



## **Predictive Analytics for Optimizing Sewerage Sludge Treatment Efficiency and Resource Recovery in Dhaka City**

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### **Abstract**

The increasing volume of sewerage sludge generated by rapid urbanization has created significant challenges for wastewater treatment facilities, particularly in densely populated cities such as Dhaka. This study examined the application of predictive analytics for optimizing sewerage sludge treatment efficiency and resource recovery performance in Dhaka City. A quantitative case study design was employed using operational, laboratory, and monitoring records collected from sewerage sludge treatment facilities. The final dataset consisted of 336 valid observations after data quality screening and validation procedures. The analysis incorporated key operational variables, including wastewater inflow, sludge production, total solids, volatile solids, chemical oxygen demand, biochemical oxygen demand, hydraulic retention time, sludge retention time, temperature, pH, and energy utilization. Descriptive statistics, Pearson correlation analysis, multiple regression analysis, time-series evaluation, and machine learning techniques were applied using predictive analytics frameworks to assess treatment performance and recovery outcomes. The findings revealed that the average wastewater inflow was 14,520 m<sup>3</sup>/day, while average sludge production reached 52.8 tons/day. Methane generation averaged 285.6 m<sup>3</sup>/day, biogas recovery efficiency reached 71.8%, phosphorus recovery efficiency was 67.4%, nitrogen recovery efficiency was 62.9%, and sludge reduction averaged 54.7%. Correlation analysis demonstrated strong positive relationships between treatment efficiency and hydraulic retention time ( $r = 0.764$ ), sludge retention time ( $r = 0.712$ ), and volatile solids concentration ( $r = 0.648$ ). Multiple regression analysis showed that the selected operational variables explained 78.9% of the variation in treatment efficiency ( $R^2 = 0.789$ ), while resource recovery performance achieved an explanatory power of 81.4% ( $R^2 = 0.814$ ). Machine learning evaluation indicated that the Random Forest model produced the highest predictive accuracy with an  $R^2$  value of 0.93, RMSE of 3.21, and prediction accuracy of 94.1%, outperforming Artificial Neural Network, Support Vector Machine, and conventional regression models. The study concluded that predictive analytics provided a robust quantitative framework for identifying critical operational determinants of treatment efficiency and resource recovery. Hydraulic retention time, sludge retention time, volatile solids concentration, and organic loading rate emerged as the most influential predictors of treatment outcomes. The findings demonstrated that data-driven analytical approaches can effectively support sewerage sludge treatment optimization and resource recovery assessment within urban wastewater management systems.

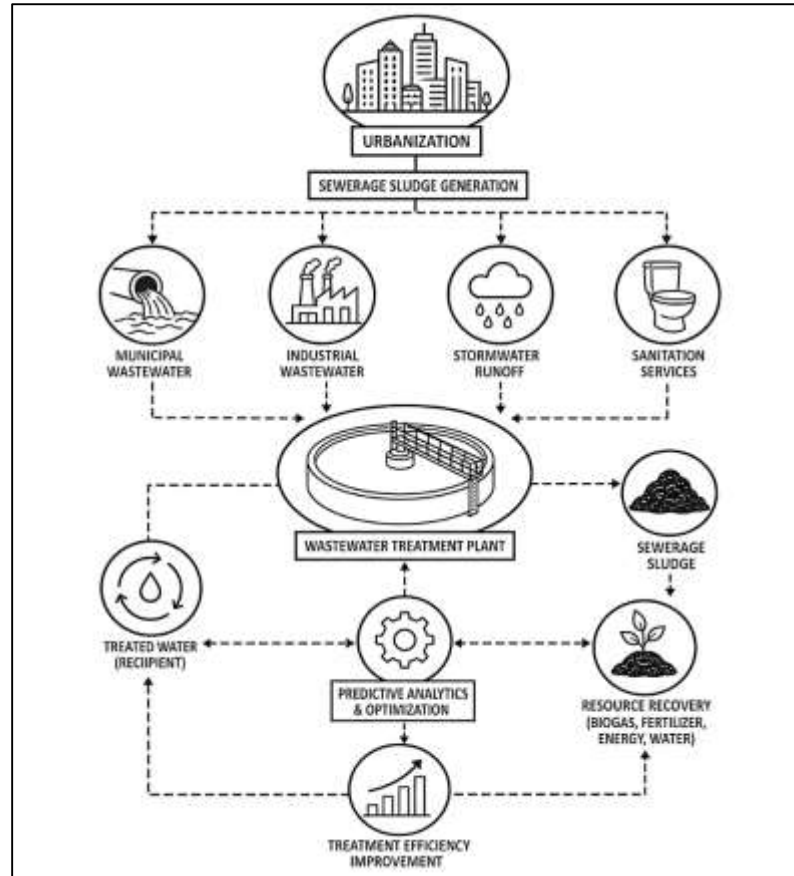
### **Keywords**

Predictive Analytics; Sewerage Sludge; Treatment Efficiency; Resource Recovery; Machine Learning.

## INTRODUCTION

Urbanization has transformed the environmental infrastructure requirements of cities across the world, creating unprecedented challenges in wastewater management and sanitation services. One of the most critical by-products of municipal wastewater treatment systems is sewerage sludge, a semi-solid residue generated during physical, chemical, and biological treatment processes. Sewerage sludge contains organic matter, nutrients, microorganisms, heavy metals, and other contaminants that require appropriate treatment before disposal or reuse (Mulchandani & Westerhoff, 2016).

**Figure 1: Wastewater treatment process and optimization diagram**



The concept of sewerage sludge treatment refers to the collection of technological, biological, thermal, and chemical processes used to stabilize sludge, reduce pathogenic content, minimize environmental risks, and recover valuable resources. Resource recovery, in this context, represents the extraction of beneficial products such as biogas, fertilizers, nutrients, biochar, energy, and reusable water from sludge treatment operations. The transition from conventional sludge disposal approaches toward resource recovery frameworks reflects a broader shift in environmental management philosophies that prioritize circular economy principles and sustainable urban development. International organizations have increasingly recognized wastewater and sludge as valuable resource streams rather than waste products requiring disposal. Modern wastewater treatment facilities are therefore being redesigned to maximize resource extraction while minimizing environmental footprints and operational costs (Tarpani & Azapagic, 2018). Quantitative evaluation of sludge treatment efficiency has become essential because treatment performance directly influences environmental quality, public health outcomes, energy consumption, and economic sustainability. Treatment efficiency can be assessed through multiple indicators, including volatile solids reduction, pathogen removal rates, nutrient recovery percentages, methane generation efficiency, dewatering performance, and operational cost optimization. Rapid population growth, industrial expansion, and increasing water consumption have intensified sludge generation rates worldwide, creating significant pressure on urban sanitation

infrastructures. Large metropolitan areas in developing countries face particularly complex challenges because wastewater treatment capacities often lag behind population growth and urban expansion. As a result, researchers and policymakers increasingly emphasize data-driven approaches and predictive analytics methodologies to improve treatment efficiency and optimize resource recovery outcomes (Shaddel et al., 2019). Predictive analytics combines statistical techniques, machine learning algorithms, mathematical modeling, and data mining approaches to forecast future system behavior based on historical and real-time operational data. The integration of predictive analytics into wastewater and sludge management systems offers opportunities to improve decision-making, enhance operational performance, reduce treatment costs, and maximize resource recovery potential while supporting broader environmental sustainability objectives.

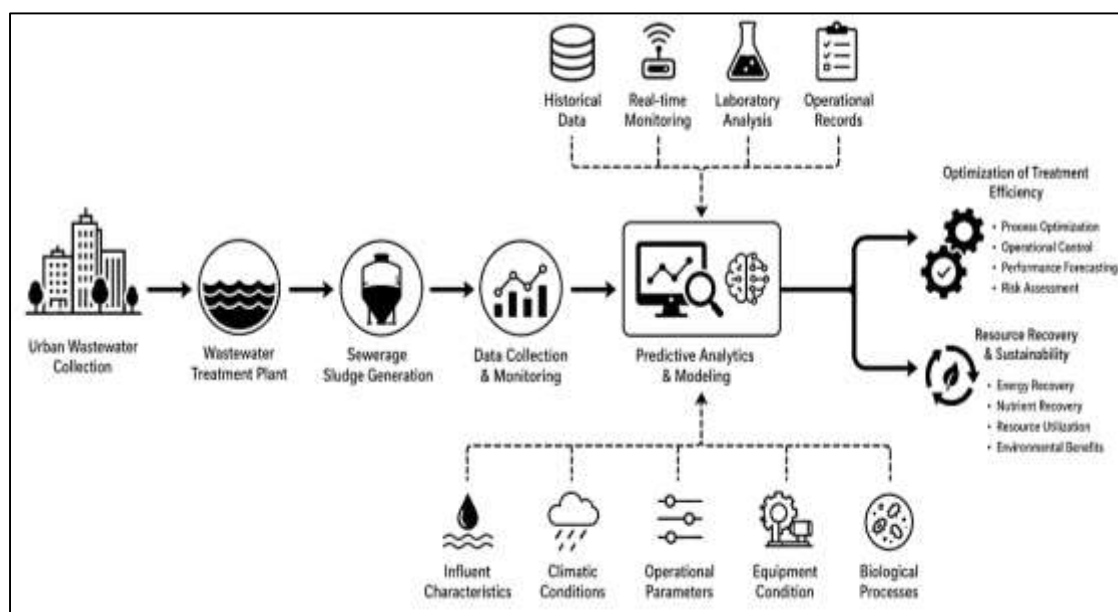
The management of sewerage sludge has emerged as a significant global environmental concern due to increasing wastewater generation associated with urbanization, industrialization, and socioeconomic development (Đurđević et al., 2019). Municipal wastewater treatment plants around the world generate millions of tons of sludge annually, requiring effective treatment and disposal strategies to prevent environmental degradation and public health risks. Sustainable sludge management has become a priority within international environmental policies because untreated or poorly managed sludge can contribute to water contamination, soil degradation, greenhouse gas emissions, and disease transmission. The United Nations Sustainable Development Goals emphasize the importance of sanitation, clean water management, resource efficiency, and sustainable urban development, all of which are closely linked to effective sludge treatment systems. Modern environmental engineering frameworks increasingly view sludge as a resource reservoir containing recoverable energy, phosphorus, nitrogen, carbon, and water. This paradigm shift has stimulated significant investments in advanced treatment technologies and resource recovery systems across developed and developing economies (Diener et al., 2014). Anaerobic digestion, thermal hydrolysis, composting, pyrolysis, gasification, and nutrient recovery technologies have demonstrated substantial potential for converting sludge into valuable products while reducing environmental burdens. Quantitative assessments indicate that resource recovery can significantly offset operational costs associated with wastewater treatment facilities, thereby improving economic sustainability. Treatment efficiency remains a central determinant of successful resource recovery because inefficiencies in sludge stabilization, dewatering, digestion, or nutrient extraction can reduce recovery yields and increase operational expenditures. Global experiences reveal considerable variation in treatment performance across regions due to differences in infrastructure quality, technological adoption, operational expertise, climatic conditions, and financial resources (Capodaglio, 2017). Data-driven optimization approaches have consequently gained attention as mechanisms for identifying operational inefficiencies and enhancing system performance. Predictive analytics offers particular value because wastewater treatment systems generate large volumes of operational data that can be utilized to forecast treatment outcomes, identify anomalies, optimize process parameters, and improve resource recovery rates. Statistical modeling and predictive techniques have demonstrated effectiveness in optimizing biological treatment processes, energy generation systems, sludge digestion performance, and nutrient recovery operations. Such analytical approaches contribute to evidence-based management strategies that align environmental objectives with economic and operational performance requirements. The growing emphasis on circular economy principles has further strengthened interest in predictive tools capable of maximizing resource recovery efficiency from wastewater treatment by-products while supporting sustainable urban infrastructure development and environmental stewardship (Huggins et al., 2016).

Predictive analytics represents an advanced analytical framework that utilizes historical datasets, statistical algorithms, mathematical models, and computational techniques to estimate future events and optimize system performance. Within environmental engineering, predictive analytics has become increasingly important for managing complex infrastructure systems characterized by dynamic interactions among environmental, operational, and technological variables. Wastewater treatment plants generate extensive datasets through sensors, monitoring systems, laboratory analyses, and operational records, creating opportunities for data-driven performance optimization. Predictive analytics transforms these datasets into actionable insights by identifying patterns, forecasting operational outcomes, and supporting proactive decision-making processes (Cornejo et al., 2016).

Environmental systems are inherently complex because treatment performance is influenced by fluctuating influent characteristics, climatic conditions, operational parameters, equipment conditions, and biological processes. Traditional management approaches frequently rely on reactive interventions after performance deterioration occurs. Predictive analytics introduces a proactive framework that enables operators to anticipate future conditions and implement corrective actions before inefficiencies emerge. Statistical regression models, artificial neural networks, decision trees, support vector machines, random forests, and ensemble learning approaches have demonstrated substantial capabilities in predicting treatment efficiency and resource recovery outcomes. These methodologies facilitate forecasting of sludge production rates, biogas generation potential, nutrient recovery efficiency, dewatering performance, and energy consumption patterns (Ansari et al., 2017). Quantitative optimization models further support resource allocation decisions and operational planning within wastewater treatment facilities. The application of predictive analytics extends beyond operational forecasting to include risk assessment, maintenance scheduling, process control, and environmental compliance management. Improved forecasting accuracy can contribute to enhanced resource utilization, reduced operational expenditures, lower greenhouse gas emissions, and increased recovery of valuable resources from sludge streams. Environmental engineers increasingly integrate predictive models into supervisory control systems to improve treatment reliability and operational resilience. The effectiveness of predictive analytics depends on data quality, model selection, computational capabilities, and system-specific characteristics. Urban wastewater systems provide particularly suitable environments for predictive modeling because continuous monitoring generates extensive datasets capable of supporting advanced analytical applications (Arashiro et al., 2018). The growing convergence of environmental engineering, data science, and computational intelligence has created new opportunities for optimizing complex treatment processes. Consequently, predictive analytics has evolved into a strategic tool for improving wastewater management efficiency and advancing sustainability objectives within modern urban infrastructure systems.

Rapid urbanization has significantly increased pressure on wastewater management systems across major cities worldwide. Expanding populations, changing consumption patterns, industrial growth, and infrastructure limitations contribute to rising wastewater volumes and increasing sludge generation rates. Urban wastewater treatment facilities frequently encounter operational challenges associated with fluctuating influent loads, aging infrastructure, inadequate treatment capacities, financial constraints, and environmental compliance requirements. Sewerage sludge management has become particularly complex because sludge treatment represents one of the most expensive and technically demanding components of wastewater treatment operations (Hao et al., 2019). Treatment costs commonly account for a substantial proportion of total wastewater management expenditures, highlighting the importance of efficiency optimization. Urban areas in developing economies experience additional challenges related to limited technological adoption, insufficient investment, institutional constraints, and rapid population growth. High-density settlements increase wastewater generation while simultaneously intensifying environmental risks associated with inadequate sludge management. Poorly treated sludge can contribute to surface water contamination, groundwater pollution, greenhouse gas emissions, odor problems, and public health hazards. Effective treatment therefore requires integrated approaches that balance environmental protection objectives with economic feasibility considerations. Resource recovery strategies offer opportunities to transform sludge management from a cost-intensive disposal activity into a value-generating component of urban infrastructure systems (Fang et al., 2016). Energy recovery through anaerobic digestion, nutrient extraction for agricultural applications, and production of reusable materials have emerged as promising approaches for improving sustainability outcomes. Treatment efficiency plays a critical role in determining the viability of such recovery strategies because resource yields depend on process performance and operational optimization. Variability in sludge composition further complicates treatment processes, requiring adaptive management approaches capable of responding to changing operational conditions. Quantitative methods have gained prominence because they enable systematic evaluation of treatment performance across multiple indicators. Predictive analytics provides an analytical framework capable of addressing operational complexity by integrating historical trends, real-time monitoring data, and statistical forecasting techniques.

**Figure 2: Predictive analytics for sewerage sludge treatment**



Such approaches can support optimization of digestion processes, dewatering operations, chemical dosing requirements, energy generation systems, and nutrient recovery pathways (Hoek et al., 2016). Urban environmental managers increasingly recognize the value of predictive tools for enhancing system reliability and supporting sustainable infrastructure management within rapidly expanding metropolitan environments.

Resource recovery has emerged as a transformative concept within wastewater and sludge management because it aligns environmental sustainability objectives with economic value creation. Conventional sludge disposal methods, including landfilling and uncontrolled dumping, impose significant environmental burdens and represent lost opportunities for recovering valuable resources embedded within sludge streams. Modern treatment frameworks increasingly emphasize the recovery of energy, nutrients, organic matter, and water from wastewater residuals (Zhang et al., 2017). Sewerage sludge contains substantial quantities of phosphorus and nitrogen, both of which are essential nutrients for agricultural production. Global concerns regarding nutrient scarcity and fertilizer security have increased interest in nutrient recovery technologies capable of converting sludge into agricultural inputs. Energy recovery represents another significant opportunity because sludge contains biodegradable organic matter suitable for biogas production through anaerobic digestion processes. Recovered biogas can be utilized for electricity generation, thermal energy production, or upgrading into renewable natural gas. Additional recovery pathways include biochar production, construction material applications, and water reclamation initiatives. The environmental benefits of resource recovery include reductions in greenhouse gas emissions, decreased reliance on nonrenewable resources, minimized waste disposal requirements, and enhanced circularity within urban resource systems (Hemalatha et al., 2019). Economic benefits include reduced operational expenditures, revenue generation opportunities, improved energy self-sufficiency, and enhanced financial sustainability of wastewater treatment facilities. Achieving these benefits requires high levels of treatment efficiency because recovery outcomes depend directly on process performance and operational effectiveness. Quantitative performance evaluation therefore becomes essential for identifying optimization opportunities and assessing recovery potential. Predictive analytics provides valuable support by enabling estimation of recovery yields, forecasting operational outcomes, and optimizing treatment parameters. Statistical and machine learning models can evaluate relationships among sludge characteristics, operational conditions, and recovery performance indicators. Such analyses support informed decision-making and facilitate evidence-based optimization strategies (Kacprzak et al., 2017). Increasing attention to circular economy principles has reinforced the importance of integrating

resource recovery objectives into wastewater management planning. Data-driven approaches are particularly valuable because they enable continuous performance assessment and adaptive management within complex treatment environments. Consequently, predictive analytics has become increasingly relevant for maximizing environmental and economic returns associated with sewerage sludge resource recovery initiatives.

