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Methods for Quantifying Data Uncertainty for Intelligent Decision Support in Computer-Integrated Oil and Gas Production Systems

Dmytro Kytsmen[1] and Olena Moiseienko[2,*]

[1]Ivano-Frankivsk National Technical University of Oil and Gas, Ivano-Frankivsk, Ukraine

[2]The department of computer systems and networks, Ivano-Frankivsk National Technical University of Oil and Gas, Ivano-Frankivsk, Ukraine

*Corresponding author (E-mail: olena.moiseienko@nung.edu.ua)

ABSTRACT Modern computer-integrated systems for oil and gas production rely on intelligent decision support systems for monitoring, forecasting, diagnostics, and control of technological processes. The effectiveness of such systems significantly depends on the reliability and completeness of input data, which are often affected by measurement errors, missing values, noise, model inaccuracies, and variability of geological and production conditions. Under such circumstances, uncertainty quantification becomes a critical component for ensuring the reliability of predictive models and supporting robust decision-making in digital oilfield environments. The purpose of this paper is to analyze and systematize modern methods for uncertainty quantification of data used in intelligent decision support systems of computer-integrated systems for oil and gas production, as well as to determine their applicability under conditions of incomplete and uncertain information. The study considers the specific features of technological data in oil and gas production, including heterogeneity of information sources, nonlinear process dynamics, measurement uncertainty, and real-time operational constraints. The paper formalizes the uncertainty quantification problem in intelligent decision support systems and analyzes the main types of uncertainty affecting technological systems, including aleatoric, epistemic, measurement, model, and simulation parameter uncertainty. A comparative analysis of Bayesian approaches, ensemble methods, Monte Carlo sampling techniques, probabilistic neural networks, and calibration-based methods is performed from the standpoint of computational efficiency, robustness to noisy and incomplete data, interpretability, and compatibility with industrial monitoring and control systems. The obtained results demonstrate that no single uncertainty quantification method fully satisfies all requirements of computer-integrated oil and gas production systems. It is shown that ensemble methods provide the most balanced solution for operational decision support tasks, while Bayesian and Monte Carlo approaches are more suitable for reservoir modeling and long-term forecasting. Calibration techniques are identified as necessary for ensuring prediction reliability in real-time applications. A decision framework for selecting uncertainty quantification methods according to operational constraints and data characteristics is proposed. The practical significance of the study lies in the possibility of applying the obtained recommendations in the development of computer-integrated systems for monitoring, diagnostics, forecasting, and intelligent decision support for technological objects operating under uncertain and incomplete data conditions.

KEYWORDS uncertainty quantification, intelligent decision support system, computer-integrated system, machine learning, predictive uncertainty.

I. INTRODUCTION

Digital transformation of the oil and gas industry has led to the rapid development of computer-integrated systems for oil and gas production (CIS), where large volumes of heterogeneous data are continuously generated by sensors, monitoring systems, geological models, and production process control equipment. These data are used in intelligent decision support systems for forecasting, diagnostics, and optimization of technological processes during exploration, drilling, and production [1-3]. The efficiency of such systems strongly depends on the reliability and completeness of the input data, which are often affected by measurement errors, missing values, noise, model uncertainty, and changing operating conditions.

Unlike many other industrial domains, technological objects in oil and gas operate under conditions of limited and expensive measurements, indirect estimation of key parameters, and strong dependence on physical and geological processes. A significant part of the data is obtained from distributed sensor networks, well logging systems, SCADA platforms, and reservoir simulation models, which may produce inconsistent or incomplete information. As a result, uncertainty becomes an inherent property of the data used in intelligent decision support systems for information-control systems of oil and gas production.

Uncertainty in input data leads to degradation of predictive model accuracy and may cause incorrect decisions in production process control, drilling optimization, reservoir monitoring, and equipment diagnostics. In critical situations, unreliable predictions can result in significant economic losses or safety risks. Therefore, the development of methods for uncertainty quantification is an important task in the design of computer-integrated information systems used in the oil and gas industry.

Machine learning methods are widely applied in computer-integrated systems for oil and gas production for forecasting production parameters, detecting anomalies, estimating reservoir characteristics, and supporting operational decisions [4-6]. However, most traditional machine learning models provide only point predictions and do not estimate the reliability of the obtained results. This limitation reduces the applicability of such models in intelligent decision support systems, where it is necessary to evaluate the confidence of predictions and take into account possible errors in input data.

In recent years, various approaches for uncertainty quantification in machine learning have been proposed, including Bayesian models, ensemble methods, probabilistic neural networks, Monte Carlo sampling techniques, and calibration methods [7-10]. These approaches allow estimating predictive uncertainty, separating different types of uncertainty, and improving the robustness of decision-making under incomplete or noisy data conditions. However, the selection of appropriate uncertainty quantification methods for intelligent decision support systems in technological systems remains a complex task due to strict requirements for computational efficiency, interpretability, real-time operation, and resistance to measurement errors [11].

Computer-integrated decision support systems for oil and gas production impose additional constraints on data processing algorithms. Such systems must operate with heterogeneous data sources, support real-time monitoring, handle missing or corrupted measurements, and provide reliable results even under limited training data. Therefore, the analysis of uncertainty quantification methods should be performed taking into account the specific features of technological system data and the requirements of computer-integrated monitoring and control systems.

