This study's object is the process of measuring control over liquefied petroleum gas components using a multilayer perceptron. The problem considered is insufficient efficiency of existing methods for measuring control over liquefied petroleum gas components. It can be partially solved by remote measurement of components of liquefied petroleum gas and processing of the received data and, accordingly, control by a neural network. However, another issue arises, associated with the complexity of using neural networks in combination with peripheral devices, in particular, means, sensors, gauges, etc., and the need for significant computing power.

This paper reports a model for measuring control over liquefied petroleum gas components, which takes into account its physical characteristics, using a multilayer perceptron, which provides communication with gas measurement devices. The mechanism for achieving these results involves training the model based on performance indicators derived from input data, taking into account the formed features. High generalization ability and efficiency are illustrated by the coefficient of determination, which is 0,845. High accuracy is illustrated by the low overall average value of the mean absolute error, which is 1,1%. That was made possible by the distinctive features of the proposed solution, namely the optimized architecture of the model in accordance with the object of study and its input features. These features are the areas of the light streaks, their logarithmic ratios, temperature, the sum and difference of densities of the components of liquefied petroleum gas.

The results can be applied practically to problems involving liquefied gas composition analysis, especially at gas filling stations, oil and gas processing plants, gas storage facilities, and similar sites

Keywords: liquefied petroleum gas, multilayer perceptron, mean absolute error, coefficient of determination

UDC 681.12:004.89
DOI: 10.15587/1729-4061.2025.340608

CONSTRUCTION OF A MODEL FOR MEASUREMENT CONTROL OVER LIQUEFIED PETROLEUM GAS COMPONENTS BASED ON A MULTILAYER PERCEPTRON

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Received 02.07.2025
Received in revised form 05.09.2025
Accepted date 17.09.2025
Published date 31.10.2025

How to Cite: *Knysh, B., Kulyk, Y. (2025). Construction of a model for measurement control over liquefied petroleum gas components based on a multilayer perceptron. Eastern-European Journal of Enterprise Technologies, 5 (6 (137)), 14–22. https://doi.org/10.15587/1729-4061.2025.340608*

1. Introduction

Liquefied petroleum gas (LPG) is widely used as a fuel in motor transport engines and installations at municipal, industrial, and agricultural facilities [1]. At the same time, there is a continuous increase in the consumption of this type of fuel, and, as a result, the task of controlling its quality arises. This is due to the fact that the mass fraction of at least one of the LPG components exceeds the specified ranges [2], is reflected in its quality, and leads to significant economic losses. One of the ways to solve this problem is measurement control over LPG components as different ratios of its components lead to changes in the basic characteristics of LPG, in particular heat transfer, the composition of emissions after combustion, etc.

Measurement control over LPG components is provided by a wide classification of various means, sensors, gauges, gas analyzers, and systems. The work of most of them is accompanied by direct human contact with LPG. As a result, various risks may occur, such as explosions, fires, burns, the formation of toxic flammable mixtures during leakage, etc. [3]. This problem can be solved by remote measurement of LPG components and processing of the obtained data and, accordingly, control by a neural network. For this purpose, there are appropriate systems [4], which provide for the presence of a sensor that, being in a hazardous working environment, transmits data on the gas composition to a remote computer where the corresponding neural network model processes the received information.

There are a large number of neural network models [5–7] for measuring control over various parameters of various gases. Their main disadvantage is the relative complexity of use in combination with peripheral devices, in particular sensors, and the need for significant computing power. This may limit their application. Therefore, there is a need to find a better solution to this problem. This can be done by building a neural network model that allows for measurement control over the LPG components based on data received remotely from the sensor on their mass fractions.

Thus, certain requirements are imposed on the appropriate neural network model for measuring control over LPG, namely:

– high speed;
– error resistance;
– high accuracy.

Therefore, there is a need to analyze neural network models for measuring control over LPG components and select the optimal one according to the above requirements, in par-

ticular high accuracy and speed. It is also worth considering the parameters that characterize these models, the change of which has a direct impact on the accuracy, speed, and overall efficiency of measuring control.

A current topical area in the evolution of neural networks is their use for remote measuring control over LPG components in various areas, in particular in autonomous gas supply systems for households and enterprises, road transport, industry, gas filling stations. At the same time, construction of an appropriate neural network model that would most effectively and accurately enable the process of measuring control over LPG components is also relevant. Important criteria in this case are the effectiveness indicators of the model, namely the mean absolute error and the coefficient of determination.

Therefore, it is a relevant task to carry out studies on the construction of a model for measuring control over LPG components using a neural network.

2. Literature review and problem statement

Current research shows that neural networks can effectively replace or supplement conventional methods for measuring control over LPG components, providing faster and less expensive analysis in real time. They also make it possible to distribute computational processes by processing data coming from sensors that directly perform measurements. This makes it possible to eliminate the cross-sensitivity of sensors and the need for their calibration, to increase the accuracy of measurements, and to reduce the cost of equipment.

