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The Role of Artificial Intelligence in Enhancing the Efficiency of Paved Drying Beds for Wastewater Sludge Treatment: A Comprehensive Review

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Abstract

Paved Drying Beds are a sustainable, low-energy technology for wastewater sludge dewatering, but their efficiency is hindered by long drying times and high land requirements, which are highly dependent on climatic and operational parameters. This comprehensive review synthesizes current research on the potential of Artificial Intelligence to optimize PDB performance. A systematic literature review was conducted, analyzing 32 key studies to evaluate the impact of parameters such as sludge depth, type, and climate on drying efficiency, and to assess the application of AI and machine learning techniques for process prediction and control. The thematic synthesis reveals that shallower sludge depths and favorable climatic conditions significantly reduce drying time. AI models, particularly Artificial Neural Networks and Gradient Boosting Machines, have demonstrated high accuracy in predicting complex sludge treatment processes like settleability and production. The review highlights the promise of hybrid models that integrate AI with physical principles to enhance robustness and generalizability. Despite this potential, significant challenges remain, including model-data mismatch, supernatant management, and a lack of real-world validation. This paper identifies critical future research directions, such as the development of real-time monitoring systems, the use of transfer learning to overcome data scarcity, and the creation of digital twins for adaptive PDB operation. By providing a critical framework for AI integration, this review aims to advance the sustainability, cost-effectiveness, and operational efficiency of PDBs within modern wastewater treatment plants.

Keywords:
Artificial Intelligence, Paved Drying Beds, Wastewater Treatment Plants, Sludge Management, Optimization, Environmental Sustainability.

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1. Introduction

Wastewater treatment processes, including primary, biological, and chemical treatments, generate substantial quantities of sludge, which predominantly consists of over 90% water. A crucial objective in sludge management before disposal is to decrease the volume of sludge. Through effective moisture removal. This practice significantly contributes to lowering transportation and handling expenses (Elbaz et al., 2020).

Among the various sludge treatment technologies, paved drying beds[1] serve as an efficient method for moisture evaporation and percolation, thereby decreasing the overall sludge volume.

To adequately address the large volumes of sludge produced, it is imperative to enhance existing treatment facilities to achieve quicker and more effective sludge processing (Wainaina et al., 2020).

PDBs are particularly suitable for arid and semi-arid regions with hot and dry climates than other methods. Additionally, these beds do not require the addition of polymers for dewatering, and they are simpler to operate compared to more complex methods such as vacuum or solar drying. They also offer several advantages, including the possibility of using mechanical equipment for sludge collection, allowing for efficient removal even when the sludge has a high moisture content, unlike manual collection methods (El Gohary et al., 2022).

PDBs are recognized as natural systems that utilize renewable energy, making them particularly advantageous for areas with unstable power supplies. However, there exists a notable lack of comprehensive engineering design methodologies for PDBs, which impedes optimal operational efficiency (Al-Nozaily et al., 2013).

There are five main categories of SDBs: Conventional sand drying beds[2] , Wedge-Wire, Vacuum-assisted, Solar, and PDBs (Metcalf et al., 2004).

Typically, paved beds are rectangular, ranging from 5 to 15 meters in width and 21 to 46 meters in length, featuring vertical walls. The common practice entails using concrete or asphalt for lining, which is supported by a 20 to 30 cm layer of sand or gravel. A minimum slope of 1.5% toward the drainage area is recommended, with an unpaved strip of 0.6 to 1 meter along the sides or center for drainage. A drainage pipe with a diameter of no less than 100 mm is utilized for transporting drainage water (Elbaz et al., 2020).

PDBs are typically constructed with a slope of 1.5 to 2% towards the center and feature a perforated drainage pipe beneath a sand drainage strip within the bed. This design facilitates the use of mechanical equipment without risking damage to the drainage system, which helps lower labor costs for sludge removal. Although mechanical methods allow for effective management of sludge with greater moisture content, the main disadvantage of paved beds is their higher upfront capital cost. It is also important to note that specific sizing criteria for paved beds have not been established (Wang et al., 2007).

Effective sludge removal necessitates that the sludge possesses sufficient dryness to be handled manually.

Pescod conducted experiments on various sludge types and treatment technologies, including lagoons and drying beds, concluding that a total solids[3] content of at least 25% is optimal for removal (Pescod, 1971).

Sludge can be removed using mechanical or manual methods, regarding not to damage the bed media. To facilitate the removal process in gathering sludge using manual methods, ramps must be constructed to provide access for handling equipment (Dodane and Ronteltap, 2014).

In Fig. 1. extracting sludge from the unplanted drying beds at the Cambérène treatment facility in Dakar, Senegal is shown.

Fig. 1. Extracting sludge from the unplanted drying beds at the Cambérène treatment facility in Dakar, Senegal (Dodane and Ronteltap, 2014)

Kinsley et al., investigate the effectiveness of freeze-thaw treatment methods for septic tank sludge through a series of pilot-scale experiments. The findings show that the quality of the filtrate produced is comparable to low-strength domestic wastewater, while the resulting sludge cake has a dry matter content of 25% and low *E. Coli* levels (below 2.0 × 10^6 CFU/g dry solids[4]). The study reported significant reductions in pollutants, with COD[5], BOD_5[6], and TSS[7] removal rates around 99, making the treated sludge suitable for land application (Kinsley et al., 2012).

The experiments indicated that snow accumulation had no significant effect on the performance of the freezing beds. New layers of sludge applied to the beds

[1] Paved Drying Bed (PDB)
[2] Conventional Sand Drying Beds (CSDB)

[3] Total Solids (TS)
[4] Dry Solids (DS)
[5] Chemical Oxygen Demand (COD)
[6] Biochemical Oxygen Demand over 5 days (BOD_5)
[7] Total Suspended Solids (TSS)

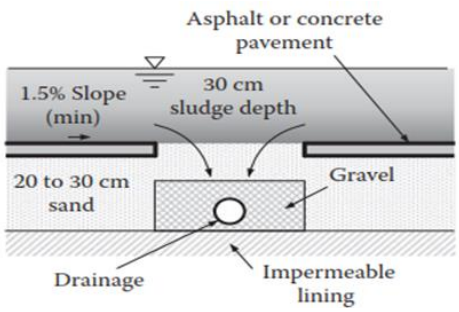
were effective in melting any snow, suggesting that it is unnecessary to cover the beds or remove snow in regions where sludge application exceeds snowfall (Kinsley et al., 2012).

When sludge exhibits favorable settling characteristics, it is feasible to extract 20-30% of the water content, although the drying duration is contingent upon climatic factors (Qasim and Zhu, 2017).

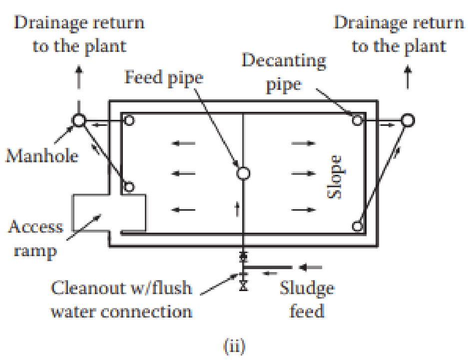
Despite the straightforward nature of drying beds, they necessitate prolonged exposure and extensive land areas, underscoring the need for process optimization to improve efficiency.

Field studies indicate that PDBs can achieve reduced drying times and more cost-effective operations compared to CSDBs. They have demonstrated effectiveness with anaerobically digested sludge, although they are less favorable for aerobically digested activated sludge (Sakellaropoulos, 1986).

The principal advantages of PDBs include the ability to employ mechanical equipment for sludge removal without compromising the integrity of underdrains or losing sand, resulting in shorter drying periods and more economical operations relative to traditional sand drying beds. Conversely, the major limitations encompass higher capital costs and greater land area requirements than those for CSDBs. Fig. 2 shows typical PDB construction (Qasim and Zhu, 2017).



(A) Drainage type bed



(B) Decanting type bed

Fig. 2. Typical PDB construction (Elbaz et al., 2020, Qasim and Zhu, 2017)

The initial solid concentration affects the drying time of sludge, with laboratory findings indicating that as solid concentration increases, the volume of drainable water diminishes. Consequently, the drying time and moisture content of the dried cake elevate with higher solid content.

1.1. Key design parameters for PDBs

Several critical parameters must be considered when designing and operating PDBs:

- Sludge type: The chemical properties of sludge vary significantly based on its type. Aerobically digested sludge tends to have elevated levels of total nitrogen[1] and carbon content, which influences its drying efficiency. Table 1 represents the typical sludge solids content.

