Optimizing Wastewater Treatment for a Carbon-Neutral Future: A Data-Driven Approach

Praifa Jaturus and Praewa Wongburi*

Faculty of Environment and Resource Studies, Mahidol University, Nakhon Pathom 73170, Thailand

ABSTRACT

The research explores the pivotal role of wastewater treatment plants (WWTPs) in addressing energy consumption and greenhouse gas (GHG) emissions to achieve carbon neutrality (CN) and the United Nations' Sustainable Development Goals (SDGs), notably promoting health, clean water, and sustainable energy while mitigating climate change impacts. In 2023, Thailand will have wastewater treatment plants capable of handling around 620 million cubic meters, or about 45% of wastewater produced, and data reveals that 3,621.574 thousand kg CO_2 eq/year is emitted from wastewater treatment, highlighting the need for sustainable practices to reduce emissions. The objective of this research is to develop a framework that integrates structured query language (SQL) with life cycle inventory (LCI) methodologies to create a comprehensive database for WWTPs. This includes goal and scope determination in assessment to identify inputs, outputs, and emissions throughout the WWTPs process lifecycle. This framework aims to analyze energy consumption and reduce GHG emissions by examining the correlations between WWTPs operational parameters and electricity consumption, thereby contributing to carbon neutrality, and supporting the United Nations' Sustainable Development Goals (SDGs). These findings emphasize the critical importance of understanding the relationship between WWTP operational efficiency and energy consumption to effectively mitigation for enhance and optimize efficiency in reducing energy consumption and GHG emissions in WWTPs. Ultimately, this framework aims to enhance and optimize the efficiency of reducing energy consumption and GHG emissions in WWTPs, thereby contributing to CN and the SDGs.

Keyword: Carbon neutrality / Greenhouse gas emissions / Wastewater treatment plants / Life cycle inventory / Database

1. INTRODUCTION

Wastewater treatment plants (WWTPs) play significant role in realizing the United Nations' Sustainable Development Goals (SDGs), contributing to clean water (SDG 6), clean energy (SDG 7), good health (SDG 3), sustainable cities (SDG 11), responsible consumption and production (SDG 12), and climate action (SDG 13) (Obaideen et al., 2022). Evaluating wastewater treatment infrastructure through the lens of SDGs is crucial for global water quality improvement, particularly in addressing issues like greenhouse gas emissions (Ho et al., 2021). The emphasis of SDG 6.3 on reducing untreated wastewater discharge necessitates a forward-looking strategy beyond the 2030 targets, addressing challenges such as greenhouse gas emissions for effective climate change (Adhikari & Halden, 2022). The importance of accurate greenhouse gas accounting, especially for N_2O and CH_4 emissions, underscores the significance of adopting a multi-criteria approach for sustainable wastewater management (Faragò et al., 2022). Monitoring and managing greenhouse gas emissions are crucial for countries addressing wastewater challenges, aligning with climate targets, and participating in the UNFCCC negotiations. Supporting partner countries, such as Thailand, in preparing Intended Nationally Determined Contributions (INDCs), is essential for collectively addressing climate-related challenges (GIZ, 2021). In 2023, Thailand's wastewater treatment capacity will cover 45% of treatable wastewater, and data reveals that 3.6 thousand kg CO_2 eq/year is emitted as greenhouse gasses from wastewater treatment (DSPOT, 2023). This underscores the need for sustainable practices in emissions reduction, aligning with the United Nations' Sustainable Development Goal by 2030.

The objective of this research is to identify and analyze the correlations between various operational parameters and electricity consumption in WWTPs. By understanding these correlations,

*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

the aim is to optimize energy efficiency and reduce greenhouse gas (GHG) emissions. This analysis provides insights into managing influent and effluent parameters and optimizing aeration processes to improve treatment efficiency and reduce energy consumption. The findings from this research are intended to contribute to the development of sustainable practices within wastewater management, ultimately supporting the achievement of carbon neutrality and the UN's SDGs.

2. LITERATURE REVIEW

2.1 Evaluating Wastewater Treatment Infrastructure Systems Based

Challenges for Wastewater Treatment Plants (WWTPs) play a vital role in addressing the United Nations' Sustainable Development Goals (SDGs), influencing various dimensions such as clean water, sanitation, clean energy, responsible consumption, climate action, and life below water (Obaideen et al., 2022). In 2015, the United Nations General Assembly established 17 interlinked goals as part of the SDGs. These goals cover a range of areas, including poverty reduction, good health, sustainable land use, zero hunger, gender equality, quality education, economic growth, clean water, reducing inequality, affordable energy, sustainable communities, life below water, responsible production and consumption, climate action, partnership for the goals, peace, industry, innovation, and infrastructure (Bebbington & Unerman, 2018). The SDGs are embedded in the United Nations Resolution known as the 2030 Agenda, with a target completion date of 2030. It mentions that while most SDG targets are set to be achieved between 2020 and 2030, some targets do not have a specific end date (Costanza et al., 2016). Monitoring progress toward these goals is essential, and various tools and techniques have been presented to track and evaluate progress. The latest data from the United Nations SDGs dashboard indicates that many countries still face significant challenges in achieving the SDG targets, with only two countries (Andorra and Monaco) doing well in SDG 6. However, the detailed data reveals that even these countries are not performing well in achieving SDG 6 targets, as illustrated in Figure 1.

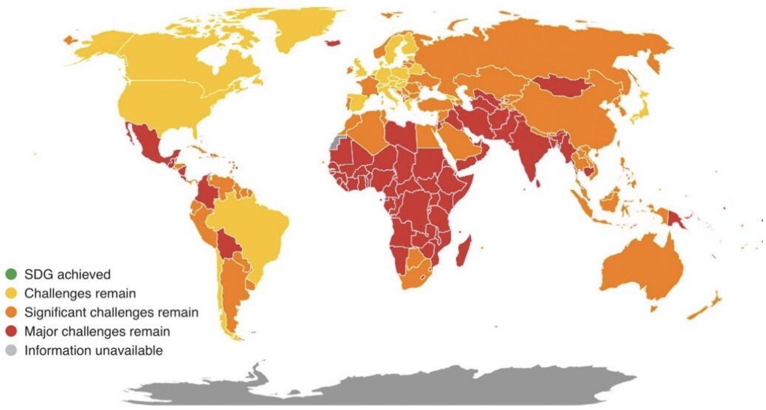

Figure 1. Status of SDG 6 (Clean Water and Sanitation) (Sustainable Development Report 2023, 2024)

According to the UN World Water Development Report 2023, global water use has increased by approximately 1% per year over the past 40 years, particularly in middle- and low-income countries, notably in emerging economies. Population growth, economic and social development, and changing consumption patterns all contribute to the increased demand for water, leading to water stress and ultimately contributing to water scarcity (United Nations, 2023). Achieving SDG 6 by 2030, as depicted in Figure 2, requires each country to commit to systematic monitoring and review of progress toward the SDGs and associated goals (Kanchanamala Delanka-Pedige et al., 2021).