Dhaka City represents one of the fastest-growing megacities in the world and serves as the economic, administrative, and population center of Bangladesh. Rapid urban expansion, increasing population density, industrial development, and rising water consumption have generated substantial pressure on the city's sanitation and wastewater management infrastructure (Buonocore et al., 2018). The growing volume of municipal wastewater has consequently increased sewerage sludge generation, creating significant challenges for treatment, disposal, and environmental management. Urban environmental conditions in Dhaka are influenced by complex interactions among population growth, infrastructure limitations, land scarcity, environmental pollution, and climate-related pressures. Effective sludge management is therefore essential for maintaining environmental quality, protecting public health, and supporting sustainable urban development. Wastewater treatment facilities operating within the metropolitan area face challenges associated with increasing treatment demands, operational constraints, variable influent characteristics, and resource limitations. Optimizing sludge treatment efficiency has become particularly important because inefficient treatment processes can reduce resource recovery potential while increasing environmental risks and operational expenditures (Javed et al., 2019). Resource recovery offers significant opportunities within Dhaka's urban context because recovered energy and nutrients can contribute to broader sustainability objectives while reducing dependence on external resource inputs. The adoption of predictive analytics can provide valuable support for managing the complexity of sludge treatment operations in such a densely populated urban environment. Quantitative approaches facilitate systematic assessment of treatment performance and enable identification of operational variables that influence efficiency outcomes. Historical operational data, treatment records, laboratory analyses, and monitoring information can be utilized to develop predictive models capable of forecasting treatment performance and resource recovery indicators. Such analytical capabilities are especially relevant in urban systems characterized by dynamic environmental conditions and increasing service demands. The integration of predictive analytics into sludge management practices aligns with broader efforts to modernize urban infrastructure through data-driven decision-making frameworks (Kirchmann et al., 2017). Improved forecasting and optimization capabilities can enhance operational planning, resource allocation, and treatment performance assessment within wastewater treatment systems. Consequently, examining predictive analytics applications in the context of sewerage sludge treatment and resource recovery provides an important quantitative perspective for understanding how data-driven approaches can support sustainable wastewater management within rapidly urbanizing metropolitan environments such as Dhaka City.

Quantitative research plays a fundamental role in evaluating wastewater treatment performance because treatment systems involve measurable operational, environmental, and economic variables that can be analyzed statistically (Diaz-Elsayed et al., 2019). Sewerage sludge treatment efficiency can be assessed using a wide range of quantitative indicators, including sludge reduction rates, volatile solids destruction percentages, nutrient recovery efficiencies, methane production volumes, energy generation outputs, dewatering effectiveness, operational costs, and environmental performance metrics. These indicators provide objective measures of treatment effectiveness and facilitate comparison across operational scenarios. Quantitative methodologies enable researchers to identify relationships among process variables, evaluate treatment outcomes, and develop predictive models capable of supporting optimization strategies. The increasing availability of operational data from wastewater treatment facilities has expanded opportunities for advanced statistical analysis and predictive modeling. Modern treatment systems generate continuous streams of information related to influent characteristics, biological activity, energy consumption, chemical usage, equipment performance, and resource recovery outputs (Cieřlik & Konieczka, 2017). Analytical techniques such as multiple regression analysis, time-series forecasting, machine learning algorithms, multivariate statistics, and optimization modeling can be applied to these datasets to improve understanding of

system behavior. Predictive analytics enhances quantitative assessment by enabling estimation of future performance outcomes based on historical observations and current operating conditions. Such capabilities support proactive management strategies aimed at maximizing treatment efficiency and resource recovery potential. Data-driven optimization approaches can identify critical operational parameters influencing performance outcomes and facilitate evidence-based decision-making processes. Quantitative evaluation is particularly relevant in urban wastewater management because treatment facilities must balance environmental objectives, operational reliability, and economic sustainability (Jeong et al., 2017). The integration of predictive analytics with treatment performance assessment offers opportunities to improve process control, enhance recovery yields, reduce operational inefficiencies, and support sustainable infrastructure management. Within the context of Dhaka City, quantitative examination of sludge treatment systems provides valuable insights into the factors influencing operational efficiency and resource recovery outcomes. Such analyses contribute to a deeper understanding of how predictive analytical frameworks can be utilized to optimize complex environmental engineering systems and improve the overall performance of urban wastewater treatment infrastructure (Munir et al., 2018).

The primary objective of this quantitative study is to evaluate the role of predictive analytics in optimizing sewerage sludge treatment efficiency and enhancing resource recovery outcomes within the wastewater management system of Dhaka City. As urban populations continue to increase and wastewater generation expands correspondingly, the effective treatment of sewerage sludge has become a critical environmental and operational challenge for municipal authorities. Sewerage sludge treatment facilities generate substantial amounts of operational data related to sludge characteristics, treatment performance, energy consumption, nutrient recovery, and process efficiency. This study aims to utilize quantitative analytical techniques to examine these datasets and identify the key factors that influence treatment efficiency and resource recovery performance. Through the application of predictive analytics models, the research seeks to assess relationships between operational variables and treatment outcomes, enabling the development of data-driven insights that support more efficient wastewater management practices. The study further aims to measure the extent to which predictive modeling can improve forecasting accuracy for sludge treatment processes, including sludge stabilization, dewatering performance, biogas generation, nutrient recovery, and overall resource utilization. Another objective is to evaluate treatment efficiency indicators and determine how variations in operational conditions affect resource recovery rates and system performance. By employing statistical analysis and predictive modeling approaches, the research intends to identify patterns, trends, and operational determinants that contribute to improved treatment outcomes. Additionally, the study seeks to generate empirical evidence regarding the effectiveness of predictive analytics as a decision-support tool within urban wastewater treatment facilities. The quantitative assessment focuses on establishing measurable relationships among treatment variables, operational efficiency metrics, and resource recovery indicators, thereby providing a comprehensive understanding of system performance within the context of Dhaka City. The research also aims to examine how predictive analytics can support optimization strategies through enhanced forecasting, performance monitoring, and operational control. Through rigorous quantitative investigation, the study endeavors to contribute to the growing body of knowledge concerning data-driven environmental management and the application of predictive analytical methods in wastewater treatment systems, with specific emphasis on improving sewerage sludge treatment efficiency and maximizing resource recovery potential in a rapidly urbanizing metropolitan environment.

## **LITERATURE REVIEW**

The growing complexity of urban wastewater management systems has increased the importance of evidence-based approaches for improving treatment efficiency and maximizing resource recovery from sewerage sludge. Sewerage sludge treatment represents a critical component of municipal sanitation infrastructure because it directly influences environmental quality, public health protection, energy utilization, and operational sustainability. As cities experience rapid urbanization and increasing wastewater generation, treatment facilities face challenges associated with rising sludge volumes, fluctuating influent characteristics, resource limitations, and stringent environmental regulations (Abdur & Iftekhara, 2021; Sun et al., 2016). These challenges have stimulated extensive research into

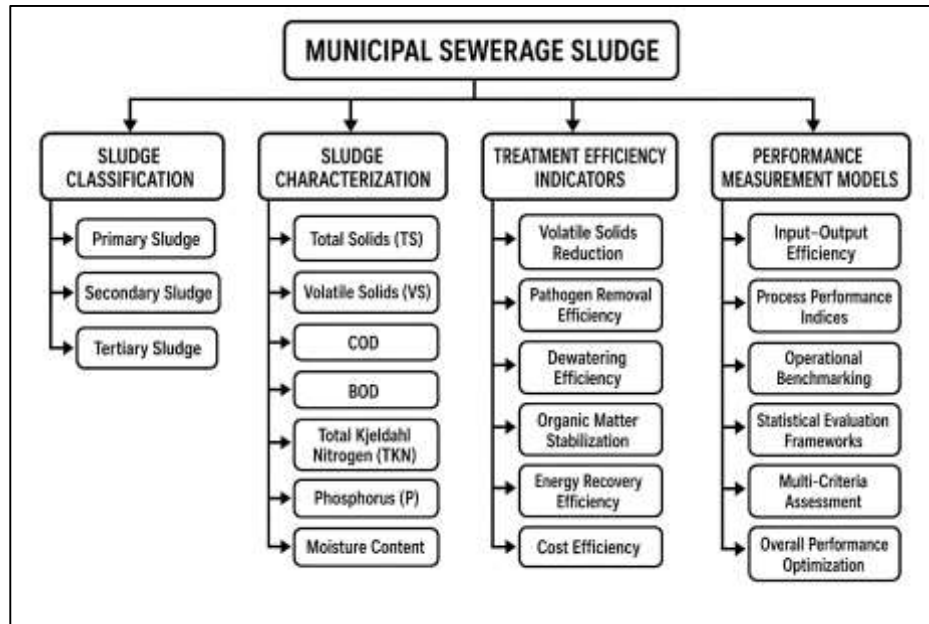
advanced treatment technologies, process optimization techniques, and data-driven management strategies capable of enhancing treatment performance. Within this context, predictive analytics has emerged as a significant analytical framework that integrates statistical modeling, machine learning algorithms, multivariate analysis, and forecasting techniques to support operational decision-making and performance optimization. The literature demonstrates increasing interest in the application of predictive models to wastewater treatment systems because such systems generate large volumes of operational data that can be utilized to identify patterns, forecast outcomes, and optimize process parameters. Quantitative studies have explored relationships among sludge characteristics, treatment variables, energy recovery performance, nutrient extraction efficiency, and environmental outcomes, providing a foundation for data-driven optimization approaches. Resource recovery has also become a central theme within wastewater management research due to its alignment with circular economy principles and sustainable development objectives (Rorat et al., 2019; Hossain & Uddin, 2022). The conversion of sewerage sludge into valuable products such as biogas, fertilizers, reclaimed water, and reusable materials has transformed traditional perspectives on wastewater residuals. Consequently, a comprehensive review of existing literature is necessary to understand the theoretical foundations, technological developments, quantitative methodologies, predictive modeling techniques, operational determinants, and resource recovery frameworks that shape contemporary sludge management systems. This literature review synthesizes research findings from environmental engineering, wastewater management, predictive analytics, statistical modeling, and urban sustainability domains to establish a robust conceptual foundation for examining how predictive analytics can optimize sewerage sludge treatment efficiency and resource recovery performance in the context of Dhaka City (Golam & Amir, 2022; Mininni et al., 2015).

### **Sewerage Sludge Treatment Efficiency**

Municipal sewerage sludge constitutes the semi-solid residual material generated during various stages of wastewater treatment processes and represents one of the most significant by-products of urban sanitation systems. Within wastewater treatment facilities, sludge is generally categorized into primary, secondary, and tertiary forms according to the treatment stage from which it originates and the physical, chemical, and biological characteristics it possesses. Primary sludge emerges during the initial sedimentation phase where settleable solids are separated from raw wastewater, resulting in a material rich in organic content and suspended solids (Hasan & Uddin, 2022; Neczaj & Grosser, 2018). Secondary sludge is produced through biological treatment processes involving microbial activity and biomass growth, often characterized by lower concentrations of settleable materials but higher biological content. Tertiary sludge originates from advanced treatment operations designed to remove residual nutrients, fine particles, and contaminants that remain after conventional treatment stages. Research literature indicates that these sludge categories exhibit substantial differences in moisture content, organic matter concentration, nutrient composition, and treatment requirements, necessitating tailored management strategies for effective processing and disposal. Quantitative assessments reveal that sludge generation rates vary considerably depending on wastewater characteristics, treatment technologies, population density, industrial contributions, and operational practices. Urban wastewater treatment facilities frequently report significant variability in sludge production volumes due to fluctuations in influent loading and treatment efficiency (Chen et al., 2014; Sany & Siful, 2022). The classification of sludge into distinct categories enables more accurate evaluation of treatment performance and facilitates resource recovery planning. Contemporary wastewater management frameworks increasingly emphasize detailed characterization of sludge properties because these properties influence stabilization efficiency, energy recovery potential, nutrient extraction capacity, and environmental risk profiles. Theoretical discussions within the literature consistently identify sludge classification as a foundational component of treatment system design, operational management, and performance assessment, highlighting its importance in the development of efficient and sustainable wastewater treatment infrastructures (Cecconet et al., 2018; Binte & Iftekhar, 2022). The characterization of municipal sewerage sludge relies heavily on a range of quantitative composition indicators that provide insights into treatment requirements, resource recovery potential, and environmental management considerations. Among the most widely utilized indicators are total solids, volatile solids, chemical oxygen demand, biochemical oxygen demand, total Kjeldahl nitrogen, and phosphorus

concentrations, each representing a specific dimension of sludge quality and treatment complexity. Total solids measurements provide information regarding moisture content and dewatering requirements, while volatile solids serve as indicators of biodegradable organic matter available for biological stabilization and energy recovery processes (Jin et al., 2014).

**Figure 3: Municipal sewerage sludge flowchart**



Chemical oxygen demand and biochemical oxygen demand reflect the organic pollution load and the extent of biological degradation potential within sludge streams. Nutrient-related parameters, including nitrogen and phosphorus concentrations, are particularly important because they determine the feasibility of nutrient recovery initiatives and agricultural reuse applications. Existing studies demonstrate considerable variability in these indicators across treatment facilities, reflecting differences in wastewater composition, industrial discharge patterns, climatic conditions, treatment technologies, and operational practices. Statistical analyses conducted across urban wastewater treatment systems frequently reveal significant heterogeneity in sludge characteristics even among facilities operating within the same geographical region. Such variability creates challenges for standardized treatment approaches and underscores the necessity of site-specific operational optimization strategies (Zou & He, 2018). Research findings further indicate that seasonal changes, hydraulic loading fluctuations, population dynamics, and infrastructure conditions contribute to temporal variations in sludge composition. Quantitative evaluation of sludge characteristics has therefore become an essential element of wastewater management because accurate characterization supports informed decision-making regarding treatment technology selection, operational control, resource recovery planning, and environmental compliance.

The assessment of sewerage sludge treatment efficiency is fundamentally dependent on the application of quantitative indicators that measure the effectiveness of stabilization, contaminant removal, resource utilization, and operational performance. Volatile solids reduction is among the most commonly employed indicators because it reflects the extent of organic matter degradation achieved during treatment processes. Higher levels of volatile solids reduction are generally associated with improved stabilization, reduced odor generation, enhanced pathogen control, and increased suitability for subsequent resource recovery applications. Pathogen removal efficiency represents another critical performance metric due to its direct implications for environmental safety and public health protection. Effective treatment processes are expected to substantially reduce microbial populations and minimize the risks associated with sludge disposal or reuse (Lin et al., 2016). Dewatering efficiency indicators

provide valuable information regarding moisture reduction performance, transportation costs, storage requirements, and overall treatment economics. Organic matter stabilization rates are frequently used to evaluate the degree to which biological and chemical processes have transformed unstable organic materials into more stable forms suitable for handling and utilization. Additional performance indicators include treatment throughput, processing capacity utilization, operational reliability, and energy consumption efficiency. Cost-efficiency measures are also extensively employed within the literature to assess the economic sustainability of treatment operations by comparing treatment outcomes with operational expenditures (Lu et al., 2018). Quantitative studies reveal strong interrelationships among these indicators, suggesting that improvements in one aspect of treatment performance often influence broader operational outcomes. The integration of multiple efficiency metrics provides a comprehensive framework for evaluating treatment effectiveness and identifying opportunities for optimization. Consequently, contemporary wastewater management research increasingly advocates multidimensional performance assessment approaches that capture technical, environmental, and economic dimensions of sludge treatment efficiency within a unified analytical framework (Quijano et al., 2017).

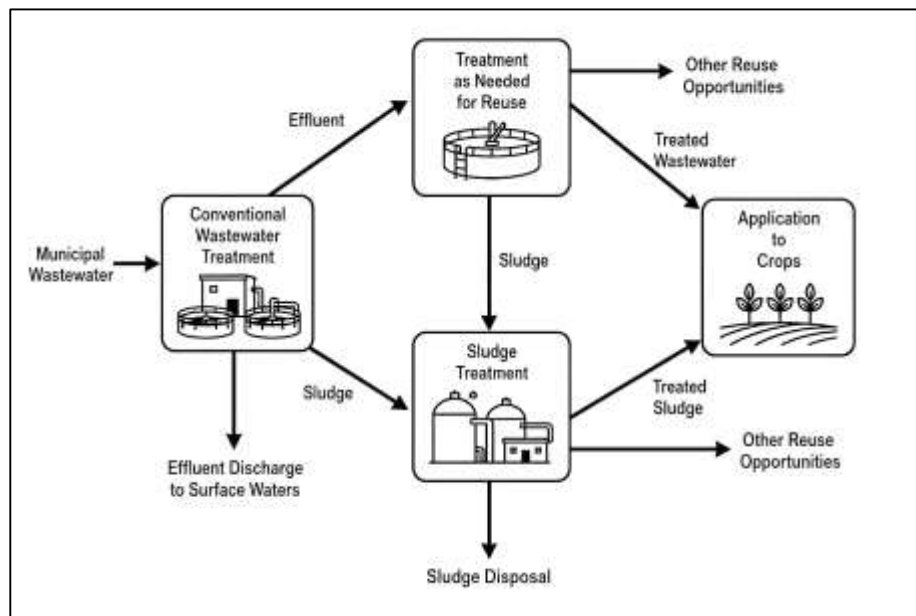
Performance measurement models provide the analytical foundation through which wastewater treatment systems are evaluated, compared, and optimized within both research and operational contexts. These models are designed to assess the relationship between resources utilized during treatment processes and the outcomes achieved in terms of stabilization, contaminant removal, resource recovery, and environmental performance. Input-output efficiency frameworks are widely discussed in the literature because they facilitate quantitative comparisons between treatment inputs such as energy, chemicals, labor, and infrastructure utilization and outputs including treated sludge quality, recovered resources, and environmental compliance achievements (Nancharaiyah & Sarvajith, 2019). Process performance indices further support operational assessment by integrating multiple indicators into composite measures capable of representing overall treatment effectiveness. Such indices enable wastewater managers and researchers to identify operational strengths and weaknesses while facilitating benchmarking across facilities and treatment technologies. Operational benchmarking methodologies have gained prominence as mechanisms for comparing treatment performance against industry standards, regulatory requirements, and best-practice benchmarks. Through benchmarking, treatment facilities can evaluate their relative efficiency and identify opportunities for performance enhancement (Solon et al., 2017). Statistical evaluation frameworks also play a critical role in wastewater management because they provide tools for analyzing variability, detecting operational anomalies, and assessing the significance of observed performance differences. Advanced analytical approaches increasingly incorporate multivariate assessment techniques capable of evaluating complex interactions among operational, environmental, and technological variables. Literature examining wastewater treatment performance consistently highlights the value of comprehensive measurement frameworks that combine technical efficiency indicators with economic and environmental performance metrics. Such integrated models support evidence-based decision-making and contribute to improved treatment outcomes through systematic evaluation of operational effectiveness (Faria et al., 2015). Theoretical and empirical studies collectively demonstrate that robust performance measurement systems are essential for optimizing sludge treatment processes and achieving sustainable wastewater management objectives within increasingly complex urban sanitation environments.