Table 1. Different sludge solids content (Qasim and Zhu, 2017)

Type of sludge	Solids content (%)
Raw or thickened sludge	
Primary sludge	4-8
Waste activated sludge	1-4
Primary and waste activated sludge	3-6
SBR/MBR process sludge	1-2
Anaerobically digested sludge	
Primary sludge	2-5
Waste activated sludge	2-3
Primary and waste activated sludge	2-4
Aerobically digested	
Waste activated sludge	1-3

According to Haseltine, raw sludge dries less effectively than digested sludge and has a stronger odor that attracts insects, making it a significant drawback. As a result, sand bed drying is typically limited to well-digested sludge. Although oil and grease can block the pores of the bed and slow down the drying process, grit can actually enhance it (Haseltine, 1951). Furthermore, biological sludge is particularly recognized for its high nutrient content, organic matter, and phosphorus (Wei et al., 2020).

Sludge typically consists of a mixture of organic matter, inorganic matter, microorganisms, and water. The composition can vary widely based on the source of the sludge e.g., municipal wastewater, industrial processes.

- Understanding the solid content is crucial for the design and optimization of PDBs, as it affects the efficiency and effectiveness of process.
- By measuring and analyzing the solid content of sludge, operators can make informed decisions regarding treatment and disposal strategies, ensuring compliance

[1] Total Nitrogen (TN)

with environmental regulations and promoting sustainability.

- The solid content of sludge can impact its classification and the regulations governing its disposal or use, including land application or incineration.

- **Drying sludge depth:** The sludge depth is a vital operational factor in drying beds. Shallower depths necessitate larger land areas for drying but facilitate quicker drying, while nutrient concentrations in the sludge can also be influenced by its depth (Badza et al., 2020).

- **Regional climate:** Seasonal climatic variations, including precipitation, evaporation rates, and wind speed, affect drying times. Notably, sludge typically requires extended drying periods during winter months to reach the desired moisture content.

- **Land utilization:** Effective management of drying beds is paramount for wastewater treatment facilities with limited land resources. Land area requirements must be carefully assessed (Badza et al., 2020).

1.2. Impact of sludge supernatant on wastewater treatment plants[1]

The supernatant produced during the drying process often returns to the beginning of the WWTP. High concentrations in the supernatant can overburden biological treatment processes, diminishing overall treatment efficiency and potentially leading to violations of discharge permits. Additionally, if the supernatant contains harmful substances, its return can adversely affect the microbial populations responsible for treatment (Arun and Lohani, 1988).

Implementing robust predictive mathematical tools based on historical data could enhance the operational efficiency of WWTPs (Hamed et al., 2004).

These insights can help optimize sludge drying processes, improve nutrient recovery, and facilitate efficient land resource management. The formula for determining the required area for PDBs is outlined as follows. The formula for required are of PDB is presented in equation 1 (Qasim and Zhu, 2017)

$$A=\frac{W_d-W_e}{R_e-R_p} \quad \text{or} \quad A=\frac{W_s}{\rho(k_cE_p-R_p)}\left(\frac{1-p_d}{p_d}-\frac{1-p_d}{p_e}\right) \tag{1}$$

Where

A: area of the paved bed at the bottom, measured in square meters (m²)

W_d: mass of water present in the sludge post-decanting, measured in kilograms per year (kg/year)

W_s: annual amount of sludge applied to the drying beds, expressed in kilograms per year of dry solids (kg/year dry solids)

W_e: mass of water in the sludge following evaporation, expressed in kilograms per year (kg/year)

R_e: annual rate of evaporation, measured in kilograms per square meter per year (kg/m²·year)

R_p: annual rate of precipitation, measured in kilograms per square meter per year (kg/m²·year)

P_w: density of water, expressed in kilograms per cubic meter (kg/m³)

k_e: efficiency of the evaporation rate from sludge compared to that from a free water surface, expressed as a decimal fraction

E_p: evaporation rate from a free water surface in a pan, measured in meters per year (m/year)

p_d: solids content of the sludge after decanting, expressed as a decimal fraction of dry solids

p_e: solids content of the sludge following evaporation, expressed as a decimal fraction (Qasim and Zhu, 2017)

The role of artificial intelligence[2] in enhancing the efficiency of sludge treatment processes in PDBs primarily revolves around optimizing operational parameters, predicting drying times, and improving overall management. AI can be utilized to analyze various factors influencing drying efficiency, making it a valuable tool in this context.

1.3. AI techniques in wastewater treatment

AI and machine learning[3] are extensively utilized in the modeling and prediction of wastewater treatment processes. The key ML tasks include clustering, regression, dimensionality reduction, and classification. Predictive models are generated through training on process data to tackle these tasks by establishing relationships between input parameters and desired outcomes. The process typically involves two main steps: (i) training the model on historical data to understand the system's behavior, and (ii) utilizing this training to predict new outputs based on the established relationships.

For nonlinear analysis, various techniques such as artificial neural networks[4], deep learning[5], random forests[6], and support vector machines[7] are employed. Principal component analysis[8] serves as a dimensionality reduction tool, particularly useful for managing complex data types. While ANN and DL mimic biological neural networks, DL is generally more complex and has a higher prediction accuracy but requires more data and is susceptible to overfitting. SVMs, with their mathematical foundation, can offer better model interpretability and address optimization problems effectively, although they may require longer training

[1] Wastewater Treatment Plant (WWTP)

[2] Artificial Intelligence (AI)
[3] Machine Learning (ML)
[4] Artificial Neural Networks (ANN)
[5] Deep Learning (DL)
[6] Random Forests (RF)
[7] Support Vector Machines (SVM)
[8] Principal Component Analysis (PCA)

times. RFs excel in determining the significance of variables in regression and classification tasks, making them advantageous in scenarios with intricate interdependencies among variables (Mathaba and Banza, 2023).

Search algorithms, particularly genetic programming[1] and genetic algorithms[2], are employed for optimization problems by mimicking natural evolutionary processes. These algorithms help identify optimal solutions for various challenges, such as pollution detection systems (Macedo et al., 2016).

Fuzzy logic techniques, which utilize multi-valued logic, facilitate the representation of uncertainty in decision-making processes and enhance the interpretability of models through systems like the adaptive neural fuzzy inference system[3] (Mathaba and Banza, 2023).

In Fig. 3. AI concepts and techniques which are often utilized in the treatment process are presented.

This article presents a systematic review that critically analyzes and synthesizes existing research on the application of AI to optimize the performance of paved sludge drying beds. It examines the fundamental principles of PDB operation, including design parameters like sludge type, depth, and climate, alongside the challenges associated with their efficiency, such as extended drying times and land requirements. The review integrates findings from studies employing diverse AI techniques, including ANN, ML models and hybrid approaches, demonstrating their potential for predicting drying kinetics, optimizing operational parameters (e.g., sludge depth, conditioning) and managing sludge quality. By addressing critical challenges like model accuracy, supernatant management, and environmental considerations, this synthesis proposes a framework for leveraging AI-driven predictive models and data analytics to enhance the sustainability, cost-effectiveness, and overall efficiency of PDB systems within WWTPs.

Saran and Devi conducted a comprehensive investigation into the necessity for enhancements in the design of Sludge Drying Beds[4] employed in wastewater treatment facilities. Notably, these systems have largely remained static since the 1950s. Their research involved the development of a simulated model utilizing Computer Aided Design[5] alongside AI methodologies, specifically the DeBono method and Fishbone diagrams, to diagnose issues present in existing SDB configurations. The application of the Fishbone diagram was particularly instrumental in elucidating the actual operational conditions of SDBs within sewage treatment plants (Saran and Devi, 2016).

Badza et al. examined the influence of drying depth and the incorporation of polymeric materials on the nitrogen content and other chemical characteristics of municipal sludge processed in sand drying beds. The study, conducted in South Africa, compared three sludge types: aerobically digested (AeD), anaerobically digested without polymer (AnDP0), and anaerobically digested with polymer (AnDP1), across varying depths (5-25 cm) during winter and spring seasons. The findings indicated that as the sludge depth increased from 5 to 25 cm, the drying time also increased in both summer and winter. Furthermore, the results demonstrated that with the same sludge concentration, drying times were longer in spring compared to winter, attributed to the higher temperatures (ranging from 11.2 to 24.5 °C) and lower rainfall during the drying period (Badza et al., 2020). The required day for sludge dewatering, according to drying depths, type of sludge, and season is presented in Fig. 4.

In this research, a two-way ANOVA indicated significant interaction effects between the type of sludge and the depth of drying on TN concentrations, with notable results observed in winter ($p=0.008$) and spring ($p=0.042$). The type of sludge had a more substantial influence on TN levels than the drying depth. Aerobic sludge consistently showed elevated TN concentrations compared to anaerobic sludge across both seasons. Additionally, a significant interaction between sludge type and drying depth was detected regarding total carbon[6] levels in winter ($p<0.001$), although no significant interaction was observed in spring ($p>0.05$). Aerated dried (AeD) sludge exhibited higher TC concentrations than anaerobically dried (AnD) sludge in both seasons. This difference is likely attributable to the greater carbon content and reduced stability of aerobic sludge in contrast to anaerobic sludge.