*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

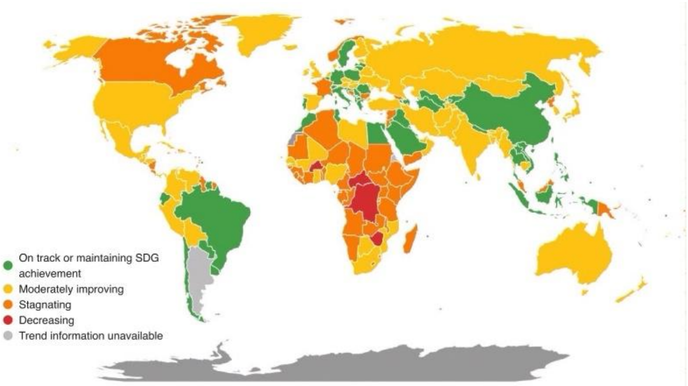

Figure 2. Trends indicate whether a country is on track to achieve the SDG 6 by 2030 (Sustainable Development Report 2023, 2024)

2.2.1 Sustainable development goals (SDGs)

Sustainable development is defined as development that meets the needs of the present without compromising the ability of future generations to meet their own needs. The challenges faced by societies globally, such as poverty, environmental degradation, climate change, and inequality, underscore the importance of SDGs as a blueprint for achieving sustainability and a better future (Obaideen et al., 2022). The broader aim of sustainable development includes mitigating poverty, protecting the planet, and ensuring prosperity and peace for individuals. It is highlighted as an approach that influences businesses and individuals to adopt behaviors that benefit societies and communities. Governments adopting a sustainable development approach are expected to bring benefits to the entire country, protecting society on all fronts. Achieving SDGs requires a commitment to social progress, economic growth, and environmental balance. Strategies to attain SDGs include promoting education, initiating fundraising campaigns, encouraging volunteering, empowering change-makers, and more (Malik et al., 2015). Wastewater infrastructure and the 17 Sustainable Development Goals can be linked by defining seven characteristics related to challenges and opportunities related to wastewater infrastructure: 1. effluent quality, 2. pathogen removal, 3. energy consumption, 4. gaseous emissions, 5. nutrient recovery, 6. footprint, and 7. reliability. The above opportunities and challenges are then mapped with appropriate SDGs and targets to achieve the following 30 sustainability indicators/measures in Table 1 (Kanchanamala Delanka-Pedige et al., 2021).

Table 1. Parameters to evaluate the sustainability of wastewater treatment technologies.

Attributes of wastewater infrastructure	Opportunities	Challenges	Linkages to SDG targets	Process parameters considered
Effluent quality	Potential for reuse high-quality effluent for potable and non-potable applications; combat water scarcity; improve resource use efficiency and conserve ecology	Poor quality effluent can contaminate surface waters, promote eutrophication, degrade soil quality; aggravate water scarcity; additional cost for effluent treatment, and ecological impact mitigation.	2.3, 2.4	Effluent BOD
			3.3, 3.9	Effluent NH_4–N
			6.1, 6.3, 6.4, 6.6	Effluent PO_4
			9.1, 9.4	Effluent COD
			11.3, 11.6, 11.9	Effluent TN
			12.4	Effluent TP
			14.1, 14.3	
			15.1, 15.3	
			17.7	

----
*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

Attributes of wastewater infrastructure	Opportunities	Challenges	Linkages to SDG targets	Process parameters considered
Pathogen control	Pathogen free effluents are safe for reuse; reduced disinfectant demand and lower possibilities of subsequent disinfection by-products (DBP) formation	Health and safety issues due to pathogen outbreak; higher disinfection demand and DBP formation; increased health risk in water reuse; transmission of antibiotic resistance.	3.3, 3.9	LRV of *E. coli*
			9.1	LRV of Fecal coliform
			11.5, 11.9	LRV of Somatic coliphages
			12.4	LRV of F-specific coliphages
				LRV of ARBs
Energy demand	Low energy consumption and energy-efficient treatment can conserve fossil- fuel reserves; reduction in operation and maintenance costs; reduction in indirect emission of greenhouse gases (GHGs); opportunities to recover energy from resulting biomass add revenue	High energy consumption contributes to depletion of limited fossil-fuel reserves; Increased emission of GHG during energy generation process degrades environmental sustainability.	7.3, 7.4, 7.5	Energy for WW treatment
			8.4	Energy for resource recovery
			9.2, 9.4	N reduction per unit energy
			11.3, 11.6, 11.9	P reduction per unit energy
			12.2, 12.9, 12.11	BOD reduction per unit energy
			13.2	Gross energy recovery
			17.7	
Emissions	Technologies with low harmful emissions promote better air quality, livable cities; prevent the greenhouse effect, and subsequent climate-change impacts.	Technologies with higher emission degrade air quality; contribute to greenhouse effects and climate-change scenarios.	3.3, 3.9	GHG-CO_2 emissions (direct)*
			9.1, 9.4	GHG – CO_2 emission (indirect)**
			11.3, 11.6, 11.9	GHG- N_2O emissions
			12.4	GHG-CH_4 emissions
			13.2	Odor-NH_3 emissions
			17.7	
Resources recovery	Ability to recover energy and nutrients embedded in wastewater as biogas, fertilizers add revenue; conserve natural resources; mitigate environmental impacts of energy and fertilizer production	If energy and nutrients embedded in wastewater are not recovered, they are dissipated into atmosphere, surface water bodies, and land causing a series of environmental impacts.	2.3, 2.4	N partitioning into gas phase
			3.3, 3.9	N partitioning into sludge/biomass
			9.1, 9.2, 9.4	P partitioning into sludge/biomass
			11.3, 11.6, 11.9 12.2,	Potential N recovery

*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

Attributes of wastewater infrastructure	Opportunities	Challenges	Linkages to SDG targets	Process parameters considered
			12.4, 12.5 12.9	
			17.7	Potential P recovery
Footprint	Lower space requirement of sewage treatment technologies best suited for dense urban areas with limited space; conserves natural ecosystems (e.g.: Forests)	Larger land requirement will be challenging for urban areas; can promote deforestation and loss of biodiversity; loss of visual appeal	8.4	Time for wastewater treatment
			9.2, 9.4	Area
			11.9	
			17.7	
Reliability/acceptability	Technologies with longer history imply greater reliability and acceptance.	Reluctance of industries to adopt innovative and novel technologies. Limited opportunities to introduce sustainable technologies	8.2	Years of operation
			9.1, 9.2, 9.3, 9.4; 9.5, 9.6, 9.7;	
			17.6, 17.7	

