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CONSTRUCTION OF A MODEL FOR MEASURING LIQUEFIED GAS VOLUME BASED ON AN ARTIFICIAL NEURAL NETWORK

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This study investigates the process of quantifying liquefied gas volume using an artificial neural network. The task addressed relates to the insufficient efficiency of existing methods for measuring liquefied gas volume. It can be partially solved by measuring the parameters of liquefied gas in cylinders remotely and by processing the data with an artificial neural network to quantify its volume. However, there is another issue associated with the complexity of using artificial neural networks in combination with corresponding peripherals, in particular devices, means, sensors, gauges, etc., and the need for significant computing power.

This paper suggests a model for measuring liquefied gas volume, which takes into account its physical characteristics, based on an artificial neural network that provides communication with gas measurement devices. The mechanism behind such result 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 equals 0.999245. High accuracy is illustrated by the overall low average value of a mean absolute error, which equals 1%. That was made possible by the distinctive features of the proposed solution, namely the optimized model architecture in accordance with the object of study and its input features. These features are the signal from a photodetector, which characterizes the level of liquefied gas, the angles of the cylinder in the vertical plane, as well as in the horizontal plane.

The results could be applied to tasks involving the measurement of liquefied gas volume, especially at oil and gas processing plants, gas filling stations, gas storage facilities, etc.

Keywords: liquefied gas, artificial neural network, mean absolute error, coefficient of determination

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1. Introduction

Liquefied gas is widely used as a fuel in motor vehicle engines and installations at industrial, agricultural, and municipal facilities [1]. There is also a continuous increase in the volume of consumption of this fuel and, accordingly, the issue of the safety of storage and transportation of cylinders with liquefied gas arises. This is due to the fact that it is forbidden to fill the cylinder to more than 85% of its volume. The remaining 15% of the volume ("vapor cushion") is needed so that when the gas is heated, for example, when the cylinder is brought from the cold into a warm room, the pressure does not rupture its walls [2]. One way to solve this problem is to measure the volume of liquefied gas, which could make it possible to control the process before, during, and after filling the cylinder.

The volume of liquefied gas is quantified by various devices, means, sensors, gauges, etc. The work of most of them involves direct human contact with liquefied gas. As a result, various risks may occur, such as explosions and fires, leading to environmental pollution, injuries, and deaths. This is accompanied by significant material damage and a negative impact on public health [3]. This problem can be solved by remotely measuring the parameters of liquefied gas in cylinders and processing the data with an artificial neural network (ANN) to quantify its volume. For this purpose, there are appropriate tools [4, 5], which contain a sensor that, being in a hazardous working environment, transmits data on the parameters of the liquefied gas to a remote computer where the ANN processes the received information.

There are a significant number of ANN models [6–8] for measuring various parameters of different types of gases. The disadvantage of their use is the difficulty of combining with peripheral devices, in particular sensors, and the need for large computing power, which can generally limit their use. This issue can be resolved by building an ANN model that

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makes it possible, based on data received remotely from the sensor, to measure the volume of liquefied gas.

Therefore, certain requirements are imposed on the appropriate ANN model for quantifying the volume of liquefied gas, namely:

– high speed;

– resistance to errors;

– high accuracy.

Thus, there is a need to analyze ANN models for measuring the volume of liquefied gas and select the optimal one according to the above requirements, in particular high accuracy and speed. In addition, it is necessary to take into account the parameters that characterize these models since their change has a direct impact on the accuracy, speed, and overall efficiency of the measurement.

A current topical direction in the evolution of ANNs is their use for remote measurement of the volume of liquefied gas, in particular in road transport, gas filling stations, industry, and autonomous gas supply systems for households and enterprises. At the same time, it is also relevant to construct an appropriate ANN model that would provide the most efficient and accurate measurement of the volume of liquefied gas. Important criteria in this case are the performance indicators of the model, namely the mean absolute error (*MAE*), the coefficient of determination (R^2), the root mean square error (*MSE*), and the root mean square error (*RMSE*).

Therefore, it is a relevant task to carry out a study aimed at building a model for measuring the volume of liquefied gas using ANNs.