The purpose of this paper is to analyze modern methods for uncertainty quantification of data used in intelligent decision support systems of computer-integrated systems for oil and gas production and to determine their applicability for computer-integrated monitoring, forecasting, and production process control systems operating under conditions of incomplete and uncertain information.

The object of the research is intelligent decision support systems integrated into computer-integrated systems for oil and gas production. The subject of the research is methods for uncertainty quantification of data applied in machine learning models and information processing algorithms for decision support under conditions of incomplete, noisy, and heterogeneous data.

The scientific novelty of the paper consists in systematization of modern uncertainty quantification methods from the standpoint of their applicability in IDSS of computer-integrated systems for oil and gas production.

The practical significance of the obtained results lies in the possibility of using the considered methods in the development of computer-integrated systems for monitoring, diagnostics, forecasting, and decision support in technological systems for oil and gas production under conditions of uncertain and incomplete data.

II. FEATURES OF DATA IN INTELLIGENT DECISION SUPPORT SYSTEMS OF COMPUTER-INTEGRATED SYSTEMS FOR OIL AND GAS PRODUCTION

One of the main characteristics of data in computer-integrated systems for oil and gas production is their heterogeneity. Information used in decision support systems may include continuous sensor measurements, discrete event logs, geological parameters, simulation results, and expert assessments. These data have different formats, sampling rates, and accuracy levels, which makes their integration in a single information system a complex task. In addition, some parameters cannot be measured directly and must be estimated using indirect methods or physical models, which introduces additional uncertainty.

Another important feature of data is the presence of measurement errors and noise. Sensors installed in wells and surface equipment of the technological object operate in harsh environmental conditions, including high pressure, temperature variations, and mechanical vibrations. As a result, measurement errors are unavoidable and may significantly affect the quality of predictions.

Computer-integrated decision support systems also have to operate with incomplete data. Missing values may appear due to sensor failures, communication errors, irregular sampling, or limitations in measurement equipment. In addition, some parameters are measured only periodically because of the high cost of logging operations or laboratory analysis. Therefore, intelligent decision support systems must be able to work under conditions of limited information and provide reliable results even when part of the data is unavailable.

A specific feature of oil and gas production processes is the strong dependence of system behavior on complex physical and geological processes. Reservoir properties, fluid dynamics, and equipment performance are described by nonlinear models with many uncertain parameters. In practice, these parameters are often known only approximately, and different models may produce different predictions for the same operating conditions. This leads to model uncertainty, which must be taken into account in decision support systems.

Another important requirement for technological systems in oil and gas production is real-time or near real-time operation. Monitoring and control systems must process incoming data continuously and provide recommendations for operational decisions without significant delay. This requirement limits the computational complexity of algorithms and restricts the use of methods that require extensive sampling or long training time. Therefore, uncertainty quantification methods used in intelligent decision support systems must provide a balance between accuracy and computational efficiency.

Decision support systems must also ensure high reliability of results. Incorrect predictions may lead to improper control actions, increased production process costs, equipment damage, or safety risks. For this reason, it is not sufficient to obtain only a predicted value of a parameter; it is necessary to estimate the confidence of the prediction and the possible range of error. The availability of uncertainty estimates allows operators and automated control systems to make more robust decisions under changing operating conditions.

In addition, data in computer-integrated systems for oil and gas production often contain correlations across different time scales and spatial locations. Measurements from different wells, production units, and monitoring systems may be interdependent, and ignoring these dependencies may lead to incorrect conclusions. Therefore, data processing algorithms must be able to take into account temporal and spatial correlations as well as possible inconsistencies between different data sources.

All these features impose strict requirements on methods used in intelligent decision support systems for digital oilfields. Such methods must be robust to noise and missing data, capable of working with heterogeneous information, computationally efficient for real-time operation, and able to provide quantitative estimates of uncertainty. Consequently, the analysis and selection of uncertainty quantification methods should be performed taking into account the specific constraints of oilfield data and the requirements of computer-integrated monitoring and control systems.

III. FORMALIZATION OF THE UNCERTAINTY QUANTIFICATION PROBLEM IN INTELLIGENT DECISION SUPPORT SYSTEMS

A. General problem statement. Let a technological object of control in oil and gas production be characterized at time t by a state vector

$$x(t) \in \mathbb{R}^{n}, \tag{1}$$

representing physical process variables (wellhead pressure, flow rate, water cut, bottomhole temperature, etc.). Direct observation of $x(t)$ is unavailable; instead, the monitoring system acquires a measurement vector:

$$z(t) = h(x(t)) + v(t), \tag{2}$$

$$v(t) \sim N(0, R), \tag{3}$$

where

$$h: \mathbb{R}^{n} \to \mathbb{R}^{p}, \tag{4}$$

is the sensor observation function, $v(t)$ is measurement noise with covariance matrix $R \in \mathbb{R}^{pxp}$, and p is the number of sensor channels.

