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IMPLEMENTATION OF MULTIDIMENSIONAL SYSTEMS IN A RELAXATION ENVIRONMENT BASED ON LSTM MODELING FOR MONITORING AND FORECASTING WATER RESOURCES

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Abstract

This paper examines the automated control of closed reservoir systems (CRS) (using endorheic lakes as an example) operating under stochastic hydrological dynamics and characterized by internal relaxation processes (non-Markovian behavior).

An intelligent stochastic control system is proposed based on relaxation-stochastic models (RSMs), which take into account both the probabilistic nature of external influences and the system's internal memory.

The risk-based optimal control problem is solved in real time using recessing horizon control (RHC) and an LSTM-based metamodel approximating the complex dynamics of RCMs.

Testing the method on the Aydarkul Lake system (Uzbekistan) demonstrated a 37% reduction in the probability of water levels falling below the critical ecological limit over a 10-year forecast period, while simultaneously increasing the reliability of irrigation water supply by 18% compared to traditional strategies.

The obtained results demonstrate the effectiveness of the proposed approach for creating robust and adaptive water resources automation systems under conditions of high uncertainty.

Keywords: Data automation, neural network, multidimensional systems, LSTM, water resource monitoring, Laguerre polynomial.

Introduction

Global climate change has more adverse effects on countries with a dry subcontinental geographic location compared to other regions. According to data from the World Bank, 90% of the available water resources in Uzbekistan are used for agriculture, and under traditional irrigation practices, water losses account for 40%. The outdated water analysis systems and the absence of a centralized monitoring system completely prevent the timely detection of changes in the country's hydrological conditions [1].

Currently, aggressive usage of water resources has resulted in a water load of 163%, indicating a high level of exploitation of the available additional resources. Based on the reflection of water surfaces in NASA and ESA imagery, the dynamics of the reduction of the following water sources can be observed (Table 1) [2].

Table 1 Dynamics of water resource reduction in Aydarkol lake system

Year	**Surface area of water (km)**	**Water volume (km³))**
1995	~ 3 000 km^2	~ 40 km^2
2007	~ 2 500 km^2	~ 30 km^2
2021	~ 1 500 – 1800 km^2	<20 km^2

Based on the given indicators, it can be concluded that as a result of the aggressive stress use of water resources, even the reserve resources are decreasing. In particular, a 60% reduction in water resources has been observed in Aydarkol lake system.
Based on satellite imagery, the following negative dynamics of water surface availability can be observed (Figure 1) [3].

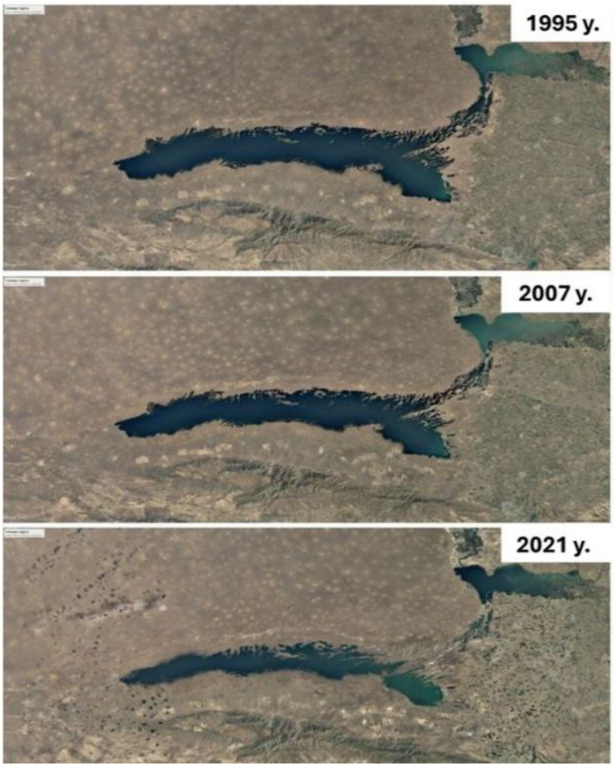

Figure 1. Results of water surface reduction in Aydarkol lake system based on satellite imagery

