GERAN PENYELIDIKAN UTM 2024
DIGITAL- INFUSED
(UTM - DiR)

Title of Research Proposal: Optimizing Electrocoagulation Energy Efficiency with Internet of Things (IoT) and Artificial Intelligence (AI) for Oily Wastewater Treatment Application

A) PARTICULAR OF RESEARCHER

Name of Project Leader : Ir. Dr. Tan Lian See

Staff No. : 14641

Type of Service : ☐ Contract

: ■ Permanent

Research Alliance : ☐ Innovative Engineering

■ Health & Wellness

☐ Smart Digital Community

☐ Resource Sustainability

☐ Frontier Material

Digital technology Area : Internet of Things (IoT) and Artificial Intelligence (AI)

B) PROJECT INFORMATION

Start Date : 1 May 2024 End Date : 30 April 2025

Duration : 1 Year

Research Area : Water Security

Keyword : Electrocoagulation; Artificial Intelligence; Internet of Things; Predictive Modelling; Wastewater Treatment; Oil Removal

Cost Centre Number (Previous / Current Grant) : Q.K130000.2443.08G06

PROJECT MEMBER

No	Staff No/IC No./Passport No.	Name	Expertise	Faculty/Institute/ Agency
1.	7264	AP Dr. Shahrum Shah Abdullah	Intelligent control, Artificial Neural Networks	Malaysia-Japan International Institute of Technology (MJIIT)
2.	16064	Dr. Zatul Alwani binti Shaffiei	Artificial intelligence, optimization	Malaysia-Japan International Institute of Technology (MJIIT)
3.	810721-01-6358	Dr. Noor Fazliani Shoparwe	Process modelling and control	Universiti Malaysia Kelantan (UMK)

1. EXECUTIVE SUMMARY (300 words)

Electrocoagulation is recognized for its rapid contaminant removal capabilities with minimal chemical usage. However, it faces challenges in consistency and energy efficiency, particularly when treating wastewater with varying oil concentrations generated from the food processing industry. Our proof-of-concept study indicated the potential for improved oil removal efficiency with an increase in applied voltage. However, we also found that excessive voltage applied to the system would lead to a reduced oil removal efficiency. Hence, this project aims to optimize the energy efficiency in electrocoagulation process when dealing with varying parameters in the system through the integration of IoT and AI technologies. This is in response to the urgent need for a more sustainable and efficient wastewater treatment method. We propose a novel approach that leverages real-time data collection via IoT and predictive analysis via AI-driven model to dynamically optimize the electrocoagulation process. By developing an IoT architecture for continuous monitoring and an AI-driven model for predicting and optimizing oil removal efficiency, we aim to achieve a more adaptive, energy-efficient treatment system. This system is expected to provide significant advancements in handling the variability of wastewater compositions, thereby reducing energy consumption, and enhancing overall treatment performance. The methodology will involve the development of an IoT-integrated experimental setup for data acquisition, followed by the development and validation of AI model to predict the performance of the treatment outcome. The final stage will focus on parameter optimization using computational intelligence, i.e. Harmony Search (HS) algorithm. It will aim to optimize the process for the most efficient energy usage and highest oil removal performance. This research is expected to contribute to the advancement of the wastewater treatment domain by offering a cost-effective solution which could increase the feasibility of the process for industrial applications. It is also expected that the integration of digital technologies will lead to the development of smart and intuitive processes for environmental management practices.

2. DETAILED PROPOSAL OF RESEARCH PROJECT

(a) Research Background including Hypothesis, Research Questions, and Literature Review with References

2.1 Research Background

The critical need for sustainable and efficient wastewater treatment technologies has led to the exploration and application of electrocoagulation processes for contaminants removal from water. It is a process that is relatively fast, with minimal addition of chemicals into the treatment process (Ammar et al. 2023). It was proven to be effective in removing organic contaminants in water, such as microplastics, dyes, pesticides as well as traces of pharmaceutical medication in water (Ayala-Chauvin et al., 2022).

This proposed research is an extension of our previously completed work which studied the efficiency of removing emulsified oil from water using electrocoagulation process. Fats, oil and grease (FOG) in wastewater could cause operational difficulties in plants with clogging and fouling of pumps and piping ((Husain et al., 2014). While bulk removal of free-floating oil could be removed through primary/physical treatment stages such as grease traps (Chinwetkitvanich and Ektaku, 2020), the residual oil presents challenges in secondary treatment processes. This is mainly due to the stability of the oil in wastewater when there is reduced interfacial tension between oil and water molecules.

