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FROM TRADITIONAL TO INTELLIGENT: AN IOT-BASED INTELLIGENT MONITORING AND EVALUATION SYSTEM FOR DISSOLVED OXYGEN IN WATERSHED WATER ENVIRONMENT

Feng Naifan

Sukhoi State Technical University of Gomel, the Republic of Belarus

Scientific supervisor Yu. V. Kryshneu

Dissolved oxygen is a core indicator for assessing the health status of water environments in river basins. This paper explores the transition from traditional manual sampling to intelligent monitoring, proposes a dedicated monitoring system architecture for dissolved oxygen based on the Internet of Things, and utilizes statistical data analysis methods to quantitatively evaluate the dynamic changes of dissolved oxygen in water bodies and the impacts of environmental events.

Keywords: Internet of Things. dissolved oxygen, watershed monitoring. Difference-in-Differences model, statistical analysis, sensor nodes.

In the watershed ecosystem, the concentration of dissolved oxygen (DO) directly determines the survival status of aquatic organisms and the self-purification capacity of the water body. Traditional monitoring methods rely on manual regular inspections and titration analysis, which are not only time-consuming and laborious, but also suffer from significant spatial and temporal lags in data, making it difficult to capture diurnal fluctuations or sudden hypoxia events of dissolved oxygen. The transition to an intelligent monitoring system based on the Internet of Things (IoT) has become the key to addressing this bottleneck.

The intelligent dissolved oxygen monitoring system designed in this study comprises a sensing layer, a transmission layer, and a data analysis layer.

Block diagram of the intelligent dissolved oxygen monitoring system for river basins based on the Internet of Things (Fig. 1).

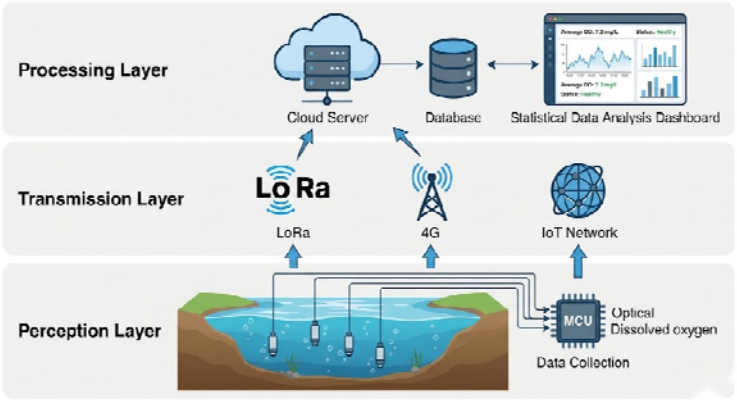


Fig. 1. Block diagram of the intelligent dissolved oxygen monitoring system for river basins based on the Internet of Things

At the sensing layer, the system deploys high-precision optical (or polarographic) dissolved oxygen sensor nodes. The microcontroller is responsible for collecting the analog signals from the sensors and removing high-frequency noise caused by water flow disturbances through a built-in low-pass filter (LPF). Subsequently, the data is transmitted back to the cloud database with low latency via a wireless communication module (such as LoRa/4G), forming a continuous time series of dissolved oxygen data.

To deeply mine these high-frequency monitoring data, this study introduces rigorous statistical data analysis methods at the cloud processing layer. Specifically, for specific environmental events within the basin (such as sudden rainfall, pollution discharge control, or ecological restoration projects), the system employs a Difference-in-Differences (DID) model for quantitative evaluation of policy or event effects.

Statistical analysis of dissolved oxygen data and evaluation process of the Difference-in-Differences (DID) model (Fig. 2).