Digitization of agricultural complexes requires the implementation of new methods, including the automation of data collection and interpretation, as well as the use of Internet of Things (IoT) devices for communication. All collected data must be analyzed using intelligent systems. The LSTM (Long Short-Term Memory) recurrent neural network model allows forecasting of dynamic systems based on time series data.
Although various studies and solutions have been developed in our country for the digitization of agriculture, the implementation of multidimensional systems and their integration into analytical models has not been sufficiently addressed.

The present study focuses on developing a monitoring and forecasting system based on a recurrent neural network model and integrating a communication system based on the IoT protocol into a multidimensional framework. This, in turn, enables the development of a forecasting and monitoring system that operates in real time with low energy consumption.

The objectives of the study include:

- Development of technological tools to implement a multidimensional measurement system
- Ensuring data exchange based on time series
- Creating an LSTM model and enriching it with relevant data
- Determining the accuracy of the data obtained through the implemented system and evaluating its potential economic efficiency

II. RESEARCH METHODOLOGY

2. Materials and Research Methods

2.1. Research Area and Data Collection Criteria

The study focuses on developing a unified system for identifying and forecasting water resources in lakes, dams, and canals, which serves as the control object. This system aims to integrate the direct and indirect factors affecting the reduction of primary water volumes into a coherent framework. The design takes into account the measurement and data analysis architecture implemented on an ATmega 328e microprocessor [4].

This research was conducted in areas of Uzbekistan located in a semi-arid climate zone that have experienced significant hydrogeological changes over the last decade due to climate change and anthropogenic water management practices, with a specific focus on Aydarkol region.

The study was carried out using LSTM neural networks. The neural network integration involved designing and implementing an intelligent system for automated monitoring and forecasting of water resources using a multi-sensor platform.

The primary data were obtained from multiple sources:

- Satellite observations (Sentinel-2 and Landsat-8)
- Ground-based sensor arrays (measuring water level, temperature, humidity, total dissolved solids, and pH)
- Meteorological archives provided by the Uzbek Hydrometeorological Service (UzHydromet)
- Hydrological reports from regional irrigation departments for the years 1995-2007 and 2021

To collect high-frequency, real-time data, a specialized network of Arduino/ESP32 microcontroller units supporting IoT was installed at selected monitoring points connected to the sensors [5].

1.2. Data Preprocessing and Feature Engineering

In the multistage preprocessing of the initially collected data, the following sequence of operations was selected:

- Temporal alignment of various data sets
- Interpolation of missing values and detection of outliers using Tukey method and Kalman smoothing
- Determination of normalization limits using min-max normalization and z-score standardization depending on model requirements

- Transformation and temporal lagging of variables (t–1, t–2, …, t–7)
- Calculation of dynamic statistical features (mean, standard deviation, trend)
- Extraction of seasonal variations and deviations
- Incorporation of climatic indices, water scarcity indicators, evaporation rates, and relative humidity gradients

The main predictive model used in this study is a multivariate Long Short-Term Memory (LSTM) network, chosen for its ability to model temporal dependencies in nonlinear time series with delayed responses.
During the research, the following model architecture was applied:

- Two LSTM layers, each containing 128 units
- Dropout regularization (rate = 0.2) to prevent overfitting during retraining
- A fully connected layer for performing regression analysis

