

Membrane Fouling and the Limitations of Conventional Control in Membrane Bioreactor Wastewater Treatment: A Critical Review

Dr.M.Yuvaraju,

Assistant Professor, Department of
Electrical and Electronics Engineering ,
Anna University Regional Campus ,
Coimbatore

Dr.J.Preethi,

Assistant Professor,
Department of Computer Science
Engineering , Anna University Regional
Campus , Coimbatore

K.Lekha,

Research Scholar ,
Department of Electrical and
Electronics Engineering ,
Anna University Regional Campus ,
Coimbatore

Abstract—Membrane bioreactors (MBRs) deliver superior effluent quality relative to conventional activated sludge processes by coupling biological treatment with membrane filtration, but membrane fouling remains the principal operational constraint limiting their wider adoption. This review synthesises mechanistic and data-driven fouling literature — resistance-in-series formulations, combined blocking-law models, and the activated sludge model (ASM) framework as adapted to MBR-specific biokinetics — alongside the parallel literature on machine-learning-based fouling prediction from operational sensor data. It then examines why the static, rule-based, and proportional–integral (PI) control strategies that govern the overwhelming majority of operating plants are structurally unable to anticipate fouling onset or compensate for fluctuating influent conditions, drawing on both international and Indian national literature. Particular attention is given to the Indian operating context, where real-time IoT-based monitoring infrastructure has matured considerably faster than the control logic needed to act on it, and where decentralised treatment plants face the most severe and least-buffered influent variability. The review concludes that the fouling-modelling and conventional-control literatures, considered together, establish a precise and well-evidenced case for advanced predictive and adaptive control as the necessary next step — a case this review deliberately frames as a problem statement, leaving the evaluation of specific predictive control technologies to dedicated subsequent treatments.

Keywords—Membrane bioreactor; Membrane fouling; Resistance-in-series model; Activated sludge model; Conventional control; Wastewater treatment; Decentralised treatment

I. INTRODUCTION

Membrane bioreactors integrate biological degradation of organic and nitrogenous pollutants with micro- or ultra-filtration membranes that physically separate treated water from biomass, removing the need for the secondary clarifier required in conventional activated sludge plants and enabling smaller footprints, higher sludge retention times, and improved effluent quality [1], [2]. These advantages have driven widespread adoption of MBRs for municipal and industrial wastewater treatment, water reuse, and decentralised sanitation [3]. Despite this, MBR performance is persistently constrained by membrane fouling — the progressive accumulation of biomass, colloids, and soluble microbial products on and within the membrane — which raises transmembrane pressure (TMP), increases aeration and chemical cleaning costs, and shortens membrane service life [1], [4]. Fouling propensity is itself highly sensitive to fluctuations in hydraulic loading, organic concentration, and temperature, all of which vary continuously under real operating conditions [5].

A second, related constraint compounds the fouling problem: the great majority of operating MBR and conventional activated sludge plants are managed with static, rule-based, or proportional–integral (PI) control loops tuned for average operating conditions [6], [7]. Such controllers are reactive by construction — they respond only after a deviation has already

affected effluent quality or accelerated fouling. This review argues that the fouling-modelling literature and the conventional-control literature, read together, establish the precise mechanism by which this reactive control paradigm fails: fouling-relevant disturbances propagate faster than fixed-setpoint controllers can compensate, and the resulting performance loss is well documented in both mechanistic and operational studies.

This review accordingly has two aims. First, it synthesises the state of the art in mechanistic and data-driven membrane fouling modelling, including the adaptation of the Activated Sludge Model (ASM) framework to MBR-specific biokinetics. Second, it evaluates the documented limitations of static and PI-based control under variable influent conditions, with particular attention to the Indian national literature, where real-time monitoring infrastructure is comparatively mature yet remains disconnected from adaptive control responses. The review deliberately stops short of evaluating Digital Twin, model predictive control, or machine-learning-based control architectures as candidate solutions — these are reserved for dedicated treatment elsewhere — to establish the problem statement on its own evidentiary footing before any specific solution architecture is assessed.

