International Journal of Scientific Research and Modern Technology (IJSRMT) ijsrmt.com
Volume 3, Issue 12, 2024
DOI: https://doi.org/10.38124/ijsrmt.v3i12.1683

Data-Driven Analysis of Gas Turbine Compressor Fouling and Water-Washing for Improving Efficiency Maintenance Planning and Wastewater Management in Sustainable Power Plant Infrastructure

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Publication Date: 2024/12/28

Abstract

Gas turbine compressor fouling is a major source of progressive efficiency degradation, increased heat rate, reduced power output, higher fuel consumption, and avoidable maintenance expenditure in combined-cycle and industrial power plants. Compressor water washing can recover lost aerodynamic performance; however, conventional washing schedules based on fixed operating hours, differential pressure thresholds, or operator experience may result in premature cleaning, excessive water consumption, unnecessary downtime, or delayed intervention. This study develops a data-driven framework for jointly predicting compressor fouling severity and optimizing water-washing and maintenance decisions while incorporating wastewater-management constraints in sustainable power plant infrastructure. A novel Fouling–Wash Adaptive Optimization Network (FW-AON) is proposed to integrate multivariate operating data including compressor inlet temperature, ambient humidity, pressure ratio, corrected mass flow, compressor efficiency, exhaust temperature, power output, fuel flow, operating hours, particulate loading, water-wash history, and wastewater volume. The FW-AON combines temporal feature learning, nonlinear fouling-state estimation, degradation forecasting, and multi-objective maintenance optimization to determine the economically and environmentally preferred washing interval. Its predictive performance is compared with Random Forest, XGBoost, Long Short-Term Memory, Gated Recurrent Unit, and Support Vector Regression using coefficient of determination, root mean square error, mean absolute error, fouling-detection accuracy, computational time, and maintenance-decision effectiveness. System-level performance is further evaluated through compressor efficiency recovery, power-output recovery, heat-rate reduction, fuel savings, wash-water consumption, wastewater generation, maintenance cost, and avoided production losses. Results are presented using time-series degradation curves, predicted-versus-observed plots, algorithm comparison charts, sensitivity graphs, Pareto-front optimization plots, and water-use versus efficiency-recovery relationships. The proposed framework is intended to provide improved fouling prediction and condition-based washing decisions compared with fixed-interval and conventional machine-learning approaches while simultaneously minimizing unnecessary water consumption and wastewater generation. The study establishes an integrated pathway for coupling gas turbine performance analytics, predictive maintenance, water-resource efficiency, and environmental management within sustainable power plant infrastructure.

Keywords: *Gas Turbine Compressor; Compressor Fouling; Water Washing; Predictive Maintenance; Wastewater Management.*

Addy, R. Z., Atoo, A. A., & Nwafor, E. O. (2024). Data-Driven Analysis of Gas Turbine Compressor Fouling and Water-Washing for Improving Efficiency Maintenance Planning and Wastewater Management in Sustainable Power Plant Infrastructure. *International Journal of Scientific Research and Modern Technology*, *3*(12), 301–322. https://doi.org/10.38124/ijsrmt.v3i12.1683

I. INTRODUCTION

- *Background to Gas Turbine Compressor Fouling and Performance Degradation*

Gas turbine compressor fouling is a progressive aerodynamic degradation mechanism caused by the deposition and accumulation of airborne contaminants on compressor blades, vanes, and associated flow-path surfaces. Typical contaminants include atmospheric dust, aerosols, hydrocarbons, salts, industrial particulate matter, and moisture-bound particles that penetrate the inlet filtration system. Their deposition changes blade surface roughness, effective camber, incidence angle, boundary-layer development, and flow separation characteristics, progressively displacing the compressor from its clean-design operating map. Igie et al. (2014) demonstrated that fouling affects individual compressor-stage characteristics and ultimately changes whole-engine performance, while Kang and Kim (2018) identified compressor fouling as a major contributor to industrial gas-turbine performance deterioration. Environmental exposure is therefore important because energy infrastructure operates continuously under variable temperature, humidity, particulate, and thermal conditions; analogous infrastructure studies also show that sustained environmental exposure influences long-term energetic and thermal performance (Ocharo et al., 2023).

For the present study, fouling is treated not as a single observable fault but as a latent degradation state inferred from interacting operational variables. The proposed FW-AON framework consequently analyzes compressor inlet temperature, relative humidity, ambient particulate loading, compressor discharge pressure, pressure ratio, corrected airflow, exhaust temperature, fuel flow, generated power, and accumulated operating hours. As deposits increase, flow capacity and aerodynamic efficiency decline, requiring the gas turbine control system to compensate through altered fuel scheduling and operating-point movement. This complicates direct diagnosis because ambient temperature, load demand, inlet-guide-vane position, and transient operation may generate parameter variations that resemble degradation. Kang and Kim (2018) showed why normalization and model adaptation are essential when distinguishing genuine deterioration from operating-condition effects. This paper therefore establishes a data-driven baseline representing clean compressor behavior and quantifies departures from that baseline as a time-dependent fouling index. Such an approach supports the later comparison of FW-AON predictions with Random Forest, XGBoost, SVR, LSTM, and GRU models and provides the technical basis for interpreting the degradation trajectories, predicted-versus-observed plots, and compressor efficiency recovery curves reported in the results.

- *Effects of Compressor Fouling on Efficiency, Power Output, Heat Rate, and Fuel Consumption*

Compressor fouling directly degrades the thermodynamic performance of a gas turbine by reducing compressor air-handling capability and isentropic efficiency while increasing the work required to deliver a given pressure ratio. Surface contamination modifies blade aerodynamic profiles, increases skin-friction losses, promotes premature boundary-layer separation, and reduces effective flow area. Talebi and Tousi (2017) demonstrated that increasing blade roughness alters compressor operating characteristics, reduces air mass flow, and changes critical gas-path temperatures. At plant level, these effects propagate through the Brayton cycle. Reduced compressor mass flow lowers the quantity of air available for combustion and turbine expansion, thereby restricting achievable shaft power. Martín-Aragón and Valdés (2014) showed that reductions in compressor efficiency, pressure ratio, and air mass flow translate into both full-load power losses and heat-rate penalties. Consequently, the turbine may consume more fuel per unit of electrical energy produced even when absolute fuel flow appears stable.