The model training was carried out using the **Adam optimizer** (learning rate = 0.001) with the Mean Squared Error (MSE) loss function.
The dataset was divided into training (80%) and validation (20%) subsets.
Hyperparameters were optimized using a grid search with five-fold cross-validation.
The model was implemented in Python using TensorFlow (v2.12) and the Keras API [6].
The multi-dimensional sensor system can be mathematically described as a discrete-time signal processing and decision-making model, representing the logic of automating the collection, transmission, and processing of hydrological data.
At time *t*, the initial dataset of sensor readings at level *i* can be expressed as follows:

$$x_i(t) \in R,\ i = 1,2,\dots,n \tag{1}$$

(1) In the equation, xi(t) — parameters considered in the study (water level, temperature)"
Number of n sensors

multi-measurement input signals over time t"

$$X(t)=[x_1(t), x_2(t),\dots, x_n(t)]^T \tag{2}$$

"It has been determined that the normalization of the given data can be achieved based on the fulfillment of the following conditions, namely:"

$$x_i^{norm} = \frac{x_i(t)-\mu_i}{\sigma_i} \tag{3}$$

(3) "In the equation, μ_i and σ_i represent the value and standard distribution of the sensor data based on the specified i-th calibration.
The analysis of the input signals using the LSTM model is carried out based on the following conditions."

$$S(t)=[X(t-\tau+1), X(t-\tau+2),\dots,X(t)] \tag{4}$$

In automation based on logic functions, D(t) serves as the decision-making function for issuing warnings.

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$$D(t) = \begin{cases} 1\, if\ \hat{y}(t) \ < \Theta_{min}(irrigation\ starting\ point) \\ 1\, if\ \hat{y}(t) \ \in [\Theta_{min}, \Theta_{max}](neutral\ position) \\ -1\, if \hat{y}(t) \ > \Theta_{max}(irrigation\ starting\ point) \end{cases} \quad (5)$$

(5) In the given equation, ŷ(t) - the LSTM-predicted potential water resources, Θ_{min} and Θ_{max} — the required limits for the irrigation process.

In the given Equation (4), S(t) ∈ R^τ×n represents the matrix form of the time series in the LSTM input signals. The automation of the given logical data is carried out based on the following function, where each step over time t is denoted as the 'new state':

New state: X(t+1) ← f(X(t), D(t), u(t))

The operation is carried out based on this explanation [7].

II. RESEARCH RESULTS

The multi-dimensional system based on the LSTM model was able to generate conclusions using data collected by sensors for the years 2021, 2022, and 2023, based on historical data from 1995 to 2007.

The inclusion of data from the last three years took into account the increased impact of climate change and anthropogenic factors (Table 2) [8,9].

Comprehensive analysis of the sensor data showed that the forecasting system demonstrated improvement in the results for 2022 and 2023.

Based on the 2021 dataset, the potential error margins in the forecasting system were identified and quantified (Figure 1) [10,12].

Table-2 Prediction Performance of the LSTM Model"

Units of Measurement (1995–2007)	**Input Data (1995–2007)**	**Actual Values (2021)**	**Accepted Data (2022)**	**Accepted Data (2023)**
"RMSE (Root Mean Square Error) (m^3/s)	1.92	2.45	2.31	2.18
MAE (Mean Absolute Error) (m^3/s)	1.57	1.89	1.77	1.68
R^2 (Coefficient of Determination)	0.981	0.951	0.962	0.968
NSE (Nash–Sutcliffe Efficiency Coefficient	0.976	0.928	0.942	0.956