2. Literature review and problem statement

The application of deep ANN (DNN) in combination with fiber-optic sensors in multiplexed liquid level measurement systems is considered in [9]; it eliminates the cross-sensitivity of sensors, contributes to the cost-effectiveness of the system and the scalability of solutions. The accuracy of this method is 95%. However, there are unresolved issues related to the need for periodic model reconfiguration and long-term calibration of expensive equipment. This limits the production stability of the model and its operation in real time.

In [10], a liquid level measurement model is proposed, in which an interferometric device records the interference pattern of the liquid surface when the level changes. In this case, the ANN analyzes the obtained interferograms and converts them into level values. The accuracy of such a model is 98%. However, there are unresolved issues related to the limited measurement range and sensitivity to liquid turbulence. This causes difficulties associated with measuring the volume of liquefied gas.

In [11], a fiber-optic system with fiber Bragg gratings (FBG) for liquid level monitoring and deep ensemble ANN (ensemble DNN) for signal processing are described, which increases the accuracy of level measurement. The accuracy of this method is 98%. However, the complexity of the model and the high cost of the equipment remain an unresolved issue. This limits the application of the model making it highly specialized.

In [12], a system is considered that combines an ultrasonic sensor with a convolutional ANN architecture with long short-term memory (CNN-LSTM), the accuracy of which is 98%. This deep learning model, built for predicting the volume of gas in pipelines in which the flow consists of three components, makes it possible to automatically focus on the most informative signals, ignoring noise, which increases the reliability of the prediction. However, unresolved issues related to the dependence of the system on the flow composition, the influence of external factors, as well as the need for constant calibration of sensors remain. A likely reason of difficulties is the propagation of ultrasonic signals in three-phase flows, in which they are exposed to many interferences simultaneously (scattering, absorption, etc.).

An option to overcome the above difficulties may be to use ANNs to directly measure the volume of liquefied gas as a two-phase medium. This is the approach used in [13], in which a combined convolutional ANN-transformer model (CNN-Transformer) is smoothed for measuring the volume in gas-liquid two-phase flows, which processes data from a system of sensors that record fluctuations in the electrical conductivity of the mixture. The accuracy of this method is 97%. However, this combined model with three modular components requires significantly more computational resources and training time compared to simpler models (multilayer perceptron (MLP)) and also has limited generalization ability.

In view of the above, in [14], an MLP model is described for measuring the volume in gas-liquid flows using a combined approach that combines a photon attenuation sensor and an electric capacitance sensor. The accuracy of this method is 98%. However, the use of a photon attenuation sensor in this model requires a gamma-ray source (e.g., cesium (Cs-137)), which raises safety issues and requires compliance with regulatory standards for radioactive materials. A similar principle is also implemented in [15], in which MLP is used to measure the volume of liquefied gas in almost real time and without laboratory analysis. The accuracy of this method is 98%. However, this approach requires periodic correction when changing process conditions and a large training data base. The model also depends on industrial data, which often contain noise and omissions, which significantly reduces the accuracy of training.

Thus, the problem of insufficient efficiency of existing models for measuring the volume of liquefied gas can be formulated as follows. Model [9] is less accurate and requires long-term equipment calibration. At the same time, models [10, 12] are more accurate, although they also require equipment calibration and are sensitive to the influence of external factors. Other models [11, 14] also demonstrate high accuracy, but are excessively complex and expensive. At the same time, models [13, 15] are suitable for a complex technological process, but require periodic correction in case of changes in process conditions and a large training data base.

Thus, our review shows that ANNs effectively replace or complement conventional methods for measuring the volume of liquefied gas, which provides faster and less expensive analysis in real time. In addition, they distribute computational processes by processing data from sensors that directly perform measurements. This eliminates the factor of cross-sensitivity of sensors and the need for their constant calibration and also increases the accuracy of measurements and reduces the cost of equipment.

All of the above allows us to argue that it is advisable to build a model that will take into account the physical features of the measurement process through input features, which could significantly improve the accuracy of measuring the volume of liquefied gas.