The economic implication is particularly important for baseload and dispatchable generation because small losses accumulated across thousands of operating hours can produce substantial fuel and opportunity costs. In this study, corrected compressor efficiency, net power output, specific fuel consumption, and heat rate are therefore analyzed simultaneously rather than independently. The methodology recognizes, consistent with broader techno-economic energy-system analysis, that operational efficiency must be interpreted together with fuel use, reliability, lifecycle cost, and uncertainty rather than through a single performance indicator (Oladoye et al., 2023). The FW-AON model will quantify the nonlinear relationships between fouling severity and these thermodynamic responses while controlling for ambient temperature and loading. The expected results are represented by degradation curves showing declining efficiency and power output alongside increasing heat rate and incremental fuel cost. Comparison of clean, fouled, and post-wash operating states will make it possible to calculate recoverable versus non-recoverable performance loss. These relationships are central to the optimization problem because washing is economically rational only when the expected value of recovered power, reduced heat rate, and avoided fuel consumption exceeds washing, downtime, water, wastewater-treatment, and maintenance costs. The findings will consequently connect machine-learning prediction accuracy to physically meaningful operational and economic consequences.

- *Compressor Water-Washing Practices and Performance Recovery*

Compressor water washing is the principal restorative intervention considered in this study because a substantial portion of fouling-induced aerodynamic deterioration is recoverable when deposits are removed before they become strongly bonded, baked, or chemically transformed. Online washing is normally performed while the gas turbine remains in operation and is principally intended to suppress the accumulation rate of water-soluble and loosely adhered deposits. Offline washing requires shutdown, cooling, cranking, and controlled introduction of demineralized water, with or without an approved cleaning agent, and generally provides deeper removal of accumulated deposits. Boyce and Gonzalez (2007) demonstrated the importance of comparing washing frequencies through compressor isentropic efficiency, overall heat rate, and thermal efficiency, whereas Schneider et al. (2010) showed from field operating data that washing frequency materially affects the rate of power deterioration. Thus, washing effectiveness must be evaluated as a dynamic recovery process rather than simply recording whether a wash occurred.

Within the FW-AON framework, each wash event is represented by pre-wash fouling severity, pre-wash efficiency, wash-water quantity, cleaning duration, post-wash corrected airflow, efficiency recovery, power recovery, and wastewater volume. The recovery ratio is computed relative to the estimated clean-performance baseline, enabling discrimination between recoverable fouling and deterioration arising from erosion, clearance changes, instrumentation error, or other permanent mechanisms. Maintenance records are equally important because reliability-centered frameworks emphasize that intervention timing should be linked to condition, failure behavior, asset criticality, and lifecycle consequences rather than arbitrary calendar intervals (Somuah et al., 2022). Accordingly, the study compares online and offline washing events according to recovered megawatts, reduction in heat rate, fuel savings, water intensity, wastewater generated, outage duration, and maintenance expenditure. These indicators support the results section's efficiency-recovery curves and water-use-versus-performance plots. A wash that recovers significant output but consumes excessive water or forces economically unfavorable downtime may not be optimal. FW-AON therefore treats washing as a multi-objective maintenance decision in which technical recovery, cost, availability, water consumption, and wastewater burden are jointly evaluated to identify the most sustainable intervention point.

➢ *Limitations of Fixed-Interval and Threshold-Based Compressor Maintenance*

Fixed-interval maintenance assumes that degradation accumulates at sufficiently predictable rates for operating hours, calendar time, or predetermined wash cycles to serve as adequate decision variables. Compressor fouling violates this assumption because deposition rate depends on local aerosol concentration, filter performance, ambient humidity, seasonal dust loading, rainfall, industrial emissions, load profile, and compressor operating regime. Two machines accumulating identical operating hours may therefore exhibit markedly different efficiency losses. Threshold-based maintenance improves on fixed schedules by initiating intervention when a measured variable exceeds a prescribed limit, but a single pressure ratio, exhaust-temperature, or efficiency threshold can still produce false alarms because these parameters vary with ambient conditions and plant dispatch. Rao and Naikan (2008) addressed this limitation by incorporating condition-based inspection and deterioration states into compressor washing policy, illustrating the value of maintenance decisions based on observed condition rather than elapsed time alone.

The main weakness of static thresholds is their inability to represent multivariable trajectory information. A compressor may be approaching economically significant degradation even though no individual signal has crossed its alarm threshold; conversely, a temporary ambient-temperature excursion can trigger an apparent deterioration signal without actual fouling. Aretakis et al. (2012) further demonstrated that washing decisions have economic consequences associated with degradation, start-up, shutdown, lost production, and maintenance, making the economically optimal intervention point plant-specific. More broadly, data-intensive automation research shows that continuously evaluated patterns and predictive risk scores can identify meaningful deviations that static periodic assessment can overlook (Frimpong et al., 2023); the present study transfers this decision principle to gas-turbine maintenance rather than treating the cited healthcare application as direct turbine evidence. FW-AON therefore replaces isolated deterministic thresholds with a temporal fouling-state estimate derived from multiple normalized measurements. Its decision layer triggers washing only when predicted deterioration, expected efficiency recovery, avoided fuel cost, water demand, wastewater burden, and outage consequences jointly justify intervention. The results will compare this adaptive strategy against fixed wash intervals, demonstrating differences in unnecessary wash events, delayed washes, annual maintenance cost, recovered generation, water consumption, and wastewater production.