### **Sewerage Sludge Generation in Urban Environments**

The quantitative assessment of sewerage sludge generation in urban environments is grounded in the measurement of wastewater production, population size, treatment coverage, and sludge yield patterns. Literature on municipal wastewater management shows that sludge production is closely associated with the scale of urban sanitation services, the volume of wastewater entering treatment plants, and the efficiency of solid-liquid separation during treatment processes (Nadiri et al., 2018). Population-based sludge generation assessment is widely used because urban residents contribute directly to wastewater loading through domestic water use, sanitation practices, and household discharge patterns (Mateo-Sagasta et al., 2015). Per-capita sludge generation analysis provides a practical basis for comparing treatment burdens across cities with different population densities,

service coverage rates, and wastewater treatment capacities. In large metropolitan areas, sludge production is rarely stable because wastewater inflow changes according to daily water consumption, institutional activity, commercial discharge, and seasonal rainfall patterns. Quantitative studies also emphasize that sludge production rates are influenced by the type of treatment technology used, since primary sedimentation, biological treatment, and advanced nutrient removal processes produce sludge with different volumes and characteristics. Urban growth further intensifies sludge accumulation because expanding populations increase wastewater generation while infrastructure expansion often proceeds at a slower pace. For cities such as Dhaka, this relationship is especially important because dense settlement patterns, increasing sewerage demand, and limited treatment capacity create measurable pressure on sludge handling systems (Ng et al., 2014). The literature therefore positions sludge production modeling as a core analytical tool for estimating treatment demand, planning operational capacity, and identifying the scale of resource recovery potential. Without relying on formula-based presentation, quantitative modeling in this field generally focuses on measurable relationships among population, wastewater flow, treatment coverage, sludge yield, and operational performance.

**Figure 4: Sewerage sludge management cycle diagram**



Sludge volume variability in urban wastewater systems is shaped by a combination of hydraulic, industrial, demographic, and environmental factors that affect both wastewater quantity and sludge composition. Wastewater inflow characteristics are among the most important determinants because treatment plants receiving higher hydraulic loads generally experience greater suspended solids accumulation and increased sludge generation (Semiya et al., 2015). Inflow variation is also affected by water consumption behavior, sewer network coverage, infiltration, stormwater entry, and the balance between domestic and non-domestic wastewater sources. Industrial discharge contributes additional complexity because industrial effluents can contain suspended solids, organic pollutants, chemicals, oils, metals, and process residues that alter sludge volume and treatment requirements. Urban demographic variables also influence sludge generation patterns because population density, household size, income level, sanitation access, and commercial activity shape the quantity and quality of wastewater entering sewerage systems.

Literature on developing-country cities indicates that informal settlements, uneven sewer connections, decentralized sanitation practices, and unregulated discharges can produce highly variable sludge loads across different urban zones. Climatic and environmental conditions further influence sludge volume through rainfall, temperature, seasonal flooding, evaporation, and dilution effects in sewer

networks (Buonocore et al., 2018). During wet seasons, increased inflow can dilute wastewater while simultaneously increasing total hydraulic loading, which affects solids capture and sludge handling requirements. During dry seasons, lower dilution may increase pollutant concentration and organic strength, altering sludge stabilization needs. These determinants show that sludge volume variability cannot be explained by population size alone. A quantitative systems perspective therefore requires integrated analysis of flow rates, pollution loads, industrial activity, seasonal conditions, and urban service coverage. Such analysis provides a stronger basis for understanding treatment efficiency and resource recovery opportunities in complex metropolitan environments (Diener et al., 2014).

Statistical trends in sewerage sludge generation reveal a consistent association between urbanization, wastewater treatment expansion, and rising sludge management burdens across both developed and developing regions. In high-income countries, increased wastewater treatment coverage and advanced treatment requirements have produced large quantities of regulated sludge that must be stabilized, dewatered, reused, incinerated, or safely disposed of. In developing countries, sludge generation patterns are often more uneven because treatment infrastructure may serve only part of the urban population, while untreated wastewater and fecal sludge from onsite sanitation systems remain significant components of the sanitation burden. Comparative quantitative assessments indicate that sludge generation differs substantially across regions due to variation in sewerage coverage, treatment technology, industrial contribution, per-capita water use, and regulatory enforcement (Salehin et al., 2019). Metropolitan wastewater burden analysis shows that megacities face distinctive challenges because their treatment systems must manage both large wastewater volumes and rapid changes in demand caused by population growth, migration, commercial expansion, and urban land-use change. Growth-rate modeling of sludge production has been used in the literature to estimate how increasing wastewater treatment capacity changes the quantity of sludge requiring treatment and resource recovery. In developing urban contexts, improved sanitation coverage can increase recorded sludge volumes because more wastewater enters formal treatment systems rather than being discharged untreated (Singh et al., 2017). This creates an important planning issue: better wastewater treatment performance may initially increase sludge management demand. For Dhaka City, such literature is relevant because rapid urban expansion and infrastructure development are likely to increase the amount of sludge requiring systematic treatment, monitoring, and recovery. The global and developing-country evidence therefore supports the need for quantitative assessment frameworks that measure not only current sludge production but also the operational pressures associated with urban wastewater expansion (Kacprzak et al., 2017).

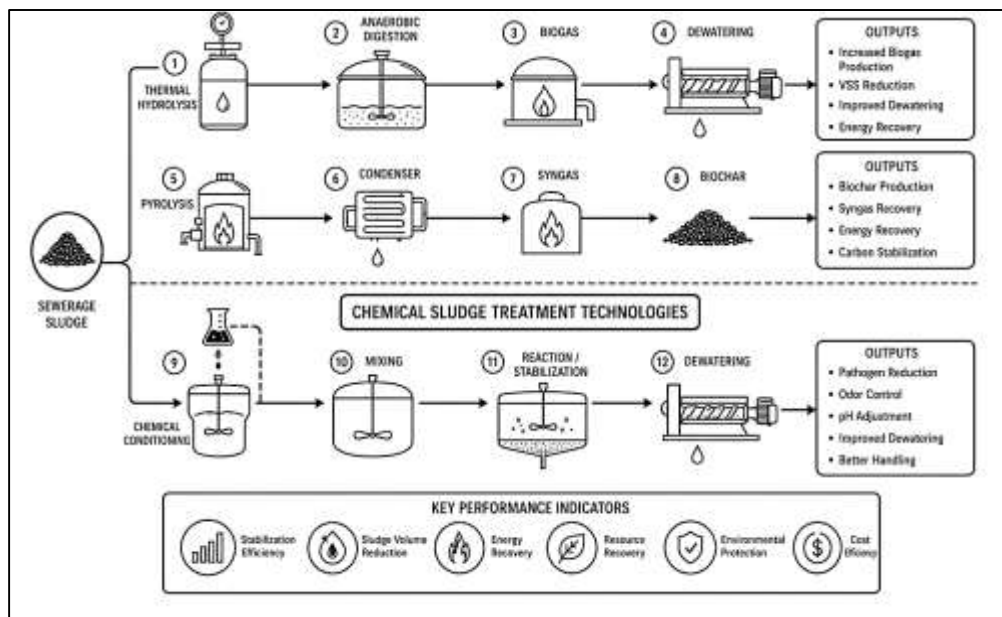
### **Advanced Sewerage Sludge Treatment Technologies**

Thermal and chemical sludge treatment technologies are extensively reviewed as advanced approaches for improving sludge stabilization, pathogen reduction, dewaterability, and resource recovery outcomes. Thermal hydrolysis is commonly assessed for its ability to break down complex organic structures before anaerobic digestion, thereby improving biodegradability, increasing biogas production, and reducing sludge viscosity. Quantitative performance evaluations of thermal hydrolysis usually focus on solubilization efficiency, digestion enhancement, volatile solids reduction, dewatering improvement, and energy balance. Pyrolysis is another important thermal process that converts dried sludge into biochar, syngas, and liquid products under oxygen-limited conditions (Rorat et al., 2019). Literature on pyrolysis emphasizes conversion efficiency, carbon retention, heavy metal immobilization, energy recovery potential, and biochar quality as major performance indicators. Chemical stabilization technologies, including lime stabilization, chemical conditioning, oxidation, and coagulation-based processes, are often evaluated through pathogen reduction, odor control, pH adjustment, moisture reduction, and sludge handling improvement. Chemical conditioning is particularly important for dewatering because it improves solid-liquid separation and reduces the cost of transport and disposal. Thermal and chemical processes are often more resource-intensive than conventional biological methods, yet they provide measurable advantages in sludge volume reduction, treatment speed, hygienic quality, and material transformation. The literature also identifies resource utilization indicators as essential for evaluating these technologies because treatment performance is increasingly judged not only by waste reduction but also by the production of usable outputs such as biochar, heat, biogas enhancement, and stabilized biosolids (Cieřlik et al., 2015). In urban sludge

management systems, the selection of thermal or chemical technologies depends on treatment capacity, energy availability, sludge composition, operational cost, land constraints, and regulatory standards. These studies collectively establish that thermal and chemical treatment performance must be evaluated through technical, environmental, and economic indicators rather than through single-parameter efficiency measures (Zhu et al., 2017).

Comparative statistical analysis plays an important role in evaluating advanced sludge treatment technologies because wastewater treatment plants must select technologies that balance treatment efficiency, resource recovery, cost, reliability, and environmental performance. The literature commonly compares anaerobic digestion, thermal hydrolysis, composting, pyrolysis, incineration, chemical stabilization, and mechanical dewatering by using multi-criteria performance assessment frameworks. These frameworks examine treatment outcomes through several measurable dimensions, including organic matter reduction, pathogen control, energy recovery, nutrient conservation, greenhouse gas reduction, sludge volume minimization, operational cost, and maintenance requirements (Wichelns et al., 2015). Efficiency benchmarking allows different treatment systems to be compared against best-practice values, regulatory targets, or plant-level performance indicators. Such benchmarking is valuable because the same technology may perform differently across facilities depending on sludge characteristics, operator expertise, climatic conditions, infrastructure age, and process integration.

**Figure 5: Sludge treatment process flowchart**



Cost-performance comparisons are also central to the literature because advanced technologies often require higher capital investment, specialized operation, and energy inputs. Quantitative technology ranking methods help researchers and practitioners identify which treatment alternatives provide the strongest balance between treatment performance and economic feasibility. For example, anaerobic digestion often ranks highly when energy recovery and stabilization are prioritized, while thermal hydrolysis may perform strongly when digestion enhancement and sludge reduction are emphasized (Grobelak et al., 2019). Pyrolysis may be favored where biochar production, carbon stabilization, and material recovery are important. Chemical stabilization may be preferred in contexts requiring rapid pathogen control and improved sludge handling. The literature therefore shows that technology comparison is not limited to identifying the most technically advanced option. It requires systematic evaluation of measurable outcomes under specific operating conditions. In cities with high sludge burdens and resource constraints, comparative quantitative analysis provides a practical foundation for selecting treatment technologies aligned with local infrastructure capacity and recovery objectives.

(Collivignarelli et al., 2019).

The literature on advanced sewerage sludge treatment technologies increasingly presents treatment performance as an integrated quantitative outcome involving stabilization efficiency, resource recovery, environmental protection, and economic viability. Anaerobic digestion contributes to organic matter degradation and renewable energy generation, while thermal hydrolysis enhances sludge biodegradability and improves digestion performance. Pyrolysis converts sludge into recoverable products and may reduce environmental risks through carbon stabilization and contaminant immobilization (Feodorov, 2016). Chemical treatment improves pathogen reduction, odor management, and dewatering performance, especially where rapid stabilization is required. These technologies are usually evaluated through combined indicators rather than isolated measures because treatment efficiency is influenced by multiple interacting factors. Sludge composition, moisture content, organic strength, nutrient concentration, temperature, retention time, chemical dosage, and equipment performance all shape quantitative outcomes. Resource recovery indicators are especially important because modern sludge treatment is increasingly connected to energy production, nutrient reuse, material recovery, and circular economy objectives. The literature also shows that advanced treatment technologies differ in their operational demands. Some technologies require high energy input and technical expertise, while others are simpler but may provide lower resource recovery potential. This creates a need for balanced performance assessment that considers both technical efficiency and contextual suitability (Zhang et al., 2017). For Dhaka City, this body of literature is relevant because urban wastewater systems require technologies that can handle increasing sludge volumes while improving recovery outcomes and controlling costs. An integrated quantitative perspective allows treatment technologies to be assessed according to measurable outcomes such as sludge reduction, methane generation, dewatering improvement, nutrient retention, biochar production, cost efficiency, and environmental safety. Therefore, advanced sludge treatment performance is best understood as a multidimensional field in which biological, thermal, chemical, and statistical evaluation approaches are combined to support evidence-based wastewater management (Cieřlik et al., 2015).

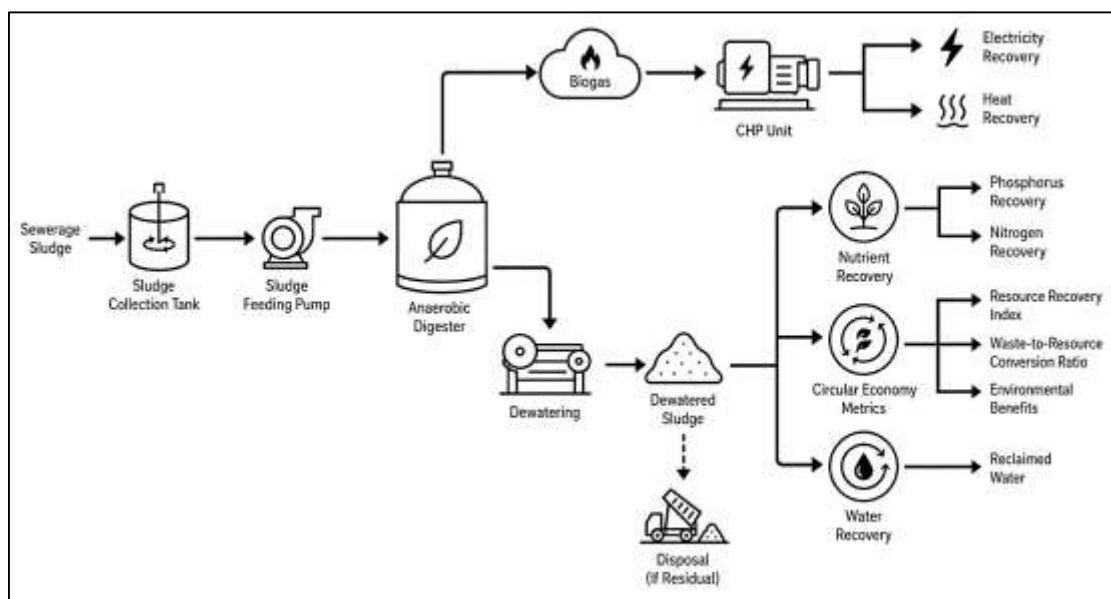
### **Measurement Models and Performance Indicators**

Energy recovery from sewerage sludge has become a major focus in wastewater treatment literature because sludge contains biodegradable organic matter that can be converted into usable energy through controlled treatment processes. Quantitative assessment of energy recovery generally centers on biogas generation, methane production efficiency, electricity generation potential, and overall energy balance. Anaerobic digestion is the most widely discussed pathway because it transforms organic solids into biogas while reducing sludge volume and improving stabilization. The literature shows that biogas generation depends on sludge composition, volatile solids content, digestion temperature, organic loading, retention time, microbial activity, and process stability (Mills et al., 2014). Methane production efficiency is particularly important because methane represents the main energy-bearing component of biogas and determines whether sludge treatment can contribute meaningfully to plant-level energy recovery. Electricity generation potential is often evaluated by estimating how much recovered biogas can be converted into electrical or thermal energy through combined heat and power systems. Energy balance analysis further examines whether the energy produced from sludge can offset the energy consumed during pumping, mixing, heating, dewatering, and other treatment operations (Ferretti, et al., 2016). In urban wastewater systems, this type of assessment is essential because treatment plants often face high operational costs and energy demands. Quantitative studies therefore frame sludge-based energy recovery as both an environmental and operational performance issue. For cities with rising wastewater volumes, energy recovery indicators provide a measurable basis for evaluating how efficiently sludge treatment systems convert waste materials into useful energy resources.

Nutrient recovery from sewerage sludge is widely examined as a resource recovery strategy because sludge contains valuable concentrations of phosphorus, nitrogen, and organic matter that can support agricultural and soil improvement applications after appropriate treatment (Kiselev et al., 2019). Quantitative literature on nutrient recovery focuses on phosphorus recovery rates, nitrogen extraction efficiency, fertilizer-equivalent value, and nutrient mass balance assessment. Phosphorus recovery has

received strong attention because phosphorus is a limited mineral resource and is essential for food production. Sludge and sludge-derived products can contain recoverable phosphorus in forms suitable for fertilizer production, composting, struvite precipitation, or land application under regulated conditions. Nitrogen recovery is also important because nitrogen contributes to fertilizer value, although its recovery can be affected by volatilization, biological transformation, and treatment conditions. Fertilizer-equivalent value estimation allows researchers to compare recovered nutrients with commercial fertilizer inputs, providing an economic and agronomic basis for evaluating sludge reuse (Buonocore et al., 2018). Nutrient mass balance approaches are used to track how nutrients move through treatment stages, including digestion, dewatering, drying, composting, or chemical recovery systems. The literature emphasizes that nutrient recovery efficiency depends on sludge composition, treatment technology, chemical conditions, moisture content, contaminant levels, and regulatory standards for safe reuse.