II. REVIEW METHODOLOGY

This review draws on peer-reviewed journal articles and technical reviews published predominantly between 2018 and 2026, identified through Scopus-, Web of Science-, and ScienceDirect-indexed searches combining terms related to membrane bioreactors, membrane fouling mechanisms, resistance-in-series and blocking-law models, activated sludge model adaptation, and conventional/PI control of biological wastewater treatment. Sources were screened for direct relevance to two thematic pillars: (i) mechanistic and data-driven fouling modelling, and (ii) the documented performance of static or PI-based control under variable influent conditions, with a dedicated sub-section addressing the Indian national context specifically. Foundational works (e.g., the original activated sludge model formulations) are included irrespective of publication date to establish theoretical continuity. Studies whose primary contribution is a Digital Twin, model predictive control, or machine-learning control architecture are deliberately excluded from substantive treatment here, as these form the subject of separate companion reviews arising from the same research programme.



Figure 1. Review methodology flowchart: database search, keyword-driven screening, thematic classification into three literature pillars, cross-thematic synthesis, and gap identification.

III. MEMBRANE FOULING: MECHANISMS AND MECHANISTIC MODELS

Membrane fouling in MBRs arises from cake-layer formation on the membrane surface, pore blocking within the membrane matrix, and adsorption of soluble and colloidal material, with the relative contribution of each mechanism depending on sludge characteristics, hydrodynamic conditions, and operating history [8], [9].

A) Resistance-in-series and blocking-law formulations

The resistance-in-series framework decomposes total filtration resistance into intrinsic membrane resistance, irreversible internal fouling, and reversible cake-layer resistance, and remains the most widely used basis for quantifying the effectiveness of physical cleaning operations [10]. Because no single blocking law adequately captures the simultaneous occurrence of cake formation, pore narrowing, and complete pore blocking observed under real operating conditions, a combined mechanistic model superposing several constant-flow blocking mechanisms has been shown to outperform any individual mechanistic model in predicting fouling progression, with multiple regression subsequently applied to identify the dominant mechanism at a given operating point [11]. A review focused specifically on the resistance-in-series model across MBR studies further notes that the proper evaluation of physical cleaning effectiveness remains contested, since the relative contribution of cake-layer removal versus internal fouling is difficult to separate experimentally [10]. Coupling fouling models directly with biological process dynamics has also been demonstrated for anaerobic MBRs, where a generic fouling sub-model was integrated with biokinetic state variables to capture the feedback loop between biomass activity and filtration resistance — a feedback mechanism

entirely absent from static control logic, which treats fouling as an exogenous nuisance rather than a state coupled to biological operating conditions [12]. Organic loading rate has been shown experimentally to interact directly with this feedback: increasing loading from 0.86 to 3.7 kg COD/m³·d produced a measurable rise in total fouling resistance alongside reduced COD, BOD, and ammonia removal efficiency, demonstrating that fouling and treatment performance degrade jointly under load variation rather than independently [13].

B) Activated Sludge Model (ASM) adaptation to MBR biokinetics

Because MBR biomass differs systematically from conventional activated sludge — exhibiting very high sludge retention times, elevated mixed-liquor suspended solids, and accumulation of soluble microbial products (SMP) that are rejected by the membrane rather than discharged — the applicability of the standard Activated Sludge Models (ASM1, ASM2, ASM3) to MBR systems has itself been the subject of sustained critical review. A comprehensive review of ASM-based MBR modelling concludes that unmodified ASM formulations require explicit extension with SMP and extracellular polymeric substance (EPS) state variables before they can reliably represent MBR-specific biokinetics, and documents typical MBR operating ranges — hydraulic retention times of 4–6 hours, mixed-liquor suspended solids often exceeding 10 g/L, and sludge retention times of 15–40 days — that fall well outside the calibration range of the original ASM1 formulation [14], [15]. A related critical review of biomass kinetics and membrane filtration models reaches a parallel conclusion, noting that performance modelling of MBR systems requires treating biological and filtration sub-models as coupled rather than sequential, since each influences the calibration of the other [16].