From our previous study, we found that oil removal percentage improved with an increase in applied voltage. However, we also found that excessive voltage supply to the process could reduce the oil removal efficiency (Soo et al., 2024). This could be due to electrode passivation or secondary reactions that redisperse coagulated particles (Hakizimana et al, 2017; Wang et al., 2022).

The concentration of oil in food industry wastewater would inevitably vary from time to time, depending on the processing condition. Therefore, despite its potential, the optimization of electrocoagulation process for such constantly varied wastewater compositions remains a challenge. Traditional electrocoagulation processes often involve manual adjustments and lack continuous real-time responses, leading to inefficient energy use and inconsistent oil removal performance.

Hence, the integration of Internet of Things (IoT) for real-time data acquisitions as well as Artificial Intelligence (AI) for predictive model analysis and process optimization presents a novel approach to address these challenges (Rane et al., 2023; Wang et al., 2023). Integrating digital technologies into the electrocoagulation process for oil removal could significantly increase the precision of the treatment. IoT sensors can provide real-time monitoring of process variables, enabling progressive adjustments to optimize the oil removal efficiency. AI algorithms could analyze data trends to predict and enhance removal efficiency, adjusting the necessary operational parameters for efficient energy usage.

Overall, digital tools can yield a smarter, more responsive treatment system which can bring upon significant improvements in energy efficiency and treatment outcome. This development is expected to lead to a more cost-effective electrocoagulation treatment system, resolving the concerns of high energy usage in industrial scale application.

2.2 Hypothesis

The integration of IoT and AI into the electrocoagulation process for wastewater treatment can significantly enhance energy efficiency and oil removal performance. By leveraging real-time data and predictive analytics, the electrocoagulation process can be dynamically optimized to adjust to varying wastewater characteristics, reducing energy consumption and improving treatment performance.

2.3 Research Questions

1. How can IoT technologies be integrated into the electrocoagulation process for real-time monitoring and data acquisition in wastewater treatment?
2. Which AI model is effective for predicting the oil removal performance of the electrocoagulation process under varying conditions?
3. How much can the dynamic optimization of electrocoagulation parameters, guided by AI predictions, improve the energy efficiency and oil removal effectiveness in real wastewater treatment application?

2.4 Literature Review

Electrocoagulation is recognized for its effectiveness in treating various types of wastewater, including industrial effluents rich in oils and fats. Recent studies have highlighted its advantages over conventional treatment methods, such as lower sludge production and the ability to remove finely dispersed pollutants (Mao et al., 2023). However, challenges persist regarding the optimization of operational parameters, which impacts the energy efficiency and overall treatment efficacy (Mousazadeh et al. 2021).

The IoT offers promising solutions to the challenges faced by traditional wastewater treatment technologies. By integrating sensors and smart devices, IoT enables the continuous monitoring of treatment processes, providing real-time data on water quality and system performance (Alfonso et al., 2023). This wealth of data can be leveraged to optimize treatment processes, improve operational efficiency, and reduce costs. This in turn would facilitate a more precise control and optimization of treatment processes, contributing to more sustainable operation practices (Ayala-Chauvin et al., 2022).

On the other hand, AI and (ML)machine learning techniques have emerged as powerful tools for predicting and optimizing wastewater treatment processes (Wang et al., 2023). The ML algorithms can process complex datasets to identify patterns, predict treatment outcomes, and optimize process parameters (Icke et al., 2020). This can lead to significant improvements in treatment efficiency, enhanced decision-making, and a smarter system.