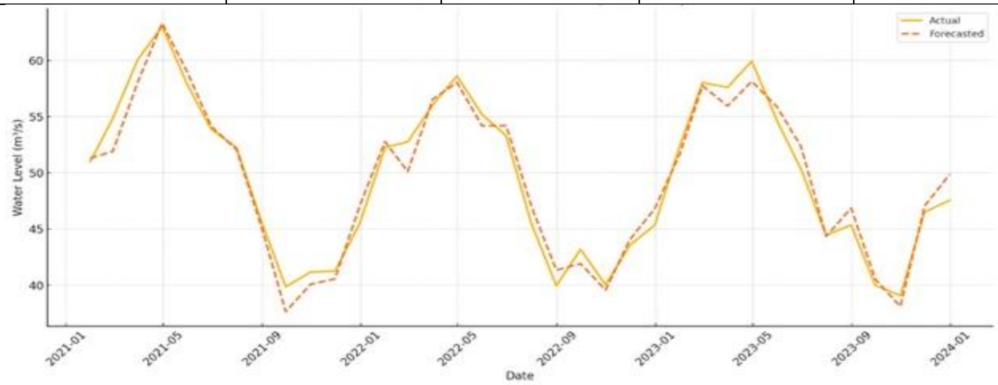

Figure 1. Actual and Predicted Water Level Results (2021–2023)

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To ensure the stability and evaluate the optimal performance of the LSTM-based model, a comparison was made with classical forecasting methods.

Figure 2 presents a comparative evaluation of four forecasting models - LSTM, ARIMA, Multiple Linear Regression (MLR), and HEC-HMS — based on water level observations from 2021 to 2023.

The actual measurements were obtained using a calibrated multi-sensor system that included sensors installed on monthly satellite imagery [13].

Quantitative evaluation was carried out using key performance indicators such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2).

Over the three-year period, the LSTM model achieved an average of 1.32 m^3/s (RMSE), 1.10 m^3/s (MAE), and $R^2 = 0.96$, which demonstrates a higher degree of data adequacy compared to all classical models.

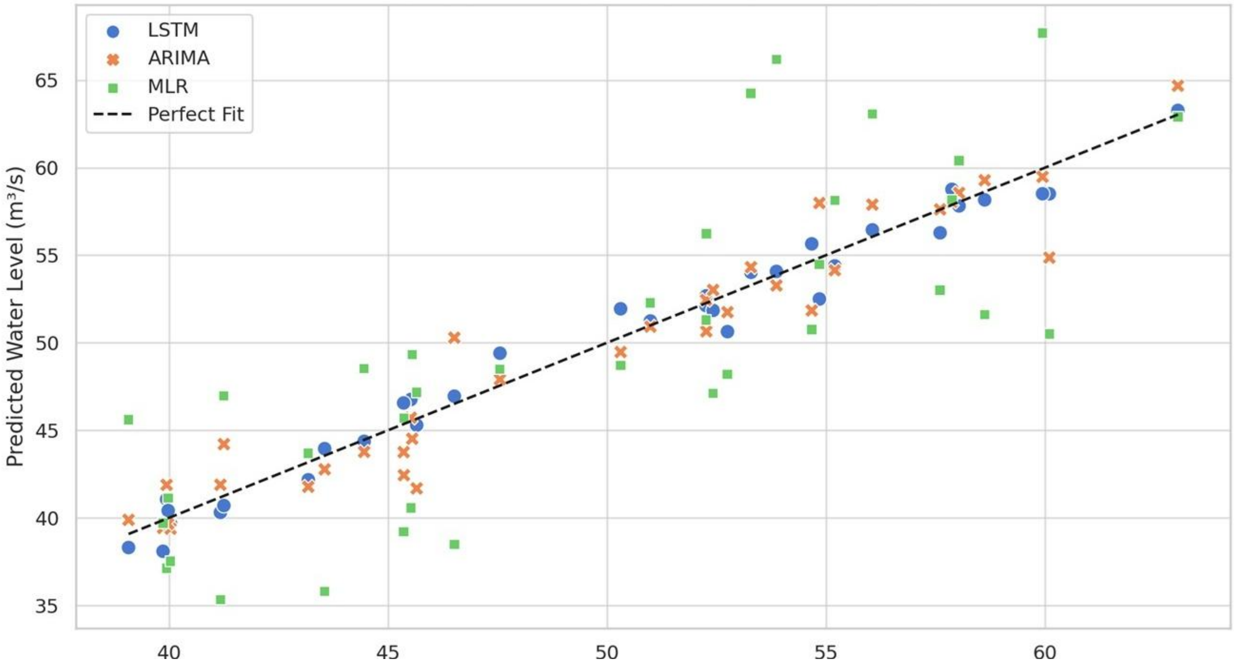

Figure 2. Comparative forecast graph based on the LSTM, ARIMA, MLR, and HEC-HMS methods