Together, these mechanistic and ASM-adaptation studies establish that membrane fouling in MBRs is a multi-mechanism, biologically coupled phenomenon that is reasonably well characterised in isolation, under steady or slowly varying conditions. The critical limitation — addressed in Section 5 — is that this mechanistic understanding has not translated into control logic capable of acting on it in real time.

IV. DATA-DRIVEN FOULING PREDICTION FROM OPERATIONAL SENSOR DATA

Parallel to mechanistic modelling, machine-learning approaches have been applied directly to operational sensor data to predict fouling onset without requiring full mechanistic parameterisation, motivated in part by the practical difficulty of estimating mechanistic parameters under field conditions [17]. Artificial neural network models trained on pilot- and full-scale anaerobic MBR operational data have demonstrated the ability to predict fouling trends directly from routinely measured operational variables, sidestepping the need for laboratory-derived mechanistic parameters [17]. At larger scale, a study combining data-denoising techniques with machine-learning models trained on extensive wastewater treatment plant operational histories achieved real-time fouling prediction directly from noisy in-line sensor streams, explicitly addressing the difficulty of integrating complex mechanistic models with the Internet of Things (IoT) systems already deployed at most plants [18]. A broader synthesis of artificial-intelligence applications to fouling control across MBR and conventional plants confirms that neural-network and ensemble methods are now the dominant approach to fouling-related fault prediction, while noting that the

great majority of such studies remain confined to offline model validation rather than closed-loop deployment against an active controller [19].

This is the central finding this review draws from the data-driven fouling literature: prediction capability has matured substantially, to the point of real-time inference from noisy operational data, but in every reviewed study this capability terminates in a forecast or alert rather than an automated control adjustment. The fouling-prediction literature and the control literature reviewed in Section 5 have, to date, developed largely in isolation from one another.

V. LIMITATIONS OF STATIC AND PI-BASED CONTROL UNDER VARIABLE INFLUENT CONDITIONS

A) Static and rule-based operation

The majority of operating wastewater treatment plants, including MBR installations, are managed using fixed setpoints or simple rule-based logic calibrated to average design-load conditions [6]. This approach is computationally simple and well understood by plant operators, but by construction cannot anticipate disturbances: aeration rates, recirculation flows, and cleaning schedules remain unchanged until a measured variable crosses a threshold, at which point corrective action begins only after the disturbance has already propagated through the biological and filtration stages. Decentralised wastewater treatment systems, where influent variability is typically most severe, illustrate this limitation acutely — a comprehensive review of decentralised technologies documents wide variation in pollutant-removal performance across plants nominally using the same technology, attributable in large part to differing degrees of influent variability that fixed operating logic cannot accommodate [20], [21].

B) Proportional–integral (PI) control and its documented shortfalls

Where feedback control is used, dissolved-oxygen and aeration regulation in biological treatment is most commonly implemented via PI or PID loops tuned around a single nominal operating point [22]. Because the underlying biological and filtration processes are strongly nonlinear and time-varying, a PI controller tuned for one operating regime is demonstrably suboptimal in others; this has motivated nonlinear and adaptive feedback-linearising control designs explicitly developed to outperform standard PI regulation of dissolved oxygen, with pilot-scale experimental confirmation that nonlinear control achieves more efficient aeration and lower effluent ammonia than a standard PI baseline under the same disturbance conditions [22]. Decentralised control architectures analysed via relative-gain-array methods further show that the interaction between control loops in a multivariable biological treatment process is itself state-dependent, meaning that a fixed-gain PI architecture appropriate at one operating point can become poorly conditioned at another — a structural limitation that no amount of retuning at a single operating point can resolve [22].