The IDSS employs a predictive model:

$$f\theta: \mathbb{R}^{pxT} \to \mathbb{R}^{m}, \tag{5}$$

parameterized by $\theta \in \Theta$ that maps a window of T consecutive measurement vectors to a prediction of m target quantities (e.g., future production rate, equipment remaining useful life, reservoir pressure):

$$\hat{y}(t+k) = f\theta(z(t-T+1), \dots, z(t)). \tag{6}$$

The uncertainty quantification problem is stated as follows: given a trained model $f\theta$, a dataset of historical observations

$$\mathcal{J} = \{(z_i, y_i)\}_{i=1}^{\circ}, \tag{7}$$

and a new input $z(t)$, determine:

– the predictive distribution capturing total uncertainty in the prediction:

$$p(y(t+k) \mid z(1{:}t), \mathcal{J}); \tag{8}$$

– the decomposition of total predictive variance into aleatoric and epistemic components:

$$Var[y \mid z] = E\theta[Var[y \mid z, \theta]] + Var\theta[E[y \mid z, \theta]]; \tag{9}$$

– a prediction interval $[y_L, y_U]$ at confidence level $(1-\alpha)$, such that

$$P(y \in [y\_L, y\_U]) \geq 1 - \alpha; \tag{10}$$

– a calibration assessment verifying that the predicted confidence level matches the empirical coverage frequency.

B. Types of uncertainty in technological systems for oil and gas production. Data used in intelligent decision support systems of computer-integrated systems for oil and gas production are affected by different types of uncertainty caused by measurement errors, incomplete information, model inaccuracies, and variability of geological and production process conditions. Correct identification of uncertainty sources is necessary for the selection of appropriate data processing and prediction methods [9]. In the context of machine learning and probabilistic modeling, uncertainty is usually divided into several categories.

Aleatoric uncertainty is related to the natural variability of the observed process and measurement noise. This type of uncertainty cannot be eliminated even if the model is perfectly known, because it is caused by random fluctuations of physical parameters, sensor errors, and environmental conditions.

Let the measured value be represented as

$$y = f(x) + \varepsilon, \tag{11}$$

where $f(x)$ is the true dependence between variables, ε is a random error term.

The error term is usually assumed to follow a probability distribution

$$\varepsilon \sim \mathcal{N}(0, \sigma^2). \tag{12}$$

In technological systems for oil and gas production, aleatoric uncertainty appears due to sensor noise, fluctuations of pressure and temperature, and variability of reservoir properties.

Epistemic uncertainty is caused by insufficient knowledge about the technological object and can be reduced by collecting additional data or improving the model. In computer-integrated decision support systems, this type of uncertainty appears when the number of observations is limited or when the parameters of the geological model are not known exactly.

Let the prediction of a model be written as:

$$\hat{y} = f(x, \theta), \tag{13}$$

where θ are model parameters. If the parameters are uncertain, they can be treated as random variables with distribution

$$\theta \sim p(\theta). \tag{14}$$

The predictive distribution is then obtained as

$$p(y \mid x) = \int p(y \mid x, \theta)\, p(\theta)\, d\theta. \tag{15}$$

This formulation is widely used in Bayesian machine learning models applied in information-control systems for oil and gas production.

Model uncertainty appears when several models can describe the same data with different accuracy. In computer-integrated systems for oil and gas production, different reservoir models, simulation settings, or machine learning algorithms may produce different predictions for the same input data.

Let the prediction be obtained from a set of models

$$\hat{y} = \frac{1}{M} \sum_{i=1}^{M} f_i\,(x). \tag{16}$$

Such an approach is widely used in ensemble methods for uncertainty quantification.

Measurement uncertainty is caused by limitations of sensors and data acquisition systems. In oil and gas production, measurements are often performed under high pressure and temperature conditions, which reduces their accuracy.

If the measured value is

$$y_m = y + \delta, \tag{17}$$

where y is the true value, δ is measurement error, the error may depend on operating conditions:

$$\delta \sim \mathcal{N}(0, \sigma_m^2(x)). \tag{18}$$

In technological systems for oil and gas production, the variance of measurement error may change depending on sensor type, well depth, and environmental conditions.

Simulation and Model Parameter Uncertainty

Decision support systems in computer-integrated systems often use reservoir simulators and physical models. These models contain parameters that are not known exactly and must be estimated from limited data.

Let the simulator output be

$$y = g(x, \phi), \tag{19}$$

where ϕ are uncertain model parameters.

If parameters are uncertain, their distribution can be written as

$$\phi \sim p(\phi). \tag{20}$$

The uncertainty of the output is obtained by sampling

$$y^{(k)} = g(x, \phi^{(k)}). \tag{21}$$

Such uncertainty is typical for reservoir simulation and production forecasting.

C. Requirements for uncertainty handling in decision support systems.

Considering the features of technological system data, uncertainty quantification methods used in intelligent decision support systems must satisfy several requirements:

- ability to work with noisy and incomplete data,
- support for heterogeneous data sources,
- possibility of real-time or near real-time operation,
- capability to provide confidence intervals or probability distributions,
- robustness to model errors,
- compatibility with machine learning and simulation models.

Therefore, the selection of uncertainty quantification methods should be based not only on prediction accuracy but also on their suitability.

The comparative analysis shows that aleatoric uncertainty is predominant in operational monitoring tasks, whereas epistemic uncertainty becomes critical in forecasting scenarios with limited historical observations. Measurement uncertainty mainly affects sensor-driven control applications, while model uncertainty is most significant in reservoir simulation and long-term production planning. This differentiation indicates that uncertainty quantification methods should be selected according to the dominant uncertainty source rather than applied uniformly across all decision support tasks.