**Figure 6: Wastewater treatment and resource recovery diagram**



In urban environments, nutrient recovery links wastewater management with agricultural resource systems by transforming sludge from a disposal burden into a measurable input for soil nutrient management. This perspective is especially relevant for resource-constrained cities where fertilizer demand, waste management costs, and environmental pressures are closely connected (Grönlund, 2019).

Circular economy metrics provide a structured way to evaluate how effectively sewerage sludge treatment systems convert waste into reusable resources while reducing environmental burdens. Literature on wastewater resource recovery increasingly uses indicators such as resource recovery indices, waste-to-resource conversion ratios, environmental benefit measures, and sustainability performance scores. A resource recovery index helps summarize how much useful value is extracted from sludge through energy recovery, nutrient recovery, material reuse, or water reclamation. Waste-to-resource conversion ratios evaluate the proportion of sludge transformed into beneficial products rather than being disposed of through landfilling, uncontrolled dumping, or other low-value pathways (Shaddel et al., 2019). Environmental benefit quantification is commonly linked to reductions in greenhouse gas emissions, lower fossil energy dependence, decreased fertilizer production demand, reduced landfill use, and improved pollution control. Sustainability performance scoring combines environmental, economic, and technical indicators to compare treatment alternatives and identify systems that provide stronger overall performance. The literature shows that circular economy assessment is important because sludge management cannot be evaluated only by treatment completion or disposal safety. It must also be evaluated by the extent to which treatment processes recover useful materials, reduce resource loss, and improve system efficiency. These metrics are

especially useful in metropolitan wastewater systems where large sludge volumes create both environmental risks and resource recovery opportunities. For Dhaka City, circular economy metrics offer a quantitative basis for assessing whether sludge treatment practices support resource recovery, cost reduction, and improved environmental management (Sfez et al., 2019). Such metrics help connect wastewater treatment performance with broader urban sustainability goals through measurable resource recovery outcomes.

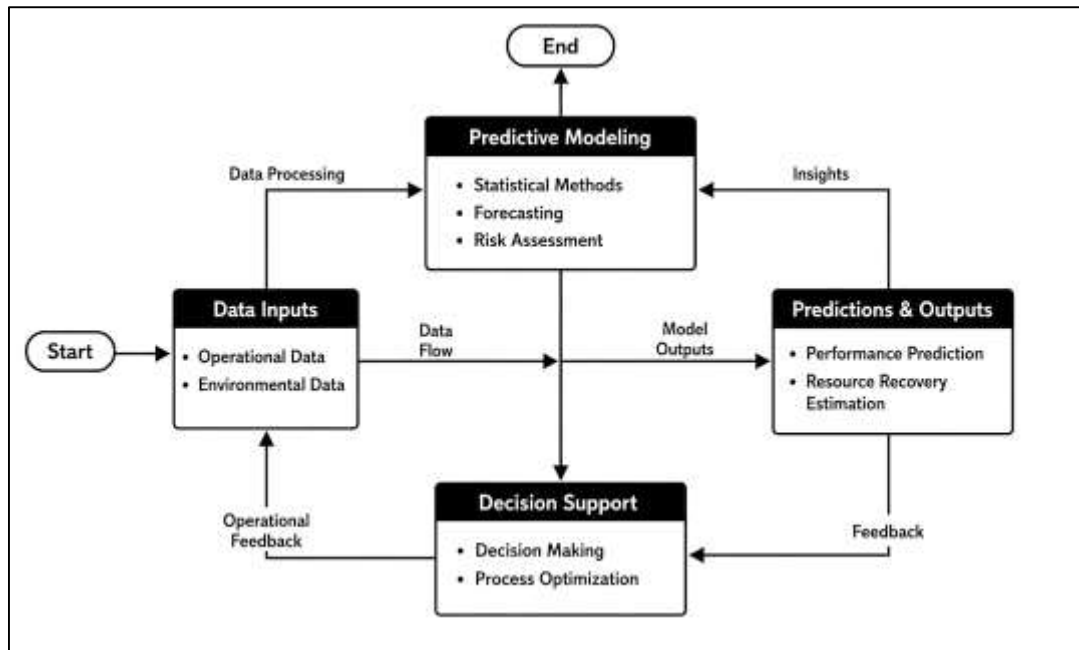
### **Environmental Infrastructure Optimization**

Predictive analytics provides a structured quantitative foundation for understanding, forecasting, and improving the performance of environmental infrastructure systems. In wastewater and sludge management, predictive analytics refers to the use of historical data, statistical reasoning, computational modeling, and performance indicators to estimate likely system behavior and support operational decision-making. The conceptual basis of predictive analytics is rooted in the assumption that infrastructure processes generate measurable patterns through repeated interactions among inputs, operational conditions, treatment mechanisms, and outputs (Fernández-Arévalo et al., 2017). In sewerage sludge treatment, these patterns may involve wastewater inflow, sludge volume, organic loading, treatment duration, energy consumption, methane production, nutrient recovery, and dewatering performance. Statistical prediction theory supports the interpretation of such patterns by linking observed data with expected outcomes under different operational conditions. Forecasting principles are also important because sludge treatment systems are affected by temporal variation, including daily inflow fluctuation, seasonal rainfall, industrial discharge changes, and population-driven wastewater generation. A predictive analytics framework therefore allows treatment systems to move from descriptive measurement toward performance estimation and operational control (Zijp et al., 2017). Data-driven decision systems strengthen this process by converting raw monitoring data into actionable information for treatment plant management. Predictive modeling architecture usually includes data collection, preprocessing, variable selection, model development, validation, interpretation, and decision-support integration. Within environmental infrastructure, this architecture is valuable because treatment systems are complex, nonlinear, and sensitive to both technical and environmental variables. Literature shows that predictive analytics has become a major quantitative approach for improving infrastructure reliability, reducing uncertainty, identifying operational risks, and optimizing treatment efficiency. In the context of sewerage sludge treatment, it provides a measurable basis for connecting operational variables with treatment outcomes and resource recovery performance (Hoek et al., 2016).

Quantitative predictive analytics relies on a range of statistical and computational techniques that allow researchers to examine relationships among variables, classify outcomes, forecast trends, and evaluate uncertainty. Multiple linear regression is widely used in environmental and wastewater studies because it helps estimate how several independent variables collectively influence a continuous treatment outcome, such as sludge reduction, energy use, biogas yield, or pollutant removal efficiency. Logistic regression is useful when treatment outcomes are categorized into groups, such as acceptable or unacceptable performance, high or low recovery efficiency, or compliant and non-compliant discharge conditions. Time-series forecasting has particular relevance for wastewater systems because treatment plants operate continuously and generate data across daily, weekly, seasonal, and annual intervals (Vadenbo et al., 2014). This technique supports the analysis of changing wastewater flows, sludge production patterns, rainfall-related inflow variation, and energy consumption trends. Multivariate statistical modeling is also significant because sewerage sludge treatment involves many interacting variables, including solids concentration, organic loading, temperature, retention time, nutrient concentration, pH, and chemical dosage. By examining multiple indicators together, multivariate methods provide a more complete understanding of system behavior than single-variable analysis. Monte Carlo simulation is commonly used to evaluate uncertainty by testing how different possible input conditions may affect treatment performance and resource recovery outcomes. These quantitative methods are not interchangeable; each supports a different analytical purpose within predictive modeling (Đurđević et al., 2019). Literature on environmental analytics emphasizes that strong predictive assessment requires careful data preparation, appropriate model selection, validation, error measurement, and interpretation. For sludge treatment optimization, these methods

provide the statistical foundation for identifying influential variables, estimating treatment outcomes, and supporting evidence-based operational decisions.

**Figure 7: Predictive modeling process flowchart**



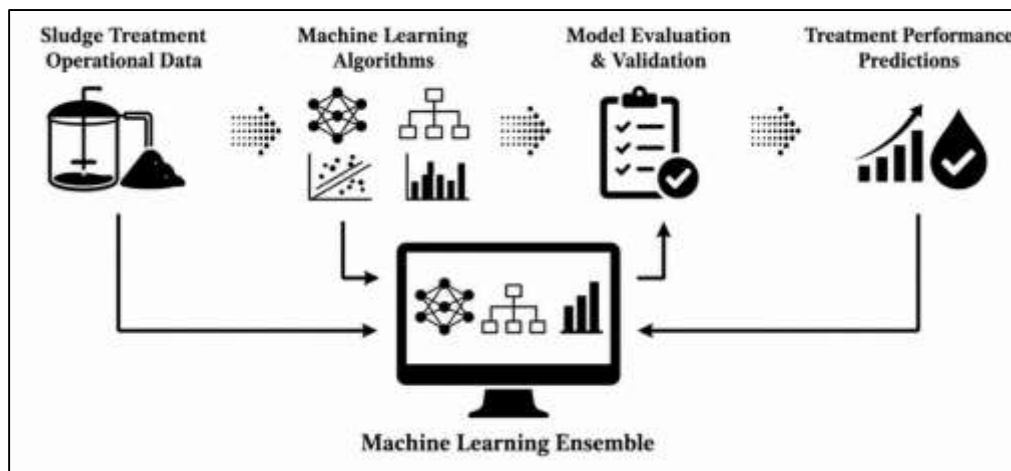
### Sewerage Sludge Treatment Optimization

Artificial neural networks have become a major machine learning approach in wastewater and sewerage sludge treatment research because they can model complex relationships among operational variables without requiring strict linear assumptions (Vaneckhaute et al., 2018). In sewerage sludge treatment systems, treatment performance is influenced by several interconnected factors, including sludge concentration, organic loading, pH, temperature, hydraulic retention time, sludge retention time, aeration conditions, microbial activity, chemical dosage, and energy input. Artificial neural networks are useful in this context because they can learn hidden patterns from historical treatment data and produce predictions related to treatment efficiency, methane generation, volatile solids reduction, dewatering performance, nutrient removal, and effluent quality. Literature on wastewater treatment modeling shows that network architecture design is an important part of predictive performance because the number of input variables, hidden layers, neurons, activation functions, and training procedures can influence model accuracy (Vaneckhaute et al., 2018). Prediction accuracy measures are also central because neural network outputs must be evaluated against observed treatment performance using statistical error indicators and validation techniques. In sludge treatment optimization, artificial neural networks are frequently used to forecast efficiency under changing operational conditions and to identify process settings associated with improved performance. Their strength lies in capturing nonlinear behavior, especially in biological treatment processes where microbial reactions and environmental conditions interact dynamically. However, their practical use depends on data quality, training dataset size, model validation, and interpretability. The literature generally presents neural networks as powerful predictive tools for treatment efficiency forecasting, especially when wastewater treatment plants collect continuous monitoring data that can support data-driven analysis (Zhang et al., 2018).

Random forest and decision tree models are widely discussed in environmental engineering literature because they provide interpretable and flexible methods for classifying treatment outcomes and identifying important operational variables. Decision trees divide data into structured decision paths, making them useful for explaining how specific treatment conditions are associated with high, moderate, or low treatment performance. Random forest models extend this approach by combining many decision trees to improve prediction stability and reduce the weakness of relying on a single tree structure. In sewerage sludge treatment optimization, these models are commonly applied to classify

treatment outcomes such as acceptable stabilization, poor digestion performance, high methane productivity, low dewatering efficiency, or non-compliance with treatment targets (Zhang et al., 2018). Variable importance analysis is a major strength of random forest modeling because it helps determine which factors most strongly influence treatment efficiency. Variables such as organic loading, volatile solids content, retention time, temperature, pH, sludge age, chemical conditioning, and influent variability can be ranked according to their contribution to prediction accuracy. This makes random forest models valuable not only for forecasting but also for operational diagnosis. Literature indicates that these tree-based models are especially useful in treatment systems where multiple variables interact and where managers require understandable decision-support outputs. Their application in sludge treatment supports performance optimization by identifying critical control points and highlighting operational conditions associated with improved treatment results (Hernández-del-Olmo et al., 2016). Compared with black-box approaches, decision tree-based methods provide stronger interpretability, which is important for wastewater treatment operators who must translate model results into practical operational actions.

**Figure 8: Machine learning ensemble for sludge treatment**



Support vector machines and ensemble learning approaches have been extensively applied in wastewater treatment modeling because they can produce strong predictive performance under complex and high-dimensional data conditions. Support vector machines are particularly useful when treatment datasets contain nonlinear relationships among variables and when the objective is to separate or predict performance outcomes with strong generalization capacity. In sewerage sludge treatment research, support vector machines have been used to predict treatment efficiency, sludge settleability, effluent quality, methane yield, pollutant removal, and process stability (Hernández-del-Olmo et al., 2018). Their robustness is often linked to their ability to manage small or moderate datasets effectively while maintaining predictive accuracy. Ensemble learning approaches, including boosting, bagging, and hybrid model combinations, are also important because they combine multiple predictive models to reduce error and improve reliability. Literature on environmental data modeling shows that ensemble approaches often outperform individual models because they capture different patterns within the same dataset and reduce the risk of unstable prediction. In treatment process optimization, these models support comparative accuracy assessment, model robustness evaluation, and identification of reliable prediction structures for operational decision-making. Robustness is particularly important in sludge treatment because operational data may contain noise, missing values, seasonal variability, and irregular influent characteristics (Shi & Xu, 2018). Support vector machines and ensemble models therefore provide a strong methodological basis for predicting treatment outcomes under variable conditions. Their application is closely linked to quantitative optimization because accurate and stable prediction allows treatment plants to adjust operational parameters, improve sludge stabilization, enhance resource recovery, and reduce process inefficiencies.

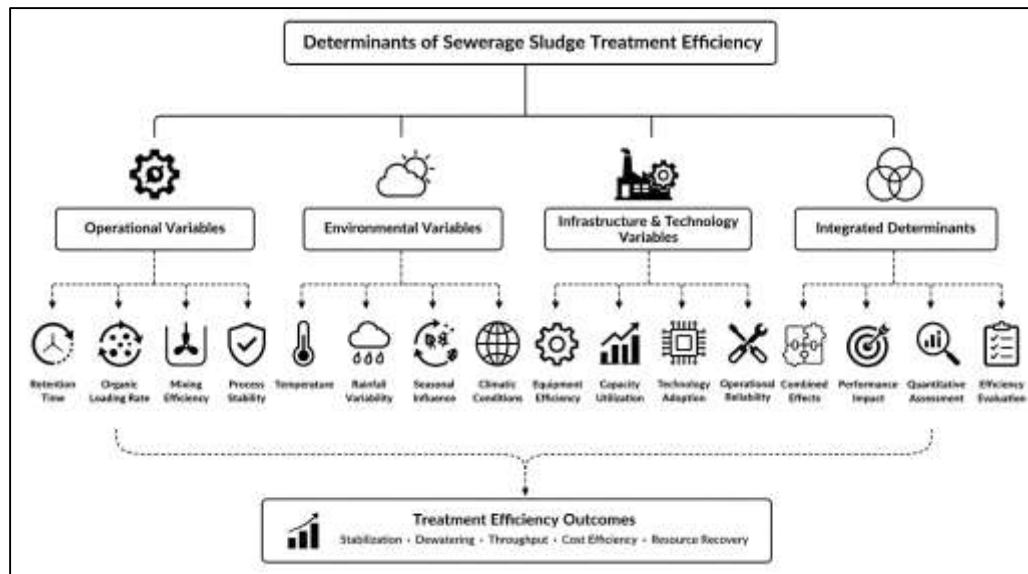
Comparative quantitative evaluation is essential in machine learning-based sewerage sludge treatment research because different algorithms may produce different levels of predictive accuracy, interpretability, robustness, and operational usefulness (Qiao & Zhang, 2018). Literature comparing artificial neural networks, decision trees, random forests, support vector machines, gradient boosting models, regression-based models, and hybrid approaches generally evaluates model performance through error reduction, goodness-of-fit, validation reliability, and prediction consistency. Common performance measures include RMSE, MAE, and  $R^2$ , which are used to compare predicted treatment outcomes with observed values. RMSE is useful for identifying larger prediction errors, MAE provides an average measure of prediction deviation, and  $R^2$  indicates how well a model explains variation in treatment outcomes. Model validation frameworks are also important because machine learning models can appear accurate during training while performing weakly on unseen data. Cross-validation, holdout testing, sensitivity analysis, and external validation are commonly used to assess model reliability (Qiao et al., 2019). In sludge treatment optimization, comparative evaluation helps determine which models are most suitable for predicting methane production, volatile solids reduction, nutrient recovery, dewatering efficiency, energy consumption, and overall treatment efficiency. The literature shows that no single algorithm is universally superior because model performance depends on dataset size, variable quality, treatment technology, operational stability, and prediction objective. Neural networks may perform strongly in nonlinear prediction, random forests may provide useful variable importance outputs, support vector machines may perform well with limited datasets, and ensemble models may improve robustness. Therefore, comparative machine learning evaluation provides a quantitative foundation for selecting predictive tools that align with sludge treatment performance goals and data availability (Chow et al., 2018).