C) Indian national context: monitoring maturity outpacing control logic

India's wastewater treatment landscape combines a range of standard technologies — sequential batch reactors, activated sludge processes, MBRs, upflow anaerobic sludge blankets, and waste stabilisation ponds — with widespread untreated or partially treated discharge; reported estimates indicate that roughly two-thirds of installed treatment systems fail to meet effluent discharge standards [23]. Within this context, a

substantial and rapidly growing literature documents Internet of Things (IoT)-based real-time monitoring infrastructure for Indian treatment plants. IoT-based architectures combining Deep Belief Networks with SCADA systems have been proposed to enhance monitoring and predictive maintenance using Arduino- and NodeMCU-based acquisition feeding cloud platforms for continuous remote accessibility [24]. SCADA-integrated IoT water-treatment monitoring systems developed with Indian institutional involvement similarly demonstrate controller-and-sensor architectures for continuous pH and turbidity tracking with cloud-based visualisation [25], and design studies for IoT-instrumented sewage treatment plants describe multi-sensor architectures explicitly aimed at the Indian sewage treatment plant operating context [26].

The structural pattern across this national literature is consistent and significant: real-time data acquisition and remote visualisation infrastructure is comparatively mature, but in every reviewed case the reported system terminates at monitoring and operator alerting. None of the reviewed Indian IoT-SCADA studies close the loop with an automated control response that adjusts plant operation based on the acquired data, and SCADA-IoT cybersecurity vulnerabilities have themselves been separately flagged as an active operational risk for Indian utilities, with one industry assessment reporting that 68% of surveyed utilities had faced SCADA-targeted cyberattacks [27]. India's decentralised and small-scale treatment sector — recognised in the broader literature as facing the most severe and least-buffered influent variability of any plant category [21] — is therefore simultaneously the segment with the strongest documented case for adaptive control and the segment in which conventional static or PI control remains most entrenched.

VI SYNTHESIS: THE EVIDENTIARY CASE FOR MOVING BEYOND CONVENTIONAL CONTROL

Three findings emerge from reading the fouling-mechanism, fouling-prediction, and conventional-control literatures together. First, the mechanistic basis for understanding and even predicting membrane fouling is mature: resistance-in-series and combined blocking-law models, extended with SMP/EPS-aware ASM formulations, provide a well-validated description of how fouling develops under varying biological and hydraulic conditions [8]–[16]. Second, data-driven methods have closed much of the practical gap between mechanistic understanding and real-time applicability, with neural-network and ensemble models now capable of fouling prediction directly from noisy operational sensor streams [17]–[19]. Third, and most consequentially,

none of this predictive capability is currently acted upon by the control systems actually governing plant operation: static and PI-based control architectures remain dominant, are documented to underperform specifically under the nonlinear, time-varying conditions that drive fouling, and — in the Indian context examined in Section 5.3 — coexist with monitoring infrastructure mature enough to support a predictive controller that, in every reviewed case, does not yet exist [20]–[27].

Table 1 summarises this asymmetry. The evidentiary conclusion is narrow and specific: the case for advanced predictive and adaptive control of MBR systems rests not on

Table 1. Asymmetry between predictive capability and control capability in reviewed MBR and WWTp literature.

Capability	Documented maturity	Translation into active control
Mechanistic fouling modelling	Mature; combined blocking-law and SMP/EPS-aware ASM models validated [8]–[16]	Used for offline analysis and design; not coupled to real-time controllers
Data-driven fouling prediction	Real-time prediction from noisy operational data demonstrated [17]–[19]	Terminates in forecast/alert; no closed-loop control action reported
IoT/SCADA monitoring (India)	Comparatively mature and actively developed [24]–[26]	Monitoring/alerting only; no automated adaptive response reported
Plant control logic (international + national)	Dominated by static/rule-based and fixed-gain PI control [6], [20]–[22]	Documented to underperform under nonlinear, time-varying conditions