Wang et al. focused on the decline in knowledge and technology concerning the performance of PDBs used for drying chemical sludge, particularly alum, a by-product of water treatment processes. The study emphasized the environmental pollution linked to untreated sludge, especially in developing nations, and aimed to formulate a mathematical model to optimize the drying process. Utilizing Polymath 5.1 software, the authors analyzed various parameters affecting drying rates, including temperature, relative humidity, wind speed, and solar intensity. The developed mathematical model was found to accurately predict the drying rate of alum sludge in a PDB by considering critical environmental parameters (Wang et al., 2007).

Elbaz et al. investigated three distinct configurations of PDBs to optimize sludge drying performance, benchmarking these against CSDBs. The study examined numerous factors, including diverse drainage pipe placements, the use of geotextile membranes, and fine gravel filters. The study evaluated the impact of different sludge layer heights (30, 50 and 72 cm) and types-including waste activated sludge, thickened

[1] Genetic Programming (GP)
[2] Genetic Algorithms (GA)
[3] Adaptive Neural Fuzzy Inference System (ANFIS)
[4] Sludge Drying Beds (SDBs)
[5] Computer Aided Design (CAD)

[6] Total Carbon (TC)

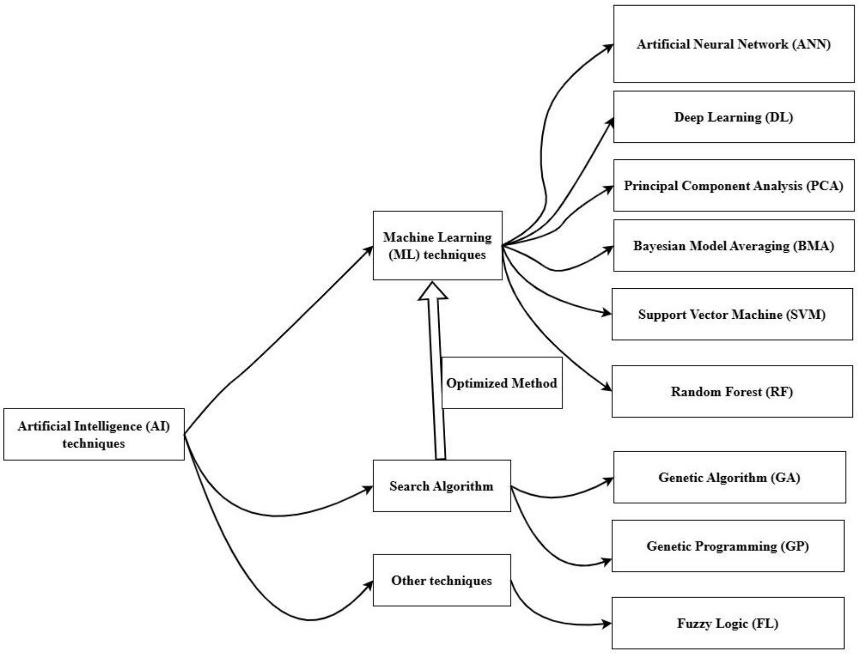


Fig. 3. AI concepts and techniques which are often utilized in the treatment process (Mathaba and Banza, 2023)

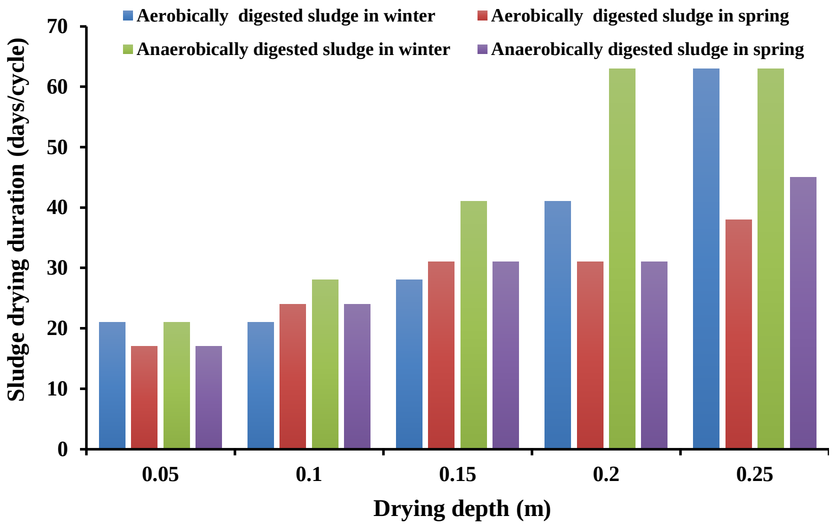


Fig. 4. Sludge dewatering day according to drying depths, type of sludge and season (Solid content of 3.5% and sludge daily production: 1.4 m^3/day of wet solid sludge) (Badza et al., 2020)

combined primary and waste activated sludge, primary sludge, and trickling filter humus-on drying results. Findings revealed that waste activated sludge produced the highest ratio of drained water and dried solid content. Notably, the modified PDB achieved a Solid Loading Rate[1] of 598 kg/m² annually, resulting in a dried solid content of 20%. The configuration with two drainage pipes-one located in the bottom channel of the tank and the other in the corner-provided the best drainage ratio and dried sludge solid content, demonstrating superior drying times relative to other setups (Elbaz et al., 2020).

El Gohary et al. highlighted the significance of their created model as a valuable tool for sludge treatment plant operators, fostering improved water security and sustainable practices in alignment with global environmental objectives. The findings suggested that optimizing PDB operations could alleviate the detrimental effects of untreated sludge and enhance resource recovery in wastewater management. (El Gohary et al., 2022). Experiment design of this study is presented in Table 2.

[1] Solid Loading Rate (SLR)

Table 2. Experiment design (El Gohary et al., 2022)

Location	El Berka WWTP						
Type of sludge	Primary and secondary sludge				Primary and secondary sludge		
Experiment cycle	Stage 1				Stage 2		
	1	2	3	4	1	2	3
Initial sludge concentration (%)	0.42	2.1	1.2	1.2	2.9	3	2.8
Type of drying bed	PDB				PDB with horizontal and bottom drainage		
Temperature	20- 35 ^{0}C				35-43 ^{0}C		
Month	March, April and May				July and August		

The study also found that gases produced by anaerobic bacteria at the bottom of the PDB rise to the surface, which speeds up the drying process and enhances moisture removal from the sludge. Fig. 5 depicts the correlation between sludge drying time and solid content in relation to the initial sludge height at the El Berka WWTP (El Gohary et al., 2022).

Nasir and Li explored the application of ML models and explainable artificial intelligence[1] techniques to predict sludge production at WWTPs. The investigation evaluated three ML models: RF, gradient boosting machine[2] and gradient boosting tree[3], analyzing their efficacy based on various statistical metrics. The results indicated that the accuracy of sludge prediction varied with the selected model and the number of input variables, with GBM and GBT demonstrating superior performance in sludge production prediction (Nasir and Li, 2024).

Deepnarain et al. conducted a study employing image processing and AI techniques to estimate the settling velocity index[4] for a full-scale wastewater treatment facility. Activated sludge samples were procured from the aeration tank of the Konya Domestic WWTP. The study utilized Cellular Neural Networks[5] to evaluate the floc and filament structures microscopically, adjusting iteration values based on captured images. The performance of the ANN in predicting SVI was assessed using mean square error[6] and correlation coefficients ®, with the ABC-ANN method yielding the highest correlation (r = 0.915) and a relatively low MSE (Deepnarain et al., 2020).

Obianyo and Agunwamba sought to create a model for estimating evaporation losses in SDBs, focusing on effectively treating waste from household septic systems. Their material balance calculations revealed that as seepage losses increased, evaporation rates decreased. They suggested that the use of conditioners and coarser sands, which have larger pore spaces, could improve this process. The study concluded that evaporation from sludge follows first-order kinetics, in line with fundamental principles, thus facilitating the design of drying beds (Obianyo and Agunwamba, 2015).

Lampreia created a model for the dewatering processes in SDBs, incorporating local meteorological factors such as temperature, solar radiation, relative humidity, and rainfall, along with the initial thickness of the sludge layer. Validation of this model was achieved through field experiments conducted at a pilot facility in Portugal, revealing that SDBs operated more efficiently-reflected in increased solid content and volume reduction-during cycles characterized by higher temperatures and solar radiation, lower humidity, and precipitation levels. Additionally, under consistent meteorological conditions, thinner sludge layers demonstrated improved dehydration capabilities (Lampreia, 2017).