The utilization of ML algorithms to analyze the vast data generated in wastewater treatment processes are currently on uptrend. Among the popular ML models for wastewater treatment are Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM) (El Alaoui El Fels et al., 2023). In fact, some models could be more suitable for certain processes compared to another, as observed by Curteanu et al. (2014). They found that SVM was more suitable than ANN in correlating the performance for electrochemical-based process. More complex models such as adaptive neuro-fuzzy inference systems (ANFIS), genetic algorithms (GA), and particle swarm optimization (PSO) had also been adapted for electrochemical based process for wastewater treatment, such as electrocoagulation process, but the data was mainly derived from lab-based experimental set-up kind of studies (Shirkoohi et al., 2022). Nevertheless, Zhang et al. (2023) highlighted that moving forward, AI research for achieving multi-objective optimization should be explored. Picos-Benitez et al. (2020) evaluated an AI-based model using ANN to predict the performance of the electro-oxidation treatment of sulfate wastewaters containing Bromophenol blue dye. The model was integrated with GA for optimization to identify the optimal operational conditions for the treatment. Their findings indicated that the combined ANN-GA AI model successfully optimized the treatment process, resulting in enhanced current efficiency. Therefore, refining the development and integration of AI models using actual wastewater could enhanced interpretability of the models. Furthermore, tailoring AI-driven multi-objective optimization for specific treatment scenarios, as shown in Figure 1, could hold significant potential for improving efficiency and outcomes.

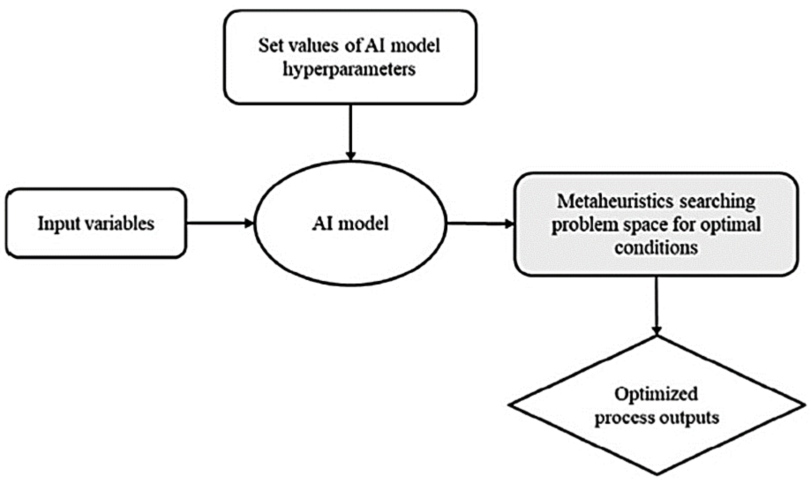

Figure 1: The integration of metaheuristic algorithms with an AI model to determine the optimal conditions.

Integrating IoT with AI would offer a dynamic approach to optimizing wastewater treatment, leveraging real-time data for automated adjustments to treatment parameters. This integration could lead to a more efficient and responsive system, significantly enhancing process performance (Nuno et al., 2022; Rane et al., 2023; Shirkoohi et al., 2022). Specifically, for this electrocoagulation process, it is expected that the integrated approach could improve the feasibility of the process by optimizing the energy usage for reducing operational costs and enhancing oil removal efficiencies. However, achieving this integration requires addressing technical challenges related to data integration and model accuracy, which will be studied and attempted to be resolved in this project.

2.5 References

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(b) Objective(s) of the Research

No.	Objective
1	To develop an IoT architecture for real-time monitoring of electrocoagulation processes.
2	To develop AI-driven predictive model based on the real-time data collection from IoT for prediction of oil removal efficiency for the electrocoagulation process.
3	To optimize the parameters for varied oil concentration using AI-driven predictive model for efficient energy usage in the electrocoagulation process.

3. METHODOLOGY

3.1 Description of Methodology

Stage 1: Development of IoT architecture

An experimental set-up integrated with IoT architecture, as shown in Figure 2, will be developed in this study. The experimental set-up will be mainly based on our previous project, but for this study, the additional element developed would be on the IoT architecture part.

