ANALYSIS OF THE DYNAMICS OF MULTIPHASE STRATIFIED FLOWS BASED ON MATHEMATICAL MODELING AND BIG DATA TECHNOLOGIES.

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Abstract: *This paper investigates the mathematical modeling and Big Data-driven analysis of multiphase stratified flow dynamics. Multiphase stratified flows are characterized by complex interactions between components with different densities, viscosities, and temperatures, as well as their temporal and spatial variations. The study employs modified Navier–Stokes equations, interphase mass exchange models, and conservation laws of mass and momentum to describe flow behavior. Special emphasis is placed on the integration of mathematical modeling techniques with modern intelligent technologies, including machine learning and neural networks. The application of Big Data technologies enables real-time processing of large-scale monitoring data, improving the accuracy of phase fraction estimation and stratification stability assessment. The Richardson number is used as a key criterion for evaluating stratification stability based on streaming data analytics. The proposed approach allows early prediction of transitions between stable and turbulent flow regimes. The results demonstrate significant scientific and practical relevance for oil and gas engineering, mining industries, water flow hydrodynamics, and environmental monitoring systems.*

Keywords. *Multiphase flows, stratified flow dynamics, mathematical modeling, Big Data technologies, machine learning, Richardson number, neural networks, hydrodynamics.*

INTRODUCTION

The development of mathematical models, numerical methods, algorithms, and software complexes aimed at the rational use of water and the effective management of water resources is of great importance worldwide, ensuring water monitoring, accounting, and reporting, In particular, to ensure water monitoring, accounting, and reporting, as well as to widely involve intelligent information technologies in these processes, our republic is carrying out large-scale measures to prevent the disruption of the balance of the water economy's natural and anthropogenic sources.

In particular, the setting of tasks, such as those defined in the Decree of the President of the Republic of Uzbekistan "On Measures to Further Improve the Water Resources Management System at the Lower Tier and Increase the Sector's Attractiveness for the Private Sector," indicates that special attention is paid by our state to water and agricultural resources [1].

Multiphase stratified flows are characterized by the time-varying flow of components that differ in density, viscosity, and temperature. Big Data technologies enable the real-time processing of millions of measurement monitoring data of these flows [2-3].

The study of multiphase stratified flows, complex systems, and natural processes is primarily carried out using mathematical modeling, numerical solutions, and a suite of software. These processes primarily involve the interactions between multiple phases (or layers) and their dynamics. Using mathematical modeling methods and new intellectual technologies, it will be possible to provide supporting information for decision-making based on a comprehensive analysis of these processes. Big Data technologies, in turn, provide the ability to collect, store, and analyze large volumes of data, which makes it possible to analyze the dynamics of multiphase stratified flows using mathematical modeling and big data technologies. is of great importance for achieving new scientific and practical results.

Multiphase stratified flows typically represent flows that arise from the interaction of two or more phases. For example, interactions between the gas and liquid phases, or interfacial boundaries between liquids (differences between thick and thin liquids). The following mathematical models are used in the analysis of these systems [4, 5, 6]:

-Navier-Stokes equations, these equations are used to describe the motion of liquids and gases and are applied in modified forms for multiphase flows;

Interphase boundary dynamics: in multiphase systems, describing the dynamics of interphase boundaries is crucial, and it primarily examines the forces that arise at the interface between a moving and a stationary phase and their interactions.

-Flows in a porous medium, if multiphase systems are in a porous medium (e.g., rock or soil), the flow's movement is directly dependent on the geometry of the porous structure, and modeling this situation involves using a porous medium and an interfacial exchange system.

Mathematical modeling approaches: in the mathematical modeling of the dynamics of multiphase stratified flows, the following methods are primarily used:

-differential equations, i.e., this method is used to describe the interaction between flows and phases and their temporal evolution, with separate differential equations formulated for each phase of the model and interconnected;

-computer simulation, i.e., since an exact mathematical modeling of the system is often complex, computer simulations are often used, which allows the system to be analyzed and forecasted under real-world conditions;

-In statistical models, random processes that occur in multiphase flows are analyzed using statistics and probability theory, ensuring this method is particularly effective for small and medium-sized systems;

Currently, with the rapid development of information and communication systems and intelligent technologies—namely neural networks, particularly Big Data technologies and their role in analyzing multi-phase streams—has been investigated [6, 7].

In recent years, Big Data technologies have provided the ability to rapidly collect, store, and analyze large volumes of data. The following Big Data technologies are used in analyzing the dynamics of multi-phase flows:

-in data collection and storage, since data related to multiphase flows can be very large in volume, NoSQL databases and knowledge bases are used for effective collection and storage of this data, Technologies such as Hadoop and Spark are used [13, 14];

-in real-time monitoring and analysis, where Big Data technologies allow for the real-time tracking and analysis of the dynamics of multiphase flows, which is used in industrial processes or environmental monitoring.