3. The aim and objectives of the study

The aim of our work is to construct a model for measuring the volume of liquefied gas using ANN. This will provide an

opportunity to obtain a new ANN with increased accuracy for quantifying the volume of liquefied gas, which could be used to control the process before, during, and after filling a cylinder.

To achieve the goal, the following tasks were set:

– to train the model according to the performance indicators for predicting the volume of liquefied gas;

– to perform a comparative analysis of ANN accuracy for measuring the volume of liquefied gas.

4. Materials and methods

The object of our study is the process of measuring the volume of liquefied gas using ANN. The corresponding model was constructed in such a way that the new model, receiving data on the level of liquefied gas and the location of the cylinder in space, which are remotely received from the device [16], measured its volume.

The principal hypothesis assumes that ANN is capable of converting input data from the device into the value of the volume of liquefied gas with high accuracy. The assumptions adopted in the study were that the law of distribution of errors in measuring the volume of liquefied gas would be close to normal over the entire measurement range. The simplifications accepted in the study were that liquefied gas was considered a two-phase medium. That is, the volume of the liquid phase was measured in it, which should not exceed 85% of the volume of the cylinder, and the remaining volume is occupied by its vapor phase [2].

The work used such research methods as mathematical statistics, neural network methods, and data processing methods. Mathematical statistics allows us to assess the adequacy of an ANN model as it makes it possible to calculate error metrics. The main modeling tool among neural network methods is the neural network approximation method based on the artificial neural network MLP, which allowed us to overcome the regression problem for a nonlinear system. To prepare the input data, the following data processing methods were used: preprocessing methods, statistical filtering, as well as feature normalization to prepare the dataset for training.

The study of the process of measuring the volume of liquefied gas was carried out using the ANN model taking into account its training parameters. To verify its effectiveness, data from device [16] were used. They are signals from the photodetector, which receives a light spot, and from the eclimeter, which determines the angles of the cylinder in two mutually perpendicular directions. The light spot is formed by a laser beam incident on the surface of the liquefied gas and then reflected onto the photodetector. Depending on the distance to the liquefied gas level, the light spot on the photodetector will have the appropriate position, and taking into account the angles of the cylinder, the volume of liquefied gas can be measured.

Other methods for measuring the volume of liquefied gas include statistical methods, such as linear regression, and machine learning methods. Among the latter, the best results are demonstrated by support vector methods, in contrast to which linear regression methods usually show worse results. Despite this, the support vector method is problematic in the case of interpreting the results and retraining the model under new conditions [17].

To train the ANN, a data set of 3000 measured volume values for a standard 50 l cylinder was formed in the format of floating-point numbers. Note that up to 85% of the cylinder volume is occupied by the liquid phase, i.e., up to 42.5 l. Each record of measured data has input parameters (features) and a known correct answer. The entire data set was divided into two parts in the ratio of 80/20, i.e., the training sample consisted of 2400 data, and the verification (test) sample consisted of 600 data.

The ANN accepts three features as input, which are independent variables for measuring the volume of liquid in the cylinder. These variables are the signal from the photodetector, which characterizes the level of liquefied gas, the angles of the cylinder in the vertical plane α and in the horizontal plane γ. At the output of the ANN, the value of the measured volume is obtained.

The signal from the photodetector demonstrates a nonlinear dependence on the level of liquefied gas in the cylinder, which is at angle α in the vertical plane and at angle γ in the horizontal plane. They are linked by the following relationship

$$\alpha = \arcsin\frac{c}{2h\sin\frac{\gamma}{2}}, \quad (1)$$

where c is the distance the cylinder was moved; h is the distance to the liquid level.

Note that the signal from the photodetector is in the range of 1–150 mV, and the angles of the cylinder in the vertical and horizontal planes are 0–1.57 rad.

Depending on the input features, the volume of liquefied gas in the cylinder is determined as

$$V = \frac{R^3}{\operatorname{tg}\alpha}\int_{u_0}^{u_L}\left(\arccos u - u\sqrt{1-u^2}\right)\mathrm{d}u, \quad (2)$$

where R is the radius of the cylinder; u is the slope coefficient; u_L is the maximum slope coefficient; u_0 is the minimum slope coefficient.