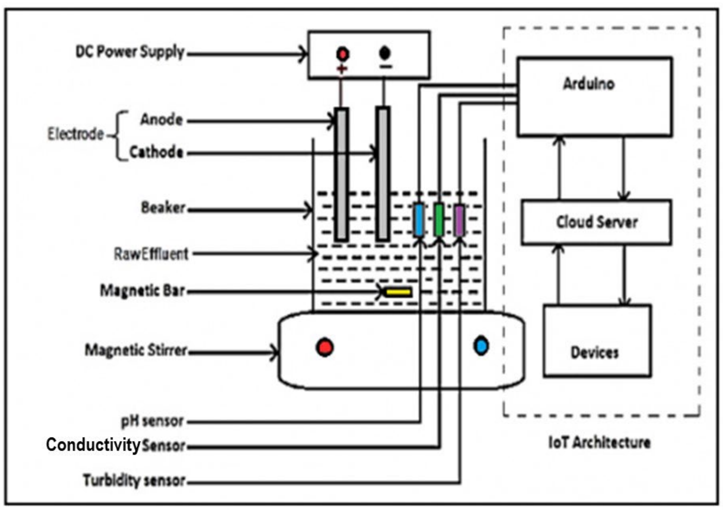


Figure 2: Proposed set-up in this study

Among the data that will be collected are turbidity, pH, voltage supplied and conductivity of the solution. Turbidity sensor, instead of UV-Vis based sensor is chosen in this study for economical reason. Prior to the measurement, a correlation between the turbidity and oil concentration would need to be established via manual UV-vis measurement.

Turbidity will be measured using turbidity sensor, pH will be measured using digital online pH sensor, voltage supplied will be recorded from voltage and current monitor sensor module, while conductivity data will be measured using conductivity sensor. These sensors would be connected to an IoT monitoring and controller unit, which will be equipped with Arduino microcontroller. Real-time data collection protocols will be transmitted to an IoT platform, i.e. ThingSpeak platform, via Wi-Fi. The collected and recorded data would be stored at the ThingSpeak's cloud partform for eventual data processing and analysis.

Stage 2: Development of AI-Driven Predictive Model

Varied oil concentration in real wastewater collected from the industry will be treated in the proposed set-up in this study. Based on the regressed model from statistical analysis software from our previous study, a series of experiment based on the parameters adjusted to achieve at least 80% of oil removal performance and minimum voltage will be conducted. The real-time data will be collected for training and validation of the AI-driven model to be developed in this study. In this study, we plan to apply supervised machine learning models such as Random Forest (RF) and/or Support Vector Machines (SVM) using Phython platform. 70% of the collected data will be used to train the model, while the remaining 30% of the data will be used to validate its predictive accuracy.

Stage 3: Optimization of Parameters Using AI-Driven Model

Optimization of the parameters will be conducted using Harmony Search (HS) algorithm. It is a type of heuristic optimization technique, which falls under the broader umbrella of computational intelligence, a subset of AI. It mimics the process of adjusting and improvising the pitches of musical instruments by musician to produce an agreeable harmony measured by aesthetic standards. Analogous to optimization problems, the population or existing solution (called as harmony vector in HS) keeps improvising to produce new solutions until the optimum result is achieved, which will be measured by objective function. The general procedures and steps of HS are shown in Figure 3.

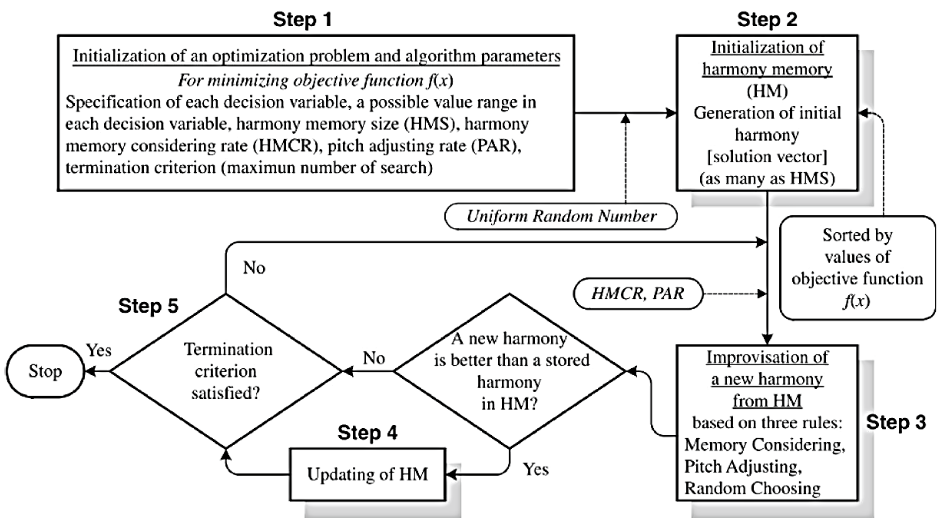


Figure 3: Steps of HS

Harmony memory (HM) is a set of solutions (a feasible schedule) like a chromosome in genetic algorithm (GA) where the objective functions can be obtained, in order to indicate the most optimum solution. The HM will be improvised to produce a new harmony vector, x_{new}, based on three parameters (operators), which are as follows:

i. Harmony memory consideration rate (HMCR),
ii. Pitch adjustment rate (PAR),
iii. Random consideration.