In work [8], an improved method of gas chromatography and mass spectrometry is proposed, which makes it possible to eliminate the cross-sensitivity of sensors, which impairs their ability to immediately determine LPG components in the environment. The accuracy of this method is 98%. But there are still unresolved issues related to the long-term calibration of expensive equipment. This limits its efficiency and flexibility.

In [9], an ensemble of neural networks for the analysis of mixtures at gas processing plants with an accuracy of 98% is described. The application of such a model in combination with an optimization algorithm for large multidimensional nonlinear data sets for decision-making in the gas complex is shown. However, unresolved issues related to the redundancy of the model remain. This causes difficulties associated with the measurement control of LPG.

In [10], a three-dimensional convolutional neural network (3D CNN) is used to process hyperspectral data, which well detects the spectral lines of gas components and processes both spatial and spectral information. The accuracy of such a method is 98%. But the excessive complexity of the model remains an unresolved problem. This causes difficulties associated with obtaining hyperspectral data.

In [11], the Mask R-CNN model is used for chromatogram analysis, in particular in the context of two-dimensional gas chromatography, with an accuracy of 97%. This deep learning model, developed for object detection and sample segmentation tasks, accurately and quickly segments chromatograms into regions representing different compounds. But there are still unresolved issues related to the complexity and insufficient speed of the model, as well as the need for expensive equipment. The reason for this may be objective difficulties associated with the complexity of the chromatographic method.

In [12], a system for estimating the molar fraction of LPG pollutants in real time is reported, which uses a deep learning model based on CNN with an accuracy of 93%. The influence of parameters on each other is shown. However, there are still unresolved issues related to the cumbersomeness and specificity of the model, in particular for installing it on industrial controllers. This limits the application of the model.

An option to overcome the difficulties noted above may be to use a multilayer perceptron (MLP) as a neural network. This is the approach used in [13], in which MLP is smoothed in combination with genetic algorithms for a sensor matrix with an accuracy of 98%. However, genetic algorithms worsen the convergence of the model, and sensor matrices are characterized by cross-sensitivity and lack of selectivity. In addition, in [14], a model is described for analyzing the yield of products, including light gases, LPG, light and heavy oil, kerosene, diesel fuel, etc., resulting from the combination of industrial hydrocracking of vacuum gas oil and MLP. The accuracy of this method is 98%. But in the case of LPG control, this model is redundant.

In turn, in [15], a method for measuring the real-time control over LPG components based on a combination of flame chemiluminescence and MLP is proposed. The accuracy of this method is 98%. However, its implementation requires expensive specialized equipment, which additionally requires calibration for specific types of fuel. A similar principle is also implemented in [16], in which an assessment of the content of LPG components is provided almost in real time and the delay between sampling and laboratory analysis is eliminated. The accuracy of this method is 98%. However, this approach requires a large training database and periodic correction when changing process conditions. The model is also prone to overtraining and drift when changing data sources, and its accuracy depends on the quality and set of input sensors.

Thus, the problem of insufficient efficiency of existing models for measuring control over LPG components can be stated as follows. Model [8] is quite simple but less accurate and requires expensive equipment. At the same time, models [15] are also simple but more accurate, although they still require expensive equipment. Other models [10–13] show high accuracy but are excessively complex. At the same time, models [9, 14] are suitable for a complex technological process but show lower accuracy since they are redundant for measurement control over LPG components.

All this allows us to argue that it is advisable to construct an MLP model that will take into account the physical features of the measurement process through input features, which will significantly improve the accuracy of measurement control over LPG components.

3. The aim and objectives of the study

The aim of our work is to build a model for measuring control over LPG components using MLP. This will provide an opportunity to obtain a new neural network with increased accuracy for measuring control over LPG components, which can be used to assess the quality of LPG.

To achieve the goal, the following tasks were set:

– to determine the structure of the model and its parameters;

– to train the model based on the performance indicators for predicting the mass fractions of LPG components;

– to perform a comparative analysis of the accuracy of neural networks for measuring control of gas composition.

4. The study materials and methods

The object of our study is the process of measuring control over LPG components using MLP. We constructed the corresponding model in such a way that the new model, receiving data on the mass fractions of LPG components, which are remotely acquired from device [17], carried out its measuring control. At the same time, it was hypothesized that the neural network is able to convert the input data from the device into the values of the mass fractions of LPG components with high accuracy. It was assumed that the law of distribution of errors in measuring the mass fractions of LPG components would be close to uniform across the entire measuring range. To simplify the measuring control, LPG was considered as a mixture consisting of three components: propane, butane, and impurities (unsaturated hydrocarbons), while the proportion of other impurities is within the normal range according to the standard in [2].