The measurement range of the liquefied gas volume is 0.1–42.5 l.

To measure the volume of liquefied gas, an ANN model of the MLP or direct propagation type was used. The number of weight coefficients, i.e., connections between neurons in the ANN layers is 10512, the number of biases is 257, and the training parameters are 10769. The ANN contains 5 layers, of which 1 is input, 3 are hidden, and 1 is output. The activation function in the hidden layers is Rectified Linear Unit (ReLU) with a transfer function of form $f(x) = \max(0, x)$, and in the output layer it is linear. In view of this, the architecture of the constructed model is given in Table 1.

Table 1 demonstrates that the input of the ANN consists of 3 neurons. This corresponds to the number of input features. To build an effective model with better generalization ability, 3 hidden layers were used. The first layer consists of 64 neurons, which is empirically determined as the smallest required size sufficient for regression with 3 inputs. This layer allows the network to build primary nonlinear combinations of input parameters. The second hidden layer has 128 neurons, which allows us to compensate for the small number of inputs and allows us to detect nonlinear interdependences between the signal of the photodetector and angles in different planes. The third hidden layer has 64 neurons, which allows us to improve the generalization ability and prevents overtraining. The output layer has 1 neuron and outputs the predicted volume value in continuous form. The activation function in the hidden layers ReLU is computationally efficient and helps ANNs approximate nonlinear dependences and does not have the problem of vanishing gradient like the sigmoid function. The loss function is MSE, which is sensitive to overfitting.

Table 1

Architecture of the constructed model

Layer	Number of neurons	Activation function	Number of connections between neurons in layers	Number of biases	Layer purpose
Input layer	3	–	–	–	Input feature acquisition
Hidden layer 1	64	ReLU	192	64	Initial detection of nonlinear dependencies
Hidden layer 2	128	ReLU	8192	128	Capturing complex nonlinear dependencies
Hidden layer 3	64	ReLU	8192	64	Dynamic dimensionality reduction, noise removal
Output layer	1	Linear	64	1	Linear transformation of measured volume

Thus, the architecture can be schematically depicted as [Input: 3] → [64] → [128] → [64] → [Output: 1].

The optimal hyperparameters for ANN training are the number of epochs (500), Random seed (42), Adam optimizer (Adaptive Moment Estimation), learning rate (0.0005), exponential decay rate for the 1st and 2nd moments (0.9 and 0.999, respectively). ANN training was performed by the supervised learning method using the error backpropagation algorithm.

ANN training and validation were performed using the Jupyter Notebook cloud computing environment in Google Colab (USA) based on Linux with Python 3.10. ANN training and validation were hardware-supported by an Intel Xeon CPU (USA) with two cores, 12 GB RAM. The construction and training of the ANN was provided by the torch 1.9.0 library, numerical data processing – numpy 1.19.0, work with tabular data – pandas 1.1.0, metrics – scikit-learn 0.24.0, graph visualization – matplotlib 3.3.0. The CUDA library was used to accelerate calculations.

5. Results of the construction of a model for measuring the volume of liquefied gas

5. 1. Training the model according to the performance indicators for predicting the volume of liquefied gas

The measured and predicted values of the volume of liquefied gas were compared. The measured values were obtained using the optical method, and the predicted values were obtained as a result of the measurement performed by the model.

The accuracy of the model was evaluated on the test data set using the following performance indicators:

– *MAE*

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|; \quad (3)$$

– R^2

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \tilde{y}\right)^2}; \quad (4)$$

– *MSE*

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}\right)^2; \quad (5)$$

– *RMSE*

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}\right)^2}, \quad (6)$$

where y_i – measured volume values; $\hat{y}_i$ – predicted volume values by the model; $\tilde{y}$ – averaged volume value; $i = 1, 2, \ldots, n$ – number of measurements; n – total number of measurements.

To assess the quality of the results obtained from the models, the selected indicators are standard. These are typical statistical metrics used to assess the correspondence between the actual measurements and the predicted results [18].