The value of HMCR, PAR parameters and random numbers, r_1 and r_2, should be set between 0 and 1. If r_1 is less than HMCR, the x_{new} will be selected from HM; otherwise, x_{new} will be produced through random consideration. Next, for PAR parameter, if r_2 is more than PAR, the x_{new} from HMCR will be retained; otherwise, the x_{new} from HMCR will be adjusted using BW value as visualized in the following equation:

$$x_{\text{new}} = x_{\text{new}} \pm r \times \text{BW},$$

where r is a random number ranging from 0 to 1. The BW value should be initialized to allow the adjustment of pitch.

The following steps are the proposed HS steps for the electrocoagulation process in this study:

Step 1: Initialization of HS parameters (HMS, HMCR, PAR, BW), maximum number of iterations, and specify decision variable (voltage *v*, conductivity *c*, initial amount of oil *io*).

Step 2: Initialization of HM (initial set of solutions – combination of voltage, conductivity and initial oil) – randomly searching the value of *v, s,* and *io*, depends on how many HMS size set. These initial solutions would need to be sorted based on the value of objective function. In this project, the objective function indicates the oil removal percentage in the wastewater, where it can be measured if the following constraints are achieved:

i. At least 80% of oil removal concentration

ii. Minimum voltage

Step 3: Improvisation of the solution in Step 2 based on the HS parameters set in Step 1 by generating a new solution. Then, the objective function of a new solution will be obtained as in Step 2.

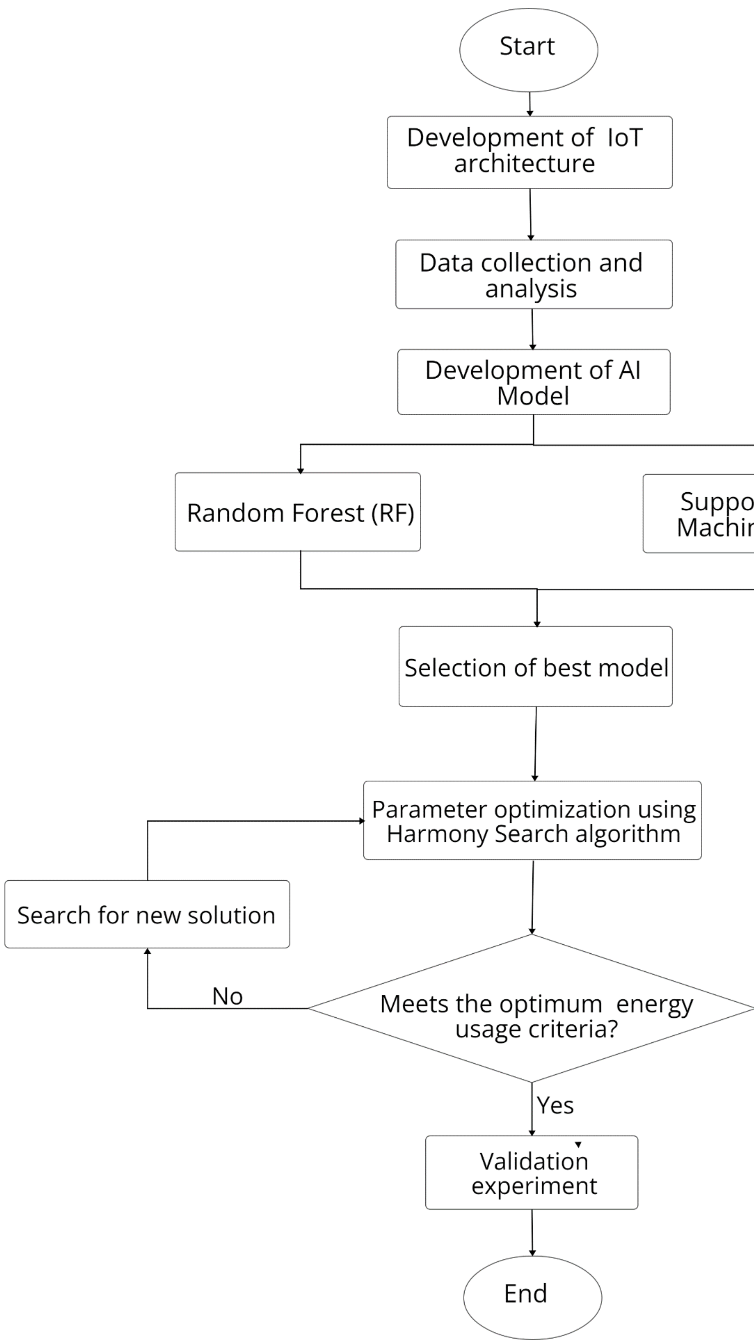
Step 4: If the objective function of the new solution is higher than the existing solution, it will replace and update the current set of solutions. The highest objective function (highest percentage of oil removal with the most optimum combination of the voltage, conductivity and oil removal will always be sorted at top.