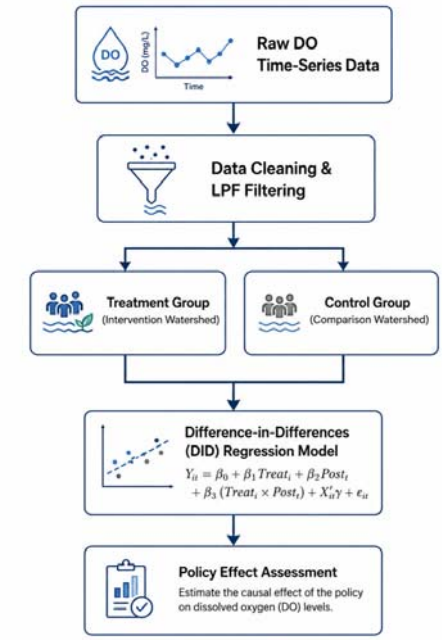


Fig. 2. Statistical analysis of dissolved oxygen data and evaluation process of the Difference-in-Differences (DID) model

Unlike simple mean comparison, the Difference-in-Differences (DID) model can effectively strip away the interference of time trends caused by changes in the natural environment. With the help of professional statistical analysis tools such as Stata, a systematic regression analysis is conducted on the dissolved oxygen panel data of the treatment group (regions affected by the event) and the control group (regions not affected). This method can accurately extract the net impact of a specific event on the dissolved oxygen concentration in water bodies (treatment effect).

The results of system simulation and empirical testing demonstrate that this intelligent monitoring architecture not only achieves round-the-clock automated collection of dissolved oxygen data, but also its embedded statistical analysis model can effectively identify key driving factors affecting water quality.

Dynamic changes in dissolved oxygen concentration before and after environmental events and DID effect analysis diagram (Fig. 3).

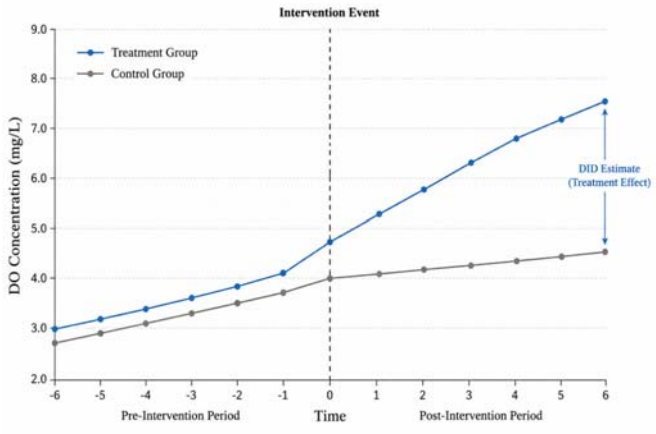


Fig. 3. Dynamic changes in dissolved oxygen concentration before and after environmental events and DID effect analysis diagram

In summary, this IoT monitoring system provides a high-timeliness and high-precision data foundation for the refined management of watershed water environment. Its analysis results can directly serve the formulation of ecological protection policies and the scientific assessment of soil and water environment.

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ПРОЕКТ УЧЕБНОГО ЦЕНТРА ПО ТЕХНОЛОГИЯМ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА С ИСПОЛЬЗОВАНИЕМ УДАЛЕННЫХ СЕРВЕРОВ С ТЕХНОЛОГИЕЙ ЛОКАЛЬНОГО ЗАПУСКА AI

А. В. Федорович, А. Э. Шлыков

Учреждение образования «Гомельский государственный технический университет имени П. О. Сухого», Республика Беларусь

Научные руководители: Ю. В. Крышнев, А. Е. Запольский

Рассмотрена концепция и архитектура учебного центра по технологиям искусственного интеллекта, объединяющего удаленные GPU-серверы и технологии локального развертывания AI-моделей. Предложена гибридная инфраструктурная модель, обеспечивающая практическое обучение работе с большими языковыми моделями, генеративным AI и системами машинного обучения при полном контроле над данными.

Ключевые слова: искусственный интеллект, большие языковые модели, локальный инференс, GPU-инфраструктура, MLOps, гибридная архитектура, учебный центр, open-source модели.

Стремительное развитие технологий искусственного интеллекта (ИИ) и, в частности, больших языковых моделей (LLM), формирует устойчивый спрос на специалистов,