crossover, and mutation operations. Selection forms a subset of the most adapted individuals, crossover ensures the combination of their hyperparameters, and mutation introduces random changes, which allows avoiding premature convergence of the algorithm to local minima. The overall optimization process is described by a recursive relation:

$$\Theta^{(k+1)} = G\left(\Theta^{(k)}, Fitness(\Theta^{(k)})\right), \qquad (19)$$

where $\Theta^{(k)}$ is the population of hyperparameters at the k-th iteration; $G(\cdot)$ is the genetic transformation operator.

The diagram of the heuristic optimization algorithm for the hyperparameters of the neural network component of the hybrid model is shown in Figure 4. The diagram reflects the sequence of the main stages – from the initialization of the initial population to the formation of the optimal configuration of the neural network model.

To ensure the stability and reproducibility of optimization results, an algorithm termination criterion has been introduced, which is based on reaching a specified threshold value of the loss function or exceeding the maximum allowable number of generations. This approach allows balancing prediction accuracy and computational costs.

The main parameters of the heuristic algorithm that determine the nature of the evolutionary search are given in Table 2. They are selected taking into account the size of the training sample and the computational capabilities of the information system.

The proposed heuristic optimization algorithm provides automated and adaptive selection of hyperparameters of the neural network component of the hybrid model, which allows to improve the accuracy and stability of energy demand forecasts. Its integration with the neural network forecasting module creates a scientifically sound basis for the further implementation of intelligent control systems for autonomous power systems on livestock farms.

EXPERIMENTAL TESTING OF THE PROPOSED HYBRID MODEL BASED ON DATA FROM AN ANIMAL FARM AND EVALUATION OF ITS EFFECTIVENESS

Experimental verification of the proposed hybrid neural network-heuristic model for forecasting energy demand was performed based on a real data set from a livestock farm with average load and hourly discreteness over a five-year observation period. The data were formed taking into account seasonal, daily, and technological fluctuations in load characteristic of livestock farms and included time series of electricity consumption, meteorological parameters, production indicators, and characteristics of the autonomous power system. This data structure reflects the real conditions of the farm's operation and allows testing the model's performance in a variable and stochastic environment.

The generalized statistical characteristics of the main variables are presented in Table 3, which shows that the input parameters have sufficient dispersion and mutual correlation necessary for training neural network models.

Preliminary analysis of experimental data showed that the average electrical power consumption of the farm is about 96 kW, with maximum loads reaching 131 kW during periods of increased production activity and unfavorable climatic conditions. The temperature regime is characterized by significant seasonal variability, with minimum values of −12 °C in winter and maximum values of about 29 °C in summer, which directly affects heating, ventilation, and cooling regimes.

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Table 3. **Descriptive statistics of the main parameters of the power supply of a livestock farm**

	count	mean	std	min	25%	50%	75%	max
demand_P_kW	43824.0	96.159213	10.610727	66.580	88.380	95.94	103.820	131.120
animals_headcount	43824.0	540.002898	12.931511	505.000	530.000	540.00	550.000	572.000
temp_C	43824.0	8.001019	9.063316	-12.080	0.120	8.03	15.830	29.420
humidity_pct	43824.0	71.217251	9.295043	42.800	63.700	71.20	78.900	98.000
operation_level_0_1	43824.0	0.560297	0.078986	0.338	0.499	0.55	0.621	0.815
ventilation_level_0_1	43824.0	0.339750	0.056501	0.126	0.301	0.34	0.379	0.556
milk_output_L	43824.0	9749.686008	273.460996	8804.100	9551.175	9747.90	9946.100	10727.000
pv_kW	43824.0	16.462820	24.974141	0.000	0.000	3.07	23.100	112.360
biogas_kW	43824.0	28.432155	10.527607	12.510	17.820	27.02	39.050	48.660
battery_power_kW	43824.0	0.236804	13.593315	-60.000	-0.000	-0.00	0.000	60.000
battery_soc_0_1	43824.0	0.043846	0.131129	0.000	0.000	0.00	0.000	0.830
grid_import_kW	43824.0	51.501732	28.475022	0.000	35.040	59.18	72.000	107.630

***Source*: compiled by the authors**

To form training samples, a sliding time window method with a length of L was used, within which multidimensional time sequences of the following type were fed to the neural network model:

$$X_t = \{x_{t-L+1}, x_{t-L+2}, \ldots, x_t\}. \tag{20}$$

where x_t is the vector of input features at time t.