The magnitude of the error on the training and validation samples should gradually decrease. This allows us to state the correctness of the ANN training and the absence of overtraining, that is, the adequacy of the model. The validation of the training results can be assessed by gradually reducing the error value on the validation sample. The number of epochs is selected from the condition of obtaining the largest accuracy value on the validation sample in the absence of significant fluctuations in numerical values. The feasibility of increasing the number of training epochs lies in the gradual increase in accuracy on the validation sample. A drop in accuracy on the validation sample is a sign of overfitting since its absence is a condition for model validation.

The input of the 3-neuron model is a vector of 3 features formed on the basis of a pre-prepared data set. The calculation of the volume of liquefied gas is performed under a soft real-time mode, which requires high-speed ANN in the case of limited memory to ensure high accuracy. The model was trained using a training sample of 80% of the total data volume. The training efficiency was tested using a test sample of 20% of the total data volume.

The model was studied by evaluating the training efficiency of the model (Fig. 1, 2) and analyzing it according to the performance indicators (Fig. 3, 4). The construction of plots illustrating our studies was performed in the Google Colab environment using the Matplotlib library.

Fig. 1 shows the curves of the loss function changes over 500 epochs on the training and test data sets.

Fig. 1 demonstrates that at the initial stage of training (epochs 0–50) there is an exponential decrease in the loss function from 0.4 to 0.01 (training sample) and from 0.33 to 0.01 (test sample). Thus, after some divergence at the initial stage of training, the curves practically coincide. At the next stage (epochs 50–150) the rate of decrease decreases and the values of the loss function change from 0.01 to 0.003. The curve has a smooth appearance, which asymptotically approaches the minimum. At the next stage (epochs 150–300) stabilization occurs and the value of the loss function practically does not change and reaches 0.001. At the last stage (epochs 300–500) the model reaches an accuracy of 1% by MAE. The deviation of the values of the learning curves is minimal (< 0.0005). Thus, the model shows good convergence. Since the model learning curves for the loss function practically coincide throughout the entire training, we can state the absence of overtraining, sufficient complexity, model size, optimality of training parameters and amount of data for training.

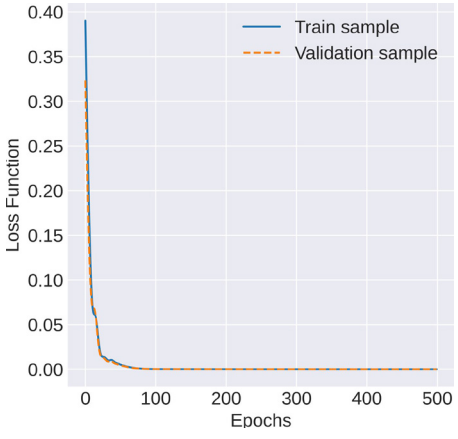


Fig. 1. Model learning curves for the loss function depending on the epoch for the training and validation datasets

Fig. 2 shows the change in R^2 on the validation set depending on the ANN training epoch.

Fig. 2 demonstrates that R^2 reaches the value of 0.999245. This is a good indicator for the model. The deviation in R^2 values is minimal (< 0.0001). Further training after 200 epochs does not provide a noticeable increase in R^2, that is, the model stabilizes in a state where it explains 99.92% of the variance.

Fig. 3 shows the distribution of absolute errors.

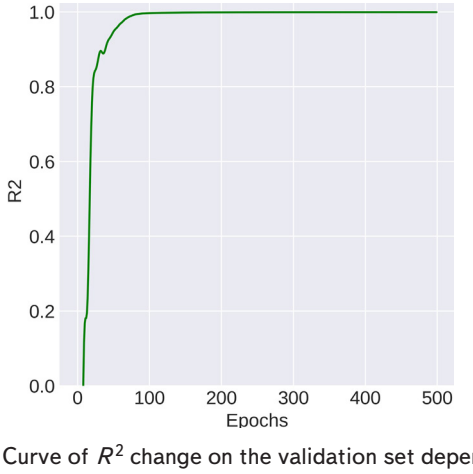


Fig. 2. Curve of R^2 change on the validation set depending on the ANN training epoch