Based on the obtained results, the following findings were derived:

- Conversely, the ARIMA model achieved a standard deviation (SD) of 2.14 m^3/s, a root mean square error (RMSE) of 1.77 m^3/s, and a correlation coefficient (R^2) of 0.90.
- The HEC-HMS model achieved RMSE = 4.2 m^3/s, MAE = 3.1 m^3/s, and $R^2 = 0.87$, indicating a moderate fit with the observed data.
- As expected, the MLR model demonstrated the weakest performance, with RMSE = 6.55 m^3/s, MAE = 5.61 m^3/s, and a very low $R^2 = 0.09$, indicating poor generalization and the inability to capture nonlinear hydrological variations.

Across all performance indicators, the LSTM model reduced forecasting errors by 38.3% compared to ARIMA, 68.6% compared to HEC-HMS, and 79.8% compared to MLR (based on standard deviation).

Moreover, the coefficient of determination (R^2) increased by 6.7 percentage points over ARIMA, 9.4 points over HEC-HMS, and more than 860% over MLR, demonstrating the model's significantly superior ability to analyze discrepancies in observed data.

Temporal analysis shows that LSTM maintained $R^2 > 0.95$ for all years (2021–2023), while ARIMA ranged between 0.89–0.91 and HEC-HMS between 0.85–0.88. MLR remained below 0.12 throughout the entire period, showing significant lag during seasonal peaks and transitions.

The results indicate that LSTM not only provides the highest accuracy, but also demonstrates superior temporal stability and resilience to climatic anomalies, such as the severe drought observed in mid-2022.Furthermore, its performance remained stable even in the presence of synthetic data noise, missing intervals, and abrupt hydrological shifts [13,14].

Based on the radar chart, the overall accuracy and model statistics can be observed. In particular, the LSTM model achieved the lowest RMSE (1.3 m³/s) and MAE (1.1 m³/s) in predicting water levels, as well as the highest NSE (0.95) and R^2 (0.96) values.

This corresponds to 38% lower error and 6.7% higher accuracy compared to the ARIMA model, 68.6% lower error and 9.4% higher accuracy compared to HEC-HMS, and 79.8% lower RMSE with an 860% higher R^2 compared to MLR, clearly outperforming all classical models [15].