The study on measuring control was carried out using the MLP model taking into account its training parameters. Data from device [17] were used to verify the effectiveness of this model. They represent signals from the segments of the composite photo detector, the number of which corresponds to the three components of LPG and on which the light strip falls. For each experimental sample, the areas of the light strip on the first segment of the composite photodetector S_1, on the second – S_2, on the third – S_3 are recorded. It is formed by the light flux passing through the LPG, which is passed through the measuring cell, where it is also heated. The displacement of this light strip, i.e., the change in the angle of incidence of the light flux, more or less on each of the segments of the composite photodetector corresponds to a greater or lesser mass fraction of an LPG component.

Alternative methods for measuring the composition of LPG can be statistical methods, in particular linear regression, as well as machine learning methods. Among the latter, the best results are shown by support vector methods, while linear regression methods in most cases show worse results. However, the support vector method has difficulties with interpreting the results and retraining the model for new conditions [18].

A data set of 1500 measurements was formed, namely 500 samples with different ratios of LPG components for 3 temperature values. The mass fractions of propane, butane, and unsaturated hydrocarbons for each sample were previously determined using the refractometric method. The entire data set was divided into training, verification, and test, which constitute 70%, 15%, and 15% of the data, respectively.

15 key features were selected for the input data. All values were normalized to the range of [0, 1]. For the most efficient operation of the neural network, data filtering was performed using the moving average method to reduce the impact of noise that may occur under the influence of temperature and other factors.

As the light beam passes through the measuring cell, the change in its direction is described by Snelius law

$$n_1 \sin(\theta_1) = n_2 \sin(\theta_2), \quad (1)$$

where n_1, n_2 are the refractive indices of the first and second media; θ_1, θ_2 are the angle of inclination of the beam to the normal in the first and second media.

In view of this, $\sin(\theta)$ is one of the key features. It is also worth considering $\cos(\theta)$ as a feature. These trigonometric transformations take into account the geometric effects of the beam passing through the cuvette. In addition, the features associated with the photodetector are the basis for the system's operation. Fixing the areas of the light strip S_1, S_2, S_3 for each segment of the photodetector faces certain difficulties since the photodetector is sensitive to contamination of the optics, fluctuations in the supply voltage, etc. Therefore, normalized logarithmic areas were used since the areas according to the law of exponents have a wide dynamic range, and their logarithm makes the distribution more normal and linearizes the distribution of errors. Thus, logarithmic areas, as features, are more stable to external influences. There are 3 logarithmic features x_1, x_2, x_3 for each segment of the photodetector, respectively, which are calculated as

$$x = \log(S + \varepsilon), \quad (2)$$

where $\varepsilon = 1e^{-9}$ is a small number used to avoid log(0).

In addition, 3 features Δx_{12}, Δx_{23}, Δx_{31} were fed to input, which show the ratio between the logarithmic areas of the light strip. They are more informative since they make it possible to eliminate cross-correlation, and are calculated as

$$\Delta x_{ij} = \log\left(\frac{S_i}{S_j}\right) = \log(S_i) - \log(S_j) = x_i - x_j, \quad (3)$$

where i and j are the segment numbers of the composite photodetector.

The densities of LPG components can be calculated through the temperature function $\rho = f(T)$ from the empirical equations of state. Given this, tabulated values of the densities at known temperatures can be used. The densities of LPG components for propane ρP, butane ρB, and unsaturated hydrocarbons ρU are used in the calculation of input features to take into account the physics of the process. Thus, to reduce the risk of multicollinearity of temperatures and densities, the following features are used: $\rho\Sigma = \rho P + \rho B + \rho U$, $\Delta PB = \rho P - \rho B$, $\Delta PU = \rho P - \rho U$.

The temperature T was also chosen as a feature since the study was conducted for three temperature values: –4°C, 4°C, and 12°C. The temperature was fed to the input of the neural network in the form of 3 features, namely a vector with one flag on one of the 3 values (one-hot): $Tf1 = [1, 0, 0]$, $Tf2 = [0, 1, 0]$ or $Tf3 = [0, 0, 1]$ for –4°C, 4°C, 12°C, respectively.

Thus, the input of the neural network was fed 3 times for 3 temperatures with the feature vector $[x_1, x_2, x_3, \Delta x_{12}, \Delta x_{23}, \Delta x_{31}, \sin(\theta), \cos(\theta), T, Tf1, Tf2, Tf3, \rho\Sigma, \Delta PB, \Delta PU]$.

The output signals are k_1, k_2, k_3 – mass fractions of propane, butane, and unsaturated hydrocarbons, respectively. The measurement range is 0–100%, but in training during data normalization we transfer it into the range of 0–1. The sum of the three values should be 100%. The measurement control over the mass fractions of propane, butane, and unsaturated hydrocarbons was executed according to the standard from [2], i.e., k_1, k_2, k_3 should be within the limits of 40–60%, 34–60%, 0–6%, respectively.

Modeling and data analysis were carried out in the Python 3.10 programming language in the Google Colab environment (USA) using the following libraries: Keras API 3.8.0 in TensorFlow 2.14 for building and training the neural network, Matplotlib and TensorBoard for visualization of the learning process, Scikit-learn for data preparation and model evaluation, as well as Pandas and NumPy for data manipulation. The CUDA library was used to accelerate calculations.