➢ *Data-Driven Predictive Maintenance and Intelligent Fouling Diagnosis*

The increasing density of gas-turbine operational data creates an opportunity to move from retrospective condition monitoring to predictive maintenance in which degradation is detected, quantified, and forecast before production losses become excessive. A data-driven fouling model can simultaneously process ambient temperature, compressor inlet pressure, relative humidity, corrected speed, mass flow, pressure ratio, fuel flow, exhaust temperature, generator output, operating hours, and previous wash history. Liu and Karimi (2020) demonstrated that machine-learning surrogate models developed from operational data can reproduce compressor and turbine operating characteristics and support continuous health monitoring. Cheng et al. (2024) advanced this concept by integrating physical prior knowledge with temporal and spatial relationships among gas-turbine measurements, demonstrating that physically informed data relationships can improve health-state characterization. In energy infrastructure more broadly, AI-driven behavioral analytics have similarly been used to identify departures from expected operating patterns in complex industrial-control environments (James et al., 2023).

This study extends those concepts through the proposed Fouling–Wash Adaptive Optimization Network. FW-AON comprises a temporal feature-learning layer, nonlinear fouling-state estimator, degradation-forecasting module, wash-effectiveness predictor, and multi-objective decision layer. Its principal distinction is that diagnosis is not the final output: the estimated fouling state is propagated into a maintenance optimization problem. Model performance is compared with Random Forest, XGBoost, SVR, LSTM, and GRU using R2R^2, RMSE, MAE, MAPE, accuracy, precision, recall, F1-score, and computational time. These comparisons are designed to determine whether improved statistical accuracy translates into better engineering decisions. For example, two algorithms may produce similar RMSE values yet recommend substantially different wash dates because of differing sensitivity to recent degradation trends. The results therefore include predicted-versus-measured fouling plots, error distributions, temporal degradation forecasts, algorithm comparison charts, and optimized maintenance schedules. Explainability is incorporated through feature-importance and sensitivity analyses to establish whether model decisions correspond to physically credible drivers such as corrected airflow loss, efficiency decline, particulate exposure, and ambient humidity. This structure ensures that intelligent fouling diagnosis remains interpretable and operationally usable rather than functioning as an isolated black-box prediction system.

- *Water Consumption, Wastewater Generation, and Sustainability Challenges in Compressor Washing*

Water washing restores compressor performance but creates a resource-efficiency problem that is often omitted from maintenance optimization. Demineralized water must be produced, stored, pumped, and delivered under controlled conditions, while offline washing additionally generates an effluent stream containing removed particulate matter, dissolved salts, oily residues, corrosion products, detergent constituents where chemicals are used, and other contaminants accumulated in the compressor flow path. Accordingly, increasing wash frequency may reduce fouling losses while increasing annual freshwater demand, wastewater-treatment requirements, chemical usage, handling cost, and environmental burden. This trade-off is particularly relevant where industrial facilities operate under water scarcity or increasingly stringent effluent controls. Walker et al. (2013) demonstrated at broader power-plant scale that wastewater utilization decisions must account simultaneously for source-water cost, treatment requirements, process fouling, and overall economic consequences. Similarly, Riggio et al. (2018) demonstrated that industrial wastewater treatment and reuse can reduce dependence on freshwater resources when appropriate treatment pathways are available.

The present framework therefore treats water and wastewater variables as decision criteria rather than peripheral environmental statistics. For every wash event, FW-AON records freshwater consumed, detergent use where applicable, wastewater volume, contaminant indicators, treatment demand, disposal or recovery cost, and associated compressor performance recovery. The optimization objective penalizes water-intensive interventions that provide only marginal incremental efficiency recovery. This aligns with circular-resource principles in which waste streams are managed as recoverable resources where technically and economically feasible rather than regarded solely as disposal burdens (Idoko et al., 2024). Results will quantify litres or cubic metres of wash water per recovered megawatt, wastewater volume per percentage point of compressor-efficiency recovery, annual water savings relative to fixed-frequency washing, and changes in wastewater generation under alternative schedules. A Pareto analysis will then identify trade-offs among maintenance expenditure, efficiency recovery, fuel saving, freshwater consumption, and wastewater production. Where wash-water quality permits, treatment and controlled reuse options can be evaluated rather than unrestricted discharge. Integrating these metrics with compressor degradation forecasting enables the study to demonstrate that sustainable gas-turbine maintenance is not synonymous with maximum washing frequency; it requires identifying the intervention point at which aerodynamic and economic recovery is achieved with the lowest practicable resource and environmental burden.

- *Research Objectives and Research Questions*

- *Research Objectives*

- ✓ To quantify the temporal effects of compressor fouling on corrected airflow, compressor pressure ratio, isentropic efficiency, gas-turbine power output, heat rate, and fuel consumption under varying ambient and operating conditions.
- ✓ To develop the *Fouling–Wash Adaptive Optimization Network (FW-AON)* for multivariate compressor-fouling detection, degradation forecasting, water-wash effectiveness prediction, and adaptive maintenance decision-making.
- ✓ To compare the predictive performance of FW-AON with Random Forest, XGBoost, Support Vector Regression, Long Short-Term Memory, and Gated Recurrent Unit models using R2R^2, RMSE, MAE, MAPE, classification metrics, and computational performance.
- ✓ To determine the relationship between compressor-fouling severity, water-wash timing, efficiency recovery, power-output recovery, heat-rate improvement, and fuel saving.
- ✓ To optimize compressor water-washing intervals by jointly considering maintenance expenditure, downtime, production losses, fuel costs, wash-water consumption, and wastewater generation.
- ✓ To quantify the water and wastewater implications of conventional fixed-interval washing relative to FW-AON-based condition-responsive maintenance.
- ✓ To evaluate the economic and environmental trade-offs among compressor efficiency recovery, maintenance frequency, water consumption, wastewater generation, and power-plant sustainability.