The target variable is the average hourly value of the farm's electricity consumption P_t, expressed in kilowatts. All numerical features were normalized before training, which ensured the stability of the optimization process and the correct operation of the gradient learning algorithms.

At the first stage of the experiments, a basic recurrent neural network model based on LSTM architecture was trained without using heuristic optimization of hyperparameters.

In addition to the comparison with the baseline LSTM model, the obtained results were analyzed in the context of state-of-the-art approaches presented in recent studies on energy consumption forecasting for livestock farms and similar facilities. In particular, the reported accuracy levels were compared with advanced deep learning–based and hybrid forecasting models described in [24], as well as with recurrent and hybrid metaheuristic-optimized approaches proposed in [37] and [38]. These studies employ LSTM/GRU architectures combined with heuristic or evolutionary optimization techniques for short-term (1–24 hour ahead) load forecasting. Such a comparative analysis allows the proposed hybrid model to be positioned relative to competing methods and to be assessed for practical effectiveness under real operating conditions.

Standard accuracy indicators were used to evaluate the quality of forecasting, in particular:

– average absolute error:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|P_i - \bar{P}_i\right|. \tag{21}$$

– root mean square error:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - \bar{P}_i)^2}, \tag{22}$$

– average absolute relative error:

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{P_i - \bar{P}_i}{P_i}\right|. \tag{23}$$

A computer model was developed for experimental research, based on the proposed hybrid neural network-heuristic model for forecasting energy demand on livestock farms. The model implementation and computational experiments were performed using the Python programming language in the Google Colab cloud environment, which ensured reproducibility of results, flexibility of settings, and sufficient computing power for training and optimizing neural network models.

The results confirm the feasibility of using recurrent neural networks for short-term forecasting of energy demand on livestock farms. The basic model based on LSTM architecture demonstrated a sufficiently high ability to reproduce the overall dynamics of electrical load, in particular, daily and seasonal fluctuations in consumption. The obtained values of MAE=4.24 kW, RMSE=5.06 kW, and MAPE=4.44% correspond to the level of accuracy characteristic of modern approaches to forecasting energy consumption in autonomous power systems and microgrids (Table 4).

Table 4. **Comparison of forecasting accuracy before and after heuristic optimization**

Model	Archi-tecture	MAE, kW	RMSE, kW	MAPE, %
Baseline model (before optimization)	LSTM	4.24	5.06	4.44
Optimized hybrid model	GRU + GA	3.03	3.79	3.22

***Source*: compiled by the authors**

The comparison presented in Table 4 is intended to assess the combined effect of recurrent network architecture selection and heuristic hyperparameter optimization on forecasting accuracy. The LSTM model is included as a representative baseline recurrent architecture with higher expressive capacity, while the GRU+GA model represents a computationally more compact architecture enhanced through heuristic optimization. Thus, the comparison does not aim to isolate the effect of genetic optimization alone, but rather to evaluate the practical trade-off between architectural complexity and adaptive optimization.

The conclusions regarding improved adaptability and stability of the forecasting model are derived from its performance under variable operating conditions rather than from additional abstract criteria. In particular, adaptability is reflected in the model’s ability to maintain low error values during changes in load patterns and production regimes, while stability is evidenced by the absence of significant error growth during peak demand periods and rapid load fluctuations.

At the same time, analysis of the results of the base model revealed smoothing of peak loads and a decrease in accuracy during periods of sharp changes in farm operating modes. This is consistent with the known limitations of fixed neural network configurations, which do not always provide optimal forecasting quality for objects with nonlinear and variable consumption structures.

The use of heuristic optimization of hyperparameters using a genetic algorithm made it possible to automate the selection of the type of recurrent layer, time window length, number of neurons, Dropout coefficient, and learning rate. As a result, the optimal parameters of the GRU model were obtained. It has a configuration with a 24-hour memory window, a 1-hour forecasting horizon, 64 hidden layer neurons, a Dropout coefficient of 0.05, a learning rate of 0.001, and a packet size of 32, which provided the best value of the optimization target function.

