Development of an Intelligent Online System for Predicting Membrane Fouling Using Real-Time TSS and SDI Estimation

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***Abstract*— Membrane fouling severely limits water filtration system performance and lifespan and increases operational costs. Lab-based monitoring of Total Suspended Solids (TSS) and Silt Density Index (SDI) is slow, labor-intensive, and unsuitable for continuous control. Water treatment facilities need rapid, onsite, energy-efficient monitoring tools.This study investigates whether an embedded, low-cost online sensing system can reliably estimate TSS and SDI in real time and serve as a predictive tool for membrane fouling risk, while reducing reliance on conventional laboratory protocols.*Methodology:* An intelligent prototype was developed using an embedded architecture comprising an Arduino UNO microcontroller, a turbidity sensor, an analog-to-digital communication module, an LCD interface, a battery power supply, and an RS-485/TTL converter for data transmission. The system continuously acquires turbidity-related signals, which are mathematically processed using linear correlation and regression to estimate TSS and SDI values. Experimental validation was performed by comparing online measurements with reference laboratory methods used for suspended solids and SDI determination.*Results:* The proposed system closely matched standard analytical techniques. TSS estimation had a Pearson correlation coefficient of 0.9191 and a relative error of 5.3760%, confirming reliable prediction. First-order polynomial regression gave a very low root mean square error (RMSE = 7.8505×10^{-16}), showing high model accuracy. For SDI estimation, the system had a Pearson correlation coefficient of 0.8673, a coefficient of determination (R^2) of 0.7523, and a mean relative error of 2.2931%, demonstrating its ability to assess particulate fouling potential. The findings show that embedded, real-time monitoring can feasibly replace traditional laboratory analyses. Strong statistical correlations demonstrate that turbidity-based sensing and data-driven modeling reliably estimate TSS and SDI. The system's portability, low energy use, and simple design enable effective continuous field deployment. *Conclusion:* The developed online preventive system provides a practical, accurate, and resource-efficient alternative for monitoring fouling-related parameters. By enabling real-time prediction of membrane fouling risk, the approach supports proactive process control and reduces operational costs. This contributes to the sustainable management of membrane-based water treatment systems.**

***Keywords*— Membrane fouling; Online monitoring; Turbidity sensor; Water treatment; Intelligent sensing system.**

I. INTRODUCTION

The real-time measurement of total suspended solids (TSS) in aquatic environments represents a crucial challenge for water quality monitoring, environmental management, and the understanding of biogeochemical processes. Modern measurement systems rely on an integrated architecture comprising two essential components: a hardware architecture ensuring the physical connection between the sensors and the processing unit, and a software architecture dedicated to data processing, quantification, and transmission via suitable protocols (Eidam et al., 2021; Guimarães et al., 2019; Kinar & Brinkmann, 2022; Lopez-Betancur et al., 2022; Mejías et al., 2017; Rajkumar et al., 1995). Concurrently, optical backscatter sensors (OBS), designed on cost-effective and easy-to-assemble printed circuit boards (PCBs), offer an accessible alternative for turbidity measurement and TSS quantification while achieving performances comparable to commercial solutions (Eidam et al., 2021; Guimarães et al., 2019; Kinar & Brinkmann, 2022).

The integration of artificial intelligence methods, particularly convolutional neural networks (CNNs), opens new perspectives for the image analysis of liquid samples, enabling a precise and rapid estimation of TSS concentration and turbidity. Furthermore, the deployment of unmanned aerial vehicles (UAVs) equipped with

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multispectral sensors, combined with the exploitation of regression or machine learning models, facilitates the spatial and temporal mapping of water quality parameters on an extended scale (Lopez-Betancur et al., 2022; Mejías et al., 2017).

Thus, the harmonious combination of flexible hardware architectures and high-performance software enables the design of compact, accurate, and real-time systems, opening innovative prospects for ecological monitoring and water resource management (Eidam et al., 2021; Guimarães et al., 2019; Rajkumar et al., 1995).

In this section, we detail all the components integrated into our prototype. The latter was designed to measure and calculate, in real time, the concentration of total suspended solids (TSS) within an aqueous sample.

II. MATERIALS AND METHODS

The hardware architecture of the prototype developed for real-time quantification of suspended solids (SS) is based on a data acquisition and processing chain centered around an Arduino UNO microcontroller.