5. Results of building the model for measuring control over liquefied petroleum gas components

5. 1. Determining the structure of the model for measuring control over liquefied petroleum gas components and its parameters

Pre-processed features are fed to the input of the MLP model. The number of input neurons required to obtain input data for such features is 15. To obtain an effective model with better generalization ability, three hidden layers were used. They perform gradual generalization and detection of nonlinear dependences between the input data from the device and the composition of LPG components and regularization with the number of neurons for each layer – 64, 128, and 64, respectively. The activation function in the hidden layers is ReLU since it works well for physical signals and allows one to avoid the problem of vanishing gradients. To prevent overtraining after the hidden layers, a Dropout layer is used. For the output layer, three neurons are used, corresponding to the calculated mass fractions of propane, butane, and unsaturated hydrocarbons. The activation function in the output layer is Softmax since it allows for the distribution of mass fractions of the components of LPG, which in sum make up one. The architecture of the constructed MLP model is given in Table 1.

Table 1

Architecture of the constructed MLP model

Layer	Number of neurons	Activation function	Purpose
Input layer	15	–	Features based on areas, angles, temperatures, and densities
Hidden layer 1	64	ReLU	Initial detection of nonlinear dependences
Hidden layer 2	128	ReLU	Deeper generalization of signals
Hidden layer 3	64	ReLU	Dimensionality balancing, regularization
Dropout	–	–	0.2 neuron exclusion probability and L2-regularization of weights
Output layer	3	Softmax	Probability of mass fractions of propane, butane, and unsaturated hydrocarbons

To assess the efficiency of training the MLP model, the optimal hyperparameters of the loss function when training the neural network are determined. These are the loss functions by the mean absolute error and the mean square error, the Adam optimizer, the learning rate (0.001) with early stopping, the data size (64), and the number of epochs (200). To assess the generalization ability of the network, 5-fold cross-validation was used. Thus, the architecture of the constructed model is built as a sequence of the input layer, three hidden layers with nonlinear activation and regularization, and the output layer, which makes it possible to calculate the mass fractions of the three components of LPG.

The measured and predicted values of the mass fractions of LPG were compared. The measured values were obtained using the refractometric method; the predicted values were obtained as a result of the model performing measurement control.

The accuracy of the model was evaluated on the test dataset using the following performance metrics:

– mean absolute error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|; \quad (4)$$

– coefficient of determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \tilde{y}\right)^2}, \quad (5)$$

where y_i – measured values of the mass fraction of the corresponding LPG component from the sensor; $\hat{y}_i$ – predicted values of the mass fraction of the corresponding LPG component by the model; $\tilde{y}$ – averaged value of the mass fraction of the corresponding LPG component from the sensor; $i = 1, 2, ..., n$ – number of measurements; n – total number of measurements.

The selected indicators are typical for assessing the quality of the results obtained from models. These are standardized statistical metrics used to assess the correspondence between actual measurements and predicted results [19].

The error value on the training and, especially, on the test sample should gradually decrease. This will indicate the correctness of the neural network training and the absence of overtraining, that is, the adequacy of the model. Validation of the training results can be defined as a gradual decrease in the error on the test sample. The number of training epochs is selected from the condition for obtaining the highest accuracy on the test sample in the absence of significant fluctuations in numerical values. The criterion for the feasibility of increasing the training epochs is a gradual increase in accuracy on the validation set. If the loss function does not decrease over 10 epochs, early training is stopped. The beginning of a decrease in accuracy on the validation set is a criterion for retraining, the absence of which is a condition for model validation. After training, to assess the effectiveness of the model, testing was performed on a test set of data that was not provided during training.

5. 2. Training a multilayer perceptron model based on efficiency indicators for predicting mass fractions of liquefied petroleum gas components

A vector of 15 features formed on the basis of a pre-prepared data set was fed to the input of the MLP model with 45 neurons. The batch size is 64. The calculation of the mass fractions of LPG components occurs under a soft real-time mode, which requires the neural network to be high-speed with limited memory to ensure high accuracy. A training data sample of 70% of the total data volume was used to train the model. A test data sample of 15% of the total data volume was used to test the training efficiency. The model efficiency was assessed by comparing the measured values from the test data set of 15% of the total data volume with the mass fraction values predicted by the model using the MAE and R^2 criteria.

The efficiency of model training was evaluated (Fig. 1, 2), and then the efficiency of predicting the mass fractions of LPG components (Fig. 3–8). The evaluation results are represented in the form of plots, which were constructed in the Google Colab environment using the Matplotlib library.

Fig. 1 shows the curves of changes in the loss function according to the mean square error of model training for the training and validation samples.