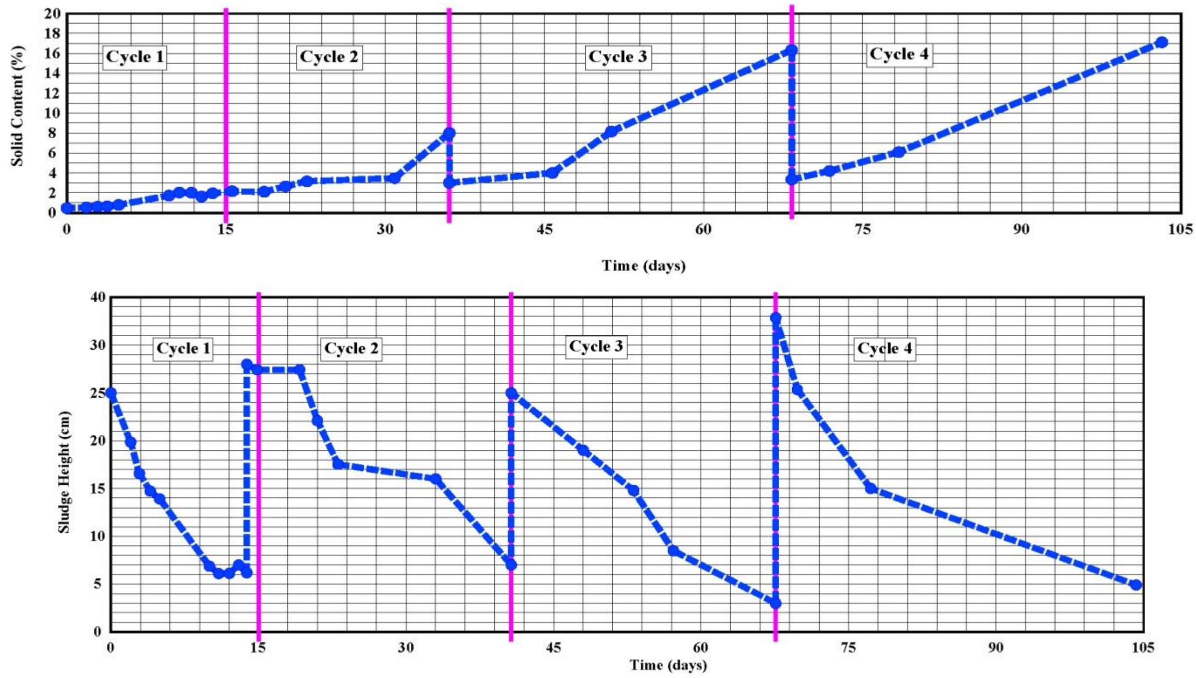
Masmoudi et al. conducted an experimental study on the drying of sewage sludge using a pilot-scale drying bed in Tunisia's Mediterranean climate, examining seasonal variations across winter, spring, and summer. The findings revealed that the time needed to reach a moisture content of 0.15 kg water/kg DS was significantly reduced during the warmer months, taking 14 days in winter, 5 days in spring, and just 4 days in summer. Furthermore, the DS content showed a remarkable increase from approximately 4% to nearly 87% throughout all seasons, accompanied by significant decreases in volatile DS content, indicating effective stabilization of the sludge (Masmoudi et al., 2019).

Manga et al. examine how varying the thickness of sand filter media affects the performance of fecal sludge[7] drying beds. The study utilized three pilot-scale drying beds with filter thicknesses of 150 mm, 250 mm, and 350 mm, analyzing their impact on dewatering time, contaminant removal efficiency, solid generation rates, nutrient content, and viability of helminth eggs in dried sludge (Manga et al., 2016).

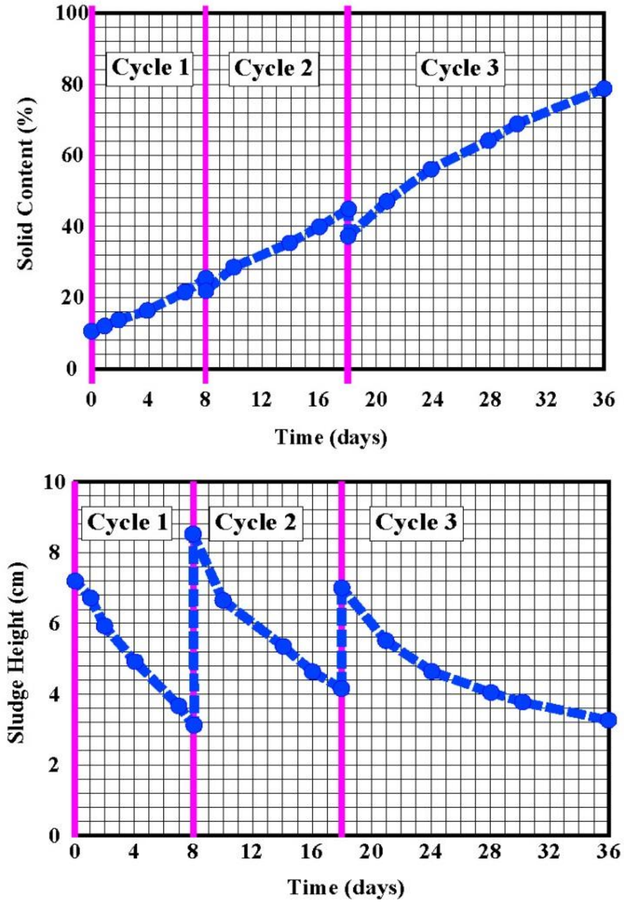
- Dewatering time: The 150 mm filter achieved the shortest average dewatering time of 3.65 days, compared to 3.83 days for the 250 mm and 4.02 days for the 350

[1] Explainable Artificial Intelligence (XAI)
[2] Gradient Boosting Machine (GBM)
[3] Gradient Boosting Tree (GBT)
[4] Settling Velocity Index (SVI)
[5] Cellular Neural Networks (CNN)
[6] Mean Square Error (MSE)

[7] Fecal Sludge (FS)



(A) Stage 1



(B) Stage 2

Fig. 5. Sludge drying time and solid content according to initial sludge height in El Berka WWTP (El Gohary et al., 2022)

mm filters. However, the differences were not statistically significant.

- **Contaminant removal efficiency**: The 350 mm filter showed the highest efficiency in removing various contaminants, including TS, nitrogen species, and biochemical oxygen demand. There were significant differences in removal efficiency based on filter thickness.

- **Nutrient recovery:** Filters with greater thickness (350 mm) yielded higher nutrient recovery from FS, particularly in terms of total phosphorus[1] and potassium (K). Conversely, the 150 mm filter generated solids with higher TN content.

- **Helminth eggs viability:** All filter thicknesses achieved 100% removal of helminth eggs in the percolate, but the concentration of viable eggs in the dried solids remained above safe levels for agricultural reuse, indicating a need for further treatment.

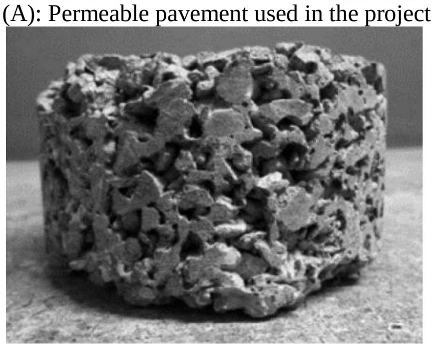
- **Solid generation:** The 350 mm filter produced the highest quantity of organic matter and nutrients for reuse, while the 150 mm filter was most efficient for annual solid generation. The result show, while thinner sand media (150 mm) optimize dewatering time and solid generation, thicker media (350 mm) enhance nutrient recovery and contaminant removal efficiency, making them more suitable for improving effluent quality. Moreover, the study highlights the importance of balancing these factors in designing effective FS drying beds. Further treatment is necessary for dewatered sludge to inactivate pathogens before reuse in agriculture (Manga et al., 2016).

Ngalonkulu et al. investigate the effectiveness of an open-loop air-source heat pump drying[2] system in South Africa, where climatic conditions vary. The study aims to assess how different ambient temperatures, specifically ranging from −10 °C to 20 °C, affect the operational and thermal performance of the HPD system. The research highlights that ambient temperature significantly influences the operational conditions, with the heat pump's performance improving significantly in warmer conditions. Moreover, the findings indicate that the HPD system performs poorly at lower temperatures, particularly below 0 °C. The study suggests that while the HPD system is feasible in South Africa, it is best suited for warmer regions or seasons due to its reduced efficiency in colder conditions (Ngalonkulu and Huan, 2024).

Manfio et al. investigated the dewatering of septic tank sludge through two different approaches: the traditional SDB and a novel SDB featuring permeable pavement[3]. The research indicated that the sludge utilized in the study had a higher TS concentration than standard values typically reported in fresh sludge due to prolonged retention in the septic tank. The findings suggested that the incorporation of permeable pavements could enhance the dewatering process while maintaining comparable solid concentrations in the resulting sludge cake, with the addition of synthetic polymer significantly reducing the dewatering time without affecting the solid content of the sludge cake (Manfio et al., 2018).

The permeable pavement (Fig. 6) minimizes surface runoff and captures suspended solids, effectively filtering pollutants from stormwater (Manfio et al., 2018).