- *Research Questions*

- ✓ How does progressive compressor fouling affect corrected airflow, pressure ratio, compressor efficiency, power generation, heat rate, and fuel consumption?

- ✓ How accurately can FW-AON identify and forecast compressor fouling from multivariate operational, environmental, maintenance, and water-wash data?
- ✓ How does FW-AON compare with Random Forest, XGBoost, SVR, LSTM, and GRU in predicting compressor degradation and supporting maintenance decisions?
- ✓ What degree of compressor efficiency, power-output, and heat-rate recovery can be achieved at different water-washing intervals and fouling severities?
- ✓ What water-washing interval minimizes the combined cost of fuel-performance deterioration, maintenance, downtime, water consumption, and wastewater management?
- ✓ To what extent can condition-responsive FW-AON scheduling reduce unnecessary water consumption and wastewater generation compared with fixed-interval washing?
- ✓ What economic–environmental trade-offs define the preferred compressor water-washing strategy for sustainable gas-turbine power-plant operation?

➢ *Research Gap, Contributions of the FW-AON Framework and Significance of the Study*

Existing gas-turbine compressor-fouling studies have extensively characterized aerodynamic degradation, gas-path performance loss, condition monitoring, and the performance recovery obtainable through online and offline washing. However, these research streams remain comparatively fragmented. Thermodynamic studies frequently terminate at efficiency or power-loss estimation, machine-learning studies often emphasize prediction accuracy without connecting the prediction to a maintenance decision, and washing-optimization studies commonly emphasize economic recovery while treating water use and wash-effluent generation as secondary variables. A further limitation is the widespread dependence on fixed intervals, single deterioration thresholds, or algorithms that do not explicitly combine temporal degradation, ambient variability, wash history, expected performance recovery, production losses, freshwater consumption, and wastewater consequences. Consequently, an integrated decision framework capable of predicting the evolving fouling state and simultaneously determining when washing is technically, economically, and environmentally justified remains insufficiently developed.

The principal contribution of this study is the development of the *Fouling–Wash Adaptive Optimization Network (FW-AON)*, which transforms compressor-fouling prediction into an integrated maintenance and sustainability decision problem. FW-AON combines temporal feature extraction, nonlinear fouling-state estimation, degradation forecasting, water-wash recovery prediction, and multi-objective optimization within a single analytical architecture. Unlike models developed exclusively for fault classification or efficiency forecasting, the proposed method maps predicted degradation directly to a recommended intervention interval based on expected recovered power, heat-rate improvement, fuel saving, maintenance expenditure, downtime, freshwater use, and wastewater generation. The framework additionally provides comparative benchmarking against Random Forest, XGBoost, SVR, LSTM, and GRU and supports engineering interpretation through sensitivity analysis, feature attribution, degradation curves, three-dimensional response surfaces, and economic–environmental Pareto fronts.

The study is significant because it connects gas-turbine thermodynamics, artificial intelligence, reliability engineering, maintenance economics, and industrial water management within a unified power-plant decision framework. For plant operators, the proposed methodology provides a mechanism for replacing rigid wash calendars with evidence-based maintenance triggered by the predicted technical and economic consequences of fouling. For maintenance engineers, it enables earlier identification of meaningful performance deterioration while reducing unnecessary washing and outages. For sustainability and environmental personnel, the inclusion of freshwater use and compressor-wash effluent creates measurable environmental performance indicators linked directly to maintenance decisions. At infrastructure level, the framework supports greater plant availability, lower fuel intensity, reduced avoidable operating expenditure, improved water productivity, and more defensible wastewater-management planning, thereby aligning equipment-level maintenance decisions with the wider objective of sustainable power-plant operation.

➢ *Scope of the Review and Structure of the Paper*

The study focuses on data-driven analysis of fouling in industrial gas-turbine compressors used for power generation, with particular attention to degradation in compressor efficiency, corrected airflow, pressure ratio, power output, heat rate, and fuel consumption. It considers environmental and operating variables that influence fouling progression, historical online and offline water-wash events, post-wash performance recovery, maintenance intervals, wash-water consumption, wastewater generation, maintenance expenditure, and production losses. The analytical scope includes development and validation of FW-AON and comparative evaluation against Random Forest, XGBoost, SVR, LSTM, and GRU. The sustainability assessment is confined primarily to the operational water, wastewater, fuel, performance, and maintenance consequences of compressor washing rather than a complete cradle-to-grave life-cycle assessment of the gas-turbine facility.

The paper is organized into five principal sections. Section 1 establishes the technical background, performance consequences of fouling, compressor water-washing practices, limitations of conventional maintenance scheduling, data-driven predictive-maintenance rationale, sustainability challenges, research objectives, questions, gap, contribution, significance, and study scope. Section 2 reviews the mechanisms and operational effects of compressor fouling, water-washing technologies, condition-based maintenance, machine-learning methods, multi-objective maintenance optimization, and sustainable wastewater management. Section 3 develops the gas-turbine compressor performance model and FW-AON architecture, defines the fouling, efficiency, water, wastewater, economic, and optimization models, and establishes the benchmark algorithms and evaluation metrics. Section 4 presents and discusses compressor degradation, algorithm comparisons, predicted-versus-measured results, optimized wash scheduling, efficiency and power recovery, fuel savings, maintenance economics, water consumption, wastewater reduction, sensitivity analysis, and Pareto optimization. Section 5 synthesizes the principal findings and provides recommendations for predictive compressor maintenance, sustainable water-washing practice, industrial implementation, wastewater management, and future integration with digital-twin and power-plant control platforms.

