Project Title: ICT-Driven Water Quality Monitoring Systems: Enhancing Precision and Sustainability under the Climate Change

Background :

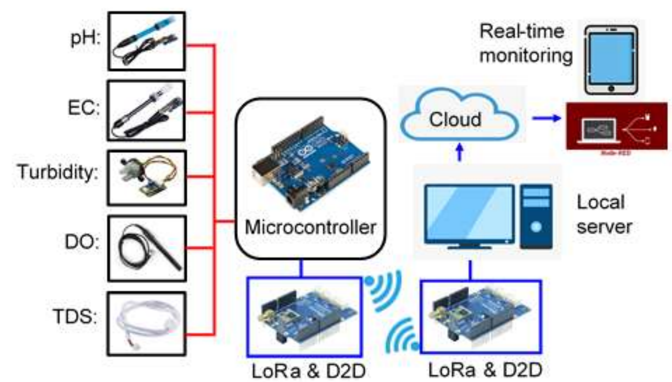
Modern water monitoring technologies, particularly those utilizing Information and Communication Technology (ICT), offer real-time data collection and analysis, enabling timely interventions to address contamination and degradation. The water quality sensors are often susceptible to problems of measurement linearity, offset, and noise-related issues, which can compromise their accuracy in measuring the water quality parameters. Thus, this project is focused on the calibration process to correct systematic errors in IoT water quality sensors, embedding the machine learning technique to learn and adjust the measurements to non-linear patterns. Using the machine learning calibrated sensors, proper monitoring and control of water quality can be employed toward the efforts in ensuring safe drinking water supplies and effective water treatment, which are aligned with SDG 6 Clean Water and Sanitation.

Targets:

(a) To enhance and improve the precision and performance of the IoT-based system through machine learning calibration.
(b) To gain insights into the water quality of the Mekong River and assess its impact on the sustainability of the river under climate change.

Speaker:

Assoc. Prof. Dr. Kok Hwa YU



Water quality IoT system

Project Title: ICT-Driven Water Quality Monitoring Systems: Enhancing Precision and Sustainability under the Climate Change

Project Members :

Assoc. Prof. Dr.
Kok Hwa YU
(Project Leader)
(USM – MY)

Dr. Matsumura
Takeshi
(NICT – JP)

Dr. Huan-Bang Li
(NICT – JP)

Prof. Dato' Dr.
Narimah Binti Samat
(USM – MY)

Prof. Ir. Dr.
Leo Choe Peng
(USM – MY)

Assoc. Prof.
Ir. Dr. Yen Kin Sam
(USM – MY)

Assoc. Prof.
GS. Dr. Tan Mou Leong
(USM – MY)

Assoc. Prof.
Ir. Dr. Teh Jiashen
(USM – MY)

Dr. Ho Ngo
Anh Dao
(TDTU – VN)

Dr. Tran Thi
Phuong Quynh
(TDTU – VN)

Mr. Nguyen
Thanh Quang
(TDTU – VN)

Dr. Hor
Mangseang
(CADT – KH)

Mr. Him
Soklong
(CADT – KH)

Mr. Pov
Phannet
(CADT – KH)

Project Duration : 2 Years

Project Budget: USD 80,000

Project Activities:

Milestones

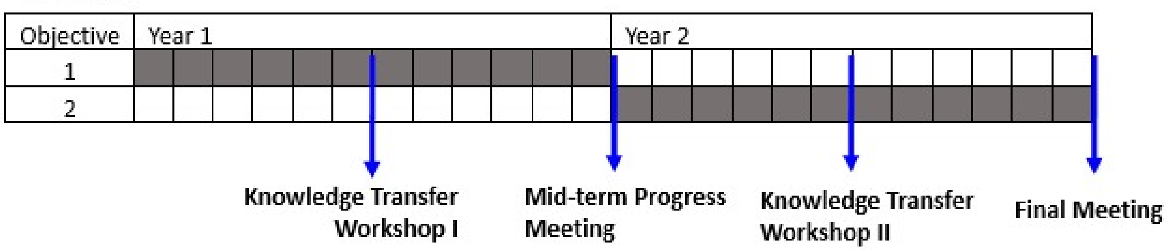
i. Perform water quality data comparison, and determine bias ratio and bias type. Train machine learning model, evaluate and analyze the data prediction. Develop the machine learning calibration on water quality measurement (i.e., pH, EC, DO, TDS, and turbidity) at USM and complete by 12 months. **[Objective 1]** **[Completed for Turbidity sensor]**

ii. Developing the floating platform and installing the water quality measurement system with integrated LoRa and D2D communication at CADT and TDTU. Tested and completed in 12 months. **[Objective 2]** **[Completed design of the floating platform]**

iii. Deploy the IoT water measurement system at CADT and TDTU. Collect and analyze the water quality data with completion by 18 months. **[Objective 2]**

iv. Assess the carbon footprint of the Mekong River water treatment based on water quality data and climate change impact (USM and TDTU) with completion by 24 months. **[Objective 2]**