(A): Permeable pavement used in the project



(B): Large-scale photo of the pavement material

Fig. 6. Permeable pavement used in the project (Manfio et al., 2018)

Huang and Chen explored the application of neural network models for predicting the drying behavior of municipal sewage sludge, focusing specifically on thin-layer drying, which entails complex heat and mass transfer processes. Their research utilized back-propagation[4] and generalized regression neural network[5] models, assessing their accuracy using MSE and the coefficient of determination (R²), as outlined in equation 2 (Huang and Chen, 2015)

$$MSE = \frac{\sum_{i=1}^{n}(|z_i - o_i|)^2}{n}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(z_i - o_i)^2}{\sum_{i=1}^{n}(z_i - oa)^2} \qquad (2)$$

[1] Total Phosphorus (TP)

[2] Heat Pump Drying (HPD)

[3] Sludge Drying Bed Featuring Permeable Pavement (SDBPP)

[4] Back-Propagation (BP)

[5] Generalized Regression Neural Network (GRNN)

Where
MSE: Mean Squared Error
R^2: Coefficient of Determination
z_i: Predicted value for observation i
o_i: Actual value for observation i
n: Total number of observations
oa: Average value of the observations

Szeląg and Gawdzik discussed the application of AI methods to predict the settleability of activated sludge in wastewater treatment. This study examines the implementation of three distinct AI techniques: GP, SVM and ANN. These methods were selected as they are established AI techniques suitable for modeling complex, non-linear processes like wastewater treatment, particularly when physical models are difficult to calibrate due to numerous uncertain parameters. However, the goal was to develop predictive models using readily available operational data (influent flow Q, temperature T, recirculation rates, and settleability values). Various input combinations were tested. Data for this analysis was meticulously collected over a two-year period from a wastewater treatment facility located in Cedzyna, Poland. Among the AI techniques evaluated, the ANN models demonstrated superior predictive capabilities when compared to the SVM and GP models. This was evidenced by a lower mean absolute error[1] and mean percentage error[2] associated with the ANN approach. Specifically, the ANN model achieved an MAE of 72.18 cm³/dm³ and an MPE of 19.28%, indicating its efficacy in accurately forecasting the settleability of activated sludge. A direct comparison with other probabilistic models (e.g., stochastic transfer functions, autoregressive models) was not performed in this specific study; the comparison focused on the three selected AI methods. The conclusion highlights ANN's superior performance among the three, while noting GP's advantage in simplicity (Szeląg and Gawdzik, 2016).

1.4. The intersection of food drying and wastewater treatment sludge management: harnessing AI

The application of AI in food drying has garnered significant attention in recent literature. However, the exploration of AI's predictive capabilities in managing wastewater treatment sludge remains relatively under-researched. In This section, it is examines how AI can optimize the drying processes in both fields, highlighting their similarities and potential benefits.

AI technologies are being increasingly utilized to enhance food drying processes. Table 3 summarizes some notable studies where AI has been applied to predict and optimize drying conditions for various food products:

Table 3. AI in food drying

Products	Aims	AI methods	Results	References
Menthaa spicata.	Predict moisture changes during mint drying	ANN	Effective prediction of water content	(Karakaplan et al., 2019)
Banana slices	Model drying of banana slices using hot air	ANN	Both ANN and RSM models predict moisture and quality changes	(Taheri-Garavand et al., 2018)
Paddy	Optimize drying conditions for rice in fluidized bed	Fuzzy logic control[3]	Controlled drying conditions for maximum efficiency	(Atthajariyakul and Leephakpreeda, 2006)

1.4.1. Bridging food drying and sludge management

AI in drying food and sludge in WWTPs can be related through several key aspects, including optimization, process monitoring and predictive analytics.

1.4.1.1. Process optimization

AI algorithms can be utilized to enhance drying conditions-such as temperature, humidity, and airflow-maximizing efficiency for both food and sludge drying. In food drying, the focus is on preserving quality and nutrients, while in sludge drying, the aim is to reduce volume and environmental impact.

1.4.1.2. Process optimization

- Sensor integration: Real-time data collection through sensors (monitoring temperature, moisture content, etc.) allows AI to analyze and optimize drying conditions. For instance, in WWTPs, sensors assess sludge moisture content to fine-tune drying times..
- **Feedback loops:** AI systems can establish closed-loop controls that adjust drying parameters based on real-time feedback, ensuring peak performance in both applications.

1.4.1.3. Predictive maintenance

- **Failure prediction**: AI can analyze historical data to forecast potential equipment failures, allowing for improved maintenance scheduling and reduced downtime for both food and sludge drying equipment.
- **Performance prediction:** ML models can predict drying outcomes based on varying input conditions, applicable to both food processing and sludge treatment.

1.4.1.4. Quality control and assurance

- **Consistency Monitoring:** Consistency is crucial in both fields. AI can monitor and adjust drying processes in real-time to ensure that food products meet quality

1 Mean Absolute Error (MAE)
2 Mean Percentage Error (MPE)
3 Fuzzy Logic Control (FLC)

standards and that sludge reaches desired dryness levels in compliance with regulatory requirements.

1.4.1.5. Resource management

Material recovery: AI can optimize the drying processes to enhance resource recovery. For instance, better moisture management in sludge drying can lead to improved water recovery, which can be reused in treatment processes, akin to the management of excess moisture in food drying.

Using AI in both food drying and sludge management is a great way to innovate and improve efficiency. AI can help optimize processes, monitor conditions, predict outcomes, and control quality. This leads to better results, more sustainability, and better resource management in both areas. As research continues to evolve, it is essential to explore the untapped potential of AI in sludge treatment, paralleling the advancements made in food drying technologies.

Summary of key studies on PDBs and AI applications in wastewater sludge management is presented in Table 4.

To ensure a systematic and transparent analysis, a clearly defined methodology for the literature search and selection process is presented in the following section.

2. Methodology

To ensure a comprehensive, unbiased, and reproducible analysis, a systematic methodology was employed for the literature review on the application of AI in PDBs. The process consisted of the following steps:

2.1. Literature search strategy

A comprehensive search was conducted using major scientific databases, including Scopus, Web of Science, and Google Scholar. The search was performed using a combination of keywords and Boolean operators to capture the relevant literature. The primary search terms included: "PDB", "SDB", "wastewater sludge dewatering", "AI", "ML", "neural network", "fuzzy logic", "SVM", "optimization", "drying kinetics" and "sludge production prediction". The search was not restricted by language, but the final selection prioritized peer-reviewed articles in English to ensure accessibility and consistency in analysis.

2.1.1. Inclusion and exclusion criteria

The initial pool of publications was screened based on the following criteria:

Inclusion criteria:

- Studies that specifically focused on the application of AI, ML or data-driven modeling in the context of sludge drying, particularly in PDBs or similar natural drying systems (e.g., sand drying beds).
- Research that investigated the use of AI for predicting drying times, moisture content, sludge production, or other key operational parameters.
- Papers that explored the integration of AI with operational parameters (e.g., sludge depth, climate) for process optimization.
- High-impact review articles on AI in water and wastewater treatment (e.g., Mathaba and Banza, 2023) were included to provide a broader context and identify key AI techniques.

2.1.2. Exclusion criteria

- Studies focused on other sludge drying technologies (e.g., thermal dryers, centrifuges, belt presses) without direct relevance to PDBs.
- Publications that were not peer-reviewed (e.g., conference abstracts, technical reports without full methodology).
- Articles where the full text was not accessible.

2.2. Screening and selection process

The search process yielded an initial set of 128 publications. After removing duplicates, the titles and abstracts of 97 records were screened for relevance. This initial screening excluded 52 publications that did not meet the inclusion criteria. The full texts of the remaining 45 articles were then obtained and thoroughly evaluated. A final set of 32 high-quality, relevant studies were selected for in-depth analysis and synthesis in this review.

2.3. Data extraction and synthesis

From the selected studies, key information was extracted and organized into a structured database. The data points included: author(s) and year of publication, AI technique(s) used, the specific aim of the AI application, the key parameters investigated, the main findings, the reported results (e.g., model accuracy, drying time reduction), and the overall significance of the study. The extracted data was then thematically synthesized to identify trends, compare the performance of different AI models, and critically evaluate the challenges and future research directions, as presented in the subsequent sections of this paper.

This systematic approach ensures that the review provides a reliable and authoritative overview of the current state of research on AI in PDBs, minimizing selection bias and providing a clear framework for the analysis presented.