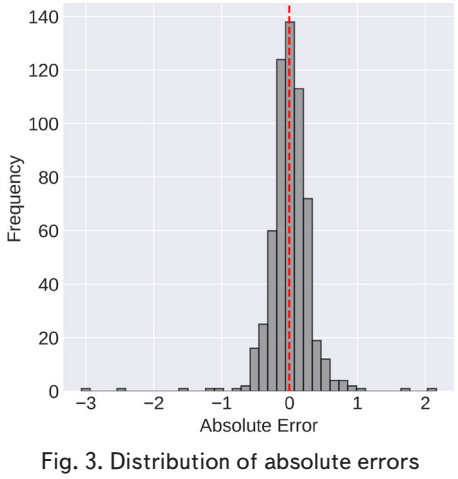


Fig. 3. Distribution of absolute errors

Fig. 3 demonstrates that the distribution of absolute errors has a distinct bell-shaped shape (Gaussian distribution). The average error value is close to 0, the standard deviation is 0.4 l, the range of 95.5% of errors is in the range from –0.7 to +0.7 l, the maximum frequency (mode) is 145 observations with an error of ±0.1. Most of the model measurements (33%) have an error of less than 0.2 l, which is a good indicator. The distribution of absolute errors is normal, which allows us to argue about the adequacy of the model from a statistical point of view; the errors are almost symmetrical and small – 68.3% are observed for less than 0.4 l. The range of 99.8% of errors is in the range from –1.1 to +1.1 l. A small asymmetry is typical for real data.

Fig. 4 shows a scatter plot comparing R^2 for measured and predicted values of liquefied gas volume.

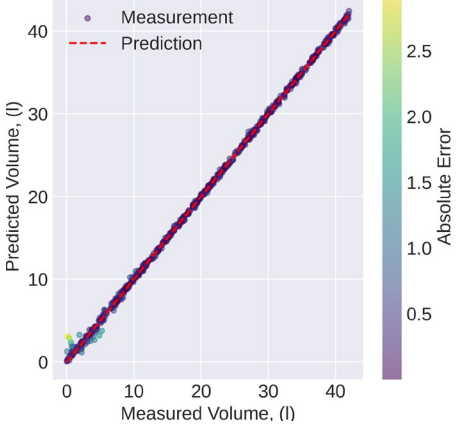


Fig. 4. Scatter plot comparison of R^2 for measured and ANN predicted values of liquefied gas volume

Fig. 4 demonstrates that the predicted values of the volume of liquefied gas are located densely and relatively evenly along the set of measured values in the range of 0–42.5 l. At small volumes (0–10 l), the vast majority of deviations are within ±0.2–0.3 l. There is a noticeable tendency towards uneven dispersion, with the largest deviations generally not exceeding 1 l and occurring rarely. At small volumes, the signal is minimal, which leads to larger errors due to noise. However, the results showed that the model performs well even at small values, which indicates its sensitivity and adaptability to different ranges. At medium volumes (10–30 l), the deviation is less than 0.2 l, and the distribution density is very high and there is almost no point scattering. On average, the model measures the volume with an error within ±0.1 l. At large volumes (30–42.5 l), the vast majority of points located around the set of measured values do not exceed 0.3–0.4 l, but there are isolated deviations of 0.6 l. The model has no systematic bias. There are no points on the diagram that are significantly distant from the set of measured values. The maximum deviation does not exceed 1.2 l and occurs very rarely. These are not errors, but part of the natural variability, which is quite acceptable for most practical applications.

Thus, the model measures the volume with high accuracy, since there are no systematic errors, the distribution of absolute errors is normal over the entire range of values, and there are almost no anomalous deviations. The average deviation of the model is ±0.2 l. Therefore, the model is reliable in practical applications.

Thus, the resulting metrics values: R^2 – 0.999245, *MAE* – 0.200164 l, *MSE* – 0.113362 l^2, *RMSE* – 0.336692 l. Based on the analysis of data in the figures, it can be stated that the model is suitable for practical application since it measures

volumes with an accuracy of ±0.2 l, which is about 1% in absolute values. Also, the model does not overtrain, is statistically adequate, uniformly processes all types of input data and explains 99.92% of the variance.