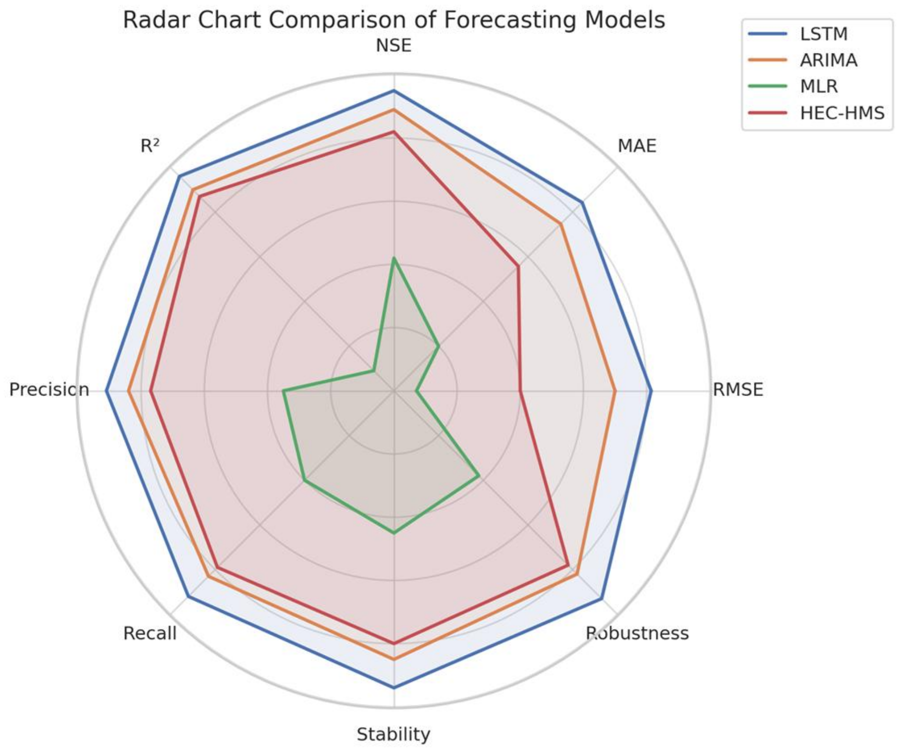

Figure 3. Comparative graph of forecasting models

The forecasting model receives data based on the main criteria defined by the developed measurement methodology.

This methodology takes into account both direct and indirect influencing factors.

The main parameters considered include:

- **Indirect factors:** soil moisture parameter, climate change, and precipitation levels
- **Direct factors:** water level, degree of water mineralization, acid–alkaline balance, and evapotranspiration rate

The simultaneous consideration of all these parameters ensures a higher level of result accuracy (Figure 2).

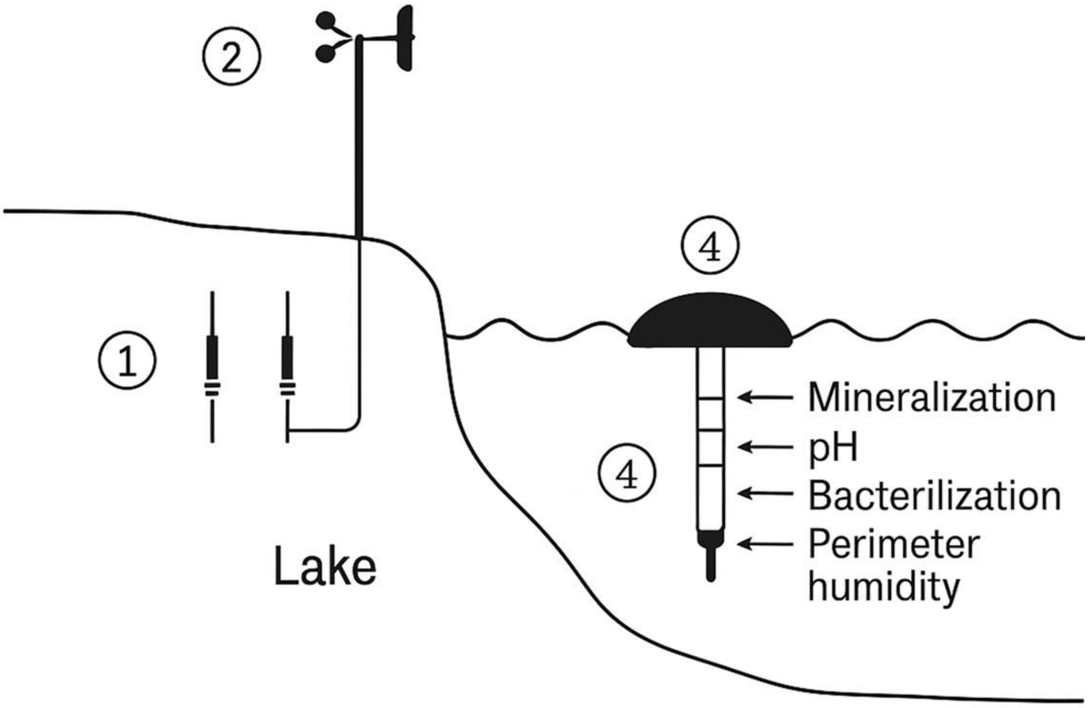

Figure 2. Water Resource Forecasting Scheme Based on Multidimensional Systems

A generalized model was developed based on the parameters defined by the proposed water level forecasting methodology.