3. Thematic synthesis of research findings

The reviewed literature consistently identifies sludge depth, type, and regional climate as the most critical operational parameters influencing PDB efficiency. Studies by Badza et al. (2020) and Lampreia (2017) demonstrate that shallower sludge layers and higher temperatures significantly reduce drying time. Furthermore, research on AI applications reveals a growing trend in using ML models-such as ANN, RF and SVM to predict drying kinetics and sludge

Table 4. Summary of key studies on PDBs and AI applications in wastewater sludge management

Significance/ Outcomes	Result	Main finding	Key parameter of investigation	AI technique used	Study (author, year)
This approach can be used to improve the design of SDBs, which have remained largely unchanged since the 1950s.	The study used AI methodologies to diagnose problems in current SDB designs.	The application of the Fishbone diagram was instrumental in elucidating the actual operational conditions of SDBs.	Issues in existing SDB configurations	DeBono method, Fishbone diagrams	(Saran and Devi, 2016)
Shallower depths and higher temperatures reduce drying time; aerobic sludge has higher nitrogen and carbon content.	For a 3.5% solid content, dewatering time varied significantly with depth, sludge type, and season (e.g., 25cm AnDP0 in winter took ~14 days).	Drying time increased with sludge depth; drying times were longer in spring than winter; sludge type had a greater influence on TN levels than depth.	Drying depth, incorporation of polymeric materials, sludge type, season	Not explicitly stated as AI, but presents experimental data	(Badza et al., 2020)
Provides a tool to optimize the drying process for chemical sludge, addressing a decline in related knowledge and technology.	The model successfully predicted the drying rate of chemical sludge in a PDB.	A mathematical model could accurately predict the drying rate of alum sludge by considering critical environmental parameters.	Temperature, relative humidity, wind speed, solar intensity	Mathematical modeling (implied, not a core AI technique like ML)	(Wang et al., 2007)
Specific configurations of drainage and sludge type can significantly improve drying performance compared to conventional beds.	The modified PDB achieved a SLR of 598 kg/m² annually with a 20% dried solid content.	Waste activated sludge had the highest drained water ratio and dried solid content; a configuration with two drainage pipes performed best.	Sludge layer heights, sludge types, drainage pipe placements	Not explicitly stated as AI, but presents experimental data	(Elbaz et al., 2021)
ML models, particularly GBM/GBT, are effective tools for predicting sludge production at WWTPs.	The accuracy of prediction varied with the model and the number of input variables.	GBM and GBT models demonstrated superior performance in predicting sludge production.	Prediction of sludge production		(Nasir and Li, 2024)
AI techniques can accurately estimate SVI, a key parameter for assessing sludge settleability in wastewater treatment.	The ANN was effective in predicting the SVI based on microscopic floc and filament structures.	The ABC-ANN method yielded a high correlation (r = 0.915) and a low MSE for predicting SVI.	SVI for activated sludge	ANN, CNN	(Deepnarain et al., 2020)

Cont. Table 4. Summary of key studies on PDBs and AI applications in wastewater sludge management

Significance/ Outcomes	Result	Main finding	Key parameter of investigation	AI technique used	Study (author, year)
Understanding the kinetics of evaporation is fundamental for the design of effective SDBs.	The study concluded that evaporation follows first-order kinetics, facilitating design.	Evaporation from sludge follows first-order kinetics; evaporation rates decrease as seepage losses increase.	Evaporation losses	Not AI; material balance calculations	(Obianyo and Agunwamba, 2015)
A model based on local weather and sludge thickness can predict dewatering performance, highlighting the importance of climate and operational parameters.	The model was validated through field experiments in Portugal.	Drying beds operated more efficiently with higher temperatures and solar radiation, lower humidity and precipitation; thinner sludge layers dehydrated better.	Local meteorological factors, initial sludge thickness	Mathematical modeling (incorporating meteorological data)	(Lampreia, 2017)
ANN is highly effective for forecasting the settleability of activated sludge using readily available operational data.	The ANN model achieved a MAE of 72.18 cm^3/dm^3 and a MPE of 19.28%.	ANN models demonstrated superior predictive capabilities compared to SVM and GP models.	Settleability of activated sludge	GP, SVM, ANN	(Szelag and Gawdzik, 2016)

production. The performance of these models varies, with ANN showing superior predictive capability for sludge settleability (Szeląg and Gawdzik, 2016) and GBM/GBT models excelling in sludge production prediction (Nasir and Li, 2024). A key finding is that hybrid approaches, combining physical models with AI, show promise for more accurate predictions (Wang et al., 2007).

The analysis of the 32 selected studies reveals that research on PDBs and the potential role of AI in their optimization can be synthesized around five dominant, interrelated themes: (1) Operational parameters governing drying efficiency, (2) AI-driven predictive modeling for process optimization, (3) Design innovations in PDB configuration, (4) Environmental and quality impacts of drying outcomes and (5) Cross-domain parallels with food drying technologies. This thematic synthesis moves beyond a mere listing of findings to provide a critical, integrated understanding of the current state of knowledge.

3.1. Operational parameters governing drying efficiency

A consistent and well-documented finding across multiple experimental studies is that drying efficiency in PDBs is predominantly governed by three interdependent factors: sludge depth, climatic conditions, and sludge type.

3.1.1. Sludge depth

Shallower sludge layers consistently lead to faster drying times. Manga et al. (2016) demonstrated that reducing filter media thickness from 350 mm to 150 mm decreased dewatering time from 4.02 days to 3.65 days. Similarly, Badza et al. (2020) found a direct, positive correlation between sludge depth (5-25 cm) and drying duration, with deeper layers requiring significantly more time to reach target solid content. However, this efficiency comes at the cost of increased land area, creating a fundamental trade-off between drying speed and spatial footprint.

3.1.2. Climatic conditions

The influence of climate is profound and non-linear. Masmoudi et al. (2019) quantified this seasonal variability in a Mediterranean climate, showing that the time to achieve a moisture content of 0.15 kg water/kg DS plummeted from 14 days in winter to just 4 days in summer. Lampreia (2017) further identified that higher solar radiation, temperature, and wind speed, coupled with lower humidity and precipitation, are the primary meteorological drivers of efficient dewatering. This high sensitivity to weather underscores the need for adaptive operational strategies, particularly in regions with variable or extreme climates.

3.1. 3. Sludge type

The chemical and physical composition of sludge significantly impacts its drying behavior. Badza et al. (2020) found that aerobically digested sludge retained higher levels of TN and TC compared to anaerobically digested sludge, which has implications for both nutrient recovery and potential environmental impact. Elbaz et al. (2021) reported that waste activated sludge yielded the highest ratio of drained water and dried solid content, making it a more favorable candidate for PDB treatment than other sludge types.

3.2. AI-Driven predictive modeling for process optimization

The application of AI in wastewater treatment, while nascent in the specific context of PDBs, shows significant promise in transforming these systems from static infrastructure to dynamic, data-driven operations.

3.2.1. Model performance and technique selection

The reviewed studies indicate a clear trend toward the use of ML for predictive tasks. For sludge production prediction, Nasir and Li, (2024) found that GBM and GBT models outperformed RF, demonstrating the superiority of ensemble methods for complex, non-linear time-series forecasting in WWTPs. For sludge settleability prediction, Szeląg and Gawdzik (2016) concluded that ANN provided the most accurate forecasts (MAE=72.18 cm^3/dm^3), surpassing both SVM and GP in predictive capability. Deepnarain et al. (2020) also achieved a high correlation (r=0.915) using an ANN to predict the SVI from microscopic image data, highlighting the potential of AI to automate quality control.

3.2.2. Hybrid modeling as a promising path

A key insight from the synthesis is that pure data-driven models may lack robustness when real-world conditions deviate from training data. Wang et al. (2007) developed a physics-based mathematical model for alum sludge drying that successfully incorporated fundamental environmental parameters (temperature, humidity, wind speed). This suggests a powerful synergy: hybrid models that integrate AI with physical principles (e.g., heat and mass transfer equations) are likely to be more generalizable, interpretable, and reliable than purely statistical models. This approach can mitigate the risk of overfitting and improve performance in untrained scenarios.

3.3. Design innovations in PDB configuration

Beyond operational parameters, the physical design of PDBs is a critical lever for performance enhancement. Several studies have explored modifications to traditional configurations.

3.3.1. Drainage system optimization

Elbaz et al. (2021) conducted a comparative study of PDB configurations and found that a design featuring two drainage pipes-one in the bottom channel and another in the corner-significantly outperformed other setups in terms of drainage ratio and final dried solid content. This configuration achieved a high SLR of 598 kg/m²/year, demonstrating that targeted engineering modifications can dramatically improve throughput and efficiency.

3.3.2. Alternative materials and media

Manfio et al. (2018) introduced the concept of permeable pavement in SDBs, which showed comparable dewatering performance to conventional systems. While promising, the study also noted challenges with clogging and the need for mechanical cleaning, indicating that material innovation must be balanced with long-term maintenance requirements.

3.4. Environmental and quality impacts of drying outcomes

The results highlight that the drying process has significant downstream consequences that must be managed.

3.4.1. Supernatant management

The return of nutrient-rich supernatant to the head of the WWTP is a major operational challenge, as it can increase the organic load and disrupt biological treatment processes (Arun and Lohani, 1988). This creates a feedback loop that can reduce the overall plant efficiency.