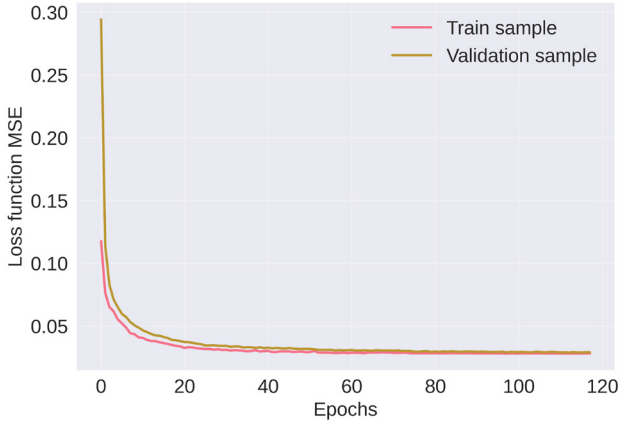

Fig. 1. MLP model learning curves for the root mean square error loss function depending on the epoch for the training and validation datasets

Fig. 1 demonstrates that at the initial stage (the first 20 epochs) both curves fall sharply from high initial values to much lower levels (less than 0.03). This indicates a rapid learning of the model at the initial stages. From 30 to 120 epochs, the learning curves of the MLP model for the loss function by the mean square error converge to close values (about 0.02) and remain stable. The curves almost coincide, which is a sign of successful learning.

Fig. 2 shows the curves of change in the loss function by the mean absolute error of the model training for the training and validation samples.

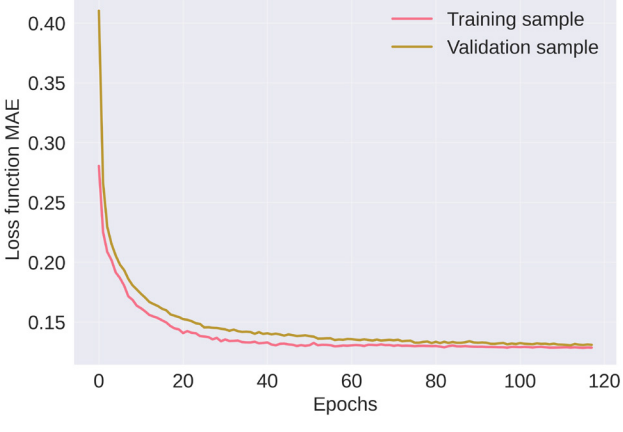

Fig. 2. MLP model learning curves for the mean absolute error loss function depending on the epoch for the training and validation datasets

Fig. 2 demonstrates that at the initial stage (the first 30 epochs) both curves fall from high initial values to much lower levels (less than 0.17 and 0.15). This indicates a fast learning of the model at the initial stages. From 30 to 120 epochs, the learning curves of the MLP model for the loss function by the mean absolute error converge to close values (about 0.07 and 0.06) and remain stable. The curves almost coincide, which indicates that the optimal performance of the model has been achieved.

Fig. 3 shows a scatter plot for the coefficient of determination R^2 for the measured and predicted values of the propane fraction in LPG.

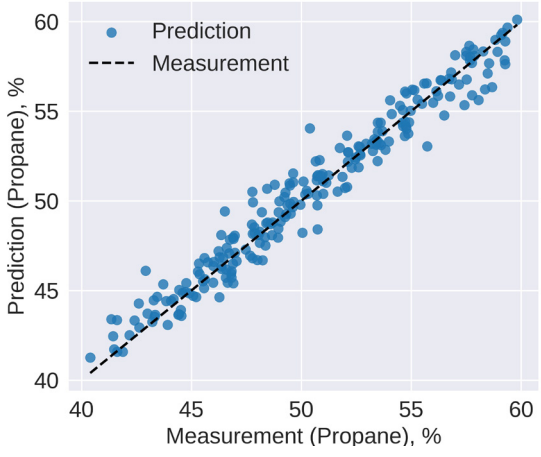

Fig. 3. Scatter plot of the coefficient of determination R^2 for measured and neural network predicted values of the mass fraction of propane in liquefied petroleum gas

Fig. 3 demonstrates that the predicted values of the mass fraction of propane are located densely and relatively evenly along the set of measured values. Deviations from them are not large over the entire range of values (from 40% to 60%). The coefficient of determination R^2 for propane is 0.872. This indicates a high generalization ability and efficiency of the performed measurement control over this component of LPG.

Fig. 4 shows a scatter diagram comparing the coefficient of determination R^2 for the measured and predicted values of the butane fraction in LPG.