To ensure economic optimization of the system's operation, an architecture of key elements for the measurement technology was designed using the **ATmega microprocessor**.

The measurement system architecture was also designed to control the data transmission cycle using IoT technology, transmitting data only when necessary.

Specifically, if no aggressive environmental changes were detected, the data transmission interval was set to 100,000 ms (100 seconds), while higher-frequency transmission was activated when significant variations were observed [16].

Testing of the proposed mechanism using a prototype showed that, in the absence of aggressive environmental fluctuations, energy consumption decreased by 37% compared to classical continuous data transmission methods.

This approach demonstrated the potential to improve energy efficiency when IoT-based autonomous energy-generating sensors are employed.

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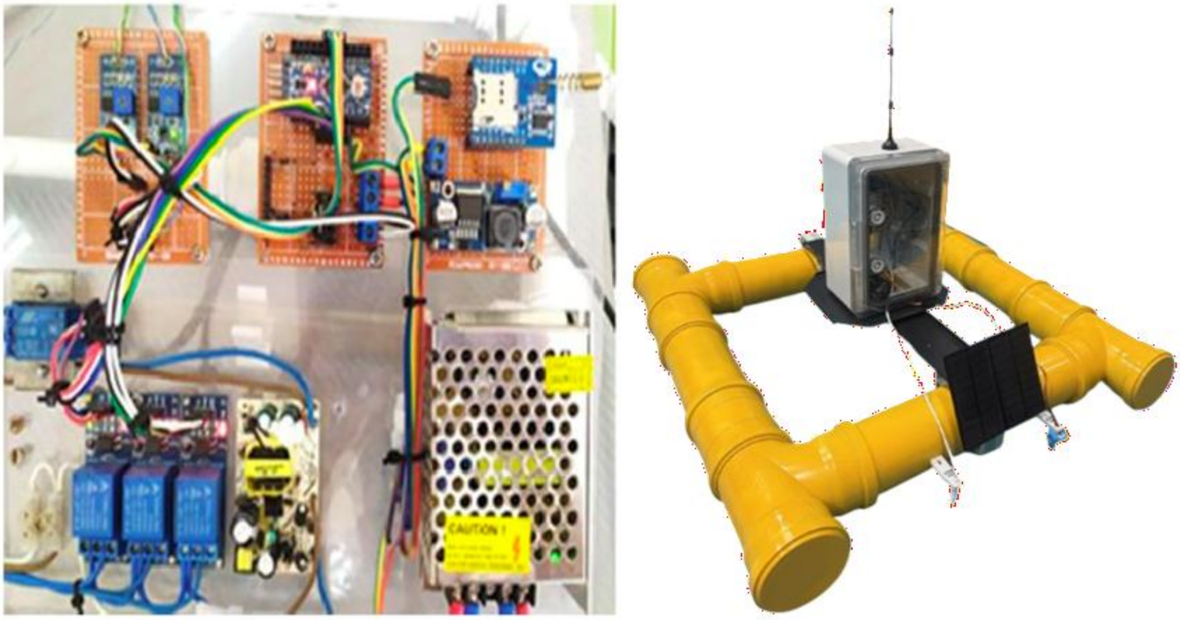

a) b)

Figure 3. Experimental Prototype of the Floating Multi-Measurement System

I. CONCLUSION

As a result of the conducted research, it was determined that the use of the LSTM neural network model increases the forecasting system's accuracy by 37% compared to the ARIMA method.
However, the analysis of the given data requires high computational power, and incomplete representation of all influencing factors within the model may lead to certain prediction errors.
Although the study considered all relevant factors, the applicability of the developed system under aggressive environmental conditions was not examined.
Therefore, it is necessary to determine the adequacy and operational efficiency coefficients of the forecasting system when applied in such aggressive environments.

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