Remark: *CO_2 emission due to biogenic oxidation is excluded. **CO_2 emission during electricity generation. (Kanchanamala Delanka-Pedige et al., 2021)

2.2 Carbon Neutrality of Wastewater Treatment

Wastewater treatment plays a critical role in sanitation systems, contributing to nearly 5% of total global greenhouse gas (GHG) emissions, with projections indicating a potential 22% increase by 2030 (Li et al., 2024; Maktabifard et al., 2023). Within the wastewater treatment plants (WWTPs) sector, CH_4 and N_2O emissions collectively account for up to 7% and 10% of anthropogenic emissions, respectively (Maktabifard et al., 2023). WWTPs currently play a crucial role in reducing CO_2 emissions through various effective measures, such as sludge anaerobic digestion. These practices aim to promote environmental sustainability. Additionally, wastewater treatment employs various technologies, including energy recovery, resource recovery, and water reuse, all of which contribute to the pursuit of carbon-neutral wastewater treatment (Li et al., 2024). Hence, wastewater systems, concerning carbon credits, carbon neutrality, and achieving net-zero emissions through environmentally friendly measures, need to undergo systematic analysis of their scope and inventories of WWTP (Li et al., 2024).

2.2.1 Greenhouse gas emission from wastewater treatment plants

Climate change introduces uncertainties in water supply, exacerbating the existing water scarcity, which affects over 40 percent of the global population (Biru et al., 2017). World Water Day, recently observed, highlighted the crucial role of wastewater management in the circular economy. Proper wastewater management is recognized as a strategic investment benefiting both human and ecosystem health. Countries' nationally determined contributions (NDCs) include energy production, methane emissions reduction, and the expansion of wastewater treatment plants (ECA, 2020). Methane emissions from wastewater contribute around 9 percent of global anthropogenic methane sources (Biru et al., 2017). While water-related concerns are expressed in the adaptation sections of many countries' NDCs, the explicit mention of "wastewater" might be limited. Effective recycling and reuse of wastewater emerge as crucial strategies, especially in regions facing increased drought and water stress due to climate change (ECA, 2020).

Evaluating GHG emissions involves determining the scope of the assessment. The Thai Government Organization (TGO) has outlined a methodology for calculating an organization's carbon

----
*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

footprint, which involves categorizing activities that emit and absorb greenhouse gases into three scopes (TGO, 2022):

Scopes 1: Direct GHG emissions arise from sources within the organization's boundaries. These emissions originate from assets owned or controlled by the organization, including stationary sources like heaters and wastewater treatment plants (WWTPs), as well as mobile sources such as vehicles.

Scopes 2: Energy indirect GHG emissions result from fuel combustion associated with final energy production and various utilities like electricity and heat. This scope excludes emissions from the extraction of fuels to the power plant gate and greenhouse gas emissions related to building electric power plants. It also includes greenhouse gas emissions allocated from transportation and losses in power distribution systems.

Scopes 3: Other indirect emissions occur outside the organization's boundaries and predominantly stem from mobile sources, particularly emissions from fuel combustion in transportation equipment. This category encompasses a broad range of activities, including upstream greenhouse gas emissions generated during fuel manufacturing and transport/distribution processes.

2.3 Life Cycle Inventory in Wastewater Treatment

The Life Cycle Inventory (LCI) involves the goal and scope of conducting a comprehensive, integrated environmental impact assessment for wastewater treatment for use in data collection and inventory development (Straub et al., 2023). In general, LCI aims to identify the inputs, the outputs, and the respective amounts of emissions over the entire life cycle of the specific process (Rashid et al., 2023). LCI aims to identify inputs, outputs, and emissions throughout the life cycle of the process. It entails compiling primary data (foreground) from operational records and detailed designs covering the entire process from influent to effluent, as well as secondary data (background) from databases such as IPCC, Eco Invent, and ELCD (Gong et al., 2024; Li et al., 2024). In the LCI phase, identified inventories are collected for all processes along the boundary and calculated to the same functional unit (Rashid et al., 2023).

Table 2. Input and output flows of the wastewater treatment process

Input	Output
Wastewater influent	Biological oxygen demand (BOD)
Electricity	Chemical oxygen demand (COD)
Natural gas	Ammonium nitrogen
Fuel oil	Nitrate nitrogen
Precipitation chemicals	Nitrite nitrogen
	Phosphorus
	Greenhouse gas emissions
	Sewage sludge
	Screenings
	Grit chamber trappings

Source: (Straub et al., 2023)

The calculation of flows in the LCI of wastewater treatment processes is a critical step in understanding the environmental impact of such systems. This comprehensive methodology is developed using Python and exemplified through a case study to calculate and standardize these flows for subsequent LCI studies (Straub et al., 2023). The process begins with a clear representation of input and output flows, as illustrated in Table 5 for the wastewater treatment case study.

----
*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

3. METHODOLOGY

The research methodology involved collecting and analyzing operational data from Siriraj Hospital and Siriraj Piyamaharajkarun Hospital, over the past five years (2020-2024). Data collected included parameters such as effluent quality, dissolved oxygen (DO) levels in aeration tanks, dewatered sludge, electricity consumption, and other significant influent and effluent parameters. These parameters were measured monthly and included pH, biochemical oxygen demand (BOD), total Kjeldahl nitrogen (TKN), suspended solids (SS), settleable solids (Set S), sulfide, total dissolved solids (TDS), and fats, oils, and grease (FOG).

The operation steps are shown in Figure 3, which presents the framework for collecting and analyzing data from WWTPs. The steps are as follows: data collection, data cleaning, data analysis, and performance assessment and optimization.

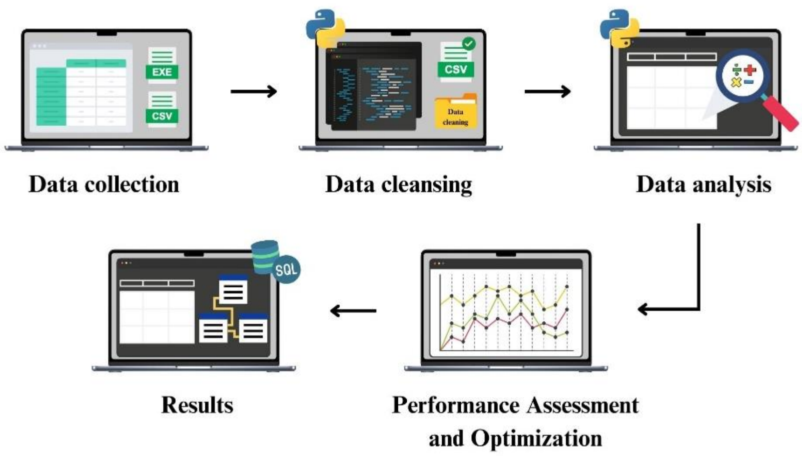

Figure 3. Framework for Collecting and Analyzing Data from WWTPs

The framework for collecting and analyzing data can be explained as follows:

3.1 Data Collection

Gathering data involves recording information from records and inputting it into a computer, including wastewater parameters, DO level in the aeration tank, and electrical consumption. Then, specify the plant ID for the WWTP data, which is imported into Python for analysis to summarize statistics for various parameters. The statistics dataset includes the maximum value (max) and minimum value (min) of the dataset. The mean (average), which represents the middle value of the dataset, is used as a representative for the entire dataset. The standard deviation measures how dispersed the data is, indicating how much or how little the data spreads from the mean. A small standard deviation suggests that each set of data is similar and accurate.