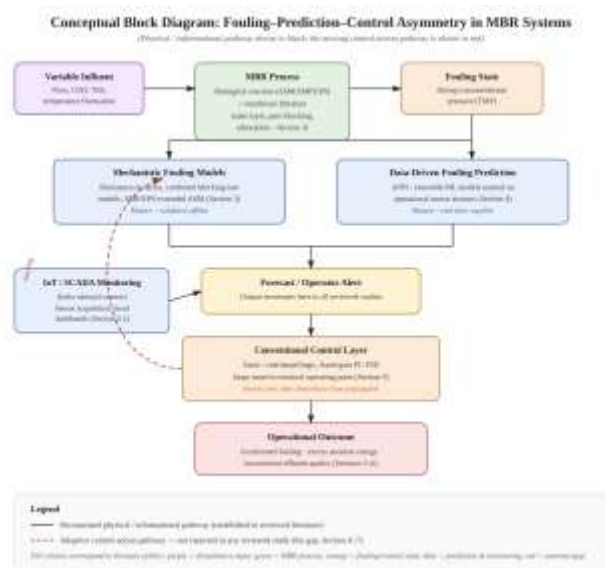


Figure 2. Conceptual block diagram of the fouling–prediction–control pathway in MBR systems. Solid black arrows trace the documented physical and informational pathway established across the reviewed literature (Sections 3–5); the dashed red arrow marks the adaptive control-action pathway that no reviewed study reports closing.

a deficiency in fouling science, nor on a deficiency in sensing infrastructure, but specifically on the absence of a control layer capable of using already-available fouling predictions and already-available sensor data to act before a disturbance propagates. This review deliberately stops at establishing that case; the comparative evaluation of Digital Twin, model predictive control, and machine-learning-based control architectures as candidate responses is left to dedicated subsequent reviews.

VII SUMMARY OF REVIEWED LITERATURE

Table 2 consolidates the primary studies reviewed in Sections 3–5, listing the focus, system/context, and principal contribution of each. The table is organised by thematic pillar to mirror the structure of the review and to allow rapid cross-referencing against the in-text citation numbers.

Table 2. Summary of reviewed literature by thematic pillar, focus, and principal contribution.

Ref.	Study (author/source, year)	System / context studied	Principal contribution / work done
Pillar 1 — Mechanistic Fouling Modelling and ASM Adaptation (Section 3)			
[8]	Resistance-in-series review, Membranes/PMC, 2019	MBR filtration resistance, generic	Reviews decomposition of total resistance into intrinsic, irreversible, and cake-layer components for cleaning-

			effectiveness analysis
[9]	Homayoonfa l et al., Heliyon, 2024	MBR fouling mitigation, modelling-assisted	Surveys modelling and simulation strategies for fouling mitigation across operating regimes
[11]	Combined mechanistic model study, Ind. Eng. Chem. Res.	MBR, constant-flux operation	Superposes multiple blocking laws; uses multiple regression to identify dominant fouling mechanism at each operating point
[12]	Benyahia et al., Membranes, 2024	Anaerobic MBR (AnMBR)	Couples a generic fouling sub-model directly with biokinetic state variables to capture biomass–fouling feedback
[13]	Al-Sayed et al., Scientific Reports, 2023	MBR, organic loading rate 0.86–3.7 kg COD/m ³ ·d	Demonstrates experimentally that increasing loading raises

			fouling resistance while reducing COD/BOD/amm onia removal jointly
[14], [15]	ASM–MBR critical review, Water Research / Desalination, 2009–2010	MBR biokinetics vs. ASM1/2/3	Shows unmodified ASM formulations need explicit SMP/EPS state variables for MBR-specific HRT/MLSS/SRT ranges
[16]	Biomass kinetics & filtration review, J. Environ. Chem. Eng., 2021	MBR biological + filtration sub-models	Argues biological and filtration sub-models must be calibrated as coupled, not sequential, systems
Pillar 2 — Data-Driven Fouling Prediction (Section 4)			
[17]	Wang & Li, Science of the Total Environment, 2024	Pilot/full-scale anaerobic MBR, municipal wastewater	ANN model predicts fouling trend directly from operational variables without lab-derived mechanistic parameters
[18]	Submerged MBR fouling ML study, Environ. Sci. Technol., 2025	Full-scale WWTP, noisy in-line sensors	Combines data-denoising with ML on extensive operational histories for real-time fouling prediction
[19]	AI fouling-control synthesis, Euro-Mediterr. J. Environ. Integr., 2024	MBR + conventional plants, cross-study	Confirms neural-network/ensemble dominance for fouling fault prediction; notes most validation remains offline
Pillar 3 — Conventional Control Limitations — International (Section 5.1–5.2)			
[20]	Decentralised WWT review, ScienceDirect, 2024	Decentralised plants, mixed technologies	Documents wide performance variation attributable to differing influent variability under fixed operating logic