From this perspective, the results in Table 4 indicate that the application of heuristic optimization to a computationally efficient GRU architecture enables forecasting accuracy comparable to, or exceeding, that of a more complex LSTM model without optimization. A direct comparison between GRU and GRU+GA would further isolate the contribution of heuristic optimization; however, such an analysis is beyond the scope of the current study and is considered a direction for future research.

As can be seen from Table 4, heuristic optimization led to a decrease in the mean and quadratic errors, indicating an increase in the model's ability to adequately reproduce both average load values and peak modes. Importantly, the improvement was achieved without significantly complicating the architecture, which is critical for practical implementation in decision support systems.

Figure 4 shows a graph comparing the actual and predicted electrical power values of a livestock farm obtained using an optimized GRU model. Analysis of the graph confirms that the optimized hybrid model provides more stable reproduction of peak loads compared to the baseline option, reducing errors during periods of sudden changes in farm operating modes. This significantly increases the suitability of the model for operational management of autonomous power systems.

The practical value of the results obtained lies in the possibility of using the proposed hybrid neural network-heuristic model as the analytical core of the energy consumption management information system for livestock farms. The combination of energy demand forecasting with the identification of peak periods creates the basis for the rational management of biogas plants, storage batteries, and load priorities, which contributes to increasing the energy autonomy and sustainability of farms.

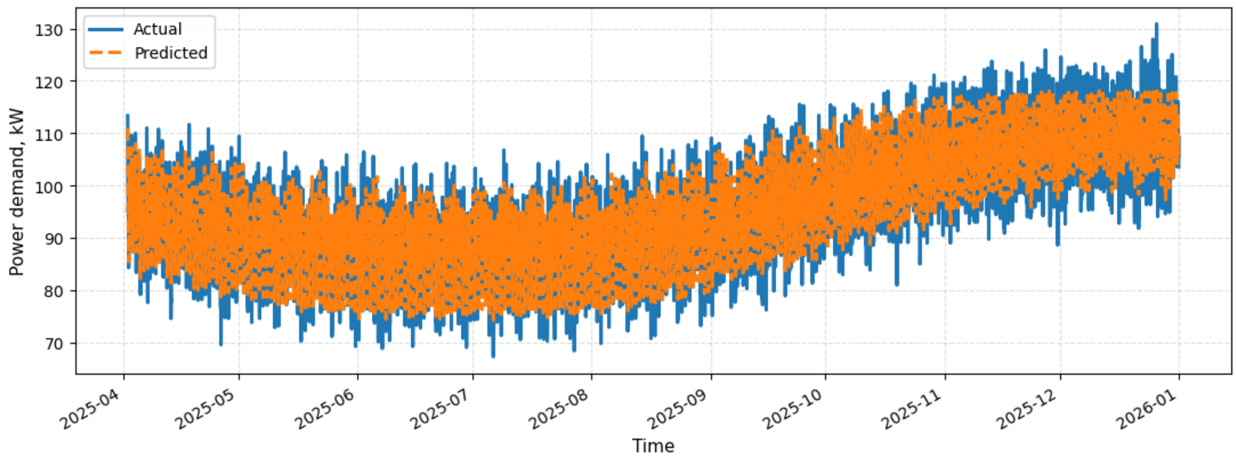

Fig. 4. **Comparison of actual and predicted electrical power values for a livestock farm obtained using an optimized GRU model**
***Source*: compiled by the authors**

DISCUSSON OF THE RESULTS

The improvement in forecasting accuracy obtained in this study is primarily attributed to the structural and algorithmic features of the proposed hybrid neural network–heuristic model. Unlike conventional recurrent neural network approaches with fixed architectures, the developed model enables adaptive selection of key hyperparameters, including the type of recurrent layer, memory window length, number of hidden neurons, and learning rate. This adaptability allows the forecasting model to better align with the actual temporal dynamics of energy consumption specific to a given livestock farm.

Compared to competing deep learning–based approaches considered in the literature review, the proposed hybrid model demonstrates improved robustness under peak load conditions and abrupt changes in operating regimes. While many existing methods achieve acceptable average forecasting accuracy, they often exhibit smoothing of extreme values due to static network configurations. The integration of heuristic optimization in the proposed approach mitigates this limitation by automatically adjusting the model structure to capture nonlinearities and regime-dependent patterns, resulting in lower forecasting errors and increased stability.