3.2 Data Cleansing

Data cleansing is a crucial step in the process of preparing data for analysis. It involves carefully examining the raw data or data that has been obtained, identifying any inconsistencies, errors, or missing values, and then interpolating statistical data from the raw dataset analyzed in Section 3.1 into the dataset to ensure completeness of the data.

3.3 Data Analysis

Data analysis focuses on understanding the correlation and GHG emissions calculations to mitigate the environmental impact of wastewater treatment, including optimizing energy usage and reducing GHG emissions.

The correlation between the involvement of various influent (INF) and effluent (EFF) water quality parameters, as well as aeration tank DO and electricity consumption for assessing the energy

----

*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

efficiency of WWTPs, as it results in indirect GHG emissions from energy use. Understanding this correlation helps optimize energy usage and reduce GHG emissions.

3.4 Performance Assessment and Optimization

Analyzing the correlations provides valuable insights into the environmental impact of wastewater treatment operations. Understanding these correlations is crucial for optimizing processes and developing guidelines to reduce GHG emissions. The core of the methodology involved correlation analysis using statistical measures to identify relationships between various operational parameters and electricity consumption. Correlation coefficients, ranging from -1.00 to +1.00, were calculated to determine the strength and direction of these relationships. Positive correlation coefficients indicate direct relationships, while negative coefficients signify inverse relationships.

These insights help in setting the scope for developing frameworks that integrate structured query language (SQL) with life cycle inventory (LCI) methodologies, aimed at optimizing performance and achieving carbon neutrality in WWTPs. By focusing on these correlations, it is possible to enhance operational efficiency, reduce energy consumption, and minimize GHG emissions, contributing to the broader goals of sustainability and the United Nations' Sustainable Development Goals (SDGs).

4. RESULTS AND DISCUSSIONS

4.1 Data collection

Statistical analysis was performed on the operational data collected from Plant 1 and Plant 2. The results include the maximum, minimum, mean, and standard deviation values for various wastewater parameters, as shown in Tables 3 and 4.

Table 3. Statistics for Data Plant 1

	count	mean	std	min	25%	50%	75%	max
INF_pH	35	7.549714	0.350516	7.01	7.33	7.46	7.72	8.8
INF_BOD	35	168.0129	61.15152	15.3	124.65	159.7	205.15	340
INF_SS	35	131.7714	56.47023	42	89	122	168	256
INF_Sulfide	35	0.280857	0.107056	0.1	0.2	0.27	0.355	0.6
INF_TDS	35	273.7054	71.27966	155.4	231.4	269.75	310.65	460.85
INF_Set S	35	4.114286	4.540675	0.2	1.4	2.5	5.25	23
INF_FOG	35	7.685714	3.570891	2	5	7	10.5	15
INF_TKN	35	34.848	23.28974	4.48	22.97	28.55	36.73	104.43
EFF_pH	35	6.966857	0.337611	6.31	6.74	6.92	7.17	7.71
EFF_BOD	35	3.878286	2.108422	1	2.63	3.5	3.98	9.2
SS_EFF	35	8.045714	6.004525	0.8	3.2	6.4	11.4	24
EFF_Sulfide	35	0.052857	0.023461	0.01	0.03	0.05	0.07	0.11
EFF_TDS	35	156.1697	65.81257	9.75	126.425	157.3	180.7	374
EFF_Set S	35	0.107143	0.029061	0.09	0.1	0.1	0.1	0.2
FOG_EFF	35	1.085714	1.358447	0	0	1	2	6
EFF_TKN	35	1.213429	1.197338	0	0.58	1.08	1.21	6.2
Dew Sludge	42	8.67881	3.260978	2.78	5.8675	8.775	11.0325	16.29
Effluent	42	115337.1	12324.78	89202.49	107541.6	116260.1	123225	143956.6
Aeration Tank 1_DO	47	2.335922	0.749809	0.612222	1.964847	2.439077	2.780122	4.473333
Aeration Tank 2_DO	47	0.79119	0.723602	0.152843	0.406058	0.651397	0.915339	4.663333
Electricity consumption	47	81924.21	8441.453	60099	77400	83100	87300	103500

----
*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

Table 4. Statistics for Data Plant 2

	count	mean	std	min	25%	50%	75%	max
INF_pH	35	7.215714	0.198676	6.84	7.05	7.2	7.385	7.6
INF_BOD	35	219.9857	116.4072	100.2	146.25	182	256.75	703
INF_SS	35	257.9429	295.0264	64	92	138	348	1650
INF_Sulfide	35	0.572	0.250961	0.2	0.395	0.6	0.7	1.25
INF_TDS	35	356.9529	68.11705	182	306.5	358.8	415.35	462.15
INF_Set S	35	13.36571	23.54053	0.1	1.2	3.5	18	130
INF_FOG	35	9.342857	6.457749	3	5	7	11.5	27
INF_TKN	35	41.63657	24.34984	10.64	27.735	33.9	48.58	122.59
EFF_pH	35	7.23	0.267087	6.7	7.015	7.28	7.48	7.67
EFF_BOD	35	7.114	3.794167	2.5	4.52	6.04	9.07	19.28
SS_EFF	35	6.468571	3.463403	0.8	4	6	8.8	15.2
EFF_Sulfide	35	0.049429	0.024488	0	0.03	0.05	0.07	0.09
EFF_TDS	35	243.65	55.62122	146.9	210.6	239.2	256.425	396
EFF_Set S	35	0.100571	0.018778	0.06	0.1	0.1	0.1	0.2
FOG_EFF	35	0.8	1.346018	0	0	0	1	5
EFF_TKN	35	8.209429	8.143892	0	2.805	5.3	11.76	28.62
Dew Sludge	43	21.48465	13.71544	0	13.615	21.39	26.31	49.36
Effluent	42	38006.05	6112.001	25214.51	33666.44	37236.44	43212.29	49786.64
Aeration Tank 1_DO	46	0.371145	0.364517	0.051429	0.166875	0.256389	0.431349	1.875
Aeration Tank 2_DO	47	0.40729	0.493343	0.048889	0.126429	0.217	0.431667	2.341667
Electricity consumption	47	38722.19	3051.896	29087	37683	39392	40162	47300

4.2 Data cleaning

The dataset from both plants had varying numbers of observations, ranging from 35 to 47 data points. To ensure consistency, data cleaning involved removing duplicates and addressing missing values where necessary. This step was essential for ensuring the accuracy and reliability of the statistical analysis. The cleaned data was then used to carry out further analyses, including correlations and performance assessments.