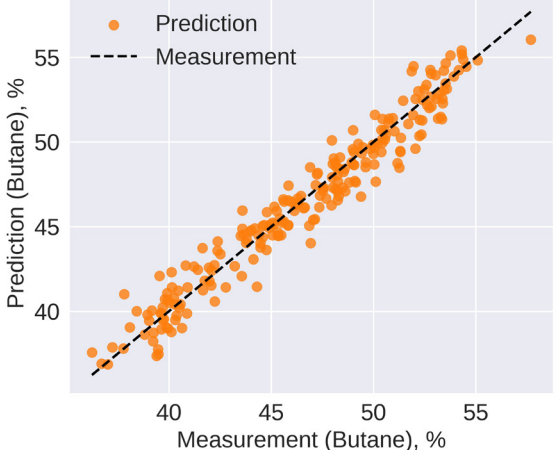

Fig. 4. Scatter plot of the coefficient of determination R^2 for measured and neural network predicted values of the mass fraction of butane in liquefied petroleum gas

Fig. 4 demonstrates that the predicted values of the mass fraction of butane are located densely and relatively evenly along the set of measured values. Deviations from them are not large over the entire range of values (from 34% to 60%). The coefficient of determination R^2 for butane is 0.876. This indicates a high generalizability and efficiency of the performed measurement control over this component of LPG.

Fig. 5 shows a scatter plot comparing the coefficient of determination R^2 for the measured and predicted values of the fraction of unsaturated hydrocarbons in LPG.

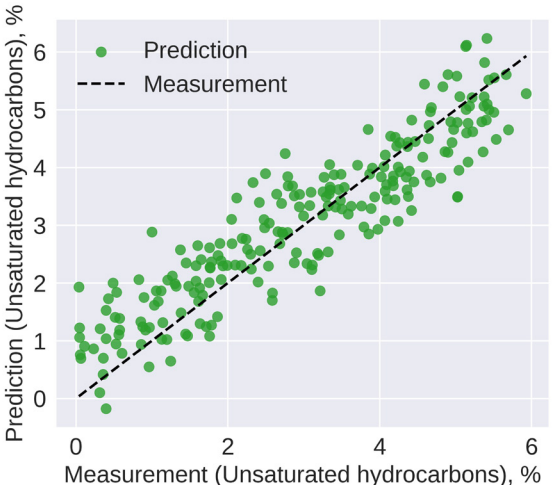

Fig. 5. Scatter plot comparing the coefficient of determination R^2 for measured and neural network predicted values of the mass fraction of unsaturated hydrocarbons in liquefied petroleum gas

Fig. 5 demonstrates that the predicted values of the mass fraction of unsaturated hydrocarbons are located quite scattered and form a "cloud" around the set of measured values. The coefficient of determination R^2 for unsaturated hydrocarbons is 0.695. This indicates a somewhat lower generalization ability and efficiency of the performed measurement control over this component of LPG.

Thus, the total value of the coefficient of determination R^2 for the measured and predicted by the neural network values of the mass fraction of LPG components was 0.845.

Fig. 6 shows a plot of change in the MAE error in the process of measuring control over the mass fraction of propane in LPG.

Fig. 6 demonstrates that the MAE errors for propane range from values close to 0% to a maximum of 3.7%. The median value is 1.05%, and the average is 1.24%. The error is random in nature without a clearly expressed trend or shape of the distribution.

Fig. 7 shows a plot of the MAE error change in the process of measuring the mass fraction of butane in LPG.

Fig. 7 demonstrates that the MAE errors for butane range from values close to 0% to a maximum of 3.2%. The median value is 1.06%, and the average is 1.4%. The error is random in nature without a clearly expressed trend or shape of the distribution.

Fig. 8 shows a plot of the MAE error change in the process of measuring the mass fraction of unsaturated hydrocarbons in LPG.

Fig. 8 demonstrates that the MAE errors for unsaturated hydrocarbons range from values close to 0% to a maximum of 1.78%. The median value is 0.65%, and the average is 0.81%. The error is random in nature without a clearly expressed trend or form of distribution.

Thus, the overall average value of the MAE error in the process of measuring the mass fraction of LPG components was 1.2%.

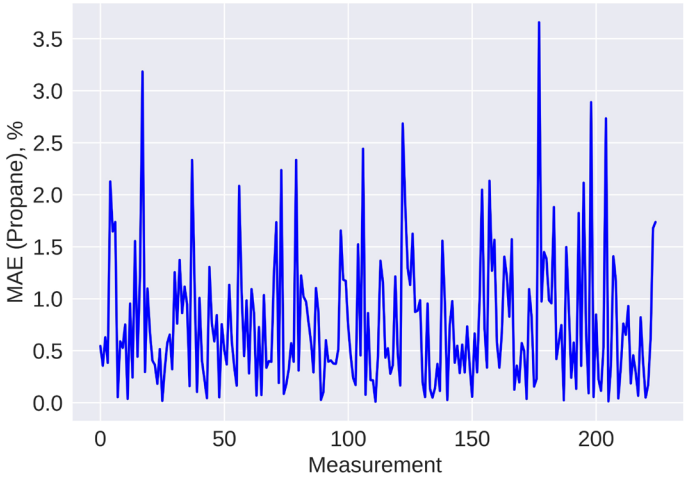

Fig. 6. Plot of change in MAE error during measurement control of the mass fraction of propane in liquefied petroleum gas

Fig. 7. Plot of change in MAE error during measurement control of the mass fraction of butane in liquefied petroleum gas