The initial physical signal is generated by a turbidity sensor, whose optical response depends directly on the particle load of the aqueous sample. This sensor is coupled with a dedicated interface module that conditions the raw signal; this module offers operational flexibility thanks to its ability to switch between an analog transmission mode (continuous voltage variation) and a digital mode (logic threshold switching).

To ensure robust communications and enable potential long-distance data transmission in industrial environments, the central processing unit incorporates an RS485-TTL converter, which converts TTL logic-level signals into differential signals immune to electromagnetic noise.

The direct and instantaneous display of calculated concentrations is handled by an LCD screen connected to the output pins of the computing board. Finally, all of these instrumentation components are powered autonomously by a regulated battery, giving the prototype the portability essential for on-site measurement campaigns.

III. Results and Discussion

Experimental Correlation between Turbidity and Suspended Solids

To enable the prototype to quantify the concentration of suspended solids (TSS) in real time based on the raw optical measurements provided by the turbidity sensor, a calibration and mathematical correlation study was conducted. The experimental data from the measurement campaigns (turbidity in instrument units vs. TSS measured in the laboratory) were subjected to a linear regression analysis. The statistical performance indicators derived from this modeling are summarized below: Regression line equation: $y = 5.5489x + 1.3041$ (where y represents the calculated TSS concentration and x the turbidity value).

Linear correlation coefficient (R): 0.9191, Coefficient of determination (R^2): 0.8447

Mean relative error: 5.3760% The statistical evaluation of these parameters confirms the validity of the model. A linear correlation coefficient of 0.9191 (close to 1) indicates a strong linear relationship between the optical opacity of the medium (turbidity) and the suspended particulate load. Furthermore, the coefficient of determination ($R^2 = 0.8447$) indicates that more than 84% of the variance in MES is accurately explained by the variation in turbidity alone. Finally, the mean relative error, limited to 5.3760%, is perfectly acceptable for environmental diagnostic and monitoring applications.

Analysis of the Variation Profile and Probe Validation

The relationship between the experimental values and the predictive model is recorded in the variation table and illustrated by the regression curve (Figure .1).

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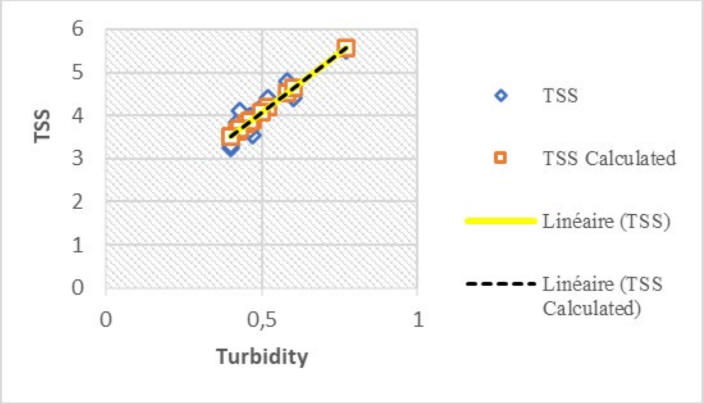

Fig.1 Variation in TSS as a function of turbidity

TABLE 1
EXPERIMENTAL AND CALCULATED TSS VARIATIONS AS A FUNCTION OF TURBIDITY.

Data Point Type	Turbidity (TUR) [NTU/Arbitrary Unit]	Measured TSS (y) [mg/L]	Calculated TSS (yc) [mg/L]
Operational	0.52	4.40	4.19
Operational	0.47	3.55	3.91
Operational	0.40	3.25	3.52
Operational	0.42	3.84	3.63
Operational	0.45	3.80	3.80
Operational	0.58	4.80	4.52
Operational	0.46	4.00	3.86
Operational	0.46	3.66	3.86
Operational	0.50	4.20	4.08
Operational	0.43	4.10	3.69
Operational	0.60	4.40	4.63
Operational	0.77	5.50	5.58
Operational	0.40	3.30	3.52
Validation Test	**0.70**	**5.55**	**5.19**
Operational	0.49	4.35	4.02

Examining Figure.1, the distribution of experimental data points (blue diamonds) shows a tight clustering around the linear trend line (yellow dashed line), which visually confirms the effectiveness of the calibration. The sensor was successfully programmed to operate within a limited turbidity range ($x < 1$), thereby ensuring optimal accuracy in areas of low to moderate concentrations. The test point introduced at a turbidity of 0.7 confirms this trend by displaying a calculated value of 5.188 for a measured value of 5.55, thereby validating the real-time predictive capability of the onboard algorithm.