4.3 Data analysis

This research analyzed data from the wastewater treatment plants (WWTPs) at Siriraj Hospital and Siriraj Piyamaharajkarun Hospital, focusing on correlations between various operational parameters and electricity consumption. Understanding these correlations is essential for optimizing operational efficiency and reducing energy costs. The correlation coefficient is a statistical measure that ranges from -1.00 to +1.00, used to analyze the relationship between two or more variables. A positive correlation indicates a direct relationship, while a negative correlation signifies an inverse relationship.

In Figure 6, the correlation heatmap for Plant 1 highlights the relationships between various operational parameters and electricity consumption. Notably, electricity consumption is moderately positively correlated with dewatered sludge (0.23), indicating that as the volume of dewatered sludge increases, energy usage also tends to rise, likely due to the energy-intensive nature of sludge processing. Additionally, there is a slight positive correlation with effluent settleable solids (Set S) (0.16), suggesting that higher levels of settleable solids may necessitate more energy for treatment processes.

The observed negative correlations between influent FOG (-0.33), TKN (-0.33), TDS (-0.23), and electricity consumption suggest that lower levels of these parameters may require more energy-intensive treatment processes. For instance, reduced FOG levels may demand higher aeration efforts to maintain oxygen transfer efficiency, while lower concentrations of TKN and TDS could necessitate

----

*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

additional treatment stages, such as nitrification and denitrification, to meet effluent standards, thereby increasing electricity consumption.

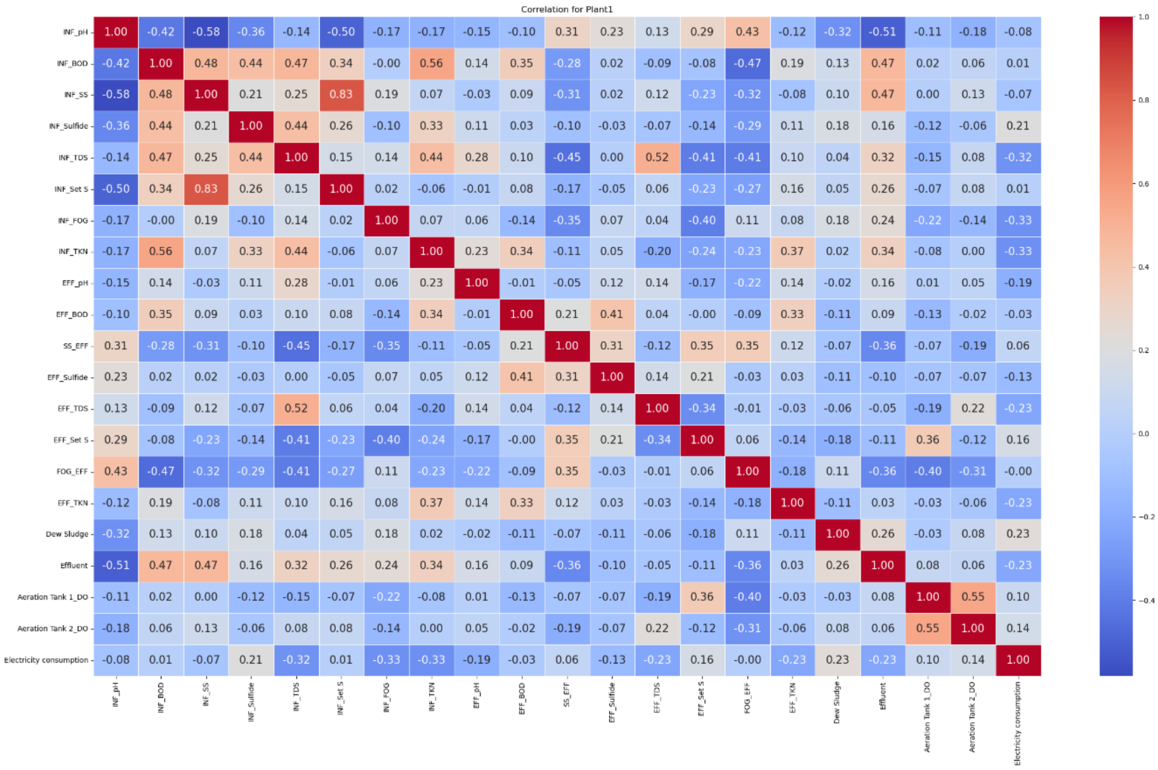

Figure 6. Correlation for Plant 1

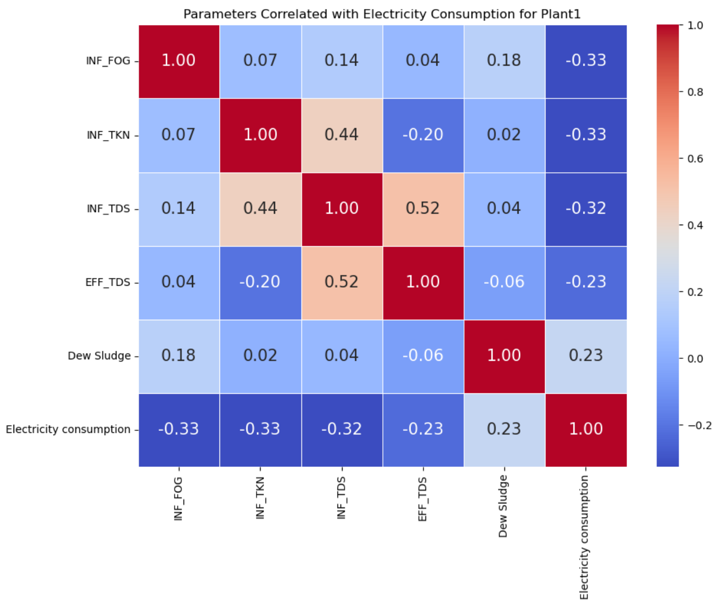

Figure 7. Parameters Correlated with Electricity Consumption for Plant 1

In Figure 7, this heatmap further delves into the specific parameters most closely related to electricity consumption in Plant 1. Similar to Figure 6, the analysis shows that electricity consumption is moderately positively correlated with dewatered sludge (0.23). On the other hand, negative correlations with influent FOG, TKN, and TDS (-0.33, -0.33, and -0.32 respectively) suggest that maintaining lower levels of these substances may demand additional energy-intensive treatments, highlighting the complexity of balancing influent composition with energy efficiency.