Step 5: Step 3 and 4 will be repeated until it meets the termination criteria.

Step 6: Validation experimental run will be conducted to verify the optimization.

3.2 Flow Chart of Research Activities

The overall flow chart of the activities in this project is as follows:



3.3 Gantt Chart of Research Activities

Stage	Activity	2024								2025			
		5	6	7	8	9	10	11	12	1	2	3	4
1	Sensor Selection												
	Attending up-skilling program and engagement with industry												
	IoT Integration												
2	Data collection and analysis												
	Correlation of turbidity with oil concentration in water												
	Data preprocessing												
	Model training and validation												
3	Parameter optimization using Harmony Search												
	Validation experiment												
	Report writing												
Miletone		Stage I			Stage II				Stage III				
		Development of IoT architecture			Development of AI-Driven Predictive Model				Optimization of Parameters Using AI-Driven Model				

3.4 Project Schedule

#	Task	Name	Start Date	End Date
1.	Sensor selection	Ir. Dr. Tan Lian See, AP Dr. Shahrum Shah Abdullah, Dr. Noor Fazliani Shoparwe	1 May 2024	31 July 2024
2.	IoT integration	Ir. Dr. Tan Lian See, AP Dr. Shahrum Shah Abdullah, Dr. Noor Fazliani Shoparwe	1 July 2024	31 July 2024
3.	Data collection and analysis	Ir. Dr. Tan Lian See, Dr. Noor Fazliani Shoparwe	1 August 2024	31 August 2024
4.	Correlation of turbidity with oil concentration in water	Ir. Dr. Tan Lian See	1 August 2024	31 August 2024
5.	Model training and validation	Ir. Dr. Tan Lian See, Dr. Zatul Binti Alwani	1 September 2024	30 November 2024
6.	Parameter optimization using Harmony Search	Ir. Dr. Tan Lian See, Dr. Zatul Binti Alwani	1 December 2024	28 February 2025
7.	Validation experiment	Ir. Dr. Tan Lian See	1 March 2025	31 March 2025

3.5 Project milestone

#	Milestone	Date
1.	Completion of development of IoT architecture	31 July 2024

#	Milestone	Date
2.	Completion of development of AI-driven predictive model	30 November 2024
3.	Completion of optimization of parameters using AI-driven model	30 April 2025

4. DEVELOPMENT PROGRAM PLAN

Upskilling Program
Project leader and at least 1 project member will attend Artificial Intelligence & Machine Learning course within 3 months after the commencement of the project to upskill and strengthen overall project members' knowledge and skills in developing and optimizing predictive modelling using AI technology. A quick survey online indicates that this kind of courses are conducted in Kuala Lumpur on regular basis. Hence, selecting and attending the right course within 3 months' time is doable.
Collaboration and Networking
We intend to establish a collaborative network with the industry such as food processing industries for mutual engagement for understanding the operational challenges with oily wastewater, collecting wastewater samples for analysis, and utilizing these insights as inputs for this research. There will be visit to the industry facilities for knowledge exchange and exploration of additional areas for joint research with the industry.