Gantt chart



Scheduled in Ho Chi Minh City in Nov 26 – 27, 2025

Project Activities:

1. Knowledge Transfer Workshop I (Ho Chi Minh City, Nov 26 – 27, 2025)

All project members will share their expertise and discuss how their work contributes to the project's objectives. Specifically:

– NICT: Wireless communication systems, D2D connectivity for IoT deployment.
– USM: Machine learning calibration for IoT sensors.
– CADT: Water quality testing equipment, water collection system, and laboratory analysis.
– TDTU: Development of floating platforms for IoT deployment, sensor testing, and sensor calibration/standardization under real en vironmental conditions.

Date and Time	Activities
26/11/2025 - Knowledge Transfer Workshop I	
08:30 – 08:35	Welcome Remarks
08:35 – 08:45	Opening Remarks
08:45 – 09:00	TDTU Introduction
09:00 – 09:30	Topic 1: Overview of research activities in wireless systems laboratory at NICT (Dr. Matsumura Takeshi)
09:30 – 10:00	Topic 2: Sensor Data Gathering Using Mobile Terminals over D2D Communications (Dr. Li Huan-Bang)
10:15– 10:45	Topic 3: Machine learning model and calibration for water sensors (Dr. Yu Kok Hwa)
10:45 – 11:15	Topic 4: Developing an IoT-Based Water Quality Monitoring Prototype: A Case Study from CADT (Dr. Hor Mangseang)
11:15 – 11:45	Topic 5: IoT system for water quality monitoring (Mr. Mai Minh Man and Mr. Le Duc Phuong)
01:30 – 03:00	Report on progress update of ASEAN IVO Project 2025
03:30 – 05:00	Discuss update on progress of ASEAN IVO Project 2025
27/11/2025 – D2D Workshop	
09:00 – 09:15	Welcome remarks and brief introduction of participants
09:15 – 10:30	Technical Discussion
10:45 – 11:30	Site Survey for D2D System Installation within the Canal at Ton Duc Thang University Campus

Project Activities:

Technological development

Issues with water quality IoT turbidity sensors

- Individual variability of sensors
- Bias problem
- Light source intensity detector sensitivity

Table: Formulations on turbidity (T_{NTU}) and output voltage (V_{out}) relationship reported in the existing studies.

No.	References	Formula	
1	DFROBOT [13]	$T_{NTU} = -1120.4V_{out}^2 + 5742.3V_{out} - 4352.9$	(1)
2	Mulyana and Hakim [14]	$T_{NTU} = 36.6V_{out}$	(2)
3	Supriyono et al. [15]	$T_{NTU} = -26.7642V_{out} + 135.0524$	(3)
4	Trevathan et al. [16]	$T_{NTU} = \left[\frac{6.8303 - \ln(V_{out})}{0.00031532}\right]^{1.0235}$	(4)

Experimental setup

(a) (b)

Figure: (a) HANNA HI98703 portable turbidity meter, and (b) Five units of DFRobot SEN0189 IoT turbidity sensors (labeled 1 to 5).

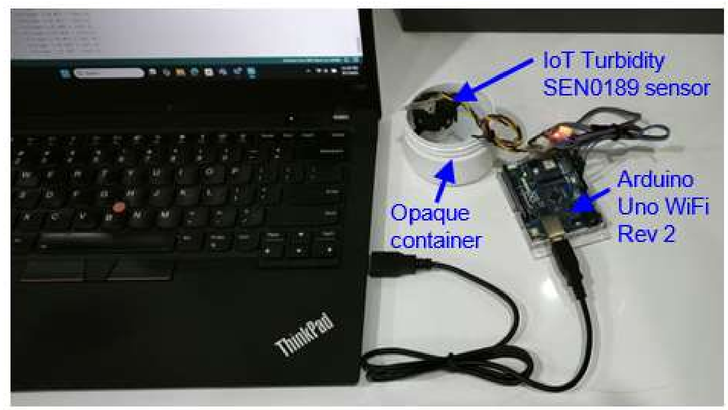


Figure: Experimental setup of IoT Turbidity SEN0189 sensor using Arduino Uno WiFi Rev 2 microcontroller.