*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

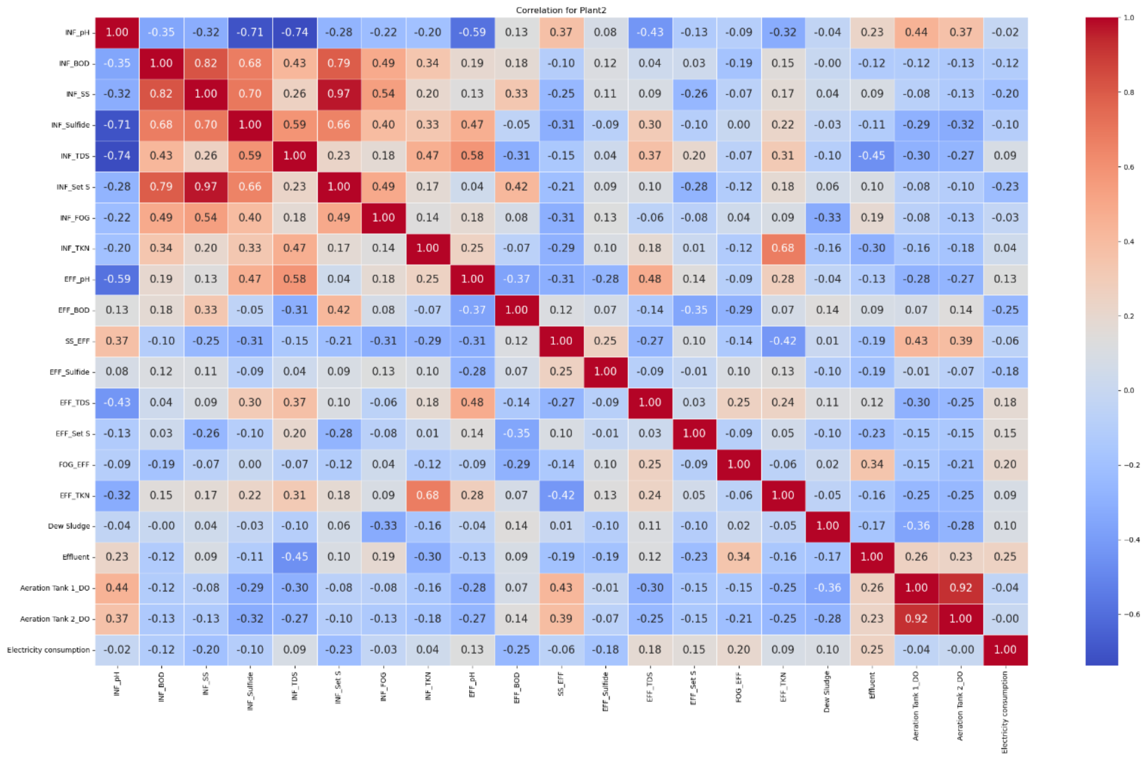

Figure 8. Correlation for Plant 2

Figure 8, the analysis of Plant 2 shows positive correlations such as effluent SS with aeration tanks 1 (0.43) and 2 (0.39), suggesting that adequate aeration promotes microbial activity and solid breakdown. Similarly, the positive correlation between influent pH and DO levels in aeration tanks 1 (0.44) and 2 (0.37) emphasizes the importance of oxygen in microbial processes and the breakdown of organic acids. Negative correlations, such as those between dewatered sludge and DO levels in aeration tanks 1 (-0.36) and 2 (-0.28), indicate that lower sludge accumulation might lead to increased aeration demands to maintain treatment efficiency.

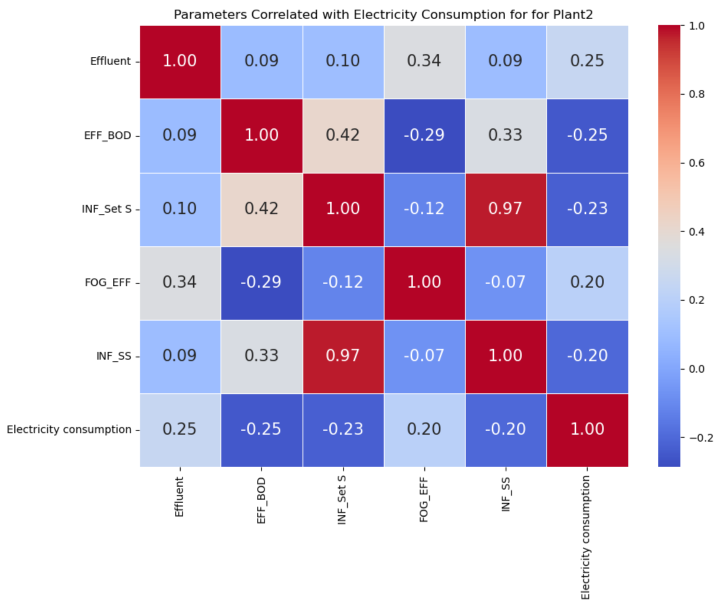

Figure 9. Parameters Correlated with Electricity Consumption for Plant 2

In the analysis of electricity consumption for Plant 2, both positive and negative correlations are observed in Figure 9. Positive correlations, such as those between effluent FOG (0.20) and electricity

*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

consumption, indicate that higher levels of FOG require more energy, likely due to the need for more intensive processes like pumping and aeration. Conversely, negative correlations with parameters like influent Settleable Solids (Set S) and SS (-0.23 and -0.20, respectively) suggest that lower levels of these parameters may lead to higher energy requirements, possibly due to the need for additional treatment steps to achieve the desired effluent quality.

The correlation analysis for both Plant 1 and Plant 2 reveals significant interdependencies between influent and effluent water quality parameters, aeration tank dissolved oxygen (DO) levels, and electricity consumption. In Plant 1, positive correlations, such as those between dewatered sludge and electricity consumption, suggest that higher sludge volumes increase energy usage, emphasizing the need for efficient sludge management. Conversely, negative correlations between influent FOG, TKN, and electricity consumption highlight that optimizing these influent parameters can reduce the energy demands of the treatment process. Similarly, in Plant 2, positive correlations, such as those between effluent FOG and electricity consumption, indicate that higher levels of FOG require more intensive energy usage. Negative correlations, like those between influent Settleable Solids (Set S) and electricity consumption, suggest that lower levels of certain influent parameters might increase energy requirements for adequate treatment. These findings underscore the importance of optimizing influent quality and aeration efficiency to improve overall treatment performance and minimize energy consumption.

4.4 Performance Assessment and Optimization

The schematic provided outlines the process flow and input-output data relevant to wastewater treatment plants (WWTPs). The performance assessment and optimization involve setting the scope for developing frameworks that enhance the efficiency of these plants while minimizing environmental impacts.