II. LITERATURE REVIEW

- *Mechanisms, Sources, and Operational Effects of Gas Turbine Compressor Fouling*

Gas turbine compressor fouling originates from the ingestion, transport, adhesion, and progressive accumulation of airborne contaminants on rotor blades, stator vanes, inlet guide vanes, and annulus surfaces. The dominant contaminant spectrum may include mineral dust, soot, salt aerosols, oil mist, unburned hydrocarbons, industrial particulate matter, and hygroscopic particles that penetrate the inlet filtration system. Particle deposition is governed by contaminant size and chemistry, blade-surface condition, local velocity field, temperature, relative humidity, rotational speed, and particle–surface intera ction as shown in figure 1. Experimental investigation by Suman et al. (2021) showed that micrometric contaminants form nonuniform deposition patterns across multistage compressor flow paths and that relative humidity and aerodynamic conditions materially influence where deposits accumulate. Deposited material increases surface roughness and modifies effective blade geometry, thereby thickening the boundary layer, increasing profile loss, promoting premature separation, and changing stage loading. Consequently, fouling should be interpreted as a coupled aerodynamic and environmental deterioration mechanism rather than merely the presence of visible dirt.

The operational effects propagate through the entire gas-turbine cycle. Progressive reductions in corrected airflow and compressor efficiency displace the compressor operating point, increase compressor work, reduce pressure-ratio capability, and potentially decrease surge margin. These changes subsequently influence turbine inlet conditions, exhaust temperature, fuel requirement, thermal efficiency, heat rate, and generator output. Aldi et al. (2019) demonstrated that susceptibility to deposition and its performance implications vary substantially across gas-turbine configurations, indicating that fouling severity cannot be represented adequately by a universal deterioration factor. This observation is central to the present FW-AON framework, which estimates fouling as a time-varying latent state from normalized compressor and plant measurements rather than relying on a single sensor threshold. The study therefore relates particulate exposure, ambient humidity, corrected airflow, pressure ratio, compressor efficiency, exhaust temperature, fuel flow, and power output to a continuously estimated fouling index, allowing the subsequent results to distinguish environmental variability from genuine aerodynamic degradation and to quantify recoverable performance loss.

Figure 1 presents gas turbine compressor fouling as a sequential degradation process linking contaminant sources and deposition mechanisms to measurable plant-performance consequences. On the left branch, airborne dust, salt aerosols, moisture, oil mist, hydrocarbons, soot, and other industrial pollutants enter through the compressor inlet airflow and progressively adhere to rotor and stator blade surfaces. Continued deposition increases surface roughness and modifies blade geometry, which promotes boundary-layer growth, flow separation, and restriction of the effective flow passage. These aerodynamic changes reduce corrected air mass flow, distort stage loading, and lower compressor isentropic efficiency. The right branch shows how these local compressor effects propagate through the gas-turbine cycle: pressure ratio decreases, compressor work rises, exhaust temperature and heat rate increase, and more fuel is required to maintain a given electrical load. As fouling advances, net power output declines and surge margin is reduced, which can affect operating flexibility and reliability. The final operational consequence is increased demand for compressor water washing and maintenance intervention. This causal structure is directly aligned with the FW-AON framework because the model uses variables such as corrected airflow, pressure ratio, compressor efficiency, exhaust temperature, fuel flow, power output, ambient humidity, particulate exposure, and wash history to infer fouling severity, predict degradation progression, and determine when cleaning becomes technically and economically justified.