IV. MACHINE LEARNING METHODS FOR UNCERTAINTY QUANTIFICATION

Machine learning methods are widely used in intelligent decision support systems of computer-integrated systems for oil and gas production to perform forecasting, anomaly detection, reservoir parameter estimation, and optimization of production processes [5, 12]. However, traditional machine learning models usually provide only point predictions and do not estimate the reliability of the obtained results. For decision support systems operating under uncertain and incomplete data conditions, it is necessary to use special approaches that allow quantifying prediction uncertainty.

Uncertainty quantification methods can be divided into several groups, including Bayesian approaches, ensemble methods, sampling-based techniques, probabilistic neural networks, and calibration methods. Each group has its own advantages and limitations when applied in computer-integrated monitoring and control systems.

Bayesian models provide a natural way to represent uncertainty by treating model parameters as random variables [9]. Instead of estimating a single value of parameters, Bayesian methods compute their probability distribution based on observed data.

Let the model parameters be denoted by θ.

The posterior distribution is defined as

$$p(\theta \mid D) = \frac{p(D|\theta)\,p(\theta)}{p(D)}, \tag{22}$$

where D – observed data, (θ) – prior distribution, $(D \mid \theta)$ – likelihood function.

Prediction uncertainty is obtained from the predictive distribution

$$p(y \mid x, D) = \int p(y \mid x, \theta)\, p(\theta \mid D)\, d\theta. \tag{23}$$

Bayesian methods are suitable for information-control systems because they allow combining measurement data, simulation models, and expert knowledge. However, their application may be limited by high computational complexity, which makes real-time use difficult.

Ensemble methods estimate uncertainty by combining predictions of multiple models [8]. Differences between model outputs are interpreted as uncertainty of prediction. Let predictions of individual models be

$$y_i = f_i(x)\,, i = 1, \dots, M. \tag{24}$$

The mean prediction is:

$$\hat{y} = \frac{1}{M} \sum_{i=1}^{M} y_i. \tag{25}$$

Uncertainty can be estimated as variance

$$\sigma^2 = \frac{1}{M} \sum_{i=1}^{M} (y_i - \hat{y})^2. \tag{26}$$

Ensemble methods are widely used in computer-integrated systems for oil and gas production because they are relatively easy to implement and provide stable results even when the data are noisy or incomplete. They are also suitable for real-time decision support systems if the number of models is limited.

Sampling-based methods estimate uncertainty by generating multiple predictions using random perturbations of model parameters or input data. One of the commonly used approaches is Monte Carlo sampling.

Let the model output depend on uncertain parameters θ

$$y = f(x, \theta). \quad (27)$$

Random samples of parameters are generated

$$\theta^{(k)} \sim p(\theta), k = 1, \dots, N. \quad (28)$$

Predictions are computed as

$$y^{(k)} = f(x, \theta^{(k)}). \quad (29)$$

The mean and variance of predictions are used as uncertainty estimates

$$\hat{y} = \frac{1}{N} \sum_{k=1}^{N} y^{(k)}, \quad (30)$$

$$\sigma^2 = \frac{1}{N} \sum_{k=1}^{N} (y^{(k)} - \hat{y})^2. \quad (31)$$

Monte Carlo methods are often used together with reservoir simulation and probabilistic forecasting models in computer-integrated systems for oil and gas production. Their main limitation is high computational cost.

Neural networks can be extended to provide uncertainty estimates by introducing stochastic elements during prediction. One of the widely used approaches is Monte Carlo Dropout [7].

During prediction, dropout is applied multiple times

$$y^{(k)} = f(x, W^{(k)}), \quad (32)$$

where $W(k)$ are randomly masked weights.

The predictive mean and variance are computed as

$$\hat{y} = \frac{1}{K} \sum_{k=1}^{K} y^{(k)}, \quad (33)$$

$$\sigma^2 = \frac{1}{K} \sum_{k=1}^{K} (y^{(k)} - \hat{y})^2. \quad (34)$$

Such methods are suitable for complex nonlinear dependencies typical for technological system data, but they require careful tuning and may be computationally expensive.

In decision support systems, it is important not only to predict values but also to estimate confidence intervals [10].

If the model predicts distribution parameters

$$y \sim \mathcal{N}(\mu, \sigma^2). \quad (35)$$

Confidence interval can be written as

$$y \in [\mu - k\sigma, \mu + k\sigma]. \quad (36)$$

Calibration methods adjust predicted uncertainty so that it corresponds to real prediction errors. This is important for decision support systems where incorrect confidence estimates may lead to wrong control actions.

When uncertainty quantification methods are used in digital oilfield decision support systems, additional requirements must be considered:

- ability to work with heterogeneous sensor data,
- robustness to missing measurements,
- compatibility with simulation models,
- real-time operation,
- interpretability for operators,
- stability under changing operating conditions.

Therefore, the choice of uncertainty quantification method should be based not only on theoretical accuracy but also on the constraints imposed by oilfield data and computer-integrated monitoring and control systems.

V. REQUIREMENTS FOR UNCERTAINTY QUANTIFICATION METHODS IN DIGITAL OILFIELD DECISION SUPPORT SYSTEMS

Intelligent decision support systems used in computer-integrated systems for oil and gas production operate under conditions that differ significantly from standard machine learning applications. The data processing algorithms must satisfy strict requirements related to reliability, real-time operation, and robustness to incomplete or noisy data. Therefore, the selection of uncertainty quantification methods cannot be based only on prediction accuracy. It is necessary to consider the constraints imposed by the oil and gas domain and by computer-integrated monitoring and control systems.