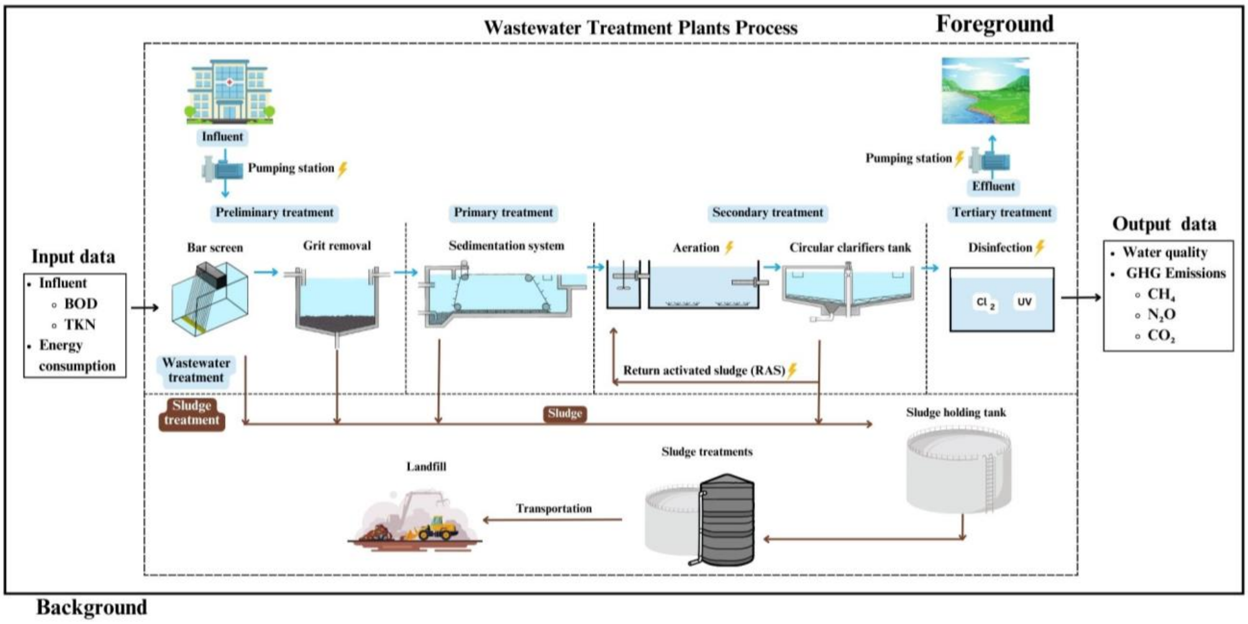

Figure 10. Framework of LCI for WWTP

Figure 10 is the Framework of LCI for WWTP, designed to systematically assess the inputs, processes, and outputs involved in the operation of a WWTP.

- Input Data: The framework integrates various influent parameters such as biochemical oxygen demand (BOD), total Kjeldahl nitrogen (TKN), and energy consumption. These parameters are crucial for assessing the operational efficiency and environmental performance of the WWTPs.

---

*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

- Treatment Processes: The diagram details the stages of wastewater treatment, including preliminary, primary, secondary, and tertiary treatments. Each stage is designed to progressively improve water quality and manage sludge generated during the treatment process.
- Sludge Management: Sludge treatment and its return as activated sludge (RAS) to the system, along with its transportation and disposal, are critical aspects of the performance assessment. Optimizing sludge management can significantly impact the plant's overall energy consumption and greenhouse gas (GHG) emissions.
- Output Data: The framework considers output data such as effluent water quality and GHG emissions (CH_4, N_2O, CO_2). These outputs are essential for evaluating the plant's environmental impact and for developing strategies to achieve carbon neutrality.

Figure 10 serves as a comprehensive framework that guides the life cycle inventory (LCI) analysis of WWTPs, providing a structured approach to assess and optimize the performance of wastewater treatment operations. By integrating input and output data with detailed process analysis, the framework helps in identifying opportunities to enhance efficiency, reduce energy consumption, and minimize environmental impacts, thereby contributing to the sustainability and resilience of WWTPs.

5. CONCLUSIONS

The correlation analysis provides valuable insights into the interdependencies between various parameters in both WWTPs, revealing significant interdependencies between influent and effluent water quality parameters, aeration tank DO levels, and electricity consumption. For Plant 1, positive correlations such as the correlation of 0.31 between effluent SS and influent pH indicate that optimizing pH can enhance solid removal. Effluent Set S correlates with aeration tank 1 at 0.36, suggesting that efficient aeration improves the settling process. Negative correlations, such as effluent FOG with aeration tanks 1 and 2 (-0.40 and -0.31, respectively), underscore the importance of FOG management to maintain adequate DO levels, thereby reducing energy consumption. Additionally, the positive correlation of 0.23 between electricity consumption and dewatered sludge highlights that higher sludge quantities increase energy use. Conversely, lower influent FOG, TKN, and TDS levels are associated with higher energy consumption, indicating the need for improved treatment processes.

For Plant 2, significant positive correlations include effluent SS with aeration tanks 1 (0.43) and 2 (0.39), indicating that adequate aeration promotes microbial activity and solid breakdown. Influent pH also shows strong positive correlations with aeration tanks, suggesting that optimal pH levels enhance oxygen availability and microbial activity. Negative correlations, such as dew sludge with aeration tanks 1 (-0.36) and 2 (-0.28), imply that less sludge accumulation may lead to higher aeration demands. Electricity consumption correlates positively with effluent FOG at 0.20 and effluent at 0.25, indicating higher energy requirements for processes like pumping and aeration when these parameters are elevated. Conversely, low influent Set S and SS correlate with higher energy consumption, highlighting the need for efficient solids removal to optimize energy use.

These findings emphasize the importance of managing influent and effluent parameters and optimizing aeration to improve treatment efficiency and reduce energy consumption in WWTPs. By implementing targeted parameter management and optimizing treatment processes, WWTPs can significantly enhance operational performance and sustainability. This approach not only contributes to achieving carbon neutrality but also aligns with the Sustainable Development Goals (SDGs), promoting environmental stewardship and resource efficiency in wastewater management.

The developed framework for Life Cycle Inventory (LCI) analysis further supports this by providing a structured approach to systematically assess and optimize the performance of WWTPs. By integrating detailed process analysis with input and output data, the framework helps in identifying

----
*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

opportunities to reduce energy consumption and minimize environmental impacts, thereby contributing to the overall sustainability and resilience of WWTP operations.