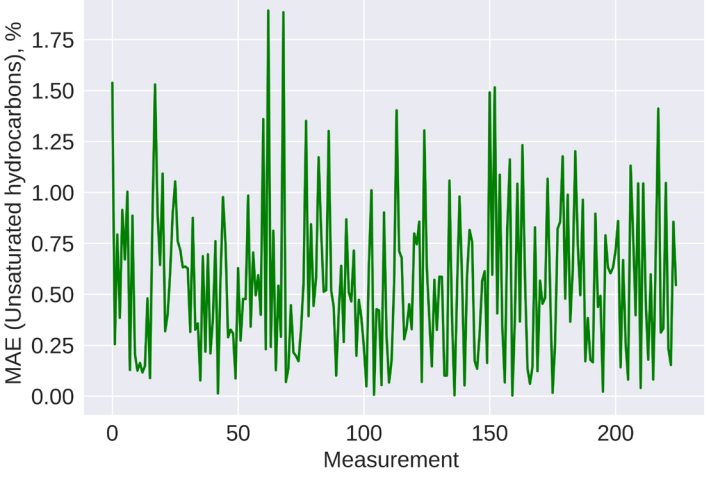

Fig. 8. Plot of change in MAE error during measurement control of the mass fraction of unsaturated hydrocarbons in liquefied petroleum gas

5. 3. Comparative analysis of the accuracy of neural networks for measuring gas composition control

The trained MLP model, based on performance indicators for predicting the mass fractions of LPG components,

demonstrated high accuracy compared to conventional methods such as gas chromatography, spectroscopy, as well as methods based on neural networks.

Conventional methods include gas chromatography and Raman spectroscopy. Their accuracy is about 95%. For regular spectroscopy, the accuracy is lower, especially for gas mixtures. The peak bands of propane and butane may coincide, making it difficult to directly separate the components. Improving accuracy requires the use of statistical methods. In addition, trading methods require careful calibration. The use of specific sensors helps alleviate the problem of overlapping spectra but requires careful calibration of each channel. For example, the accuracy of the sensor for propane without calibration was 72.3% [8].

Methods for measuring control over LPG components based on neural networks combine conventional methods and neural networks. Neural networks help quickly obtain results, solve the problems of cross-sensitivity, measurement drift, overlapping spectra, and increase the overall accuracy. Since the vast majority of publications consider the construction of a model for a specific task, this complicates the comparison of models and their accuracies. Therefore, sources that have neural network models were selected for comparison, although could be used for other industries. Such models were selected as models for chemiluminescent flame analysis, for electronic "sniffing", for two-dimensional gas chromatography, for predicting the concentration of particles in a two-phase gas-solid flow, as well as for predicting the gas composition [11, 15, 20–22]. The results of accuracy assessment of the models are given in Table 2.

Table 2

Results of model accuracy assessment

ID	Model	Accuracy, %
A model for the analysis of chemiluminescent flames	MLP	98
Model for electronic «sniffing»	1D-CNN	91
Model for 2D gas chromatography	Mask R-CNN	97
A model for predicting the concentration of particles in a two-phase gas-solid flow	RNN	92.4
	LSTM	92.7
	BPNN	92.5
Model for predicting gas composition	MLP	96.5
Proposed model	MLP	99

Table 2 demonstrates that the highest accuracy, namely 99%, is shown by the proposed model. This accuracy is comparable to other models, which allows us to state that the proposed model is verifiable from the point of view of its practical application. This gives grounds to consider this model as a suitable tool for use in applied problems related to analysis of the composition of liquefied gas.

6. Discussion of results based on investigating the process of measuring control over liquefied petroleum gas components using a multilayer perceptron

The results of our studies show the successful training of the constructed model for measuring control over LPG components using MLP, its high accuracy and small average error. The effectiveness of training the model is illustrated by the plots of training curves shown in Fig. 1, 2 of the loss functions for the mean absolute error and the mean square error. For the test data set, they do not increase relative to the training set, which means the absence of overtraining. In addition, the closeness of these curves indicates that the model has good generalization ability on new data. This indicates the success of training the model without signs of overtraining or undertraining. The scatter diagram in Fig. 3, 4 demonstrates that the coefficient of determination R^2 for the measured and predicted by the neural network values of mass fractions of propane and butane is characterized by high density, as well as high R^2 values. For unsaturated hydrocarbons (Fig. 5), the data density in the scatter diagram is somewhat higher. Despite this, the constructed model demonstrates high accuracy of the measurement control over LPG components. Fig. 6–8 demonstrate that changes in the MAE error in the process of measuring the mass fraction of LPG components fluctuates within small limits of low values. This indicates a consistently small average error, about 1%, although sometimes there are single spikes up to 2–3%, which is random in nature without a clearly expressed trend or distribution shape.