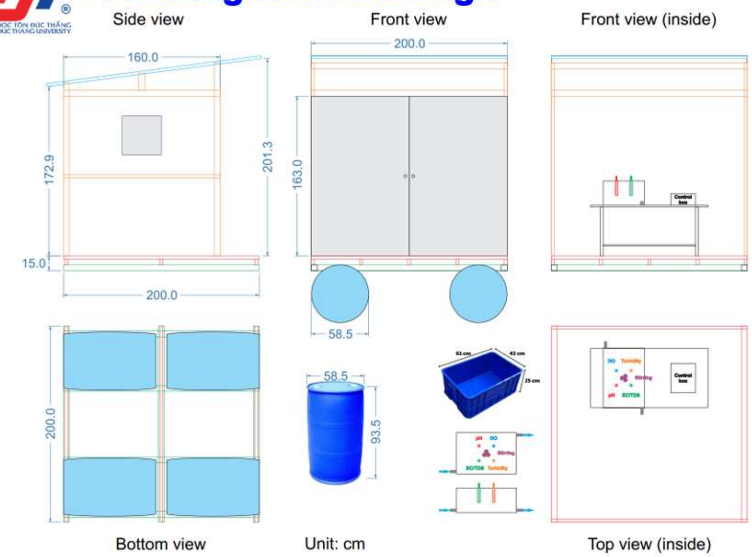
By Dr. Yu, Prof. Leo, Dr Yen

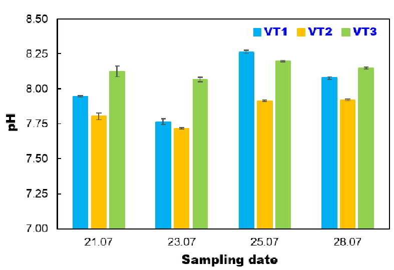
Project Activities: (Max. 5 slides)

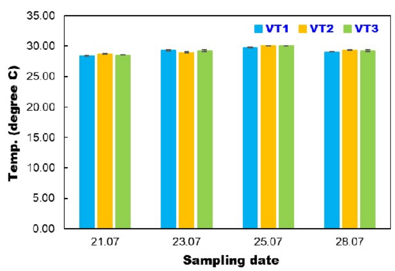
Experimental setup and manual field test

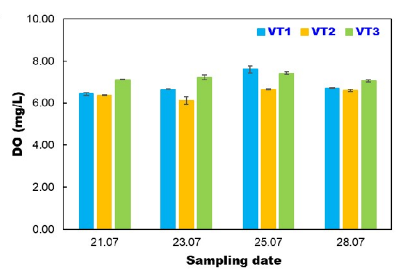
1. Canal System at TDTU Main Campus

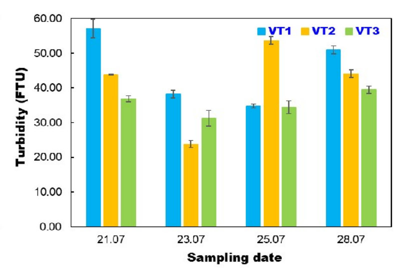
- Floating House Design











By Dr. Anh Dao,
Dr. Quynh, Mr Quang

Project Activities: (Max. 5 slides)

Budget in planning

No.	Details	Budget Allocation USD $
1	Multiparameter instrument for pH, electrical conductivity, total dissolved solids and dissolved oxygen	3,300.00
2	Benchtop meter for pH, dissolved oxygen and ammonia ISE	3,948.49
3	Knowledge transfer workshop I (Ho Chi Minh, Nov 26-27, 2025)	2,458.20
4	Purchase of pH, TDS-EC, DO and Turbidity sensors	724.00
5	ICETI 2025 Conference	1,842.84
	Total	12,273.53

R&D results:

Uncalibrated Turbidity sensor data

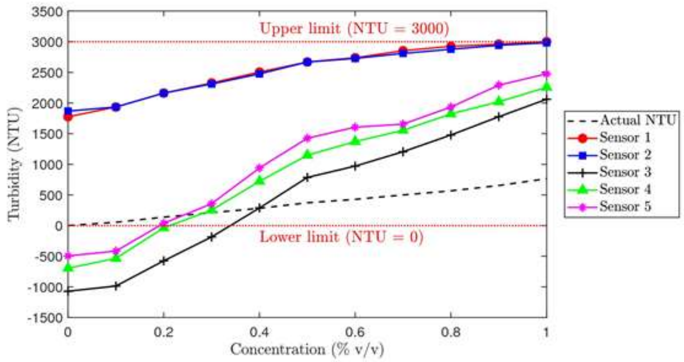


Figure: Turbidity NTU values of the SEN0189 IoT turbidity sensors, yielded by Eq. (1), as compared with actual turbidity values from turbidity meter.

Findings

- Sensors 1 and 2 significantly overestimate turbidity as compared to the actual NTU values, with reading starting above 2000 NTU, even at low concentration solution.
- Meanwhile, for Sensor 3, 4, and 5, the prediction errors increase with the concentration of the dairy product solution.

Output voltage

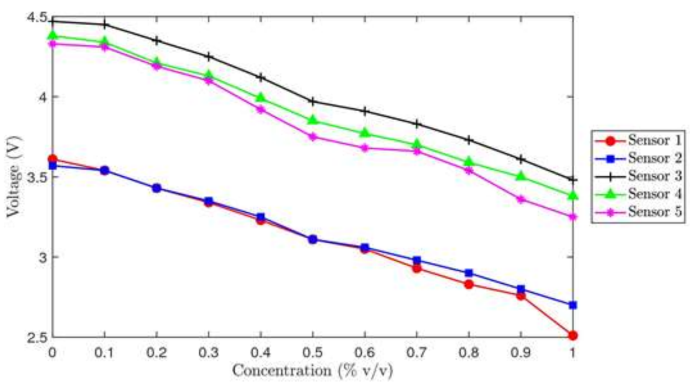


Figure: Voltage output of SEN0189 IoT turbidity sensors as a function of dairy product concentration (% v/v) in water.

Measurement error

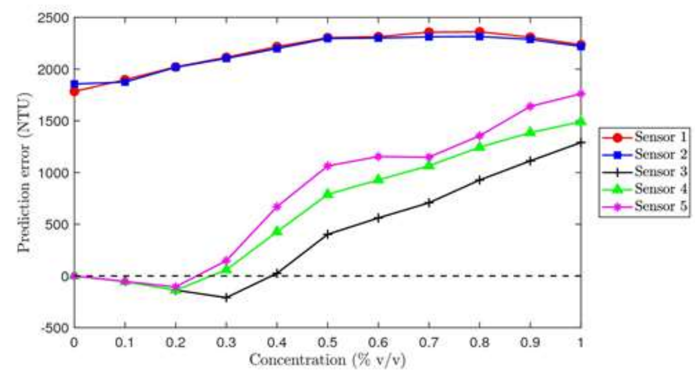
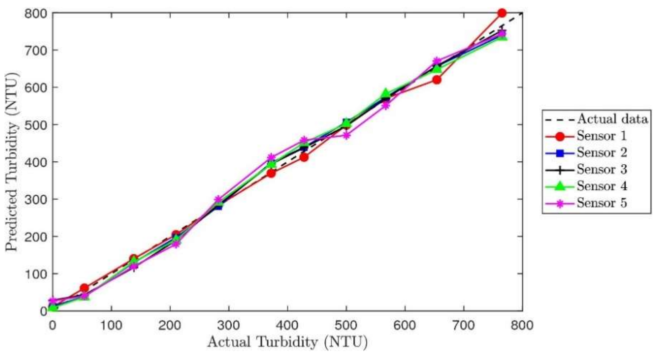


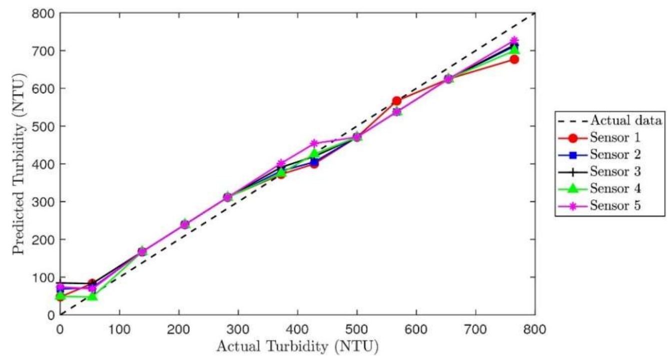
Figure: Prediction error for IoT turbidity sensor without calibration.