One of the main requirements is the ability to operate with heterogeneous data sources. Information may be obtained from downhole sensors, surface equipment, geological models, reservoir simulators, and historical databases. These data may have different formats, sampling rates, and accuracy levels. Therefore, uncertainty quantification methods must be able to process multi-source data and provide consistent estimates even when the input information is incomplete or partially contradictory.

Another important requirement is robustness to noise and measurement errors. Sensors used in technological system conditions operate under high pressure, high temperature, and mechanical stress, which leads to significant measurement uncertainty. In addition, some parameters are obtained indirectly through calculations or simulation models. For this reason, uncertainty quantification methods must provide stable results even when the input data contain random errors or systematic bias.

Decision support systems for oil and gas production must also operate in real time or near real time. Monitoring and control system algorithms should process incoming data continuously and provide recommendations without significant delay. This requirement limits the computational complexity of uncertainty estimation methods. Algorithms that require long training time or large numbers of samples may be difficult to use in operational systems. Therefore, the selected methods must provide a compromise between computational cost and accuracy of uncertainty estimation.

Another important requirement is interpretability of results. In oilfield applications, the output of the decision support system is often used by operators or engineers who must understand the reliability of the prediction before taking action. Therefore, uncertainty quantification methods should provide results in a form that can be easily interpreted, such as confidence intervals, probability distributions, or risk indicators. Black-box models without reliability estimates are not suitable for critical decision-making tasks.

Computer-integrated decision support systems must also be compatible with physical and simulation models. Many operational decisions are based on reservoir simulation, production models, or engineering calculations. Machine learning algorithms should be able to work together with these models and take into account their uncertainty. Therefore, uncertainty quantification methods must support integration with simulation-based predictions and allow combining data-driven and physics-based approaches.

Another requirement is stability under changing operating conditions. Oil and gas production processes are non-stationary, and the statistical properties of data may change over time due to equipment wear, reservoir depletion, or changes in operating mode. Uncertainty estimation methods must remain reliable even when the distribution of input data changes. This requirement is especially important for long-term monitoring systems.

For intelligent decision support systems, it is also important to estimate not only the predicted value but also the confidence of the prediction. Let the model output be represented as

$$y = \hat{y} \pm \Delta, \tag{37}$$

where $\hat{y}$ is predicted value, Δ is uncertainty estimate.

For reliable decision making, the uncertainty estimate must correspond to the real prediction error. This requirement can be expressed as

$$P(|y - \hat{y}| \le \Delta) \approx \alpha, \tag{38}$$

where α is the required confidence level.

Such formulation allows evaluating whether the uncertainty quantification method provides calibrated predictions suitable for decision support systems.

Taking into account the considered constraints, uncertainty quantification methods for information-control systems in oil and gas production must satisfy the following criteria:

- robustness to noisy and incomplete data;
- ability to process heterogeneous information;
- low computational complexity for real-time operation;
- interpretability of uncertainty estimates;
- compatibility with simulation and physical models;
- stability under non-stationary conditions;
- ability to provide calibrated confidence intervals.

The analysis of machine learning methods from the standpoint of these requirements allows selecting the most suitable approaches for intelligent decision support systems.

VI. SELECTION OF UNCERTAINTY QUANTIFICATION METHODS FOR COMPUTER-INTEGRATED DECISION SUPPORT SYSTEMS

The selection of uncertainty quantification methods for intelligent decision support systems used in computer-integrated systems should be based on the specific requirements of technological object data processing, real-time operation, and reliability of predictions. Different methods considered in the previous sections have different computational complexity, robustness, and applicability to heterogeneous data sources. Therefore, their suitability for oil and gas production applications must be analyzed taking into account the constraints imposed by monitoring, forecasting, and production process control systems.

Bayesian methods provide a theoretically correct framework for uncertainty estimation and allow combining measurement data with prior knowledge and simulation models. This makes them suitable for reservoir characterization and long-term forecasting tasks. However, Bayesian approaches often require significant computational resources due to the need to evaluate posterior distributions, which limits their use in real-time control systems.

Ensemble methods are widely used in practical applications because they provide stable uncertainty estimates and can work with noisy and incomplete data. They are relatively easy to implement and can be applied to different types of machine learning models. Ensemble approaches are suitable for many tasks in computer-integrated systems, including production process forecasting, anomaly detection, and equipment diagnostics. Their main limitation is the increased computational cost when a large number of models is used.

Sampling-based methods, including Monte Carlo techniques, allow estimating uncertainty for complex nonlinear models and simulation-based predictions. These methods are often used together with reservoir simulators and probabilistic production models. However, they require multiple evaluations of the model, which may be computationally expensive. For this reason, such methods are more suitable for offline analysis or decision support systems that do not require strict real-time performance.

Probabilistic neural networks and Monte Carlo Dropout methods allow estimating uncertainty in deep learning models and are suitable for complex nonlinear dependencies typical for technological system data. These methods can be used in tasks such as pattern recognition, anomaly detection, and prediction of production parameters. However, they require careful tuning and may be sensitive to the amount of training data, which is often limited in oil and gas applications.