5. EXPECTED RESULT

1. Publication :
   - 1.1 No. of article in indexed (Q1/Q2) journal : -
   - 1.2 No. of article in indexed journal : -
   - 1.3 No. of Indexed WOS : -
   - 1.4 No. of Indexed SCOPUS : 1
2. Talent
   - 2.1 No. of RO/RA : 1
3. No. of IPR granted/filed : 1

6. ACCESS TO RESOURCES, EQUIPMENT, AND MATERIALS

No	Resource, Equipment and Materials	Source
1	UV-Vis Spectrometer	Separation and Purification Lab, MJIIT

7. BUDGET

V-Series	SODO Type	Description	Cost	Justification	Total Cost
V11000 Salary & Wage / Overtime (Capping 0.00%)	B11000 Salary & Wages	1 Research Assistant (RM3600 per month including EPF and Socso for 12 months)	43200	To perform the research work to achieve the milestone in this project	43200
	Total Per Sodo				43200
Total Per VSeries					43200
V21000 Travelling Expenses & Subsistence (Capping 0.00%)	B21000 Transport of Goods	**Local:** Travelling to visit food factories (3 days) Transportation: RM1000 (flight/milage) + RM300 (others) Accommodation: RM250 x 4 = RM1000 Allowance: RM100 x 4 x 3 persons = RM1200	3500	Travelling to visit food factories for engagement/networking/wastewater sample collection	3500
		Local: Research meeting with project collaborator and seminars	1000	Detailed discussion on the design of system and other information exchange activities	1000
		Overseas: Transportation: RM 800 for round trip flight/person x 2 + RM500 (others) x 2 = RM2600 Accommodation: RM 250 x 4 (sharing room) = RM 1000 Allowance: RM 100 x 5 x 2 persons = RM 1000	4600	Travelling to build collaboration network with Universitas Indonesia for future expansion of this technology in this region (2 persons)	4600
	Total Per Sodo				9100
Total Per VSeries					9100
V26000 Research Materials & Supplies (Capping 0.00%)	B26000 Raw Materials & Spare Parts	Glassware and carboy containers	1000	To conduct electrocoagulation process operation and storage of solutions	1000

V-Series	SODO Type	Description	Cost	Justification	Total Cost
		Grade Stainless Steel Type 316 container	1500	To conduct electrocoagulation process operation	1500
		References electrode	1500	To conduct electrocoagulation process operation	1500
		Sensor electrode for pH	2000	Part of IoT architecture	2000
		Sensor electrode for turbidity	2000	Part of IoT architecture	2000
		Sensor electrode for conductivity	2000	Part of IoT architecture	2000
		Tubing and connector	2500	To conduct electrocoagulation process operation	2500
		Monitoring and controller unit (including Arduino microcontroller, actutators, communication modules, temporary storage for data buffering, etc)	2600	Part of IoT architecture	2600
		Voltage regulator	501	To conduct electrocoagulation process operation	501
		Current regulator	400	To conduct electrocoagulation process operation	400
		Voltage and Current Monitor sensor module	1500	Part of IoT architecture	1500
	Total Per Sodo				16501
	B27000 Supplies & Consumable Goods	Consumables and disposable (electrolyte, surfactant, PPE, fiter paper, tissue paper, detergent, etc)	1500	General lab consumables supply to conduct the research work	1500
	Total Per Sodo				1500
Total Per VSeries					18001
V29000 Professional Services	B29000 Professional Services & Hospitality	Machine learning course 1 (beginner) (RM 5,000 x 2 persons)	10000	Upskilling training course for team leader and 1 member	10000

V-Series	SODO Type	Description	Cost	Justification	Total Cost
(Capping 0.00%)					
		Fabrication of acrylic types of electrocoagulation setup	4000	Technical assistance service to assemble the setup	4000
		Upah (RM1500 x 2 times)	3000	Service to assist on the development machine learning predictive model	3000
		Wastewater sample analysis and characterization	3000	Comprehensive analysis on the characteristics of the real wastewater and the treated water	3000
	Total Per Sodo				20000
Total Per VSeries					20000
V35000 Special Equipment & Accessories (Capping 0.00%)	B35000 Assets & Equipments	Computer for machine learning modelling and optimization	4899	A computer with high processing power to perform the AI modelling and optimization at a faster rate	4899
	Total Per Sodo				4899
Total Per VSeries					4899
Grand Total Per Year					95,200
				Grand Total	95,200

8. DECLARATION BY PROJECT LEADER

DECLARATION BY PROJECT LEADER	
/	All information given is correct. UTM has the right to reject or to cancel the offer without notice if there is any incorrect information given.
	I am heading a research project registered with RMC which is currently active.
/	I hereby agree to accept the offer to conduct research upon generation and activation of the cost center to the proposed research project and will understand and comply to all terms and conditions as the following.
/	This proposed research is my original work, is not copied from any other work (published or unpublished) and has not been submitted for grant application elsewhere.

NAME :

(Signature and Official Chop)

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DATE : 6 May 2024