R&D results:

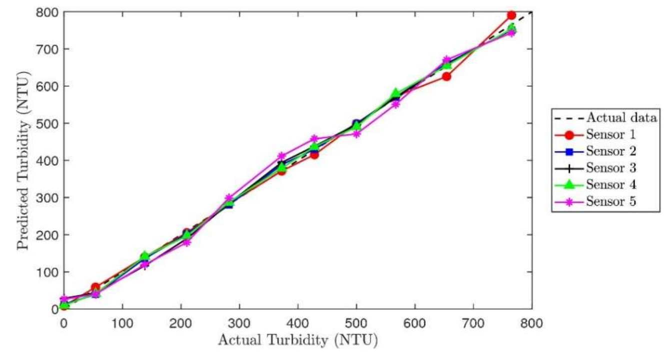
Machine learning-based calibration



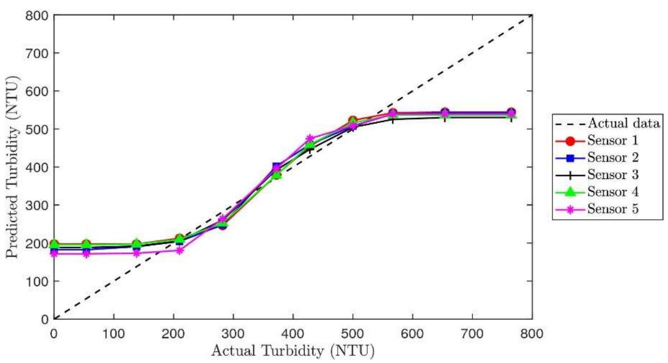
Linear regression



Support vector machine



Gaussian process regression



Random forest model

Table: Performance comparison of machine learning models for turbidity prediction using SEN0189 IoT turbidity sensor data.

Machine learning model	MAE	RMSE	R^2
Linear regression	14.58	17.34	0.9944
Random forest	79.40	104.87	0.8043
Support vector machine	32.21	37.44	0.9749
Gaussian process regression	12.13	14.31	0.9958

R&D results:

Gaussian process model

$$T_{NTU} = f(V_{out}) + \varepsilon$$

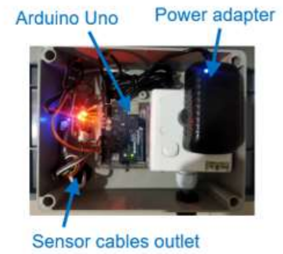
where

Latent function	:	$f \sim \mathcal{GP}\left(m(V_{out}), k(V_{out}, V'_{out})\right)$
Gaussian noise	:	$\varepsilon \sim \mathcal{N}(0, \sigma_n^2)$
Mean	:	$m(V_{out}) = \beta_0 + \beta_1 V_{out}$
Kernel	:	$k(V_{out}, V'_{out}) = \sigma_f^2 \exp\left(-\frac{(V_{out} - V'_{out})^2}{2\ell^2}\right)$

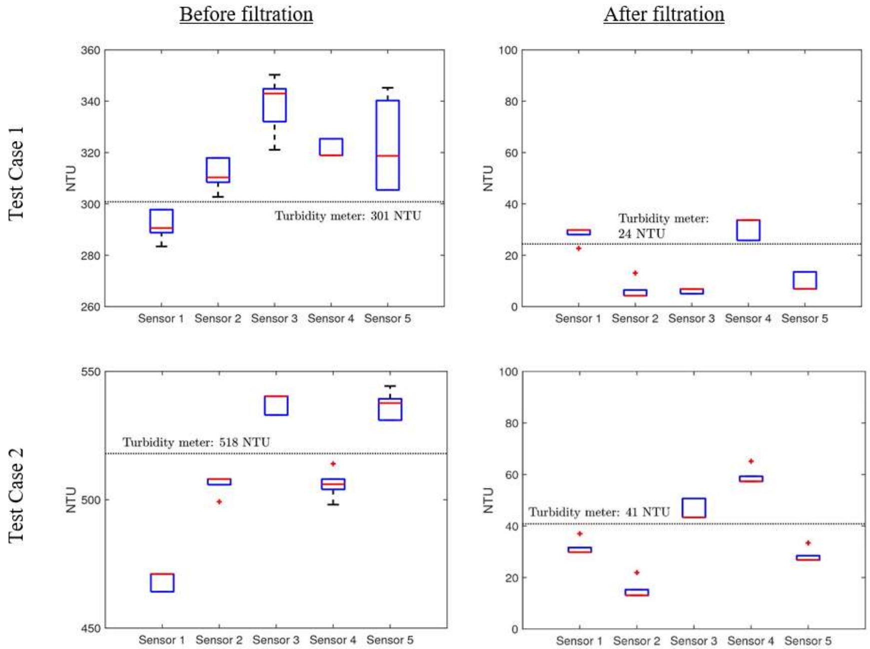
Hyperparameters for Gaussian process regression model