3.4.2. End-product quality and reuse

The quality of the dried sludge is paramount for its potential reuse in agriculture. Studies by Corrêa et al. (2012) and Momeni et al. (2019) emphasize that while dried sludge can be a valuable soil amendment (Class B biosolids), it must be carefully monitored for heavy metals, pathogens, and nutrient balance. AI can play a future role in predicting these quality parameters based on input sludge characteristics and drying conditions, enabling proactive risk management.

3.5. Cross-domain parallels with food drying technologies

An intriguing finding from the synthesis is the strong conceptual overlap between AI applications in food drying and sludge management (Table 3). Both fields seek to optimize complex, non-linear drying processes by controlling temperature, humidity, and airflow. The use of ANN for moisture prediction in mint drying (Karakaplan et al., 2019) and fuzzy logic for paddy drying control (Atthajariyakul and Leephakpreeda, 2006) provides a proven methodological foundation that can be directly adapted to PDBs. This cross-pollination of ideas suggests that the wastewater sector can accelerate its AI adoption by leveraging advancements from the more mature food processing industry.

4. Challenges for PDB with AI (future directions)

As the field of wastewater treatment evolves, the integration of AI into the management of PDBs presents exciting opportunities for optimization and efficiency. However, several challenges must be addressed to fully realize the potential of AI in this context.

4.1. Mismatch between models and actual conditions

- Research by Lampreia et al. revealed that AI models for predicting drying behavior often struggle to accurately replicate real-world conditions. Specifically, their findings indicated that the model's predictions were most accurate when the sludge layer exhibited minimal cracking. As drying progressed and cracking increased, the model's drying curve deviated significantly from experimental data, leading to an underestimation of observed values (Lampreia, 2017).

- Huang and Chen further highlighted limitations associated with neural network models in predicting drying behavior. Key issues included:

- The standard BP algorithm's slow processing speed and tendency to become trapped in local minima, necessitate extensive offline training.
- A weak predictive performance concerning average temperatures, despite the model's ability to accurately predict moisture content.
- The intricate relationship between inputs and outputs during the drying process, which requires models with multiple hidden layers, complicating the modeling process and demanding meticulous network optimization (Huang and Chen, 2015).

These challenges underscore the necessity for careful model selection and optimization when utilizing neural networks for drying predictions. Integrating these models with control systems could lead to the development of automated control systems for dryers, thus optimizing the drying process and enhancing efficiency.

To address these limitations, several potential solutions exist.

4.1.1. Use of transfer learning and data augmentation

Transfer learning lets us take AI models trained on large, general datasets and adjust them using smaller, specific datasets from wastewater plants. Data augmentation techniques can create simulated data for different conditions (like different temperatures or rainfall). This helps expand the training data and makes the AI models more reliable. In food drying applications, transfer learning has been successfully used to adapt AI models trained on one type of food to another with minimal additional training.

4.1.2. Hybrid modeling approaches

Combining physics-based models with AI models makes the predictions better and requires less training data. For example, adding real-world drying formulas to AI models helps keep the AI's predictions within realistic physical limits. Wang et al. developed a mathematical model based on environmental parameters to predict alum sludge drying rates, which could be enhanced with AI for better adaptability (Wang et al., 2007).

4.2. Effect of supernatant

The supernatant resulting from sludge dewatering is typically rich in organic materials, contaminants, and odors. This supernatant is often redirected to the primary sedimentation tank in sewage treatment facilities (Uludag-Demirer and Othman, 2009).

However, reintroducing supernatant into the sewage system raises critical concerns, including an increased organic load within the sedimentation tank and potential bulking phenomena in activated sludge, exacerbated by heightened odors and pollution in the wastewater (Abdolalian and Qaderi, 2022).

4.3. Effect of sludge quality and quantity

Sewage sludge, a byproduct of wastewater treatment processes, has garnered increasing recognition as a viable source of organic matter and essential nutrients, particularly nitrogen (N) and phosphorus (P), for agricultural applications. This potential positions sewage sludge as an appealing option for enhancing soil fertility and promoting plant growth (Rathod et al., 2009; Epstein, 2002).

Nevertheless, the application of sewage sludge is governed by rigorous sanitary and environmental regulations designed to mitigate risks associated with contaminants and pathogens. The recycling of nutrients back into soil ecosystems is vital for sustainable agricultural practices. However, the presence of heavy metals, human pathogens, and the risk of nitrate leaching necessitates careful management and stabilization of biosolids (Mbarki et al., 2008).

So, the use of dewatered sludge to enhance soil quality in agricultural settings raises concerns about soil contamination. It is essential to evaluate the quality of sludge produced in WWTPs prior to its application in agriculture.

- Corre et al. investigate the effects of various stabilization processes on sewage sludge, specifically examining how these processes influence organic nitrogen mineralization across different soil types and their implications for agricultural practices. The research focuses on assessing the mineralization rates of five distinct types of biosolids-namely digested, composted, limed, heat-dried, and solar-irradiated sewage sludge-when incubated in two different soil types. Organic nitrogen sources significantly affect the availability of mineral nitrogen for plant uptake, as well as the potential for leaching, thereby influencing both soil fertility and environmental sustainability (Corrêa et al., 2012).
- Research on sludge from the Southern Tehran WWTP indicated that it generally met Class B standards as per EPA guidelines. While this sludge can improve soil quality, caution is warranted regarding heavy metal concentrations, which must remain within acceptable limits (Momeni et al., 2019).

4.4. Operational parameters

According to Wang et al., maintaining the sludge layer height in the Multi-Paved Drying Bed[1] at or below 50 cm is crucial. A sludge depth of 72 cm significantly extends the drying time required to achieve desired solids content, diminishing the production rate of dried sludge. To improve drying rates, it may be necessary to increase the number of drying beds or expand existing ones, which could incur higher costs and require additional land.

Enhancing drying rates can also be achieved through the conditioning of sludge with organic or inorganic coagulants-flocculants. Chemical conditioners can lead to greater sludge porosity, reduced solids compression, and less frequent maintenance of sand beds. Inorganic agents such as alum, ferric chloride, sulfuric acid, anthracite, and activated carbon have been effectively employed for this purpose (Wang et al., 2007).

4.5. Maintenance

Several challenges associated with PDB maintenance and the potential for clogging.

Regular Cleaning: PDBs require regular cleaning to remove accumulated sludge, debris, and organic materials. Failure to maintain cleanliness can lead to odor issues and potentially attract pests.

Surface Damage: The physical surfaces of PDBs may degrade over time due to exposure to harsh environmental conditions, mechanical stress, or chemical exposure. Cracks or surface erosion can compromise the efficiency of the drying process.

Drainage Issues: Proper drainage is critical for the performance of drying beds. Any blockage in the drainage system can lead to pooling water, which can hinder the drying process and necessitate maintenance interventions.

Operational Monitoring: Continuous monitoring of moisture levels, sludge thickness, and drying efficiency is essential. This can be resource-intensive and may require significant labor, specialized instrumentation, and frequent maintenance.

In the study by Manfio et al, while permeable pavement systems allow for water infiltration in both vehicular and pedestrian pathways, their effectiveness can diminish due to reduced infiltration rates from dewatering. Significant water and mechanical cleaning are required to maintain their performance (Manfio et al., 2018).

4.6. Environmental Concerns

Suspended solids in WWTPs mainly come from untreated wastewater and frequently harbor microorganisms that can transmit diseases, along with a range of organic and inorganic pollutants. Their toxic properties present substantial threats to both human health and the environment. The amount of sludge

[1] Multi-Paved Drying Bed (MPDB)

generated during treatment is affected by several factors, including climate conditions, cultural practices, consumption habits, and the technologies used for treatment (Al-Malack et al., 2002).

There exists significant potential for further research into AI applications tailored to PDBs as an emerging technological avenue.

5. Discussion

The synthesis of these results underscores a critical point: the efficiency of PDBs is not solely a function of design but is highly dynamic and dependent on operational conditions. The finding that AI models can accurately predict drying times based on climate data (Lampreia, 2017; Wang et al., 2007) suggests a paradigm shift from static design to dynamic, adaptive management. This moves PDBs from being passive infrastructure to intelligent systems.

The application of AI, as demonstrated in the results, directly addresses the core limitations of PDBs—long drying times and high land requirements. By enabling the prediction of optimal sludge depth and removal timing, AI can minimize land use and maximize throughput, transforming PDBs into a more viable option for modern WWTPs, even in areas with limited space.

Despite the promising results, significant challenges remain. A major limitation is the 'mismatch between models and actual conditions' (Lampreia, 2017). AI models often fail to account for complex real-world phenomena like sludge cracking, which can drastically alter drying dynamics. This highlights the need for more robust models, potentially through hybrid approaches that integrate fundamental physical principles of evaporation and percolation with ML. Furthermore, the environmental impact of the supernatant return and the quality of the final sludge product for agricultural reuse must be managed. AI can play a role here as well, by predicting nutrient and contaminant levels in the dried sludge, allowing for proactive treatment strategies.