Calibration methods are important for information-control systems because they allow adjusting uncertainty estimates so that predicted confidence intervals correspond to real prediction errors. This property is critical in operational decision making, where incorrect confidence estimation may lead to wrong control actions. Calibration techniques can be combined with different machine learning models and are suitable for monitoring systems and control systems.

Taking into account the requirements formulated in the previous sections, the applicability of uncertainty quantification methods for computer-integrated decision support systems can be summarized in Table 1.

TABLE 1. Applicability of uncertainty quantification methods for decision support systems in computer-integrated systems for oil and gas production.

Method	Accuracy	Computational cost	Real-time use	Robust to noise	Suitable for simulation models	Interpretability	Recommended application
Bayesian methods	High	High	Limited	High	Yes	High	Reservoir modeling, forecasting
Ensemble methods	High	Medium	Yes	High	Yes	Medium	Monitoring, prediction, diagnostics
Monte Carlo methods	High	High	Limited	High	Yes	Medium	Simulation, offline analysis
MC Dropout / probabilistic NN	Medium–High	Medium	Possible	Medium	Limited	Low–Medium	Pattern recognition, prediction
Calibration methods	Medium	Low	Yes	Medium	Yes	High	Decision support, control systems

The analysis shows that no single method satisfies all requirements of computer-integrated decision support systems. Bayesian and Monte Carlo approaches provide the most accurate uncertainty estimation but may be too computationally expensive for real-time control system operation. For computer-integrated oil and gas production systems operating under strict latency constraints, ensemble methods demonstrate practical superiority over Bayesian approaches. Although Bayesian models provide more theoretically rigorous uncertainty estimates, their computational overhead limits operational deployment in real-time monitoring environments. Therefore, ensemble-based architectures should be considered the baseline solution for field-level decision support systems.

For intelligent decision support systems of computer-integrated systems, the most effective approach is often a combination of several methods. For example, ensemble models may be used for prediction, while calibration techniques are applied to adjust confidence intervals, and simulation-based methods are used for long-term forecasting. Such hybrid approaches allow improving reliability of decisions under conditions of uncertain and incomplete data. The selection of the appropriate hybrid configuration follows Algorithm 1 (Fig. 1).

Algorithm 1. Selection of uncertainty quantification method for an intelligent decision support system of a computer-integrated system

Input: D_char = (N_samples, N_features, stationarity, noise_level);

B = (T_max, memory_limit);

A_req = (output_type, coverage_level α, real_time_flag, interpretability_need)

Output: Selected UQ method M_UQ, configuration parameters P_config

Step 1. Determine the uncertainty type profile.

1.1. Known sensor accuracy classes → flag measurement uncertainty as quantifiable.

1.2. N_samples < 500 or out-of-distribution regime → flag high epistemic uncertainty.

1.3. Stochastic production process (multiphase flow) → flag high aleatoric uncertainty.

1.4. Both flags raised → require uncertainty decomposition capability.

Step 2. Evaluate computational feasibility.

2.1. real_time_flag = TRUE and T_max < 1 s → class := ‘lightweight’.

2.2. T_max ∈ [1 s, 60 s] → class := ‘moderate’.

2.3. T_max > 60 s → class := ‘unrestricted’.

Step 3. Select the UQ method:

3.1. IF lightweight AND coverage guarantee → M_UQ := Split Conformal;

P_config := {α, cal_fraction=0.2}.

3.2. IF lightweight, no decomposition → M_UQ := MC Dropout;

P_config := {T=10, dropout=0.1}.

3.3. IF moderate AND decomposition required → M_UQ := Deep Ensemble (PPM-UD);

P_config := {M=5, NLL_loss=TRUE}.

3.4. IF unrestricted, full posterior→ M_UQ := Bayesian NN (VI);

P_config := {prior=N(0,1), KL=1/N}.

Step 4. Apply calibration verification.

4.1. Compute ECE on calibration set D_cal.

4.2. IF ECE > 0.05 → apply post-hoc recalibration (temperature scaling or isotonic regression).

Step 5. Validate integration with CIS.

5.1. Verify M_UQ output compatible with DSS reasoning engine R.

5.2. Verify inference latency ≤ T_max on target hardware.

5.3. IF fails → return to Step 3, select next best method.

Step 6. Return (M_UQ, P_config).

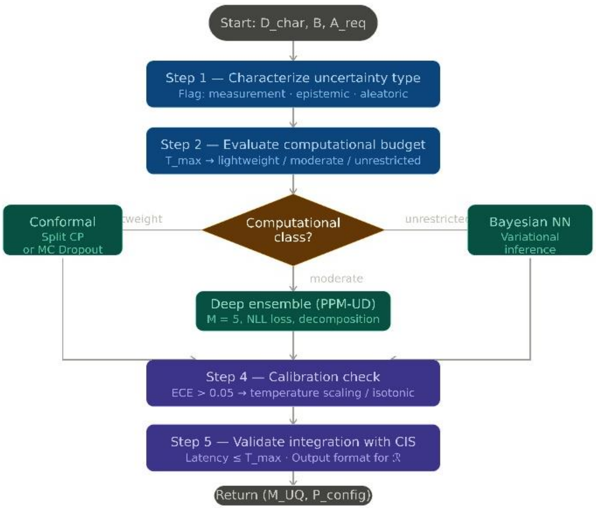

FIG. 1. Decision framework for selecting uncertainty quantification methods for intelligent decision support systems of computer-integrated oil and gas production.