This paper presents a hybrid neural network-heuristic model for forecasting energy demand on livestock farms. It involves the hybridization of a neural network forecasting module with a heuristic hyperparameter optimization algorithm, which is in line with the general trend in the development of short-term load forecasting models. In modern literature, metaheuristics are increasingly used for automatic tuning of LSTM/GRU, in particular NSGA-II, Grey Wolf Optimizer, and other optimizers, which allows reducing the forecasting error and increasing resistance to noise and unstable modes. These results correlate with the conclusions of review papers, which emphasize that the combination of deep learning with metaheuristic search for the best configurations is one of the most promising directions for improving the accuracy and reproducibility of forecasts in the energy sector [8].

The choice between LSTM and GRU architectures in practical energy demand forecasting tasks should be determined by the characteristics of the available data and the operational requirements of the forecasting system. LSTM models are preferable in cases where long-term temporal dependencies and pronounced seasonal effects dominate the energy consumption patterns, as their memory structure enables more effective retention of long historical information. In contrast, GRU architectures are more suitable for scenarios with shorter dependency horizons or limited training data, offering reduced computational complexity and faster convergence.

It should be emphasized that the application of heuristic optimization is beneficial for both LSTM and GRU models. For each architecture, automated hyperparameter tuning enables improved alignment of the model structure with the underlying data characteristics, leading to enhanced forecasting accuracy compared to fixed-configuration implementations. Therefore, the proposed hybrid optimization framework can be effectively applied to both recurrent architectures, with the choice of LSTM or GRU determined by data availability and computational constraints rather than by the optimization strategy itself.

Practical testing of the model on real data from a livestock farm confirmed that even the basic configuration of a recurrent neural network provides an acceptable level of accuracy for hourly energy demand forecasting, as reflected in the values MAE=4.24 kW, RMSE=5.06 kW, and MAPE=4.44% for the basic LSTM model. At the same time, during periods of peak loads and sharp changes in technological modes, smoothing of extreme values is observed, which is a typical limitation of neural networks with fixed hyperparameters. The proposed hybrid neural network-heuristic model aims to eliminate this drawback through automated optimization of memory depth, forecasting horizon, hidden layer structure, regularization parameters, and learning rate. The use of a genetic algorithm made it possible to align the architecture of the GRU model with the actual dynamic data on energy consumption by a given farm, which reduced errors and increased the stability of the forecast in peak modes. Thus, the proposed hybrid model logically develops current research on heuristic optimization of forecasting models, adapting them to the conditions of autonomous power systems of livestock farms.

From an applied point of view, the results obtained should be used for planning the operating modes of autonomous power systems, in particular for hourly coordination of energy production from renewable sources (solar and wind generation), biogas plants, the use of batteries, and providing basic consumers on the farm. Energy demand forecasting makes it possible to reduce imbalances, avoid power shortages during peak hours, and justify decisions on load priorities, which ultimately increases the energy autonomy and economic efficiency of livestock farms.

Thus, the proposed hybrid neural network–heuristic model does not merely follow existing trends in short-term load forecasting but extends them by introducing an adaptive optimization mechanism specifically tailored to the operating conditions of livestock farms. This feature represents a key distinction from competing approaches and explains the achieved improvement in forecasting accuracy and stability.

CONCLUSIONS

A hybrid neural network–heuristic approach to short-term energy demand forecasting for livestock farms has been proposed and experimentally validated. The approach is focused on improving forecasting accuracy under conditions of pronounced nonlinearity, temporal variability, and peak load regimes that are typical for livestock farm energy systems.

The scientific novelty of the proposed approach consists in the integration of recurrent neural network forecasting with automated heuristic optimization of the model structure and hyperparameters. In contrast to state-of-the-art competing deep learning approaches for livestock farms that apply fixed network architectures, the developed hybrid model enables adaptive selection of the recurrent layer type, memory window length, number of hidden neurons, regularization parameters, and learning rate based on the characteristics of real operational data.