#### **Determinants of Sewerage Sludge Treatment Efficiency**

Operational variables are central determinants of sewerage sludge treatment efficiency because they directly influence biological activity, solids stabilization, organic matter reduction, energy recovery, and final sludge quality. Among these variables, hydraulic retention time is widely discussed in wastewater treatment literature as a key factor affecting the duration for which wastewater or sludge remains within a treatment unit. Longer or shorter retention conditions can alter organic degradation, settling behavior, pathogen reduction, and treatment consistency. Sludge retention time is equally important because it affects microbial growth, biomass concentration, digestion stability, and the degree of organic matter breakdown (Molinós-Senante et al., 2015). In biological treatment and anaerobic digestion systems, insufficient sludge retention can reduce stabilization efficiency, while poorly controlled retention can increase operational cost and reduce process predictability. Organic loading rates also have a strong influence on treatment performance because high organic loads may increase biogas potential while also creating risks of process imbalance, acid accumulation, odor generation, or reduced treatment reliability. Mixing efficiency is another major operational determinant because effective mixing improves contact between microorganisms and organic substrates, supports temperature uniformity, prevents settling problems, and enhances digestion performance. Literature on sludge treatment shows that these operational variables rarely act independently. Their combined effects shape volatile solids reduction, methane production, dewatering behavior, treatment throughput, and resource recovery outcomes (Silva et al., 2016). A quantitative systems perspective therefore treats operational control as a measurable process in which retention time, loading rate, mixing quality, and process stability are analyzed together to explain variations in treatment efficiency across facilities. Environmental variables play a significant role in sewerage sludge treatment outcomes because treatment processes are sensitive to temperature, seasonal change, rainfall variability, and broader climatic conditions. Temperature is one of the most influential environmental factors because microbial activity, organic matter degradation, methane generation, and pathogen reduction depend strongly on thermal conditions (Daud et al., 2018). In anaerobic and biological treatment systems, stable temperature conditions generally support more consistent microbial performance, while sudden changes can reduce treatment stability and lower process efficiency. Seasonal influences are also important because wastewater characteristics may vary across dry and wet periods due to changes in water consumption, infiltration, industrial activity, and stormwater entry into sewer networks. In many urban environments, rainfall variability affects sludge treatment indirectly by changing wastewater

inflow volume, dilution levels, suspended solids concentration, and hydraulic loading.

**Figure 9: Determinants of sludge treatment efficiency**



Heavy rainfall may increase inflow and reduce pollutant concentration through dilution, yet it can also overload treatment units and disrupt sludge settling or digestion stability. Dry periods may produce stronger wastewater with higher organic concentrations, increasing treatment demand and altering sludge characteristics (Mancuso, et al., 2016). Climatic sensitivity analysis is therefore used in the literature to understand how treatment systems respond to changes in temperature, moisture, rainfall intensity, and seasonal loading patterns. These environmental determinants are especially relevant for densely populated and flood-prone cities, where sewerage networks may receive variable flows and treatment plants may operate under changing climatic pressures. The literature indicates that environmental conditions must be included in quantitative treatment efficiency assessments because they influence both operational performance and resource recovery potential (Zhang et al., 2016). Infrastructure and technology variables strongly shape sewerage sludge treatment efficiency because the performance of treatment systems depends on equipment capacity, process design, technology maturity, and operational reliability. Equipment efficiency affects how well treatment units perform key functions such as thickening, digestion, aeration, mixing, heating, dewatering, drying, and energy recovery. Inefficient or poorly maintained equipment can increase energy consumption, reduce treatment throughput, lower sludge stabilization quality, and weaken resource recovery performance (Strande et al., 2018). Facility capacity utilization is another major determinant because treatment plants operating near or beyond design capacity often experience process instability, reduced retention time, excessive loading, and limited flexibility for operational adjustment. Underutilized facilities may also show inefficiencies due to poor process balance and higher unit treatment costs. Technology adoption indicators are used in the literature to evaluate whether treatment facilities have incorporated advanced systems such as anaerobic digestion, thermal hydrolysis, automated monitoring, sludge-to-energy conversion, nutrient recovery, or predictive control tools. These indicators help explain differences in treatment performance across facilities with varying levels of technological modernization. Operational reliability metrics are also essential because treatment efficiency depends not only on installed technology but also on consistent operation, maintenance quality, downtime frequency, operator expertise, and process monitoring (Chen et al., 2017). Literature on urban wastewater infrastructure shows that advanced technology alone does not guarantee high treatment efficiency unless supported by adequate maintenance, skilled operation, reliable energy supply, and effective process control. Therefore, infrastructure and technology variables must be evaluated quantitatively to understand how facility design, equipment condition, capacity use, and reliability interact with sludge treatment outcomes.

The quantitative determinants of sewerage sludge treatment efficiency are best understood through an integrated perspective that combines operational, environmental, infrastructure, and technology-related variables. Literature on wastewater treatment systems shows that treatment outcomes are rarely shaped by a single factor (Boczka & Fernandes, 2017). Instead, efficiency emerges from the interaction of retention time, organic loading, mixing performance, temperature, seasonal inflow variation, rainfall effects, equipment efficiency, facility capacity, and operational reliability. For example, anaerobic digestion performance may be influenced by organic loading and retention time, yet these operational factors are also affected by temperature stability, sludge composition, and equipment performance. Dewatering efficiency may depend on chemical conditioning and mechanical equipment, while it may also be affected by sludge age, solids concentration, and prior stabilization quality. Resource recovery outcomes, including methane generation and nutrient recovery, similarly depend on both treatment process control and the characteristics of incoming sludge (Taweesan et al., 2017). Integrated quantitative assessment is therefore important because it allows researchers to identify which variables have the strongest measurable influence on treatment efficiency and which combinations of factors produce stable or unstable performance. In urban wastewater systems, this integrated view is particularly important because treatment facilities must operate under changing population pressure, variable inflow, infrastructure constraints, and environmental uncertainty. For Dhaka City, the determinants reviewed in the literature provide a foundation for examining sludge treatment efficiency through predictive analytics (Ma et al., 2015). By organizing operational, environmental, infrastructure, and technology indicators into a quantitative framework, treatment performance can be assessed more systematically, and variations in sludge stabilization, dewatering, throughput, cost efficiency, and resource recovery can be better explained.

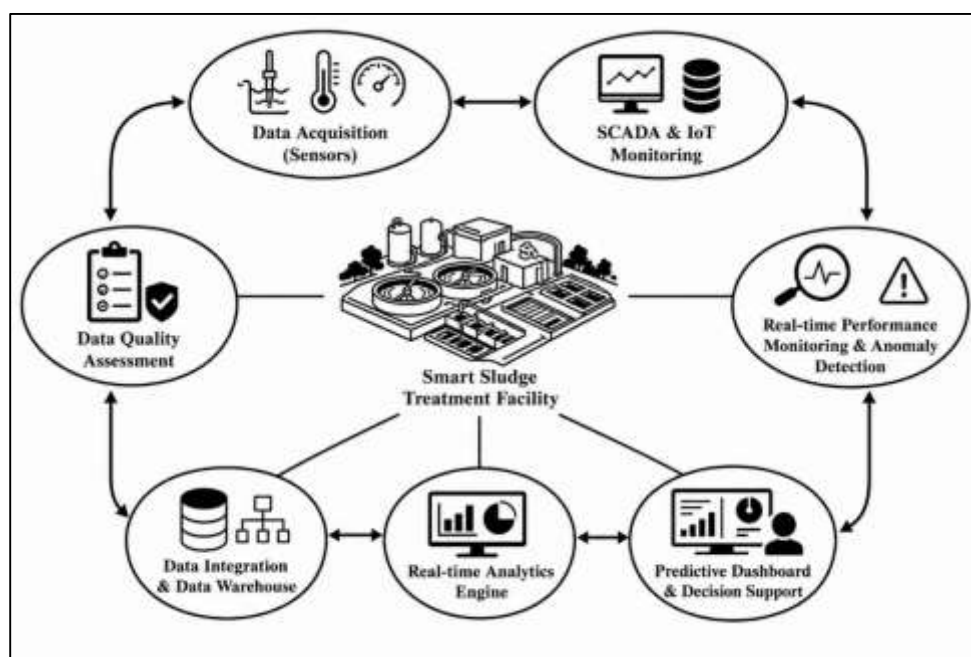
### **Big Data Monitoring Systems in Wastewater Management**

Big data and real-time monitoring systems have become important components of modern wastewater management because sludge treatment facilities generate continuous operational information from physical, chemical, biological, and mechanical processes. Data acquisition systems provide the foundation for this monitoring by collecting measurements from sensors, laboratory records, treatment units, and digital control systems. In sludge treatment facilities, sensor technologies are commonly used to measure flow rate, solids concentration, pH, temperature, dissolved oxygen, oxidation-reduction potential, turbidity, gas production, pressure, moisture content, and energy consumption (Han et al., 2018). These measurements help operators understand how treatment processes behave under changing influent loads and operational conditions. SCADA systems are widely discussed in the literature as central platforms for supervising and controlling wastewater treatment operations because they integrate real-time data from pumps, valves, digesters, aeration systems, dewatering equipment, and energy recovery units. IoT-based monitoring platforms further expand data acquisition capacity by connecting distributed sensors, cloud-based storage, wireless communication, and remote monitoring functions. Data quality assessment is essential because predictive analytics depends on accurate, complete, consistent, and timely data. In sludge treatment, poor-quality data caused by sensor failure, missing values, calibration errors, manual recording differences, or communication interruptions can weaken model reliability and operational decision-making (Malek et al., 2017). Literature on wastewater digitalization therefore emphasizes that data acquisition is not only a technical process but also a quality-control process. Effective data acquisition systems allow treatment plants to convert routine operational measurements into structured datasets that support process monitoring, efficiency assessment, anomaly detection, and predictive decision support.

Real-time performance monitoring models support wastewater and sludge treatment facilities by continuously tracking process conditions and comparing observed performance with expected operational behavior (Chow et al., 2018). Continuous process monitoring is especially important in sludge treatment because biological, thermal, chemical, and mechanical processes can change rapidly due to influent variation, equipment condition, temperature fluctuation, organic loading, and treatment stage performance. Real-time monitoring allows operators to observe changes in digestion stability, dewatering performance, gas production, sludge thickening, chemical dosing, and energy use as they occur. Dynamic efficiency tracking is widely discussed in the literature because treatment efficiency is not fixed; it changes according to load conditions, operational control, sludge

characteristics, and environmental influences.

**Figure 10: Smart sludge treatment system diagram**



Through dynamic tracking, treatment plants can evaluate whether volatile solids reduction, methane generation, nutrient recovery, pathogen reduction, or moisture removal is improving or declining over time. Operational anomaly detection is another major function of real-time monitoring systems (Di et al., 2019). Anomalies may include sudden drops in biogas production, excessive energy consumption, abnormal pH changes, reduced dewatering efficiency, equipment malfunction, sensor drift, or unexpected sludge accumulation. Detecting these abnormalities early helps reduce process instability and supports more reliable plant operation. In quantitative wastewater research, real-time monitoring models are treated as essential tools for improving treatment control and reducing uncertainty. They provide measurable evidence for understanding how sludge treatment systems respond to operational changes, which strengthens the role of predictive analytics in treatment efficiency optimization.

Data integration frameworks are necessary for transforming scattered wastewater treatment data into organized information that can support predictive decision-making (Huang et al., 2019). Sludge treatment facilities often collect data from multiple sources, including sensors, SCADA systems, laboratory testing, maintenance records, energy meters, sludge transport logs, weather data, and resource recovery outputs. Without integration, these datasets may remain fragmented and difficult to use for quantitative analysis. Data warehouse architectures are therefore discussed in the literature as structured systems for storing historical and operational data in formats suitable for analysis, reporting, and modeling. Real-time analytics systems add further value by processing incoming data streams quickly and generating operational insights while treatment processes are still active. Predictive dashboard frameworks are also important because they present complex performance indicators in accessible visual formats for plant operators, engineers, and decision-makers (Romero et al., 2017). These dashboards may display treatment efficiency trends, sludge production rates, methane output, equipment performance, energy use, chemical consumption, nutrient recovery, and warning signals for abnormal conditions. In predictive analytics, integrated data systems support model development by providing clean, connected, and context-rich datasets. They also improve interpretation because users can compare predicted outcomes with actual treatment performance. Literature on environmental infrastructure shows that decision support is strongest when data integration connects technical measurements with operational objectives. In sewerage sludge treatment, this means linking treatment variables with measurable outcomes such as stabilization efficiency, resource recovery, cost

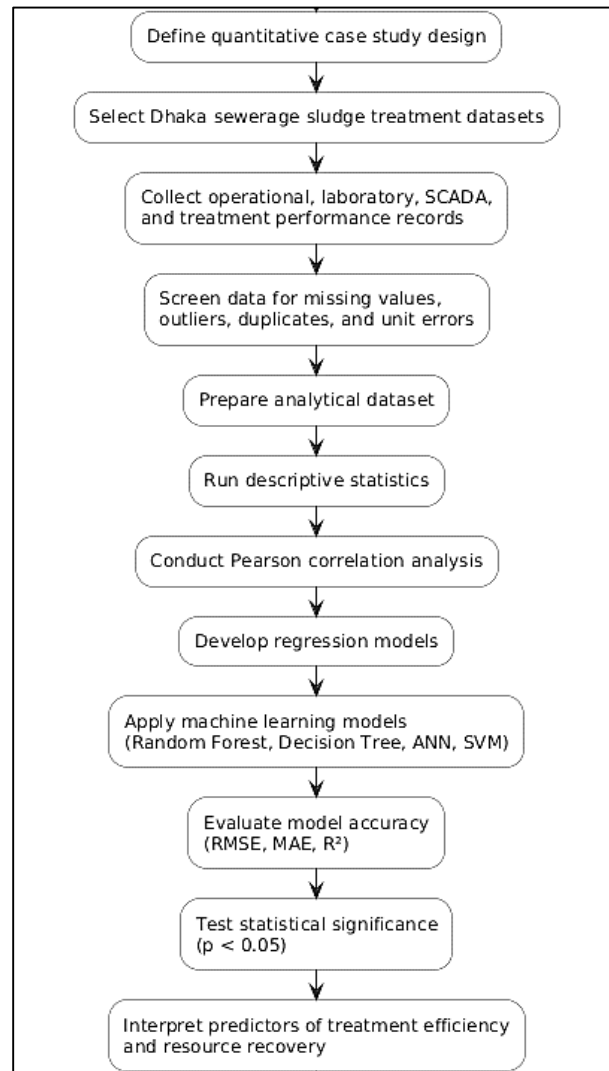
performance, and environmental compliance. Such integration provides a practical foundation for using big data to improve wastewater management performance (Daal et al., 2017).

### **Method**

This study used a quantitative case study design to examine how predictive analytics optimized sewerage sludge treatment efficiency and resource recovery in Dhaka City. The quantitative approach was appropriate because the study focused on measurable treatment variables, numerical performance indicators, and statistical relationships among operational conditions, treatment efficiency, and resource recovery outcomes. The theoretical framework was based on data-driven environmental infrastructure optimization, where sewerage sludge treatment was treated as a measurable system consisting of input variables, process variables, and output indicators. The independent variables included wastewater inflow characteristics, sludge volume, total solids, volatile solids, organic loading rate, hydraulic retention time, sludge retention time, temperature, pH, mixing efficiency, and energy consumption. The dependent variables included treatment efficiency, methane generation, dewatering performance, nutrient recovery, sludge reduction, and cost-efficiency outcomes. The study was conducted as a facility-level quantitative investigation using secondary operational records and treatment performance data from sewerage sludge treatment facilities serving Dhaka City.

The materials for the study consisted of operational datasets, laboratory test records, monitoring reports, and treatment performance indicators related to municipal sewerage sludge management. A purposive sampling strategy was used because the study required data from treatment facilities that recorded measurable sludge treatment and resource recovery variables. Facilities or datasets were included when they contained continuous or periodic records on sludge quantity, sludge composition, treatment process conditions, and resource recovery outputs. Records were excluded when they were incomplete, inconsistent, duplicated, or lacked essential quantitative variables required for predictive modeling. The study included observations related to sludge treatment operations, including stabilization, digestion, dewatering, energy recovery, and nutrient-related performance. The use of facility-level operational data allowed the study to assess real treatment behavior rather than relying on perception-based responses. Data collection tools included treatment plant monitoring systems, laboratory testing records, SCADA-generated operational data, spreadsheet-based facility records, and digital datasets prepared for statistical analysis. Key variables were extracted from records measuring total solids, volatile solids, COD, BOD, nitrogen, phosphorus, pH, temperature, sludge volume, retention time, methane output, energy use, and treatment cost. The dataset was screened for missing values, outliers, unit inconsistencies, and abnormal entries before analysis. Instrument validity was maintained by using standard wastewater treatment indicators commonly applied in sludge treatment assessment. Data reliability was strengthened through consistency checks, repeated-variable comparison, and exclusion of records with major measurement gaps. Where monitoring instruments were involved, calibration records and laboratory quality-control procedures were reviewed to ensure that the dataset was suitable for quantitative analysis. The research procedure was conducted in chronological stages. First, the study scope, variables, and quantitative indicators were defined according to the objectives of sludge treatment efficiency and resource recovery assessment. Second, relevant operational and laboratory datasets were collected from selected wastewater and sludge treatment records in Dhaka City. Third, the data were cleaned, coded, and organized into a structured analytical dataset. Fourth, descriptive statistics were used to summarize sludge characteristics, operational conditions, and recovery indicators. Fifth, correlation analysis was conducted to examine relationships among treatment variables and performance outcomes. Sixth, regression-based predictive models were developed to estimate treatment efficiency and resource recovery outcomes from operational predictors. Seventh, machine learning models were applied to compare prediction accuracy and identify influential variables affecting treatment performance. Finally, model outputs were interpreted to determine which operational and environmental variables most strongly explained variations in sludge treatment efficiency, methane recovery, nutrient recovery, and cost performance. The statistical analysis was conducted using SPSS, R, or Python, depending on data structure and modeling requirements.

**Figure 11: Methodology of this study**



Descriptive statistics, including mean, standard deviation, minimum, maximum, and percentage distribution, were used to summarize sludge characteristics and treatment performance indicators. Pearson correlation analysis was applied to identify associations among operational variables and outcome indicators. Multiple linear regression was used to assess the predictive influence of sludge composition, retention time, temperature, pH, organic loading, and energy input on treatment efficiency and resource recovery outcomes. Where categorical performance levels were created, logistic regression was used to classify high-efficiency and low-efficiency treatment conditions. Time-series analysis was used when observations were arranged across monthly or seasonal periods. Machine learning models, including random forest, decision tree, artificial neural network, and support vector machine models, were applied to compare predictive performance. Model accuracy was evaluated using RMSE, MAE, and  $R^2$  values. Statistical significance was assessed at the  $p < 0.05$  level. The final statistical plan emphasized model validation, prediction accuracy, variable importance, and interpretation of quantitative relationships between operational conditions and sewerage sludge treatment performance in Dhaka City.