5. 2. Comparative analysis of the accuracy of artificial neural networks for measuring the volume of liquefied gas

The trained model, based on the performance indicators for predicting the volume of liquefied gas, demonstrated high accuracy compared to conventional methods and methods based on ANNs.

Conventional methods include optical, dynamic, geometric. Their accuracy is in the range of 90–95%. This is due to the high sensitivity to temperature fluctuations, for example, changes in the season, dependence on the phase state, since liquefied gas is a two-phase medium, and mechanical wear of measuring equipment. The latter applies to sensors, gauges, and meters that implement standard methods, since the presence of moving parts that constantly operate in an aggressive environment leads to rapid wear and, accordingly, a decrease in measurement accuracy. In addition, conventional methods require careful calibration, which must be carried out periodically. Also worth considering is the human factor. The participation of the operator or consumer directly in the process of measuring the volume of liquefied gas as an additional external factor could significantly reduce the accuracy or even sharply distort it or disable the entire system. A reliable solution is the automation of the process, in particular by combining remote measurement of liquefied gas parameters with appropriate sensors and processing the resulting ANN data to measure its volume [19, 20].

Methods for measuring the volume of liquefied gas based on ANN combine conventional methods and ANN. ANN makes it possible to quickly obtain results, perform measurements in real time, solve the problems of cross-sensitivity and measurement drift, which ultimately increases the overall measurement accuracy. For comparison, the models of a stepped multilayer perceptron in combination with non-selective infrared spectroscopy, physically informed ANN, graph ANN, recurrent ANN were selected [21–24]. A comparison of the accuracy of the selected models with the proposed one is given in Table 2.

Table 2

Results of model accuracy assessment

ID	Model	Accuracy, %
Stepped multilayer perceptron model combined with non-selective infrared spectroscopy	NDIR-SMLP	98
Physically informed ANN model	PINN	98
Graphic ANN model	GNN	98
Recurrent ANN model	RNN-LSTM	98
Proposed model	MLP	99

Table 2 demonstrates that the highest accuracy, namely 99%, is shown by the proposed model. Since this value is commensurate with other models, it allows us to state that the proposed model is verifiable from the point of view of practical application. This indicates the suitability of the model for use in applied tasks of measuring the volume of liquefied gas.

6. Discussion of results based on investigating the process of measuring the volume of liquefied gas using an artificial neural network

The results of our study showed the successful training of the constructed model for measuring the volume of liquefied gas using ANN, its high accuracy, and small average error. The effectiveness of the model training is illustrated by the plot of the training curves shown in Fig. 1 for the MSE loss function. For the test data set, the curve initially decreases exponentially, then the rate of decline decreases, the curve stabilizes and the value of the loss function practically does not change, reaching an accuracy of 1%. This indicates that the model demonstrates good convergence. Also, the closeness of the training curves indicates the absence of overtraining, sufficient complexity, model size, optimality of training parameters and the amount of data for training. Fig. 2 shows that R^2 reaches a value of 0.999245. This is a good indicator for the model, which stabilizes in a state where it explains 99.92% of the variance. The distribution of absolute errors in Fig. 3 corresponds to the Gaussian distribution and is normal. That is, the model is statistically adequate, and the errors are almost symmetric and small, which is typical for real data. The scatter plot comparison in Fig. 4 shows that the scatter plot for almost all measured and predicted ANN values of the liquefied gas volume is characterized by high density. This indicates a high accuracy of measuring the liquefied gas volume, since the average deviation does not exceed ±0.2 l. Thus, the model performs well even at small values, where certain minor deviations are observed, which indicates its sensitivity and adaptability to different ranges.

The accuracy of the model built for measuring the volume of liquefied gas using ANN is 4–8% higher than that of conventional methods [19, 20]. At the same time, the problem of expensive and complex equipment that needs to be constantly and carefully calibrated is overcome, the model is easier to use, works faster, takes into account the two-phase nature of the environment, and the human factor is eliminated. Compared (Table 2) with methods based on ANN [21–24], our model has a 1% higher accuracy. At the same time, the accuracy of the model is comparable to a more complex stepwise multilayer perceptron [21], while maintaining low requirements for the hardware base [22], and approximates nonlinear dependence, overcoming cross-sensitivity [23, 24]. This becomes possible due to the design of the model's own architecture (Table 1), adapted to measuring the volume of liquefied gas.