Extended Calibration: SDI and TSS Correlation Analysis

To enhance the preventive capabilities of the monitoring system, a secondary experimental campaign was conducted to evaluate the correlation between the Silt Density Index (SDI) and Total Suspended Solids (TSS). The SDI is a critical industrial parameter used to quantify the fouling potential of water, particularly in reverse osmosis and fine membrane filtration systems. Establishing a direct mathematical link between TSS and SDI allows the prototype to predict multi-parameter fouling risks from a single analytical chain.

The experimental data points were subjected to a rigorous linear regression analysis, yielding the following mathematical model: $y = 1.0621x + 1.6147$

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Where y represents the predicted SDI value and x denotes the measured TSS concentration. The statistical reliability of this predictive model is confirmed by the following calculated performance indicators:

Linear Correlation Coefficient (R): 0.8673,Coefficient of Determination (R^2): 0.7523,Mean Relative Error**:** 2.2931%

A correlation coefficient of 0.8673 indicates a strong, positive linear relationship, proving that suspended particulate mass variations directly dictate the siltation behavior of the fluid. Moreover, the coefficient of determination ($R^2 = 0.7523$) demonstrates that 75.23 % of the SDI variability is successfully explained by the TSS linear model.

Industrial Integration of the Minimum Viable Product (MVP)

The fundamental principle of this project is based on automated, *in-situ* water quality monitoring, specifically applied to the intelligent and preventive management of membrane filtration systems. The Minimum Viable Product (MVP) algorithm follows a strict logical routine (described in the flowchart in Figure 2): after program initialization and variable declaration, the system acquires the turbidity value, calculates the instantaneous TSS concentration, and applies a conditional structure.

If the calculated concentration exceeds a predefined critical threshold (set here at 0.3 mg/L), the system triggers a visual alert by switching the indicator LED from green to red. This rapid automated response allows the flow to be isolated or a backwashing cycle to be initiated before the accumulation of solids causes irreversible membrane clogging.

By integrating both TSS and SDI thresholds into this conditional loop, the MVP establishes a multi-barrier defensive routine. When particle accumulation threatens membrane integrity, the immediate logic output acts as a crucial industrial safeguard, lowering maintenance costs and extending the operational lifespan of the filtration infrastructure.

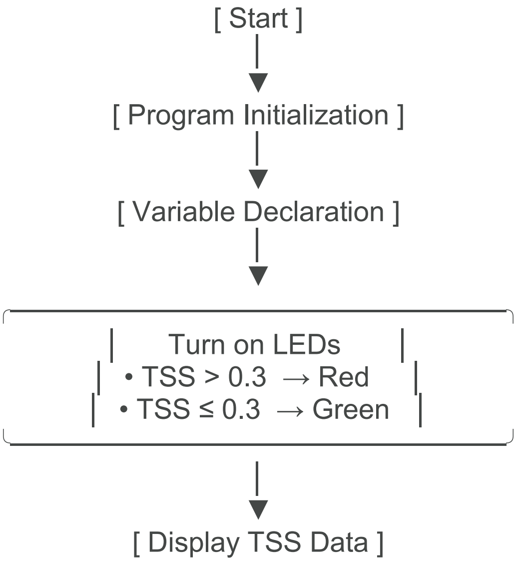

Fig.2: Prototype Flowchart

IV. CONCLUSIONS

In conclusion, the results obtained in this study demonstrate the effectiveness and feasibility of our in situ measurement system. This preventive device offers an excellent alternative to conventional laboratory methods for the real-time estimation of suspended solids (SS). Unlike the traditional gravimetric technique—which requires a cumbersome, time-consuming protocol and the systematic use of restrictive equipment (vacuum pump, filters, precision balance, and drying oven)—our prototype offers an automated, robust approach that is highly economical in terms of time and logistical resources. From a metrological standpoint, calibration of the probe established a strong linear correlation between turbidity and TSS concentration, limiting the average relative error to just 5.38 %. This level of accuracy fully validates the integration of this minimum viable product (MVP) as an early warning tool for the intelligent management of filtration facilities and the prevention of membrane fouling.

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