	β_0	β_1	σ_f	ℓ	σ_n
Sensor 1	2590.20	-714.26	7.42	0.08	14.17
Sensor 2	3026.00	-844.75	8.91	0.13	11.07
Sensor 3	3295.41	-730.80	6.53	0.01	15.38
Sensor 4	3256.08	-742.74	13.81	0.18	11.40
Sensor 5	2899.59	-663.47	327.57	0.02	24.76

(a)



(b)



Scientific Contribution:

Presentations at International Conferences:

No:	Paper title:	Author names	Affiliation	Conference name:	The date of the conference	The venue of the conference
1	Calibration of Low-Cost IoT Turbidity Sensor using Neural Network Regression Model	Kok Hwa Yu, Ying Nie, Choe Peng Leo, Kin Sam Yen, Jiashen Teh, Mou Leong Tan, Narimah Samat	Universiti Sains Malaysia	The 5th International Conference on Environmental Technology and Innovations (ICETI 2025)	27-28/11/2025	Ton Duc Thang University, Ho Chi Minh City, Vietnam
2	Water Quality Dynamics under Climate Change: Challenges in the Carbon Footprint Reduction of Water Treatment	Choe Peng Leo, Kok Hwa Yu, Kin Sam Yen, Mou Leong Tan and Jiashen Teh	Universiti Sains Malaysia	The 5th International Conference on Environmental Technology and Innovations (ICETI 2025)	27-28/11/2025	Ton Duc Thang University, Ho Chi Minh City, Vietnam
3	Dynamic Line Rating for Enhancing Power System Reliability under High Wind Penetration	Jiashen Teh, Xi He, Kok Hwa Yu, Choe Peng Leo, Mou Leong Tan	Universiti Sains Malaysia	The 5th International Conference on Environmental Technology and Innovations (ICETI 2025)	27-28/11/2025	Ton Duc Thang University, Ho Chi Minh City, Vietnam

Societal Impact:

- Using this machine learning calibration, the low-cost IoT sensors can be deployed to achieve reliable and comparable performance for practical water quality monitoring applications.
- By deploying ICT-enabled and ML-calibrated sensors and monitoring systems in freshwater bodies and water supply systems, communities gain real-time or near real-time data on water quality. This enables faster detection of contamination events (e.g., elevated turbidity, pH shifts, pollutant spikes) and hence faster response or prevention measures.
- Access to precise data on water quality enables municipalities, industries, and agricultural sectors to make informed decisions, promoting sustainable water resource management that minimizes wastage and pollution.

Conclusion:

- In this study, calibration using machine learning model is recommended, arising from the superior accuracy and minimal prediction error of the sensors, within ± 40 NTU, examined in the range of 0 to 800 NTU.
- Linear regression also performed well, while support vector machine showed moderate accuracy and random forest underperformed due to saturation at extremes.
- Field deployment in a water reuse system further confirmed the robustness of the GPR-calibrated sensors, which produce significantly more accurate turbidity meter measurements.

Future works:

Machine learning calibration on water quality measurement sensors

Machine learning calibration study shall be performed to other water quality parameters, including pH, EC, DO, TDS. The data shall be compared with the benchmark data attained from the commercial testing equipment.

Field test

Floating platforms shall be developed and installed at two locations (Phnom Penh – Cambodia, Ho Chi Minh – Vietnam) to assess the water quality of the lower basin of Mekong River. The IoT systems consisting of water quality measurements shall be stationed at these locations to gauge the water quality.

Sustainability study

Using the water quality data of the Mekong River, the carbon footprint of the Mekong River shall be assessed. The river water quality directly impacts the emissions from the energy-intensive treatment process.