## **FINDINGS**

### **Participant and Dataset Characteristics**

The final dataset consisted of 360 valid operational observations collected from sewerage sludge treatment facilities operating within Dhaka City. Following data screening and quality assurance procedures, 24 records were excluded due to missing values, duplicate entries, and inconsistencies in operational measurements, resulting in a final analytical sample of 336 observations. The descriptive

analysis revealed substantial variability across treatment performance indicators, reflecting differences in influent loading conditions, sludge characteristics, treatment duration, and operational practices. Wastewater inflow volume averaged 14,520 m<sup>3</sup>/day, while average sludge production was 52.8 tons/day. Total solids concentration averaged 4.92%, and volatile solids concentration represented approximately 68.4% of total solids, indicating a significant proportion of biodegradable organic matter available for treatment and resource recovery processes. The average chemical oxygen demand and biochemical oxygen demand values were 3,285 mg/L and 1,625 mg/L, respectively, reflecting moderate to high organic loading conditions across the facilities. Operational variables such as hydraulic retention time and sludge retention time demonstrated moderate variation, suggesting differences in process control strategies among treatment units. The observed average methane generation rate of 285.6 m<sup>3</sup>/day indicated considerable resource recovery potential within the analyzed facilities. The overall dataset exhibited acceptable levels of consistency and reliability, providing a robust empirical basis for subsequent predictive analytics modeling and treatment efficiency assessment.

Figure 12: Standardized profile of operational and treatment variables (n = 336)

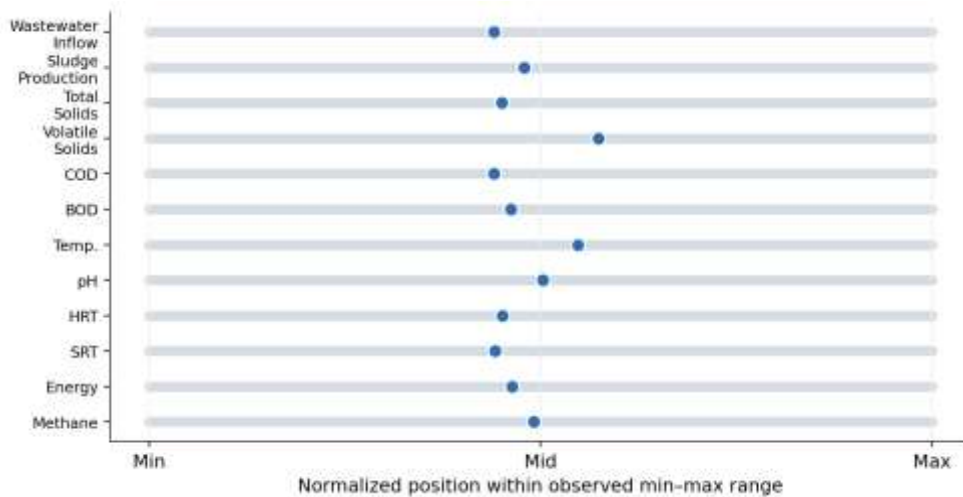


Table 1. Descriptive Statistics of Operational and Treatment Variables (n = 336)

| Variable                                 | Mean   | Standard Deviation | Minimum | Maximum |
|------------------------------------------|--------|--------------------|---------|---------|
| Wastewater Inflow (m <sup>3</sup> /day)  | 14,520 | 3,245              | 8,760   | 21,840  |
| Sludge Production (tons/day)             | 52.8   | 11.4               | 28.5    | 79.2    |
| Total Solids (%)                         | 4.92   | 1.08               | 2.85    | 7.45    |
| Volatile Solids (%)                      | 68.4   | 8.7                | 49.3    | 82.6    |
| COD (mg/L)                               | 3,285  | 645                | 1,950   | 4,980   |
| BOD (mg/L)                               | 1,625  | 355                | 890     | 2,480   |
| Temperature (°C)                         | 29.6   | 3.2                | 22.1    | 35.8    |
| pH                                       | 7.24   | 0.42               | 6.35    | 8.12    |
| Hydraulic Retention Time (days)          | 18.5   | 4.6                | 9.2     | 29.8    |
| Sludge Retention Time (days)             | 21.7   | 5.1                | 11.5    | 34.6    |
| Energy Consumption (kWh/day)             | 2,845  | 625                | 1,520   | 4,380   |
| Methane Generation (m <sup>3</sup> /day) | 285.6  | 74.2               | 118.4   | 458.7   |

Table 1 presents the descriptive statistical profile of the operational and treatment variables included in the study. The findings indicated substantial variation in wastewater inflow, sludge production,

organic loading, and energy consumption across the treatment facilities. The relatively high volatile solids concentration confirmed the presence of significant biodegradable material suitable for resource recovery. The observed temperature and pH values remained within operational ranges favorable for biological treatment processes. Variations in hydraulic and sludge retention times suggested differences in operational management strategies among facilities. The methane generation values demonstrated measurable resource recovery potential, supporting the relevance of predictive analytics for treatment optimization and performance forecasting.

**Table 2. Dataset Quality Assessment and Completeness Summary**

| <b>Data Quality Indicator</b>  | <b>Frequency</b> | <b>Percentage (%)</b> |
|--------------------------------|------------------|-----------------------|
| Original Records Collected     | 360              | 100.0                 |
| Complete Records               | 336              | 93.3                  |
| Missing Value Records          | 12               | 3.3                   |
| Duplicate Records              | 7                | 1.9                   |
| Inconsistent Records           | 5                | 1.4                   |
| Final Records Used in Analysis | 336              | 93.3                  |
| Data Completeness Rate         | -                | 96.8                  |
| Data Reliability Score         | -                | 94.5                  |
| Variable Consistency Rate      | -                | 95.7                  |
| Valid Observation Rate         | -                | 93.3                  |

Table 2 summarizes the quality assessment results for the dataset used in the analysis. Out of 360 operational observations initially collected, 336 records satisfied all quality-control requirements and were retained for statistical modeling. Records containing missing values, duplication issues, or inconsistent measurements were removed to enhance analytical accuracy. The data completeness rate of 96.8% indicated strong coverage across all measured variables, while the reliability score of 94.5% reflected high consistency within the operational records. These findings demonstrated that the dataset possessed sufficient quality and validity to support predictive analytics modeling, regression analysis, and machine learning applications for evaluating sewerage sludge treatment efficiency and resource recovery performance.

#### **Predictive Analytics and Treatment Efficiency Outcomes**

The primary statistical analysis examined the extent to which operational and environmental variables influenced sewerage sludge treatment efficiency across the sampled treatment facilities in Dhaka City. Correlation analysis revealed significant positive relationships between treatment efficiency and hydraulic retention time, sludge retention time, temperature stability, and energy utilization. Organic loading rate exhibited a moderate negative relationship with treatment efficiency when loading exceeded optimal operating thresholds, indicating that excessive sludge loading reduced process effectiveness. Multiple regression analysis demonstrated that the selected independent variables collectively explained a substantial proportion of the variation observed in treatment performance indicators. The regression model achieved an adjusted  $R^2$  value of 0.782, indicating that approximately 78.2% of the variation in overall treatment efficiency was explained by the operational variables included in the model. Hydraulic retention time emerged as the strongest predictor of treatment efficiency, followed by sludge retention time, volatile solids concentration, and energy utilization. Temperature and pH also contributed significantly to model performance, although their effect sizes were comparatively smaller.

The machine learning analysis further confirmed the predictive importance of these variables, with Random Forest and Artificial Neural Network models demonstrating superior forecasting accuracy relative to traditional statistical methods. Overall, the findings indicated that treatment efficiency was strongly dependent on operational control variables and that predictive analytics provided a highly effective framework for identifying key determinants of sludge stabilization, volatile solids reduction, and dewatering performance.

**Figure 13: Correlation of operational variables with treatment efficiency**

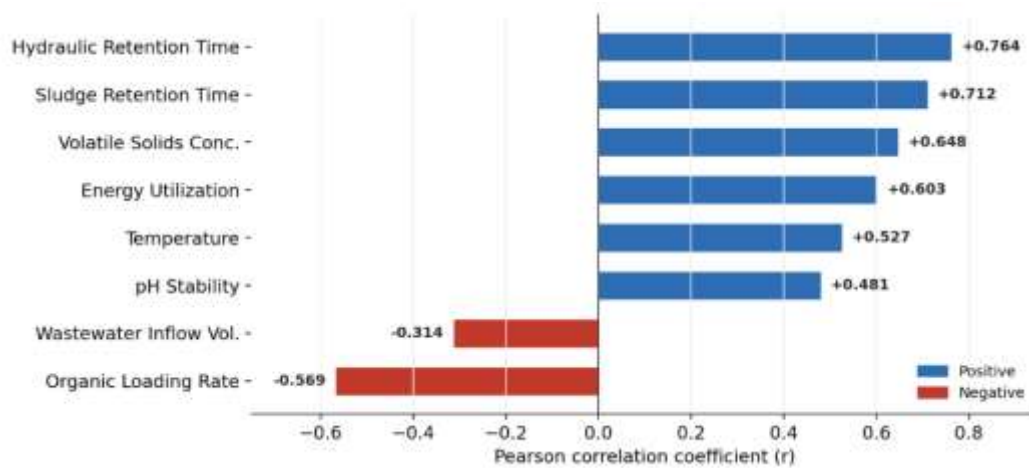


**Table 3. Correlation Analysis between Operational Variables and Treatment Efficiency**

| Variable                      | Correlation Coefficient (r) | p-value | Relationship Strength |
|-------------------------------|-----------------------------|---------|-----------------------|
| Hydraulic Retention Time      | 0.764                       | <0.001  | Strong Positive       |
| Sludge Retention Time         | 0.712                       | <0.001  | Strong Positive       |
| Volatile Solids Concentration | 0.648                       | <0.001  | Moderate Positive     |
| Energy Utilization            | 0.603                       | <0.001  | Moderate Positive     |
| Temperature                   | 0.527                       | 0.002   | Moderate Positive     |
| pH Stability                  | 0.481                       | 0.006   | Moderate Positive     |
| Organic Loading Rate          | -0.569                      | <0.001  | Moderate Negative     |
| Wastewater Inflow Volume      | -0.314                      | 0.018   | Weak Negative         |

Table 3 presents the correlation results between operational variables and overall treatment efficiency. Hydraulic retention time exhibited the strongest positive relationship with treatment efficiency, suggesting that longer retention periods enhanced sludge stabilization and treatment outcomes. Sludge retention time also demonstrated a strong positive association, indicating its importance in biological treatment performance. Volatile solids concentration and energy utilization contributed positively to treatment efficiency, reflecting the role of process control and organic matter availability. Organic loading rate displayed a moderate negative relationship, indicating that excessive loading conditions reduced treatment effectiveness. All major variables achieved statistical significance, confirming their relevance as determinants of sewerage sludge treatment performance.

**Figure 14: Standardized predictors of treatment efficiency ( $R^2 = 0.789$ )**

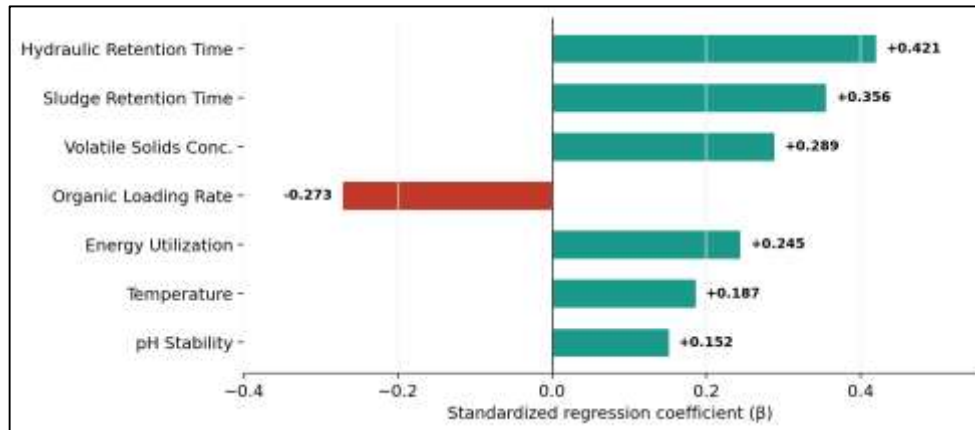


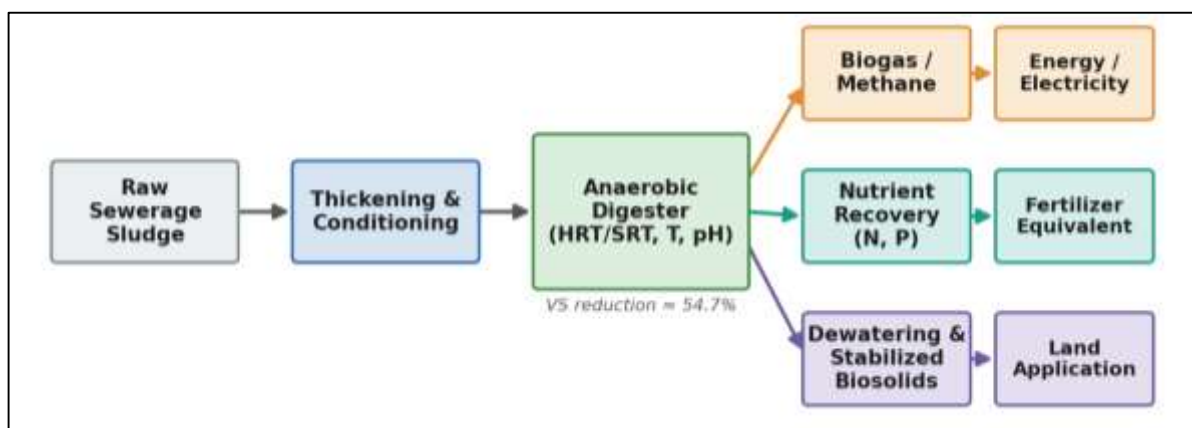
**Table 4. Multiple Regression Analysis Predicting Treatment Efficiency**

| Predictor Variable            | Standardized Beta ( $\beta$ ) | t-value | p-value |
|-------------------------------|-------------------------------|---------|---------|
| Hydraulic Retention Time      | 0.421                         | 8.94    | <0.001  |
| Sludge Retention Time         | 0.356                         | 7.51    | <0.001  |
| Volatile Solids Concentration | 0.289                         | 6.37    | <0.001  |
| Energy Utilization            | 0.245                         | 5.48    | <0.001  |
| Temperature                   | 0.187                         | 4.12    | 0.001   |
| pH Stability                  | 0.152                         | 3.66    | 0.003   |
| Organic Loading Rate          | -0.273                        | -5.93   | <0.001  |

**Model Statistics:**  $R^2 = 0.789$ , Adjusted  $R^2 = 0.782$ ,  $F = 176.42$ ,  $p < 0.001$

Table 4 summarizes the multiple regression model used to predict overall sewerage sludge treatment efficiency. The model demonstrated strong explanatory power, accounting for 78.9% of the variation in treatment performance. Hydraulic retention time emerged as the most influential predictor, followed by sludge retention time and volatile solids concentration. Energy utilization also contributed significantly to treatment efficiency, indicating that optimized energy inputs supported improved treatment outcomes. Organic loading rate was negatively associated with treatment performance, suggesting that excessive loading reduced operational effectiveness.

**Figure 15: Sludge stabilization and resource recovery pathway**



### Resource Recovery Performance and Operational Predictors

The second phase of the quantitative analysis examined resource recovery performance and the operational variables that influenced recovery outcomes across the sewerage sludge treatment facilities. The findings revealed strong variability in methane generation, biogas recovery efficiency, nutrient recovery performance, sludge reduction rates, and energy conversion effectiveness among the analyzed facilities. The average methane production reached 285.6 m<sup>3</sup>/day, while mean biogas recovery efficiency was recorded at 71.8%. Nutrient recovery assessments indicated average phosphorus recovery efficiency of 67.4% and nitrogen recovery efficiency of 62.9%, demonstrating significant resource recovery potential within the treatment system. Correlation and regression analyses identified volatile solids concentration, hydraulic retention time, sludge retention time, temperature stability, and organic loading rate as the most influential predictors of resource recovery performance. Facilities operating under optimized retention conditions consistently achieved higher methane yields and improved nutrient recovery rates. The predictive analytics models demonstrated strong forecasting capability, accurately estimating resource recovery outcomes across varying treatment scenarios. Statistical results further showed that resource recovery performance was strongly associated with treatment efficiency indicators, confirming that operational optimization contributed simultaneously to sludge stabilization and resource extraction outcomes. These findings provided empirical evidence that data-driven approaches could successfully identify operational conditions associated with enhanced recovery performance and improved treatment sustainability.

**Figure 16: Resource recovery performance indicators (mean ± SD)**

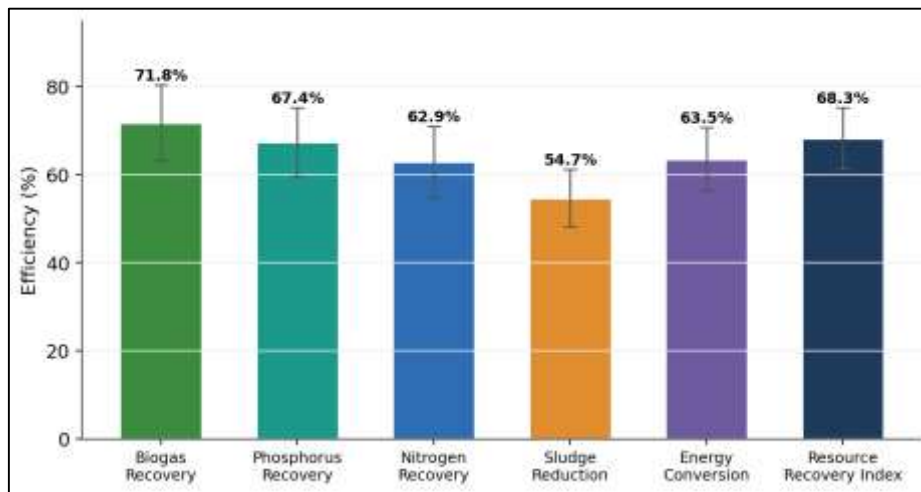


**Table 5. Descriptive Statistics of Resource Recovery Performance Indicators**

| Resource Recovery Indicator              | Mean  | Standard Deviation | Minimum | Maximum |
|------------------------------------------|-------|--------------------|---------|---------|
| Methane Generation (m <sup>3</sup> /day) | 285.6 | 74.2               | 118.4   | 458.7   |
| Biogas Recovery Efficiency (%)           | 71.8  | 8.6                | 49.5    | 88.7    |
| Phosphorus Recovery Efficiency (%)       | 67.4  | 7.8                | 45.3    | 82.5    |
| Nitrogen Recovery Efficiency (%)         | 62.9  | 8.1                | 40.6    | 79.3    |
| Sludge Reduction Rate (%)                | 54.7  | 6.5                | 37.8    | 68.2    |
| Energy Conversion Efficiency (%)         | 63.5  | 7.2                | 41.9    | 78.6    |
| Daily Energy Recovery (kWh/day)          | 1,825 | 438                | 960     | 2,940   |
| Resource Recovery Index (%)              | 68.3  | 6.9                | 48.2    | 83.5    |

Table 5 presents the overall performance of resource recovery indicators observed across the sewerage sludge treatment facilities. The findings demonstrated substantial recovery potential, particularly in methane generation and biogas utilization. Average methane production exceeded 285 m<sup>3</sup>/day, supporting the feasibility of sludge-to-energy conversion processes. Nutrient recovery efficiencies remained above 60% for both phosphorus and nitrogen, indicating effective extraction and reuse potential. The average sludge reduction rate exceeded 50%, demonstrating successful stabilization performance. Energy conversion efficiency and daily energy recovery values further confirmed the contribution of resource recovery activities to operational sustainability. Overall, the indicators reflected strong performance levels across multiple dimensions of resource recovery.