-Machine Learning, machine learning algorithms, which help in studying the dynamics of multiphase flows and the interaction between phases, using training algorithms, the system can be predicted and optimized in advance.

Data Visualization: Visualization techniques are used to understand the complex dynamics of multiphase flows, using Big Data technologies. Using 3D graphics and interactive visualizations, the system's evolution over time is displayed.

Given the scientific and practical importance of multiphase flows, the analysis of stratified flows has significant practical relevance in many fields. For example, in the oil and gas industry: multiphase flows occur during the extraction of oil and gas from underground. Their mathematical modeling and analysis are necessary for the efficient extraction of resources and the optimization of transportation systems;

in ecology and environmental protection, that is, multiphase flows are important for ecological systems and water resource management, providing information on the flow of water and other liquids, the interaction between surface and groundwater, and helping to improve environmental monitoring;

-In industrial processes, multiphase flows arise in the flow processes of many industrial wastes, for example, in the chemical industry, pharmaceutical manufacturing, and other sectors, Understanding the dynamics of flows is particularly necessary in the mining industry for effective process management and ensuring safety.

The mathematical modeling of multiphase stratified flow dynamics and the use of big data technologies create great opportunities for better understanding, optimizing, and forecasting these systems. These approaches can be effectively applied not only to scientific research but also in practice, in the mining, water, agriculture, and ecology sectors. Due to the complexity of the systems and the large volume of data, many more research and innovations can be expected in these fields.

The mathematical model of multiphase stratified flows is considered under the following main assumptions:

-The flow consists of N phases;

-Each phase has a density ρ_i and a velocity u_i;

-There is exchange between phases.

Data are obtained in real time via sensors (Big Data), and the mass conservation equation (for each phase) is expressed as follows [6, 7, 8]:

$$\frac{\partial(\propto_i \rho_i)}{\partial t} + \nabla \cdot (\propto_i \rho_i \vec{u}_i) = G_i$$

where: $\propto_i$ – the volume fraction of phase i, G_i– interphase mass transfer, ∇ – the gradient operator.

In Big Data applications, $\propto_i$ (t,x) and G_i are determined using statistical or ML models on large volumes of time-series data obtained from sensors. In the integrated application of Big Data + ML, neural networks or regression models are used to determine $\propto_{ij}$. The

Richardson number is used to assess stratification stability as a stratification stability criterion [9–14]:

$$R_i = \frac{g}{\rho}\frac{\partial\rho/\partial z}{\rho_0(\partial u/\partial z)^2}$$

$$R_i > 0.25 \quad \text{stable stratification}$$

$$R_i < 0.25 \quad \text{is turbulent mixing}$$

In this context, the importance of Big Data technology lies in the fact that this parameter is calculated in real time at thousands of points and analyzed through streaming analytics [15–16]. In the Big Data–based statistical and ML modeling approach, the data set or information model is implemented based on the following observation matrix:

$$R_i = \begin{bmatrix} u_1 & \rho_1 & \propto_1 & T_1 \\ u_2 & \rho_2 & \propto_2 & T_2 \\ \vdots & \vdots & \vdots & \vdots \\ u_n & \rho_n & \propto_n & T_n \end{bmatrix}$$

As a result: Y = flow state (steady / turbulent)

Machine learning model [16-19] : $\hat{Y} = f(X)$

where f is Random Forest, LSTM, or Deep Neural Network. Mathematical models based on physical laws, algorithms for implementing the models, neural networks, and the integration of real data [20-21], the basic parameters, definitions, units of measurement, and model characteristics based on Big Data sources are presented in Table 1.

Characteristics of multiphase flow parameters

Table 1

№	Parametr	Designation	Unit of Measurement	Big Data Source
1	Velocity	u	m/s	Sensor, CFD
2	Density	ρ	kg/m^3	Laboratory
3	Volume fraction	α	-	Image analysis
4	Pressure	p	Pa	Real-time sensor
5	Turbulence	k	m^2/s^2	ML estimation

The neural network prediction is given by $\varepsilon(t) = |u_{real} - u_{pred}|$, where the time-wise reduction of the error indicates model training.

CONCLUSION

Thus, in conclusion, it can be said that while mathematical models are the basis for the physical process, Big Data technologies ensure adaptation with real data, and with the help of machine learning:

-the accuracy of phase-to-phase exchange increases

-stratification breakdown is predicted in advance.

Based on these approaches, high efficiency is achieved in the fields of fluid flow hydrodynamics, oil and gas, and environmental ecological monitoring.

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