6. RECOMMENDATIONS

Future research should prioritize the development of a comprehensive database aimed at enhancing pollutant removal efficiency while simultaneously reducing energy consumption and greenhouse gas emissions. Recommendations for future research include:

Expanding data collection is a crucial step. This includes capturing data on direct, energy indirect, and other indirect GHG emissions, alongside critical parameters like chemical oxygen demand (COD), total nitrogen (TN), sludge management, and chemical usage. Utilizing automatic measurement equipment for continuous data recording will improve accuracy and minimize missing data, enhancing GHG emission assessments. Additionally, it is necessary to study the formula for calculating greenhouse gas emissions appropriate for the wastewater treatment system used in the study and to conduct regular monitoring and updating of Thailand's emission factor (EF) values, which may fluctuate over time. This practice would reduce discrepancies and enhance the reliability of research analyses.

Equally important is the creation of a comprehensive database, integrating structured query language (SQL) with life cycle inventory (LCI) methodologies. This database will serve as a foundation for evaluating the energy efficiency and carbon neutrality of WWTPs. It will guide the development of frameworks to optimize processes and reduce emissions, offer insights into achieving net-zero GHG emissions, and support sustainable development goals.

Acknowledgement

The authors acknowledge and express gratitude for the support provided by the Bachelor of Science Program in Natural Resources and Environmental Management (International Program), Faculty of Environment and Resource Studies, Mahidol University, as well as the wastewater treatment plant departments of Siriraj Hospital and Siriraj Piyamaharajkarun Hospital for their graciousness in allowing the use of data in this study.

References

Adhikari, S., & Halden, R. U. (2022). Opportunities and limits of wastewater-based epidemiology for tracking global health and attainment of UN sustainable development goals. *Environment International*, *163*, 107217. https://doi.org/10.1016/j.envint.2022.107217

Bebbington, J., & Unerman, J. (2018). Achieving the United Nations Sustainable Development Goals: An enabling role for accounting research. *Accounting, Auditing & Accountability Journal*, *31*(1), 2-24. https://doi.org/10.1108/AAAJ-05-2017-2929

Biru, H., Otto, B., & Schleifer, L. (2017). *INSIDER: Rethinking Wastewater Can Help Achieve Both Climate and Development Goals*. https://www.wri.org/technical-perspectives/insider-rethinking-wastewater-can-help-achieve-both-climate-and-development-goals

Costanza, R., Daly, L., Fioramonti, L., Giovannini, E., Kubiszewski, I., Mortensen, L. F., Pickett, K. E., Ragnarsdottir, K. V., De Vogli, R., & Wilkinson, R. (2016). Modelling and measuring sustainable wellbeing in connection with the UN Sustainable Development Goals. *Ecological Economics*, *130*, 350–355. https://doi.org/10.1016/j.ecolecon.2016.07.009

DSPOT. (2023). *Database System for Publicly Owned Treatment Works*. https://dspot.pcd.go.th/

ECA. (2020). *Nationally Determined Contributions (NDCs) United Nations Economic Commission for Africa*. https://www.uneca.org/african-climate-policy-centre/nationally-determined-contributions-%28ndcs%29

Faragò, M., Damgaard, A., Rebsdorf, M., Nielsen, P. H., & Rygaard, M. (2022). Challenges in carbon footprint evaluations of state-of-the-art municipal wastewater resource recovery facilities. *Journal of Environmental Management*, *320*, 115715. https://doi.org/10.1016/j.jenvman.2022.115715

GIZ. (2021, December 6). *DSPOT supports Thailand's data management of domestic wastewater treatment plants – Thai-German Cooperation*. https://www.thai-german-cooperation.info/en_US/dspot-supports-thailands-data-management-of-domestic-wastewater-treatment-plants/

Gong, Y., Wang, X., Bao, X., & Lam, K. L. (2024). Life cycle assessment of ammonium sulfate recovery from urban wastewater. *Blue-Green Systems*, *6*(1), 90–99. https://doi.org/10.2166/bgs.2024.054

Ho, J. Y., Wen, K. T. K., Wan, Y. K., & Andiappan, V. (2021). Synthesis of a Sustainable Wastewater Treatment Plant for Sago Industry using Fuzzy Optimisation. *Chemical Engineering Transactions*, *83*, 373-378. https://doi.org/10.3303/CET2183063

*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu

Kanchanamala Delanka-Pedige, H. M., Munasinghe-Arachchige, S. P., Abeysiriwardana-Arachchige, I. S. A., & Nirmalakhandan, N. (2021). Evaluating wastewater treatment infrastructure systems based on UN Sustainable Development Goals and targets. *Journal of Cleaner Production*, *298,* 126795. https://doi.org/10.1016/j.jclepro.2021.126795

Li, P., Hu, X., Yuan, J., Sun, F., Li, P., Dong, W., Du, E., & Peng, M. (2024). Life cycle and environmental impact assessment of vegetation-activated sludge process (V-ASP) for decentralized wastewater treatment. *Current Research in Biotechnology*, *7*, 100172. https://doi.org/10.1016/j.crbiot.2023.100172

Maktabifard, M., Al-Hazmi, H. E., Szulc, P., Mousavizadegan, M., Xu, X., Zaborowska, E., Li, X., & Mąkinia, J. (2023). Net-zero carbon condition in wastewater treatment plants: A systematic review of mitigation strategies and challenges. *Renewable and Sustainable Energy Reviews*, *185*, 113638. https://doi.org/10.1016/j.rser.2023.113638

Malik, O. A., Hsu, A., Johnson, L. A., & de Sherbinin, A. (2015). A global indicator of wastewater treatment to inform the Sustainable Development Goals (SDGs). *Environmental Science & Policy*, *48*, 172-185. https://doi.org/10.1016/j.envsci.2015.01.005

Obaideen, K., Shehata, N., Sayed, E. T., Abdelkareem, M. A., Mahmoud, M. S., & Olabi, A. G. (2022). The role of wastewater treatment in achieving sustainable development goals (SDGs) and sustainability guideline. *Energy Nexus*, *7*, 100112. https://doi.org/10.1016/j.nexus.2022.100112

Rashid, S. S., Harun, S. N., Hanafiah, M. M., Razman, K. K., Liu, Y.-Q., & Tholibon, D. A. (2023). Life Cycle Assessment and Its Application in Wastewater Treatment: A Brief Overview. *Processes*, *11*(1), Article 1. https://doi.org/10.3390/pr11010208

Straub, J., Hofmann, J., & Hehenberger-Risse, D. (2023). Data management in life cycle assessment: A case study of wastewater treatment. *Water Science and Technology*, *88*(1), 123–135. https://doi.org/10.2166/wst.2023.200

Sustainable Development Report 2023. (2024). https://dashboards.sdgindex.org/

TGO. (2022). *Requirements for calculating and reporting the organization's carbon footprint by the Greenhouse Gas Management Organization. (Public organization) 8th printing (6th revised edition, July 2022)*.

United Nations. (2023, March 15). *UN World Water Development Report 2023*. UN-Water. https://www.unwater.org/publications/un-world-water-development-report-2023

---

*Corresponding Author: Praewa Wongburi
E-mail address: praewa.won@mahidol.edu