When designing computer-integrated decision support systems for digital oilfields, the choice of uncertainty quantification method should be based on the following factors:

- required prediction accuracy;
- available computational resources;
- need for real-time operation;
- amount and quality of training data;
- necessity of integration with simulation models;
- required level of interpretability.

Considering these factors allows selecting uncertainty quantification methods that provide reliable operation of intelligent decision support systems in digital oilfield environments.

Unlike existing comparative reviews that mainly provide qualitative descriptions of uncertainty quantification approaches, the proposed selection algorithm introduces a structured decision framework that explicitly incorporates operational constraints of computer-integrated oilfield systems, including latency requirements, interpretability demands, and uncertainty decomposition capability.

VII. DISCUSSION

The performed analysis shows that uncertainty quantification is a critical component of intelligent decision support systems of computer-integrated systems for oil and gas production. Unlike many standard machine learning applications, data of technological objects are characterized by heterogeneity, measurement errors, incomplete information, and strong dependence on complex physical processes. These features impose additional constraints on data processing algorithms and require the use of special methods that allow estimating the reliability of predictions.

The comparison of different uncertainty quantification approaches demonstrates that no universal method can satisfy all requirements of information-control systems for oil and gas. Bayesian methods provide the most rigorous probabilistic interpretation of uncertainty, but their computational complexity may limit their use in real-time control systems. Ensemble methods offer a good compromise between accuracy and computational cost and can be applied in monitoring systems, forecasting, and diagnostics tasks. Sampling-based approaches, including Monte Carlo methods, are suitable for simulation-based analysis and reservoir modeling, but they may be too expensive for operational decision support systems.

Neural network-based approaches with uncertainty estimation, such as Monte Carlo Dropout and probabilistic neural networks, are effective for modeling complex nonlinear dependencies typical for oil and gas production data [4, 7]. However, their performance strongly depends on the availability of training data and correct model configuration. In practical applications, these methods should be combined with calibration techniques that allow adjusting uncertainty estimates to real prediction errors.

An important feature of computer-integrated systems for oil and gas production is the need to integrate machine learning models with physical and simulation models. Reservoir simulators, production process models, and engineering calculations are widely used in the oil and gas industry, and uncertainty in these models must also be taken into account [6, 11, 13]. Therefore, the most effective solutions are hybrid approaches that combine data-driven methods with physics-based modeling.

Another important aspect is the requirement for interpretability of results in the decision support system. In operational conditions, decisions are often made by engineers or operators who must understand the reliability of the predicted values. For this reason, uncertainty quantification methods should provide confidence intervals, probability distributions, or risk indicators that can be used in decision making. Methods that do not provide interpretable uncertainty estimates are not suitable for critical applications.

The results of this study confirm that the selection of uncertainty quantification methods for intelligent decision support systems in computer-integrated systems for oil and gas production should be performed taking into account the specific features of technological object data, computational constraints, and the need for reliable operation under uncertain and incomplete information. The proposed analysis can be used as a basis for the development of computer-integrated monitoring and decision support systems for technological systems in oil and gas production.

A significant limitation of current uncertainty quantification approaches is their insufficient adaptation to concept drift caused by long-term reservoir depletion and changing operational regimes. This issue remains underexplored in existing studies and requires dedicated investigation.

VIII. CONCLUSION

Intelligent decision support systems play an important role in computer-integrated systems for oil and gas production, where large volumes of heterogeneous data are used for monitoring, forecasting, and control of technological processes. One of the main problems in such systems is the presence of uncertainty caused by measurement errors, incomplete information, model inaccuracies, and variability of geological and production process conditions. Without proper uncertainty estimation, the reliability of predictions decreases, which may lead to incorrect decisions and increased operational risks.

In this paper, modern methods for uncertainty quantification used in machine learning and probabilistic modeling have been analyzed from the standpoint of their applicability in intelligent decision support systems of information-control systems for oil and gas production. The main types of uncertainty – aleatoric, epistemic, measurement, and model uncertainty – have been considered and their influence on the performance of decision support systems discussed.

The specific features of oil and gas production-related data have been analyzed, including heterogeneity of information sources, presence of noise and missing values, limited availability of measurements, dependence on physical models, and requirements for real-time operation. These factors impose strict constraints on uncertainty quantification methods used in computer-integrated monitoring and control systems.

A comparative analysis of Bayesian, ensemble, sampling-based, neural network, and calibration methods has been performed. Based on the performed analysis, deep ensemble models combined with post-hoc calibration appear to be the most practically justified uncertainty quantification strategy for intelligent decision support systems in digital oilfields due to their balance between predictive reliability, computational feasibility, and robustness to heterogeneous industrial data.

It has been shown that the most effective solution for oil and gas production applications is the use of hybrid approaches that combine several uncertainty quantification methods and allow integrating machine learning models with physical and simulation models. Such approaches provide more reliable operation of intelligent decision support systems under conditions of incomplete and uncertain data.

The scientific novelty of the obtained results consists in the systematization of uncertainty quantification methods from the standpoint of their applicability in intelligent decision support systems for oil and gas production and in the analysis of constraints imposed by oil and gas data on machine learning algorithms and predictive models.