The accuracy of the constructed model for measuring control over LPG components using MLP is 4% higher than similar values obtained using conventional methods such as gas chromatography [8] and mass spectrometry [8]. At the same time, the problem of complex equipment is eliminated, the model is easier to use and works faster. Compared (Table 2) with methods based on neural networks [11, 15, 20–22], the constructed model has a higher accuracy of 1–9%. At the same time, the accuracy of the model is comparable to more complex hybrid architectures [10] while maintaining low requirements for the hardware base [15] and approximates nonlinear dependences by eliminating cross-sensitivity [4, 20, 22]. This becomes possible due to the development of our own model architecture (Table 1), adapted to measuring control over LPG components.

The scope of application of our results includes the use of the proposed model to solve the tasks to analyze the composition of LPG, in particular at gas filling stations, oil and gas refineries, gas terminals, storage facilities, etc.

The conditions for applying the results are the initial and periodic calibration, the availability of trained personnel, the stability of the operating conditions of the model, and the controlled environment. Calibration involves conducting a series of measurements on gases with a known composition, checked on a reference chromatograph. The model must work with LPG, the parameters of which are within the calculated range of temperatures, pressures, and component composition on which the model was trained.

The potential effects of using the constructed model are quite significant. When pumping LPG from one container to another, the model makes it possible to quickly check and control the composition of LPG and the presence of possible contaminants. For boiler houses or gas turbines, accurate knowledge of the composition of LPG as a fuel makes it possible to optimize the air supply, which increases efficiency and reduces harmful emissions. Measuring control using a neural network, unlike conventional methods, makes it possible to prevent the occurrence of emergencies and eliminate delays in decision-making. The model could also be integrated directly into the production line for continuous monitoring of the composition of LPG, which is impossible with conventional laboratory analysis. This would potentially improve commercial accounting of LPG, reduce costs that may be associated with non-compliance with LPG quality standards, which could ultimately simplify the process of certification of LPG during inspections.

The constructed model for measuring control over LPG components using MLP has certain limitations that should be taken into account when interpreting the results and applying them in practice. Note that the model was trained only on data that correspond to the mass fractions of LPG components specified in a specific standard. In addition, the correctness of the model depends on the quality and stability of the measurements of the tool, which makes it sensitive to systematic errors and noise. In addition, although the model demonstrates satisfactory performance, its application, for example, when changing the pressure or content of the gas mixture, requires additional training. In addition, the explanatory power of the model remains limited, and its application in industry will require further efforts in terms of scalability, reliability, etc.

The disadvantages include the difficulty of accurately determining the mass fraction of unsaturated hydrocarbons since this is a small number of many components, which is characterized by a weak "signal" in the input data, which is more difficult to distinguish from random noise. This drawback could be overcome by using more powerful software environments and hardware resources and parallel computing.

Future studies may involve further improving the accuracy in determining unsaturated hydrocarbons by increasing the amount of training data, especially samples with different contents of unsaturated hydrocarbons, complicated architecture, added new features. This will require complex mathematical modeling, taking into account the subject area of application and developing software modules adapted for a specific system.

7. Conclusions

1. We have determined the structure of the model for measuring control over LPG components. It was established that 6 layers are sufficient to obtain an effective model with better generalization ability. Thus, the input layer consists of 15 input neurons. The three hidden layers, which perform gradual generalization and detection of nonlinear dependences between the input data from a device and the composition of LPG components, consist of 64, 128, and 64 neurons, respectively. In addition, a Dropout layer is used to prevent overtraining after the hidden layers. For the output layer, three neurons are used, corresponding to the calculated mass fractions of propane, butane, and unsaturated hydrocarbons. Such a structure makes it possible to achieve optimal model training efficiency.

2. The MLP model has been evaluated according to the efficiency indicators, namely the mean absolute error (MAE) and the coefficient of determination (R^2). It was found that the coefficient of determination R^2 for propane is 0.872, for butane – 0.876, and for unsaturated hydrocarbons – 0.695. Thus, the total value of the coefficient of determination R^2 for the measured and predicted by the neural network values of the mass fraction of LPG components was 0.845. This indicates a high generalization ability and efficiency of the performed measurement control of LPG components. It was found that the median value of the MAE error for propane is 1.05%, for butane – 1.06%, for unsaturated hydrocarbons – 0.65%. It was found that the average value of the MAE error for propane is 1.24%, for butane – 1.4%, for unsaturated hydrocarbons – 0.81%. Thus, the overall average error value of MAE in the process of measuring the mass fraction of LPG components was 1.1%. This indicates a high accuracy of the constructed model.

3. We have performed a comparative analysis of the accuracy of the constructed MLP model with conventional methods, namely gas chromatography, spectroscopy, as well as methods based on neural networks. It was found that the highest accuracy, namely 99%, is demonstrated by the proposed model, while the accuracy of conventional methods varies within 70–95%, and methods based on neural networks – 90–98%. Thus, the accuracy of the constructed model is commensurate with methods based on neural networks while the model itself does not require complex equipment, unlike traditional methods. This indicates the verification of the proposed model from the point of view of its practical application, which could be used in applied tasks for analyzing the composition of liquefied gas.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

Funding

The study was conducted without financial support.

Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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