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

The conditions for applying the results are the availability of qualified personnel, stable operating conditions of the model, and the controlled environment. The model must work with liquefied gas, the parameters of which are within the calculated range of temperatures, pressures, and volumes on which the model was trained.

The expected effects of using the constructed model are significant. The model makes it possible to quickly control the volume of liquefied gas before, during, and after its pumping from one container to another. For boiler houses or gas turbines, accurate knowledge of the volume of liquefied gas makes it possible to optimize the air supply, which reduces harmful emissions and increases the efficiency of the system. Measuring the volume of liquefied gas using ANN, unlike

conventional methods, eliminates the human factor, which is often a source of emergency situations, and eliminates delays in decision-making. In addition, the model can be integrated directly into the production line for continuous monitoring of the volume of liquefied gas, which is impossible to do with conventional laboratory analysis. This could potentially improve commercial accounting of liquefied gas, reduce costs that may be associated with non-compliance with standards, which would ultimately simplify the process of working with liquefied gas.

The model built for measuring the volume of liquefied gas using ANN has certain limitations that should be taken into account when interpreting the results and applying them in practice. That is, the model was trained only on data that correspond to the volume of liquefied gas specified in a specific standard. It is worth considering multiplicative effects since the correct operation of the model depends on the stability and quality of the measurement by the device, which makes it sensitive to various errors and noise. Despite the fact that the model shows satisfactory efficiency, its use, for example, when changing pressure, temperature, or volume, requires additional training. In addition, the problem of interpreting any ANN also exists, and use on an industrial scale will require further efforts.

The disadvantages include the influence of the environment, equipment vibrations, temperature drift of electronics, contamination of optical elements, which induce dynamic interference that is difficult to predict at the stage of network training. This disadvantage is overcome by using more powerful software environments with the involvement of additional hardware resources and parallel calculations.

The development of the research may consist in further increasing the accuracy of measuring the volume of liquefied gas. This can be achieved by increasing the scale of training data sets by covering wider ranges of temperatures, pressures, and volumes, using transfer learning techniques to adapt models to new conditions, adding new features. This will require complex modeling, taking into account the subject area of use and developing software modules for a specific system.

7. Conclusions

1. The training of the model built for measuring the volume of liquefied gas using ANN has been shown. It was established that the training curves of the model for the loss function practically coincide (especially at the final stage, where the deviation is less than 0.0005) throughout the entire training. This indicates the absence of overtraining, sufficient complexity, model size, optimality of training parameters and the amount of data for training. The model was evaluated according to the performance indicators, namely *MAE*, R^2, *MSE* and *RMSE*. It was established that R^2 is 0.999245, *MAE* – 0.200164 l, *MSE* – 0.113362 l^2, *RMSE* – 0.336692 l. This indicates that the model is suitable for practical application as it makes it possible to measure the volume with an accuracy of ±0.2 l, i.e., in absolute values – 1%, which indicates the high accuracy of our model. It is also not retrained, statistically adequate, uniformly processes all types of input data and explains 99.92% of the variance.

2. A comparative analysis of the accuracy of the constructed model with conventional methods, which include optical, dynamic, geometric, and methods based on ANNs, was carried out. It was found that the highest accuracy, 99%, is shown by the proposed model, while for conventional methods it varies within 90–95%, and for methods based on ANNs it is 98%. Thus, the accuracy of the constructed model is commensurate with methods based on ANNs, and the model itself does not require complex and expensive equipment, unlike conventional methods. This indicates the verifiability from the point of view of practical application of the proposed model, which could be used in applied tasks to measure the volume 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.

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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.

Authors' contributions

Bogdan Knysh: Conceptualization, Methodology, Writing – Original Draft; **Yaroslav Kulyk**: Methodology, Software, Writing – Review & Editing; **Oleksandr Pavlyuk**: Resources, Software, Visualization.

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