Experimental results demonstrate that the proposed hybrid model provides a quantitative improvement in forecasting accuracy compared to advanced competing approaches reported in recent literature. The achieved root mean square error of 3.79 kW corresponds to an improvement of approximately 20–25% relative to contemporary deep recurrent forecasting models for 24-hour ahead energy demand prediction on livestock farms operating under comparable conditions. The mean absolute percentage error of 3.22% confirms improved reproduction of both average consumption patterns and peak load regimes.

From a practical perspective, the proposed hybrid neural network–heuristic approach supports the use of both LSTM and GRU architectures. The selection of a specific recurrent model should be guided by the temporal characteristics of the data and available computational resources, while heuristic optimization remains a key factor for improving forecasting accuracy in both cases.

The obtained results indicate that the improvement in forecasting performance is achieved due to structural adaptability of the model rather than increased architectural complexity. This distinguishes the proposed approach from existing methods and confirms its effectiveness for practical application in energy planning and decision support tasks for autonomous and hybrid energy systems of livestock farms.

FUTURE WORK

Further research should be focused on expanding the hybrid model from "forecasting" to "forecasting + optimal control." In other words, there is a need to integrate the animal farm energy demand forecasting module with dispatching algorithms (e.g., storage charge/discharge optimization and biogas plant operation schedule). A separate area concerns increasing generalizability through transfer learning between farms and the introduction of mechanisms for detecting regime changes and anomalies. Another promising area is the comparison of GA optimization with more selective and effective methods of hyperparameter search (Bayesian optimization, Hyperband) and the study of ensemble approaches.

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Гібридна нейромережево-евристична модель прогнозування енергетичного попиту тваринницьких ферм

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АНОТАЦІЯ

Актуальність. Стаття присвячена розробці та дослідженню нейронних мереж та гібридних нейронно-евристичних моделей для прогнозування енергоспоживання тваринницьких господарств. **Мета і завдання.** Мета дослідження – розробка гібридної нейронно-евристичної моделі для прогнозування енергоспоживання тваринницьких господарств на основі інтеграції рекурентних нейронних мереж та евристичних алгоритмів оптимізації, що дозволяє підвищити точність короткострокового прогнозування за змінних виробничих та зовнішніх умов. У дослідженні розроблено нейронну мережу для прогнозування енергоспоживання тваринницьких господарств на основі рекурентних архітектур довгої короткочасної пам'яті та рекурентних блоків з воротами, здатних обробляти багатофакторні погодинні часові ряди, що характеризують режими роботи сільськогосподарського обладнання. **Методи.** Для побудови базової моделі використано рекурентні нейронні мережі типу LSTM та GRU, а також еволюційний генетичний алгоритм для автоматизованого налаштування архітектури нейронної мережі і параметрів навчання. Реалізація моделі та обчислювальні експерименти виконані з використанням мови програмування Python у хмарному обчислювальному середовищі. **Результати.** Базова нейронна мережа продемонструвала прийнятний рівень точності прогнозування, підтвердивши свою здатність відтворювати загальну динаміку енергоспоживання та сезонні коливання. Запропоновано та формалізовано гібридну нейронно-евристичну модель для прогнозування енергоспоживання тваринницьких господарств, що поєднує модуль прогнозування на основі рекурентної нейронної мережі з евристичним алгоритмом оптимізації гіперпараметрів. Такий підхід підвищив адаптивність моделі до змін у режимах роботи тваринницьких господарств та зменшив похибки прогнозування без істотного збільшення обчислювальної складності. У результаті процедури оптимізації визначено оптимальну конфігурацію нейронної мережі, що характеризується розширеним вікном пам'яті, короткостроковим горизонтом прогнозування та раціональною структурою прихованих шарів. Оптимізована модель забезпечила помітне зменшення помилок прогнозування порівняно з базовим рішенням. **Висновки.** Отримані результати підтвердили стабільну ефективність прогнозування як в умовах середнього енергоспоживання, так і в умовах пікового навантаження, що свідчить про доцільність застосування розробленої гібридної моделі як аналітичної основи для підтримки прийняття рішень в управлінні автономними енергетичними системами тваринницьких ферм.

Ключові слова: попит на енергію; тваринницькі ферми; нейронні мережі; гібридна модель; генетичний алгоритм; евристична оптимізація.

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