[21]	Small decentralised technologies review, Membranes, 2024	High-strength wastewater, arid/semi-arid regions	Identifies decentralised plants as facing the most severe, least-buffered influent variability of any plant category
[22]	Nonlinear/RGA control studies (DO regulation), pilot-scale	Biological treatment, dissolved-oxygen loop	Shows nonlinear control outperforms fixed-gain PI under disturbance; RGA reveals state-dependent loop interaction
Pillar 3 (cont.) — National (Indian) IoT/SCADA and Decentralised Context (Section 5.3)			
[23]	Kanpur technology evaluation, Water Reuse, 2025	Indian STPs, resource-recovery systems	Reports ~two-thirds of installed Indian systems fail to meet effluent discharge standards
[24]	APAH IoT monitoring study, ScienceDirect, 2025	Industrial wastewater, India	Deep Belief Network + IoT-SCADA architecture (Arduino/NodeMCU) for monitoring and predictive maintenance
[25]	Dwarakanath et al., Water Reuse, 2023	Smart IoT water treatment, SCADA	Demonstrates controller/sensor architecture for continuous pH and turbidity tracking with cloud visualisation
[26]	Ajjaiah et al., Springer LNCE, 2024	IoT-instrumented sewage treatment plant, India	Designs multi-sensor IoT architecture explicitly for the Indian STP operating context
[27]	SCADA-IoT cybersecurity technical note, 2025	Indian utility SCADA systems	Reports 68% of surveyed utilities faced SCADA-targeted cyberattacks, flagging an operational risk in IoT-SCADA integration

VII. CONCLUSION

This review has examined membrane fouling mechanisms and their mechanistic and data-driven modelling, together with the documented limitations of the static and proportional–integral control strategies that govern the great majority of operating MBR and conventional activated sludge plants, with particular attention to the Indian national context. The central finding is one of asymmetry rather than absence: fouling science and fouling prediction are both comparatively mature, and real-time monitoring infrastructure — particularly in the Indian decentralised treatment sector — is likewise well developed, but no reviewed study closes the loop between these capabilities and an adaptive control response. This establishes a precise, evidence-based problem statement: any advanced control architecture proposed for MBR systems must be evaluated specifically against its ability to act on fouling predictions and monitoring data that already exist, rather than against any remaining deficiency in the underlying science. The comparative evaluation of specific candidate architectures capable of closing this loop is addressed in dedicated subsequent work