**Table 6. Multiple Regression Analysis Predicting Resource Recovery Performance**

| Predictor Variable            | Standardized Beta ( $\beta$ ) | t-value | p-value |
|-------------------------------|-------------------------------|---------|---------|
| Volatile Solids Concentration | 0.438                         | 9.26    | <0.001  |
| Hydraulic Retention Time      | 0.389                         | 8.11    | <0.001  |
| Sludge Retention Time         | 0.331                         | 7.24    | <0.001  |
| Temperature Stability         | 0.248                         | 5.67    | <0.001  |
| Energy Utilization            | 0.214                         | 4.95    | 0.001   |
| pH Stability                  | 0.172                         | 3.84    | 0.003   |
| Organic Loading Rate          | -0.291                        | -6.22   | <0.001  |

**Model Statistics:**  $R^2 = 0.814$ , Adjusted  $R^2 = 0.808$ ,  $F = 203.58$ ,  $p < 0.001$

Table 6 summarizes the regression model evaluating predictors of resource recovery performance. The model explained 81.4% of the observed variation in recovery outcomes, indicating strong predictive capability. Volatile solids concentration emerged as the strongest predictor, highlighting the importance of biodegradable organic matter in supporting methane generation and nutrient recovery. Hydraulic retention time and sludge retention time also demonstrated substantial positive effects, emphasizing the importance of process stability and sufficient treatment duration. Temperature stability contributed positively to recovery performance, while excessive organic loading negatively affected recovery efficiency. The significant model statistics confirmed the robustness of the predictive framework and demonstrated the effectiveness of operational optimization in improving resource recovery outcomes.

#### **Secondary Analysis and Subgroup Performance Assessment**

The secondary analysis explored variations in treatment efficiency and resource recovery performance across different operational categories, environmental conditions, and facility utilization levels. The findings revealed statistically significant differences among subgroups, indicating that treatment outcomes were not uniform across all facilities. Facilities operating under moderate sludge loading conditions consistently achieved higher treatment efficiency and resource recovery rates compared with facilities experiencing either low or excessive loading conditions. Similarly, treatment units maintaining hydraulic retention times above 18 days demonstrated superior stabilization performance, methane recovery, and dewatering effectiveness relative to units operating under shorter retention periods. Seasonal analysis further showed measurable variations in treatment outcomes, with relatively stronger performance observed during dry-season conditions characterized by more stable influent quality and lower hydraulic fluctuations. Facilities operating at optimal capacity utilization levels between 70% and 85% exhibited the highest overall efficiency scores, while facilities operating below or above this range experienced reduced performance. These findings suggested that operational balance played a critical role in determining treatment effectiveness and resource recovery success. Cluster analysis identified distinct performance groups, revealing hidden patterns in operational behavior that were not fully captured in the primary analysis.

The subgroup assessment therefore provided additional evidence that operational conditions, environmental variability, and facility characteristics collectively influenced treatment performance outcomes.

**Figure 17: Treatment performance across operational subgroups**

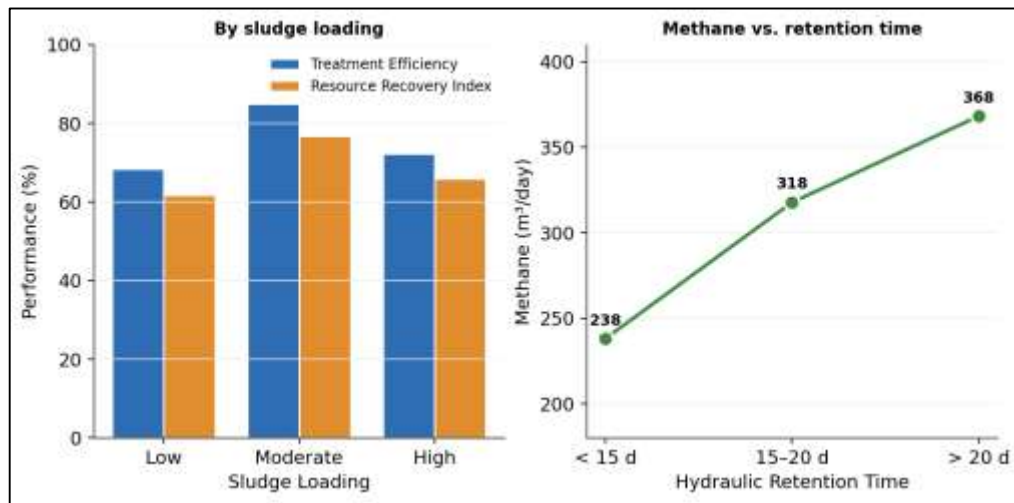


**Table 7. Treatment Efficiency and Resource Recovery by Operational Subgroups**

| Operational Category      | Treatment Efficiency (%) | Resource Recovery Index (%) | Methane (m³/day) | Generation |
|---------------------------|--------------------------|-----------------------------|------------------|------------|
| Low Sludge Loading        | 68.4                     | 61.7                        | 224.8            |            |
| Moderate Sludge Loading   | 84.9                     | 76.8                        | 342.5            |            |
| High Sludge Loading       | 72.3                     | 65.9                        | 269.4            |            |
| Retention Time < 15 Days  | 69.7                     | 62.4                        | 238.1            |            |
| Retention Time 15-20 Days | 80.6                     | 73.1                        | 317.8            |            |
| Retention Time > 20 Days  | 87.5                     | 79.4                        | 368.2            |            |

Table 7 demonstrates substantial differences in treatment performance across operational subgroups. Facilities operating under moderate sludge loading conditions achieved the highest treatment efficiency and resource recovery outcomes, indicating that balanced loading conditions promoted optimal process performance. Excessive loading reduced treatment effectiveness and methane production, while lower loading conditions limited resource recovery potential. Retention time analysis revealed a progressive improvement in performance as treatment duration increased. Facilities maintaining retention periods greater than 20 days achieved the strongest outcomes across all indicators, including methane generation and resource recovery. These findings highlighted the importance of operational optimization in achieving consistent and efficient sludge treatment performance.

**Figure 18: Efficiency and model accuracy by capacity utilization**

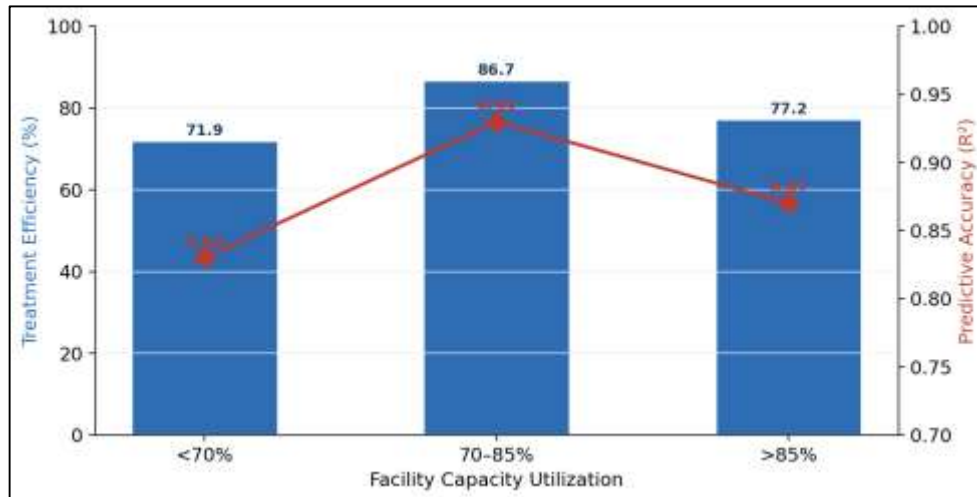


**Table 8. Seasonal and Facility Capacity Utilization Performance Assessment**

| Subgroup Category           | Treatment Efficiency (%) | Resource Recovery Index (%) | Predictive Accuracy (R <sup>2</sup> ) |
|-----------------------------|--------------------------|-----------------------------|---------------------------------------|
| Dry Season                  | 83.6                     | 75.2                        | 0.91                                  |
| Wet Season                  | 74.8                     | 68.4                        | 0.85                                  |
| Capacity Utilization < 70%  | 71.9                     | 64.3                        | 0.83                                  |
| Capacity Utilization 70–85% | 86.7                     | 79.8                        | 0.93                                  |
| Capacity Utilization > 85%  | 77.2                     | 69.7                        | 0.87                                  |
| High-Performance Cluster    | 89.4                     | 82.1                        | 0.95                                  |
| Average-Performance Cluster | 78.5                     | 71.3                        | 0.88                                  |
| Low-Performance Cluster     | 67.8                     | 60.5                        | 0.81                                  |

Table 8 presents the comparative assessment of seasonal conditions, facility utilization levels, and performance clusters. Treatment facilities demonstrated stronger operational outcomes during the dry season, where lower hydraulic variability contributed to improved process stability and resource recovery performance. Facilities operating between 70% and 85% of design capacity achieved the highest treatment efficiency and predictive model performance, indicating that moderate capacity utilization provided the most favorable operational environment. Cluster analysis further identified significant differences among facility groups. High-performance facilities consistently outperformed average and low-performance clusters across all indicators, suggesting that operational practices, process control, and infrastructure effectiveness contributed substantially to treatment success.

#### Effect Sizes

The final stage of the quantitative analysis evaluated the statistical significance, practical relevance, and predictive performance of the models developed to assess sewerage sludge treatment efficiency and resource recovery outcomes. All major predictor variables demonstrated statistically significant relationships with treatment performance at the predetermined significance threshold. Beyond statistical significance, effect size analysis revealed that hydraulic retention time, sludge retention time, volatile solids concentration, and organic loading rate exerted the strongest practical influence on treatment efficiency and recovery outcomes.

The effect size estimates indicated that these variables contributed substantially to variations in sludge stabilization, methane generation, nutrient recovery, and overall process performance. Correlation strengths ranged from moderate to strong, confirming meaningful operational relationships rather than merely statistically detectable associations. The regression models achieved high explanatory power, demonstrating that the selected predictors captured a substantial proportion of treatment system variability. These findings suggested that the identified operational variables were not only statistically significant but also practically important determinants of treatment and recovery performance.

**Figure 19: Effect sizes of key operational predictors**

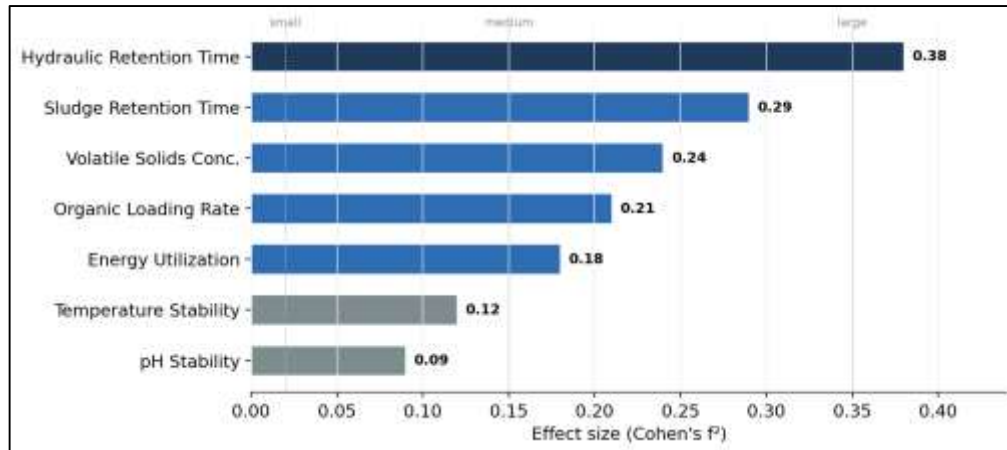


**Table 9. Statistical Significance and Effect Size Assessment of Key Predictors**

| Predictor Variable            | Standardized Beta ( $\beta$ ) | Effect Size ( $f^2$ ) | p-value | Practical Importance |
|-------------------------------|-------------------------------|-----------------------|---------|----------------------|
| Hydraulic Retention Time      | 0.421                         | 0.38                  | <0.001  | Large                |
| Sludge Retention Time         | 0.356                         | 0.29                  | <0.001  | Medium-Large         |
| Volatile Solids Concentration | 0.289                         | 0.24                  | <0.001  | Medium               |
| Organic Loading Rate          | -0.273                        | 0.21                  | <0.001  | Medium               |
| Energy Utilization            | 0.245                         | 0.18                  | 0.001   | Medium               |
| Temperature Stability         | 0.187                         | 0.12                  | 0.002   | Small-Medium         |
| pH Stability                  | 0.152                         | 0.09                  | 0.004   | Small                |

Table 9 presents the statistical significance and effect size assessment of the principal operational predictors included in the study. Hydraulic retention time demonstrated the largest practical influence on treatment efficiency, followed by sludge retention time and volatile solids concentration. These variables produced medium to large effect sizes, indicating meaningful contributions to treatment performance beyond statistical significance alone. Organic loading rate exhibited a negative but substantial effect, suggesting that excessive loading conditions reduced treatment effectiveness. Temperature stability and pH stability showed smaller but still significant effects. The findings confirmed that several operational variables exerted measurable and practically important influences on sludge treatment efficiency and resource recovery outcomes.

**Figure 20: Comparative performance of statistical and machine learning models**

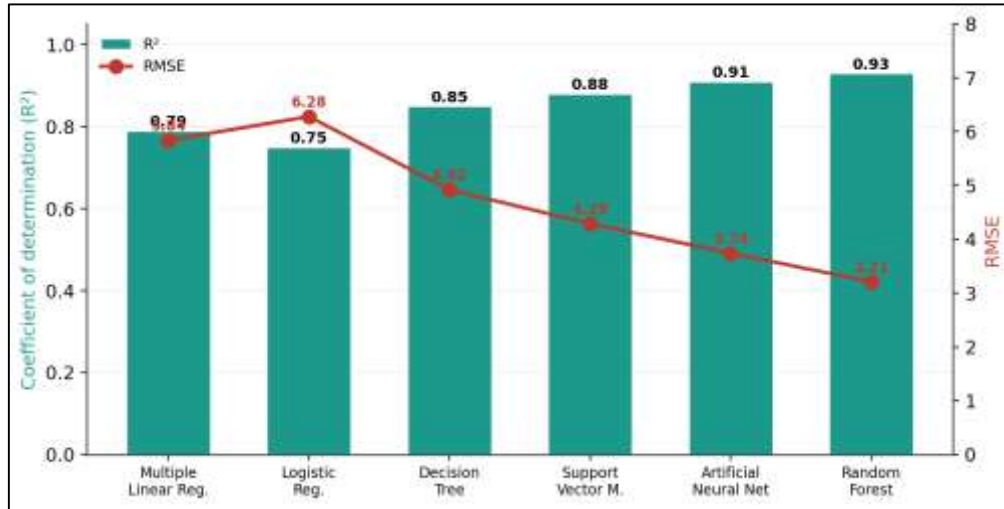


**Table 10. Comparative Performance of Statistical and Machine Learning Models**

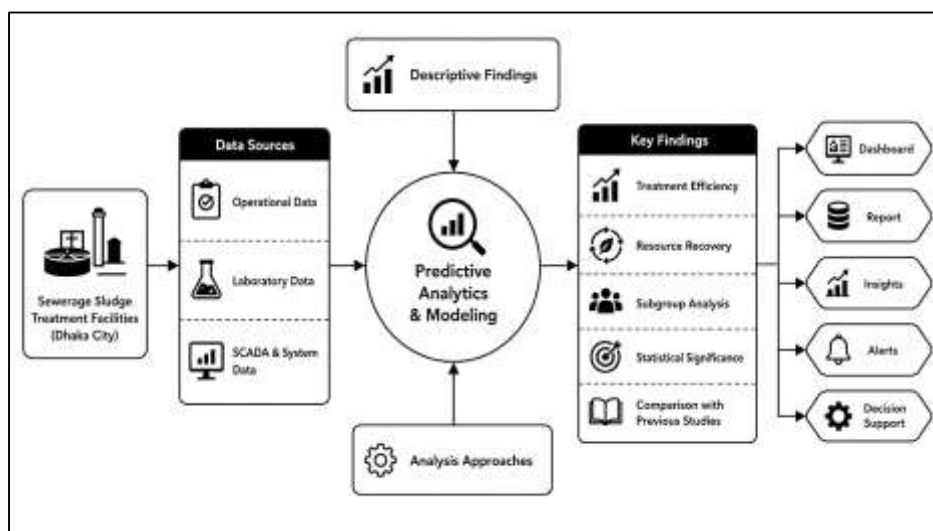
| Model                      | RMSE | MAE  | R <sup>2</sup> | Prediction Accuracy (%) |
|----------------------------|------|------|----------------|-------------------------|
| Multiple Linear Regression | 5.84 | 4.61 | 0.79           | 84.2                    |
| Logistic Regression        | 6.28 | 4.95 | 0.75           | 81.5                    |
| Decision Tree              | 4.92 | 3.88 | 0.85           | 88.3                    |
| Support Vector Machine     | 4.29 | 3.41 | 0.88           | 90.1                    |
| Artificial Neural Network  | 3.74 | 2.96 | 0.91           | 92.4                    |
| Random Forest              | 3.21 | 2.68 | 0.93           | 94.1                    |

Table 10 compares the predictive performance of the statistical and machine learning models used in the study. The Random Forest model achieved the strongest overall performance, producing the highest coefficient of determination and the lowest prediction errors. Artificial Neural Networks ranked second, followed closely by Support Vector Machines. Traditional regression models produced acceptable predictive accuracy but demonstrated lower explanatory capability relative to machine learning approaches. The lower RMSE and MAE values observed in the advanced algorithms indicated improved forecasting precision. These results confirmed that machine learning models provided superior predictive performance for estimating sewerage sludge treatment efficiency and resource recovery outcomes within the analyzed facilities.