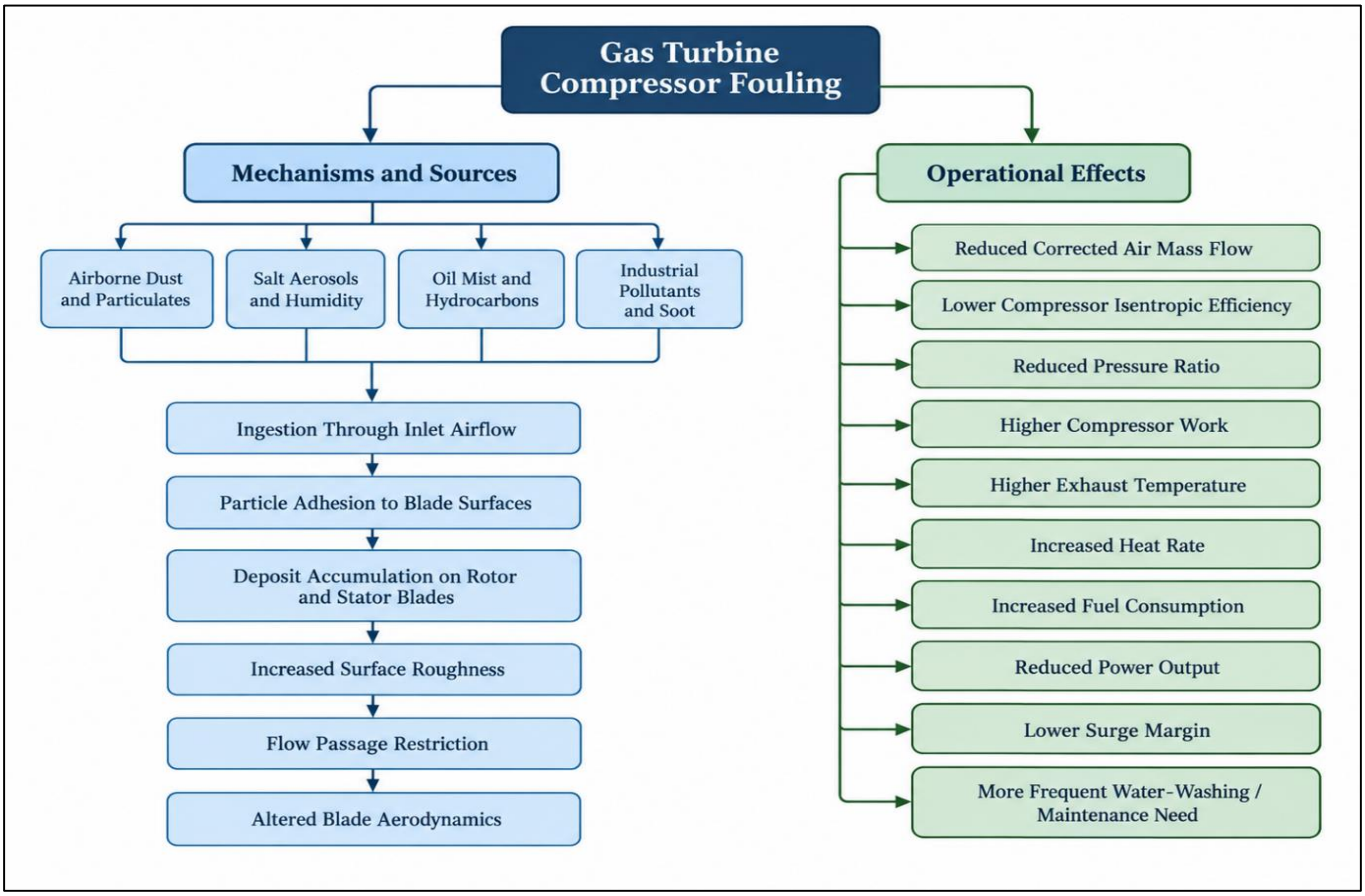

Fig 1 Mechanisms, Contaminant Sources, and Operational Performance Effects of Gas Turbine Compressor Fouling

- ➢ *Online and Offline Water-Washing Techniques for Compressor Performance Recovery*

Online and offline compressor washing represent complementary restoration strategies whose effectiveness depends on fouling composition, adhesion strength, compressor operating condition, wash-fluid characteristics, and intervention frequency. Online washing introduces atomized demineralized water, and where permitted an appropriate cleaning medium, into the compressor while the engine remains in service. Its principal purpose is to suppress the progressive accumulation of loosely adhered and water-soluble deposits without incurring a complete production outage as shown in figure 2. Offline washing, by contrast, is undertaken after shutdown and cooling, with the rotor generally operated under controlled cranking conditions while washing and rinsing sequences provide prolonged surface contact. It therefore offers greater capability for removing strongly accumulated contamination but imposes outage time, start–stop costs, labor requirements, and generation losses. Hanachi et al. (2018) demonstrated that compressor washing decisions should account for variable fouling rates and power demand because the economically preferred interval results from the trade-off between recovered performance and the cost imposed by washing and production interruption.

The technical challenge is therefore not whether compressor washing restores performance, but when the magnitude of recoverable degradation becomes sufficient to justify intervention. Chen et al. (2022) combined gas-path analysis with LSTM forecasting to predict compressor flow-capacity and efficiency degradation before optimizing offline washing schedules; their case study showed that predictive scheduling could materially improve plant economics relative to the operating schedule. The present study extends this concept beyond economic optimization by incorporating water intensity and wastewater production directly into FW-AON. Each washing event is characterized through pre-wash fouling severity, compressor efficiency, corrected airflow, power output, wash-water volume, outage duration, post-wash recovery, and generated effluent. Recovery curves can consequently distinguish rapid post-wash restoration from subsequent refouling. The resulting efficiency-recovery, power-recovery, and water-consumption graphs provide the physical basis for evaluating whether frequent online washing, less frequent offline washing, or an adaptive combination produces the preferable balance among compressor cleanliness, generation availability, water consumption, wastewater generation, and maintenance expenditure.

Figure 2 distinguishes online and offline compressor water washing as complementary maintenance strategies for restoring gas turbine performance under different fouling conditions. In the online washing branch, demineralized water, with an approved detergent where required, is atomized into the compressor inlet while the turbine remains in operation at a controlled load. The injected droplets interact primarily with loosely bonded dust, salts, soot, and water-soluble deposits, thereby slowing deposit accumulation and partially restoring corrected air mass flow, compressor efficiency, and pressure-ratio stability without requiring a major shutdown. Its principal limitation is reduced effectiveness against strongly adhered or thermally baked deposits. The offline washing branch is intended for deeper cleaning and is performed after shutdown, cooling, and controlled rotor cranking. Longer liquid–surface contact time, repeated wash and rinse cycles, and the possible use of detergent enable removal of more persistent contamination from rotor and stator surfaces. This generally produces greater recovery in compressor isentropic efficiency, corrected airflow, pressure ratio, and electrical output, while reducing heat rate and fuel consumption, although it also introduces outage losses, greater maintenance duration, and higher wastewater generation. Both branches converge on optimized compressor performance recovery, where the preferred intervention depends on fouling severity, expected thermodynamic recovery, plant availability, wash-water requirement, maintenance cost, and wastewater-treatment burden. This structure is directly consistent with the FW-AON framework, which evaluates wash mode and timing as a multi-objective decision rather than treating cleaning as a fixed periodic activity.