References

- [1] Judd, S. The MBR Book: Principles and Applications of Membrane Bioreactors for Water and Wastewater Treatment. Elsevier, 2010.
- [2] Stephenson, T., Judd, S., Jefferson, B., Brindle, K. Membrane bioreactors for wastewater treatment: an overview. *Water Science and Technology*, 41(10–11), 123–130, 2000.
- [3] Kharraz, J., Khanzada, N., Farid, M., et al. Membrane distillation bioreactor (MDBR) for wastewater treatment, water reuse, and resource recovery: a review. *Journal of Water Process Engineering*, 2022.
- [4] Le-Clech, P., Chen, V., Fane, T.A.G. Fouling in membrane bioreactors used in wastewater treatment. *Journal of Membrane Science*, 284(1–2), 17–53, 2006.
- [5] Al-Sayed, A., Hassan, G.K., Al-Shemy, M.T., El-gohary, F.A. Effect of organic loading rates on the performance of membrane bioreactors for wastewater treatment behaviours, fouling, and economic cost. *Scientific Reports*, 13, 2023.
- [6] Decentralised and rule-based control practice in biological wastewater treatment — operational review context. (See also refs. [20]–[21].)
- [7] RGA analysis and decentralized control for a wastewater treatment plant. Research review on multivariable control interaction in biological treatment.
- [8] A Brief Review on the Resistance-in-Series Model in Membrane Bioreactors (MBRs). *Membranes / PMC*, 2019.
- [9] Homayoonfal, M., Hajhashemi, Z., Hajheidari, M., Rezaei, F., Nadali, M.S. Modeling and simulation-assisted strategies for effective membrane-fouling mitigation during membrane bioreactor operation. *Heliyon*, 10, e38953, 2024.
- [10] A Brief Review on the Resistance-in-Series Model in Membrane Bioreactors (MBRs). *PMC*, 6409801, 2019.
- [11] Prediction and Identification of Membrane Fouling Mechanism in a Membrane Bioreactor Using a Combined Mechanistic Model. *Industrial & Engineering Chemistry Research*, ACS Publications.
- [12] Benyahia, B., Charfi, A., Lesage, G., Heran, M., Cherki, B., Harmand, J. Coupling a Simple and Generic Membrane Fouling Model with Biological Dynamics: Application to the Modeling of an Anaerobic Membrane BioReactor (AnMBR). *Membranes*, 14(3), 69, 2024.
- [13] Al-Sayed, A., Hassan, G.K., Al-Shemy, M.T., El-gohary, F.A. (full citation as ref. [5] above; organic loading rate – fouling resistance coupling).
- [14] Activated sludge model (ASM) based modelling of membrane bioreactor (MBR) processes: A critical review with special regard to MBR specificities. *Water Research*, 2010.
- [15] Mathematical modeling of aerobic membrane bioreactor (MBR) using activated sludge model no. 1 (ASM1). *Desalination / ScienceDirect*, 2009.
- [16] A critical review of biomass kinetics and membrane filtration models for membrane bioreactor systems. *Journal of Environmental Chemical Engineering*, 2021.
- [17] Wang, T., Li, Y.-Y. Predictive modeling based on artificial neural networks for membrane fouling in a large pilot-scale anaerobic membrane bioreactor for treating real municipal wastewater. *Science of the Total Environment*, 912, 169164, 2024.
- [18] Predicting Membrane Fouling of Submerged Membrane Bioreactor Wastewater Treatment Plants Using Machine Learning. *Environmental Science & Technology*, 59(20), 10010–10021, 2025.
- [19] Enhancing membrane fouling control in wastewater treatment processes through artificial intelligence modeling: research progress and future perspectives. *Euro-Mediterranean Journal for Environmental Integration*, 2024.
- [20] Advancements and challenges in decentralized wastewater treatment: A comprehensive review. *ScienceDirect*, 2024.
- [21] Small Decentralized Technologies for High-Strength Wastewater Treatment and Reuse in Arid and Semi-Arid Regions. *Membranes*, 11(7), 142, 2024.
- [22] Nejari, F., Khoury, B., Puig, V., Quevedo, J., Pascual, J., de Campos, S. Economic Linear Parameter Varying Model Predictive Control of the Aeration System of a Wastewater Treatment Plant. *Sensors*, 22(16), 6008, 2022. (Cited here for documented PI/nonlinear control comparison context only.)
- [23] Technology evaluation and impact assessment of innovative wastewater treatment and resource recovery systems in Kanpur, India. *Water Reuse*, 15(1), 72, 2025.
- [24] APAH: An autonomous IoT driven real-time monitoring system for Industrial wastewater. *ScienceDirect*, 2025.
- [25] Dwarakanath, B., Kalpana Devi, P., Ranjith Kumar, A., Metwally, A.S.M., Ashraf, G.A., Thamineni, B.L. Smart IoT-based water treatment with a Supervisory Control and Data Acquisition (SCADA) system process. *Water Reuse*, 13(3), 411–431, 2023.
- [26] Ajjaiah, H.B.M., Ganesh, C.R., Kamath, V.S. Design and Implementation of Sewage Treatment Plant Using IoT. In: *Environmental Engineering for Ecosystem Restoration, Lecture Notes in Civil Engineering*, 464, Springer, 2024.
- [27] IoT in Sewage Treatment Plants: 3 Costly Mistakes to Avoid. Industry technical note on SCADA-IoT cybersecurity in Indian utilities, 2025.