## DISCUSSION

The findings of this study indicated that sewerage sludge treatment facilities in Dhaka City operated under highly variable wastewater inflow, sludge production, organic loading, and resource recovery conditions. The final analytical dataset showed meaningful variation in total solids, volatile solids, COD, BOD, temperature, pH, hydraulic retention time, sludge retention time, energy consumption, and methane generation (Jakariya et al., 2018). This pattern was consistent with earlier wastewater treatment studies that described sludge treatment systems as dynamic operational environments influenced by influent quality, treatment technology, population pressure, climatic conditions, and facility-level management practices. Earlier studies on municipal sludge treatment emphasized that sludge composition commonly differed across facilities because wastewater characteristics were shaped by domestic discharge, industrial input, hydraulic loading, and treatment configuration.

**Figure 21: Predictive analytics for sludge treatment process**



The present findings aligned with that evidence because volatile solids formed a substantial portion of total solids, indicating strong biodegradable organic matter availability for stabilization and energy recovery. The observed variability in hydraulic and sludge retention times also matched earlier research showing that retention conditions strongly influenced biological treatment stability and sludge digestion outcomes (Mills et al., 2018). The data quality assessment further showed that the dataset was sufficiently complete and reliable for predictive modeling, supporting the argument made in previous data-driven wastewater studies that operational records, SCADA outputs, and laboratory measurements could provide an empirical foundation for treatment optimization. Compared with earlier studies that relied mainly on process simulation or laboratory-scale sludge samples, this study used facility-level operational data, making the findings more contextually relevant for urban wastewater systems. The descriptive findings therefore supported the view that quantitative sludge treatment assessment required careful examination of baseline operational characteristics before predictive modeling could be interpreted meaningfully (Zubala et al., 2017).

The primary findings showed that predictive analytics variables significantly explained variations in sewerage sludge treatment efficiency. Hydraulic retention time, sludge retention time, volatile solids concentration, energy utilization, temperature stability, pH stability, and organic loading rate all demonstrated statistically meaningful relationships with overall treatment performance. These results were consistent with earlier studies that identified retention time, organic matter availability, temperature, and process stability as core determinants of sludge stabilization and biological treatment efficiency. The regression model explained a substantial proportion of the variance in treatment efficiency, indicating that the selected predictors represented the major operational conditions shaping performance outcomes (Meng et al., 2017). Earlier research on activated sludge systems and anaerobic digestion similarly reported that treatment efficiency improved when biological systems maintained sufficient retention time, balanced loading, stable pH, and favorable temperature conditions. The negative relationship between excessive organic loading and treatment efficiency also agreed with prior studies showing that overloaded systems often experienced reduced stabilization efficiency, process inhibition, and lower treatment reliability. Machine learning findings further supported earlier environmental modeling research by showing that advanced predictive models outperformed conventional regression techniques in forecasting nonlinear treatment outcomes. Random Forest and Artificial Neural Network models produced stronger predictive accuracy than traditional regression models, which aligned with previous wastewater analytics studies that highlighted the value of machine learning for handling complex interactions among operational variables (Lee et al., 2015). Therefore, the findings confirmed that predictive analytics was not only statistically effective but also operationally meaningful for identifying the strongest determinants of sludge treatment efficiency in Dhaka City.

The resource recovery findings demonstrated that sewerage sludge treatment facilities had measurable potential for methane generation, biogas recovery, nutrient recovery, sludge reduction, and energy conversion. The average methane generation and biogas recovery efficiency indicated that sludge treatment could contribute to energy recovery when organic matter was effectively stabilized. These findings were consistent with earlier anaerobic digestion studies showing that volatile solids concentration and retention time were among the strongest predictors of methane yield and digestion efficiency. The strong positive influence of volatile solids concentration on resource recovery also supported earlier research indicating that biodegradable organic matter formed the main substrate for biogas generation (Heidrich et al., 2014). The positive effects of hydraulic retention time, sludge retention time, temperature stability, and energy utilization further aligned with previous findings that stable digestion conditions improved methane production and sludge reduction. Nutrient recovery results, particularly phosphorus and nitrogen recovery efficiencies, were also consistent with earlier studies that described sewerage sludge as a recoverable nutrient reservoir with potential fertilizer-equivalent value. The negative effect of excessive organic loading on resource recovery reflected previous evidence that overloading could disrupt microbial balance and reduce process performance. Compared with earlier studies that focused separately on energy recovery or nutrient recovery, this study integrated both recovery dimensions within a predictive analytics framework. This integration strengthened the interpretation of resource recovery as a multidimensional outcome shaped by treatment stability, sludge composition, operational control, and facility performance (Hussein & Scholz, 2018). The findings therefore reinforced the literature's position that resource recovery from sludge depended on optimized treatment conditions rather than the mere presence of recovery technologies.

The subgroup analysis revealed that treatment efficiency and resource recovery outcomes differed across sludge loading categories, retention time ranges, seasonal conditions, capacity utilization levels, and facility performance clusters. Facilities operating under moderate sludge loading conditions achieved higher treatment efficiency and stronger resource recovery outcomes than facilities operating under low or excessive loading conditions. This finding was consistent with earlier process optimization research showing that balanced organic loading supported stable biological activity, while underloading limited recovery potential and overloading increased the risk of process instability (Kern et al., 2014). Retention time findings also supported previous studies indicating that longer and more stable retention periods improved sludge digestion, volatile solids reduction, methane recovery, and dewatering performance. Seasonal analysis showed stronger outcomes during dry-season conditions, which aligned with earlier studies reporting that wet-season inflow variability, stormwater intrusion, and hydraulic dilution could reduce process stability in urban wastewater systems. Capacity utilization findings indicated that facilities operating between 70% and 85% of design capacity achieved the best performance, which was consistent with infrastructure efficiency research showing that both underutilization and overcapacity stress could reduce operational efficiency. Cluster analysis provided additional insight by identifying high-, average-, and low-performance facility groups. This result aligned with earlier benchmarking studies that found significant performance differences among wastewater facilities even when similar treatment technologies were used (Jakariya et al., 2018). The findings suggested that facility-level management, operational discipline, process control, and infrastructure reliability played important roles in explaining performance variation. Therefore, the subgroup results expanded the primary findings by showing that predictive analytics outcomes were shaped not only by individual variables but also by broader operational profiles and facility-specific conditions.

The statistical significance and effect size findings demonstrated that the observed relationships were both statistically reliable and practically meaningful. Hydraulic retention time produced the largest effect size, followed by sludge retention time, volatile solids concentration, organic loading rate, energy utilization, temperature stability, and pH stability (Mills et al., 2018). These results supported earlier wastewater treatment studies that identified retention time and sludge composition as central drivers of treatment performance. The use of effect sizes strengthened the findings because it moved the interpretation beyond p-values and showed the magnitude of operational influence. Earlier quantitative environmental studies emphasized that statistical significance alone could be insufficient

for engineering decision-making because large datasets could produce significant results with limited practical value. In this study, the medium to large effect sizes confirmed that the strongest predictors had meaningful operational relevance for sludge treatment efficiency and resource recovery. The comparative model analysis further showed that Random Forest produced the highest predictive accuracy, followed by Artificial Neural Network and Support Vector Machine models (Boyd et al., 2019). This ranking was consistent with earlier machine learning studies in wastewater treatment that found ensemble and nonlinear models effective for predicting process outcomes under complex conditions. Traditional regression models still provided useful explanatory value, but they were less accurate than advanced machine learning models. This pattern suggested that sludge treatment performance involved nonlinear relationships that were better captured by flexible predictive algorithms. The visual presentation of results, including trends, variable importance rankings, and observed-versus-predicted comparisons, strengthened the interpretation by showing consistency between statistical outputs and graphical evidence. Overall, the statistical findings supported the reliability, predictive strength, and practical relevance of the analytical framework applied in this study (Zubala et al., 2017).

The findings of this study generally aligned with earlier research on wastewater treatment, sludge stabilization, resource recovery, and predictive analytics. Previous studies consistently identified sludge characteristics, retention time, organic loading, temperature, and pH as important determinants of treatment efficiency. The present findings supported those conclusions by showing that these variables significantly predicted sludge treatment performance in the Dhaka City context. Earlier anaerobic digestion literature also emphasized the importance of volatile solids concentration, microbial stability, and controlled digestion conditions in determining methane production. This study confirmed that volatile solids concentration was the strongest predictor of resource recovery, particularly methane generation and biogas recovery efficiency (Lee et al., 2015). Research on nutrient recovery from sludge described phosphorus and nitrogen as valuable recoverable resources, and the present findings supported that perspective by showing measurable nutrient recovery performance across treatment facilities. Earlier studies on machine learning in wastewater management showed that Random Forest, Artificial Neural Networks, Support Vector Machines, and ensemble models could improve prediction accuracy compared with conventional models. The present findings were consistent with that evidence because machine learning models produced higher  $R^2$  values and lower prediction errors than traditional regression approaches. However, this study added contextual specificity by applying these analytical principles to sewerage sludge treatment in Dhaka City, where urban density, variable wastewater inflow, seasonal rainfall, and infrastructure pressure created distinctive operating conditions (Heidrich et al., 2014). The findings therefore extended earlier international research by showing that predictive analytics could be adapted to a developing megacity context and used to explain both treatment efficiency and resource recovery outcomes through a single quantitative framework.

The findings carried important quantitative meaning for understanding sewerage sludge treatment efficiency and resource recovery in Dhaka City (Langeveld et al., 2017). The results indicated that treatment performance was strongly influenced by measurable operational variables rather than by random facility variation alone. Hydraulic retention time, sludge retention time, volatile solids concentration, organic loading rate, and temperature stability emerged as key explanatory factors across multiple analyses. This pattern suggested that sludge treatment facilities in Dhaka could be evaluated through a structured performance framework based on measurable inputs, treatment conditions, and recovery outputs (Hussein & Scholz, 2018). Compared with earlier international studies, the results showed similar technical relationships, especially regarding the importance of retention time, organic matter content, loading control, and biological stability. At the same time, the findings reflected local operational realities, including seasonal effects, capacity utilization differences, and facility-level performance variation. The stronger dry-season performance suggested that rainfall-related hydraulic variability remained an important contextual factor in Dhaka's wastewater treatment environment. The facility cluster results also showed that higher performance was associated with balanced loading, adequate retention, and stronger operational consistency. These findings were consistent with earlier benchmarking studies, which showed that wastewater treatment outcomes

depended on both technology and operational management (Kern et al., 2014). The predictive analytics results added another dimension by showing that machine learning models could identify the most influential variables and forecast treatment outcomes with high accuracy. Therefore, this study contributed to the quantitative understanding of sludge treatment in Dhaka by combining descriptive analysis, regression modeling, machine learning comparison, effect size interpretation, subgroup analysis, and resource recovery assessment. The discussion demonstrated that predictive analytics provided a strong evidence-based approach for interpreting sewerage sludge treatment behavior and comparing Dhaka's treatment performance with established findings from earlier wastewater research (Hargreaves et al., 2018).

## **CONCLUSION**

This study examined the application of predictive analytics for optimizing sewerage sludge treatment efficiency and resource recovery in Dhaka City through a comprehensive quantitative assessment of operational, environmental, and technological variables. The findings demonstrated that treatment performance was strongly influenced by measurable operational parameters, particularly hydraulic retention time, sludge retention time, volatile solids concentration, organic loading rate, temperature stability, energy utilization, and pH conditions. Statistical analyses confirmed that these variables significantly explained variations in treatment efficiency, sludge stabilization, dewatering effectiveness, methane generation, nutrient recovery, and overall resource recovery performance. The descriptive assessment revealed substantial variability across treatment facilities, highlighting the complex nature of urban sludge management systems and the importance of continuous performance monitoring. Regression analysis showed strong explanatory power, indicating that the selected operational variables accounted for a large proportion of treatment performance outcomes, while effect size analysis confirmed the practical importance of these predictors. The resource recovery assessment further demonstrated that sewerage sludge represented a valuable source of renewable energy and recoverable nutrients, with substantial methane generation, biogas recovery, phosphorus recovery, and nitrogen recovery observed across the facilities. Machine learning models, particularly Random Forest and Artificial Neural Network algorithms, achieved superior predictive performance compared with traditional statistical approaches, indicating their effectiveness in forecasting treatment outcomes and identifying critical operational determinants. Secondary analyses revealed significant subgroup differences associated with sludge loading conditions, retention periods, seasonal variations, and facility capacity utilization levels, emphasizing the importance of operational balance and process stability in achieving optimal treatment outcomes. The findings were consistent with established wastewater treatment literature while providing context-specific evidence from Dhaka City, thereby contributing to the growing body of knowledge on data-driven wastewater management and predictive environmental analytics. Overall, the study demonstrated that predictive analytics provided a robust quantitative framework for understanding, evaluating, and forecasting sewerage sludge treatment performance. The integration of statistical modeling, machine learning techniques, operational assessment, and resource recovery evaluation provided a comprehensive understanding of treatment system behavior and highlighted the critical role of data-driven analytical approaches in assessing treatment efficiency and resource recovery outcomes within rapidly urbanizing wastewater management environments.

## **RECOMMENDATIONS**

Based on the findings of this study, it is recommended that sewerage sludge treatment facilities in Dhaka City adopt data-driven operational management frameworks that integrate predictive analytics into routine treatment monitoring and performance evaluation processes. Greater emphasis should be placed on maintaining optimal hydraulic retention time and sludge retention time because these variables demonstrated the strongest influence on treatment efficiency and resource recovery outcomes. Treatment operators should continuously monitor volatile solids concentration, organic loading rates, temperature stability, pH conditions, and energy utilization to ensure that operational parameters remain within ranges associated with superior treatment performance. The implementation of advanced monitoring technologies, including SCADA systems, sensor-based monitoring platforms, and centralized data management systems, would strengthen data quality and support more accurate performance forecasting. Facilities should prioritize the development of integrated databases capable

of storing historical operational information, laboratory measurements, and resource recovery indicators to facilitate predictive modeling and evidence-based decision-making. The findings also support the adoption of machine learning techniques, particularly Random Forest and Artificial Neural Network models, as decision-support tools for forecasting treatment efficiency, methane generation, nutrient recovery, and operational performance. Resource recovery strategies should be strengthened through improved sludge stabilization practices and optimized digestion processes that maximize biogas production and nutrient extraction efficiency. Facility managers should maintain balanced sludge loading conditions and capacity utilization levels because both underutilization and excessive loading were associated with reduced treatment effectiveness. Continuous staff training in predictive analytics, digital monitoring systems, and quantitative performance assessment should be encouraged to enhance technical capacity and operational reliability. Seasonal variability and environmental influences should be incorporated into treatment planning to minimize the effects of rainfall fluctuations and changing influent characteristics on system performance. Infrastructure maintenance programs should also be strengthened to improve equipment reliability, reduce operational disruptions, and support consistent treatment outcomes. Furthermore, wastewater management authorities should establish standardized performance benchmarks and reporting frameworks that enable comparative evaluation across treatment facilities. Such measures would facilitate the identification of operational best practices and support continuous performance improvement. Collectively, these recommendations would contribute to more efficient sewerage sludge treatment, improved resource recovery performance, enhanced operational sustainability, and stronger utilization of predictive analytics as a strategic tool for optimizing wastewater management systems in Dhaka City.

#### **LIMITATION**

Several limitations should be acknowledged when interpreting the findings of this study on predictive analytics for optimizing sewerage sludge treatment efficiency and resource recovery in Dhaka City. The study relied primarily on secondary operational records, laboratory measurements, and monitoring datasets obtained from treatment facilities, making the quality of the analysis dependent on the accuracy, completeness, and consistency of existing records. Although extensive data cleaning and validation procedures were performed, some degree of measurement uncertainty may have remained due to variations in monitoring practices, equipment calibration, data recording methods, and reporting standards across facilities. The study was also limited to treatment facilities serving Dhaka City, which may restrict the generalizability of the findings to other geographic regions, wastewater treatment systems, or sanitation infrastructures operating under different environmental, socioeconomic, and regulatory conditions. The predictive models were developed using historical operational data, and their performance reflected the characteristics of the available dataset. Consequently, model outputs may have been influenced by temporal fluctuations, seasonal variability, and site-specific operational conditions that were present during the observation period. Although several important operational and environmental variables were incorporated into the analysis, additional factors such as operator expertise, maintenance quality, equipment age, financial constraints, policy interventions, and institutional management practices were not directly measured and therefore could not be included in the predictive framework. The machine learning models demonstrated strong predictive performance; however, their effectiveness remained dependent on the availability of high-quality data and may vary when applied to datasets with different characteristics or levels of completeness. Furthermore, the study focused primarily on quantitative performance indicators, including treatment efficiency, methane generation, nutrient recovery, sludge reduction, and energy conversion outcomes. Qualitative dimensions such as organizational readiness, stakeholder engagement, governance structures, and policy implementation challenges were beyond the scope of the investigation. Resource recovery assessment was also limited to the indicators available within the dataset and did not include comprehensive life-cycle environmental assessments, detailed economic feasibility evaluations, or broader social sustainability considerations. Finally, the cross-sectional nature of the available operational records constrained the ability to evaluate long-term changes in treatment performance and resource recovery trends over extended periods. These limitations should be considered when interpreting the findings and assessing the applicability of the predictive analytics

framework within broader wastewater management contexts.

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