The practical significance of the work lies in the possibility of using the proposed recommendations when developing computer-integrated systems for monitoring, diagnostics, forecasting, and decision support in technological systems for oil and gas production operating under uncertain and incomplete data conditions.

Further research may be related to the development of hybrid uncertainty estimation methods adapted to real-time decision support systems and to the integration of machine learning algorithms with reservoir simulation models and industrial monitoring platforms.

AUTHOR CONTRIBUTIONS

D.K. – performed the literature review, systematized modern uncertainty quantification methods, developed the formal problem statement and comparative analysis framework, prepared the algorithm for method selection, and drafted the manuscript; O.M. – supervised the research, formulated the conceptual direction of the study, contributed to the methodological design, critically revised the analytical content, and provided scientific guidance during manuscript preparation.

Both authors contributed to the interpretation of results, discussion of findings, and approved the final version of the manuscript.

COMPETING INTERESTS

The authors declare no conflict of interest.

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Dmytro Kytsmen

In 2018, graduated from the National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute" with a degree in "Computerised and Robotic Systems." In 2022, entered a PhD program in the specialty "Automation, Computer-Integrated Technologies and Robotics" at Ivano-Frankivsk National Technical University of Oil and Gas. Research interests include distributed data processing systems, data science, and signal processing decision support systems.

ORCID ID: 0009-0004-6913-3183

Olena Moiseienko

In 2000, graduated from the Ivano-Frankivsk State Technical University of Oil and Gas. In 2004, defended a PhD dissertation in the specialty "Instruments and Methods of Control and Determination of the Composition of Substances." Currently, serves as an Associate Professor at the Department of Computer Systems and Networks of the Ivano-Frankivsk National Technical University of Oil and Gas. Research interests include cybersecurity, forecasting, data analysis, and artificial neural networks.

ORCID ID: 0000-0002-7995-2949

Методи кількісної оцінки невизначеності даних для інтелектуальної підтримки-прийняття рішень у комп’ютерно-інтегрованих системах нафтогазовидобутку

Дмитро Кицмен[1], Олена Мойсеєнко[2,*]

[1]Івано-Франківський національний технічний університет нафти і газу, Івано-Франківськ, Україна

[2] Кафедра комп’ютерних систем і мереж/ Івано-Франківський національний технічний університет нафти і газу, Івано-Франківськ, Україна

*Автор-кореспондент (Електронна адреса: olena.moiseienko@nung.edu.ua)

АНОТАЦІЯ Сучасні комп’ютерно-інтегровані системи видобутку нафти і газу широко використовують інтелектуальні системи підтримки прийняття рішень для моніторингу, прогнозування, діагностики та керування технологічними процесами. Ефективність функціонування таких систем значною мірою залежить від достовірності та повноти вхідних даних, які часто характеризуються наявністю похибок вимірювань, шуму, пропущених значень, неточностей моделей та мінливістю геологічних і виробничих умов. За таких обставин кількісна оцінка невизначеності є критично важливим компонентом для забезпечення надійності прогнозних моделей та підтримки обґрунтованого прийняття рішень у цифрових нафтогазових системах. Метою роботи є аналіз і систематизація сучасних методів кількісної оцінки невизначеності даних, що використовуються в інтелектуальних системах підтримки прийняття рішень комп’ютерно-інтегрованих систем видобутку нафти і газу, а також визначення їх придатності для роботи в умовах неповної та невизначеної інформації. У дослідженні розглянуто специфічні особливості технологічних даних нафтогазової галузі, зокрема: неоднорідність джерел інформації, нелінійний характер процесів, невизначеність вимірювань та вимоги до функціонування в режимі реального часу. У статті формалізовано задачу кількісної оцінки невизначеності в інтелектуальних системах підтримки прийняття рішень та проаналізовано основні типи невизначеності, що впливають на технологічні системи, а саме: алеаторну, епістемічну, вимірювальну, модельну та параметричну невизначеність симуляційних моделей. Проведено порівняльний аналіз баєсівських підходів, ансамблевих методів, методів Монте-Карло, ймовірнісних нейронних мереж і методів калібрування з позицій обчислювальної ефективності, стійкості до шумових і неповних даних, інтерпретованості результатів та сумісності з промисловими системами моніторингу й керування. Отримані результати показали, що жоден окремий метод не задовольняє повною мірою всі вимоги комп’ютерно-інтегрованих систем видобутку нафти і газу. Встановлено, що ансамблеві методи забезпечують найбільш збалансоване співвідношення між точністю оцінювання, обчислювальною складністю та можливістю використання в оперативних системах підтримки прийняття рішень, тоді як баєсівські методи та методи Монте-Карло є доцільними для задач моделювання пластів і довгострокового прогнозування. Запропоновано підхід до вибору методів кількісної оцінки невизначеності залежно від характеристик даних та операційних обмежень системи. Практичне значення роботи полягає у можливості використання отриманих рекомендацій під час розроблення комп’ютерно-інтегрованих систем моніторингу, діагностики, прогнозування та підтримки прийняття рішень для технологічних об’єктів видобутку нафти і газу в умовах невизначених і неповних даних.

КЛЮЧОВІ СЛОВА кількісна оцінка невизначеності, інтелектуальна система підтримки прийняття рішень, комп'ютерно-інтегрована система, машинне навчання, прогностична невизначеність.