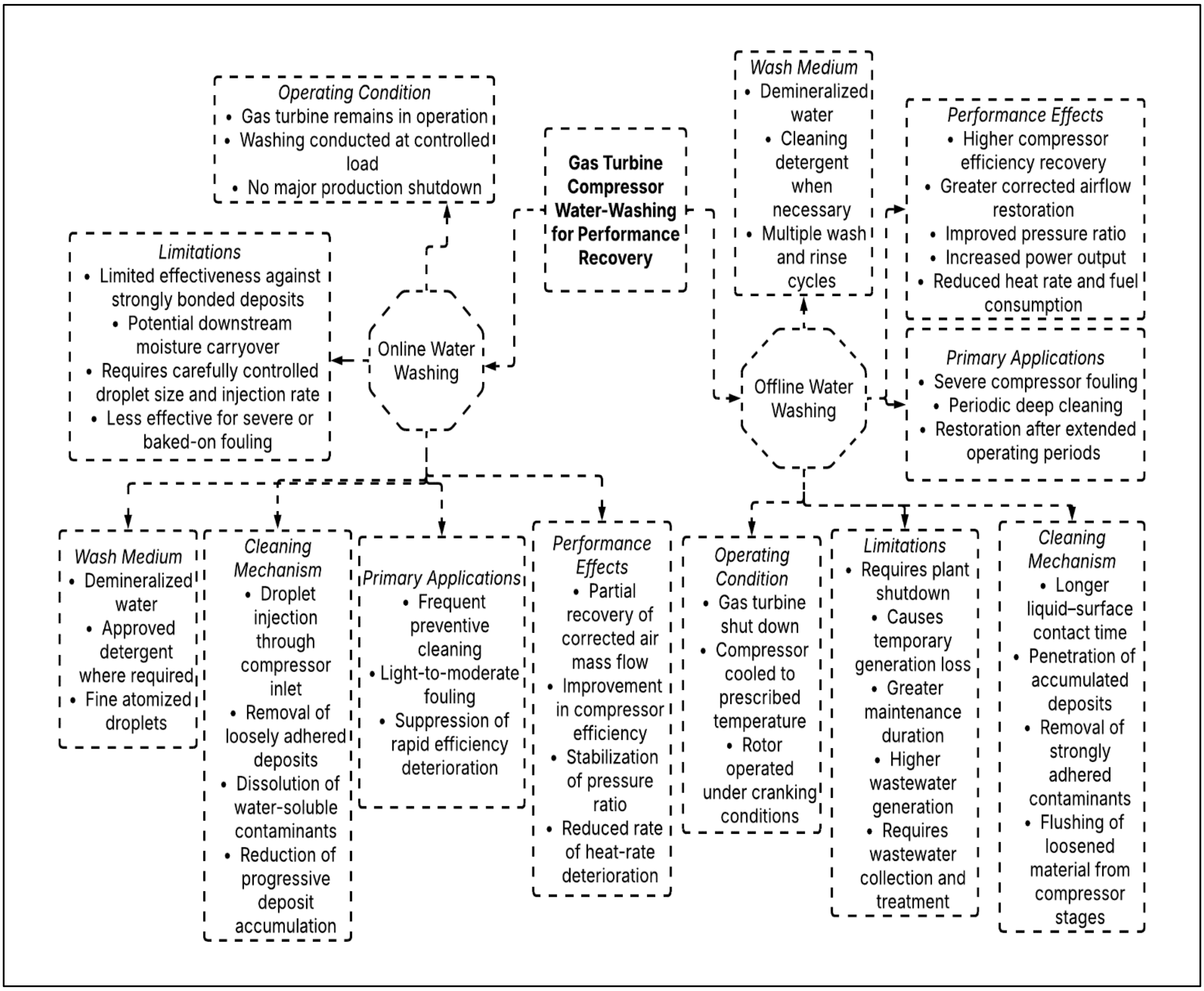

Fig 2 Comparative Online and Offline Compressor Water-Washing Techniques for Gas Turbine Performance Recovery.

➢ *Condition-Based and Predictive Maintenance Strategies for Gas Turbine Compressors*

Condition-based maintenance represents a transition from scheduled intervention toward maintenance decisions triggered by the measured or inferred health state of the gas turbine. For compressor fouling, this transition is especially important because degradation is strongly nonstationary: identical operating-hour accumulation can produce different contamination levels under dry, dusty conditions than under cleaner or seasonally humid environments. Tahan et al. (2017) identified gas-path performance monitoring, diagnostics, and prognostics as fundamental elements of gas-turbine condition-based maintenance because measurable deviations in pressure, temperature, airflow, fuel consumption, and efficiency can be translated into component health information. The maintenance problem therefore involves three related tasks: identifying whether deterioration exists, estimating its severity and probable source, and forecasting when the degradation will reach a technically or economically significant level. This structure is directly applicable to compressor washing, where premature intervention wastes resources while delayed washing permits avoidable fuel and power penalties.

Predictive maintenance extends condition-based maintenance by forecasting the future deterioration trajectory rather than reacting only to the present condition. Wan et al. (2018) demonstrated a multi-environmental prognostic approach that explicitly recognizes variations in gas-turbine operating environments when estimating future degradation and maintenance requirements. For the present research, this principle is incorporated into FW-AON by constructing temporal input windows containing normalized gas-path parameters, ambient conditions, particulate exposure, accumulated operating time, and previous washing history. The network estimates the current fouling state and forecasts its future development sufficiently far ahead to evaluate alternative intervention dates. Maintenance effectiveness is subsequently assessed through avoided efficiency deterioration, recovered megawatt output, heat-rate improvement, reduced incremental fuel expenditure, maintenance cost, downtime, and water-related consequences. The results therefore move beyond a binary “wash/no-wash” decision by comparing predicted maintenance trajectories. This provides a technically defensible basis for demonstrating whether adaptive FW-AON scheduling can outperform fixed-hour and threshold-based strategies in both equipment performance and resource efficiency.

- *Machine Learning and Deep Learning Methods for Fouling Detection and Degradation Prediction*

Machine-learning approaches are attractive for compressor-fouling detection because industrial gas turbines generate large multivariate datasets in which degradation signatures are nonlinear, correlated, and partially masked by ambient and load variations. Classical algorithms such as support vector machines, Random Forest, and gradient-boosted trees can identify relationships between gas-path measurements and degradation without explicitly solving every thermodynamic process as shown in figure 3. Fentaye et al. (2019) combined an autoassociative neural network, support vector machine, and multilayer perceptron to preprocess measurements, classify gas-path faults, and estimate fault severity, illustrating the value of separating noise suppression, fault identification, and magnitude estimation. Such decomposition is particularly relevant to compressor fouling because reductions in discharge pressure or power output can also arise from ambient-temperature changes, turbine deterioration, sensor bias, or load variation. The diagnostic model must therefore learn a multivariable degradation signature instead of attributing every unfavorable operating deviation to fouling.