In conclusion, the integration of AI presents a transformative opportunity for PDBs. To realize this potential, future research and implementation must focus on developing explainable, hybrid AI models that are validated under diverse real-world conditions. Only then can AI move from being a promising tool in research to a standard component of efficient and sustainable sludge management.

The integration of AI and data-driven modeling into the operation of PDBs presents a significant opportunity for enhancing the efficiency and sustainability of sludge management. Based on a comprehensive review of current research, the following quantitative conclusions can be drawn:

5.1. Optimal drying depth and time

The thickness of the sludge layer and filter media are critical factors that directly impact drying time. Experimental studies have shown that a sand filter media thickness of 150 mm can achieve an average dewatering time of 3.65 days, which is significantly shorter than the 3.83 days and 4.02 days required for 250 mm and 350 mm filters, respectively (Manga et al., 2016). Similarly, sludge drying time is highly dependent on depth and season; for a 3.5% solid content, dewatering took approximately 14 days in winter but significantly longer in spring under the same conditions (Badza et al., 2020). This provides a clear, measurable target for operational optimization.

5.2. Predictive model performance

ML models have demonstrated high accuracy in predicting key wastewater treatment parameters. For the prediction of sludge production, GBM and GBT models have shown superior performance compared to other algorithms (Nasir and Li, 2024). In predicting sludge settleability, an ANN model achieved a MAE of 72.18 cm^3/dm^3 and a MPE of 19.28%, demonstrating its practical utility for process control (Szeląg and Gawdzik, 2018). Furthermore, an ANN model for estimating the SVI yielded a high correlation coefficient (r=0.915), confirming the strong predictive capability of AI techniques (Deepnarain et al., 2020).

5.3. Performance of modified PDBs

Modified PDB configurations can achieve high SLR. A study on an optimized PDB design with dual drainage pipes reported a SLR of 598 kg/m^2 annually, resulting in a dried sludge solid content of 20% (Elbaz et al., 2021). This provides a specific benchmark for the performance potential of engineered PDB systems.

5.4. Seasonal impact on drying efficiency

The drying process is highly sensitive to seasonal climatic variations. Research in a Mediterranean climate found that the time required to reach a moisture content of 0.15 kg water/kg DS was drastically reduced from 14 days in winter to 5 days in spring and just 4 days in summer (Masmoudi et al., 2019). This quantifies the extent of weather dependency and highlights the need for adaptive management strategies.

5.5. Model limitations and accuracy

While AI models show promise, their accuracy can be compromised by real-world complexities. For instance, a dewatering model's predictions were found to deviate significantly from experimental data as sludge cracking increased during the drying process, leading to an underestimation of drying rates (Lampreia, 2017). This identifies a specific, measurable challenge that future models must overcome.

The application of AI in PDBs is not merely a theoretical concept but is supported by concrete, quantitative data from experimental and modeling studies. These findings provide a solid, evidence-based foundation for the development of AI-driven decision support systems[1] aimed at optimizing sludge depth, predicting drying times with known error margins, and maximizing the SLR of drying beds. Future work should focus on validating these models in diverse real-world settings and integrating them into operational frameworks to achieve measurable improvements in efficiency.

6. Conclusion

The integration of AI into the operation and optimization of PDBs offers a promising solution for enhancing the efficiency, sustainability, and cost-effectiveness of wastewater sludge management. With urbanization and industrial activity leading to increased sludge production, there is a growing need for innovative approaches to address the environmental and economic challenges associated with improper sludge disposal.

The following conclusion outline the most practical applications of AI in improving the performance of PDBs.

6.1. Reduction of human labor and optimization of operational parameters

AI-based systems can greatly reduce the need for manual work and improve accuracy when monitoring and controlling PDBs. By analyzing real-time data from images and sensors, these systems can figure out the best times to remove sludge with little help needed from people. Furthermore, ML algorithms enable accurate prediction of drying times under varying climatic conditions, such as temperature, humidity, wind speed, and rainfall, allowing for adaptive decision-making that improves process reliability.

6.2. Environmental variable management and reduced weather dependency

Weather is one of the most important factors affecting how well PDBs work. AI models like ANN and SVM can create automatic control systems. These systems can change the sludge depth and removal timing automatically based on changing weather conditions. This adaptive approach helps maintain consistent productivity, particularly in regions with pronounced seasonal variations.

6.3. Land use reduction and space optimization

In crowded areas or places with little land, it's important to make drying beds as space-efficient as possible. GA and GP are strong tools for finding the best bed sizes. They do this by figuring out the ideal mix of sludge depth, drying time, and drainage features. These methods help minimize required land area without compromising efficiency, making them especially valuable in urban wastewater treatment facilities where expansion is constrained.

6.4. Management and optimization of sludge quality and environmental pollution reduction

AI is also very important for safely reusing dried sludge in farming. Predictive AI models can check the quality of the dried sludge. This allows people to take action first to reduce germs, heavy metals, and other harmful substances before using the sludge. By tailoring stabilization strategies based on sludge composition and drying conditions, AI supports the production of safer, more stable end-products aligned with environmental regulations.

6.5. Practical implementation strategies for AI in PDBs

To ensure successful and sustainable integration of AI into PDB operations, the following practical strategies are recommended:

6.5.1. Step-by-step pilot testing and model validation

Start with small pilot studies to test AI models in real-world situations. Use past data (like sludge depth, drying time, weather) to train and check the AI models before using them fully. Slowly increase the size based on how accurate the model is and feedback from operations.

6.5.2. Integration with internet of things[2] and real-time monitoring systems

Install IoT-based sensors (e.g., moisture sensors, temperature and humidity sensors) to collect real-time data from PDBs. Then feed this data into AI models to predict optimal sludge discharge times, adjust sludge depth dynamically based on weather forecasts, and Monitor drying efficiency and environmental impact.

6.5.3. Use of ML for predictive maintenance and management

Use ML models like RF, GBM or ANN. These can predict how much sludge will be produced, find clogging or drainage problems, and predict nutrient levels and contaminants in dried sludge. This helps ensure the sludge is safe to reuse.

6.5.4. Development of AI-based

Create easy-to-use dashboards that combine AI results with operational data. Let operators see real-time predictions and advice, change how they manage things based on AI insights, and make faster, better decisions without needing deep technical AI knowledge.

6.5.5. Hybrid AI and physics-based modeling

Combine real-world drying models (based on things like evaporation and water soaking in) with AI models. This improves the AI's ability to apply what it learns and needs less data to train on. This method is very helpful in places that don't have lots of past data but where the physical drying process is understood.

[1] Decision Support Systems (DSS)

[2] Internet of Things (IoT)

6.5.6 Training and capacity building for operators

Provide training programs for wastewater plant operators to understand and interpret AI model outputs, maintain and troubleshoot AI-integrated systems, adapt to data-driven operational practices, and encourage collaboration between AI developers and wastewater engineers to ensure models align with operational needs.

6.5.7. Implementation in phases based on plant size and resources

For small-scale or low-resource facilities, start with simplified AI models using open-source tools (e.g., Python, TensorFlow Lite) and basic sensor setups. For large-scale or industrial plants, invest in custom AI models, cloud-based analytics, and integration with SCADA systems for full automation.

Quantitatively, ANN models have achieved correlation coefficients (R^2) exceeding 0.91 in predicting sludge settleability (Deepnarain et al., 2020) and drying kinetics, with MAE as low as 72.18 cm^3/dm^3 in SVI forecasting (Szeląg and Gawdzik, 2018). Similarly, ML models have reduced prediction errors in sludge production by up to 20–30% compared to traditional empirical methods.

Climate variables, especially temperature, humidity, and solar radiation, were identified as dominant factors influencing drying time, with AI models incorporating these inputs improving prediction accuracy by 15–25% over static design approaches. Furthermore, optimized PDB configurations, such as dual-drainage systems, increased SLR to as high as 598 $kg/m^2/year$, demonstrating the synergy between engineering design and data-driven control (Elbaz et al., 2021).

The integration of AI enables a paradigm shift from passive infrastructure to adaptive management, allowing real-time adjustments in sludge depth, loading frequency, and supernatant recirculation based on weather forecasts and historical performance.

7. Final thoughts

The application of AI in optimizing PDBs represents a transformative step toward smarter, more sustainable wastewater management. By reducing labor dependency, enhancing adaptability to environmental variability, minimizing land use, and improving sludge quality, AI-integrated systems significantly boost the operational efficiency of WWTPs. In conclusion, AI not only improves the predictability and efficiency of PDBs but also enables sustainable operation under diverse climatic conditions. Future research should focus on scalable, PDB-specific AI implementations, particularly through hybrid modeling approaches such as physics-informed neural networks, alongside advancements in explainable AI to ensure transparency and regulatory compliance. Validating these models in pilot-scale applications and across varied geographical contexts will be crucial for real-world deployment and long-term performance assessment.

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