Deep-learning architectures extend this capability by extracting higher-order representations directly from complex sensor patterns. Zhou et al. (2020) developed a partly interpretable convolutional neural-network framework for gas-turbine fault diagnosis and incorporated XGBoost to improve interpretation of measurement sequencing, demonstrating the value of combining nonlinear feature learning with diagnostic transparency. FW-AON adopts the same general need for representation learning but is specifically structured around temporal fouling evolution and water-wash decision support. Its performance is benchmarked against Random Forest, XGBoost, SVR, LSTM, and GRU so that tree-based, kernel-based, and recurrent-learning paradigms are evaluated under identical data partitions. Comparison is based on R2R^2, RMSE, MAE, MAPE, classification accuracy, precision, recall, F1-score, and computational burden. Predicted-versus-measured plots and residual distributions are combined with degradation curves to determine whether statistically superior predictions also produce more reliable wash timing. This distinction is essential because lower prediction error is operationally valuable only when it improves maintenance decisions and reduces unnecessary performance and resource losses.

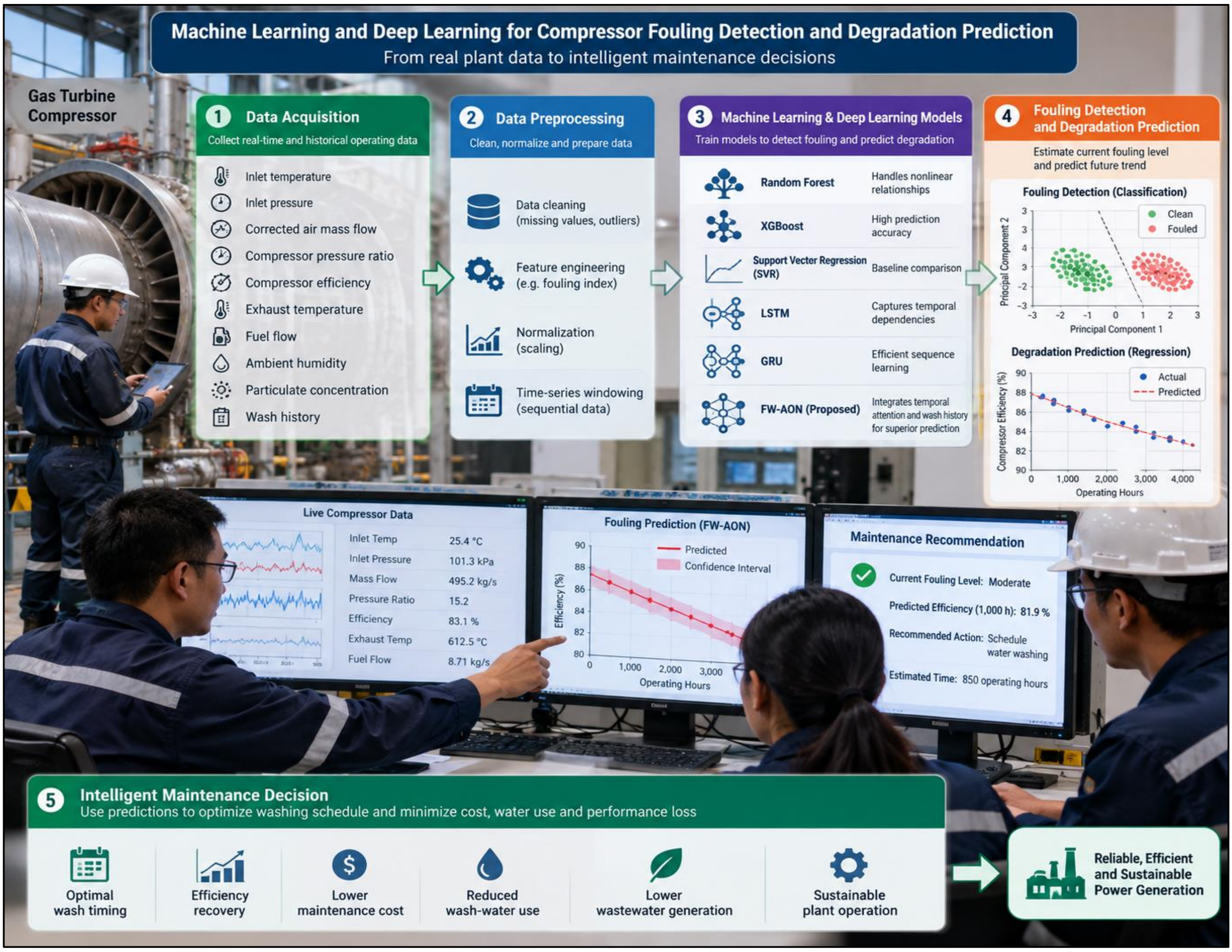

Fig 3 Machine Learning and Deep Learning Workflow for Gas Turbine Compressor Fouling Detection, Degradation Prediction, and Intelligent Water-Wash Maintenance Decision-Making

Figure 3 illustrates the complete data-driven workflow described in Section 2.4 for applying machine learning and deep learning to gas turbine compressor fouling detection and degradation prediction. At the plant level, operating and environmental measurements such as compressor inlet temperature and pressure, corrected air mass flow, pressure ratio, compressor efficiency, exhaust temperature, fuel flow, ambient humidity, particulate concentration, and water-wash history are continuously acquired from the compressor and associated control systems. These raw measurements are then cleaned, normalized, screened for missing values and outliers, and converted into engineered features such as a fouling index and sequential time windows. The processed dataset is supplied to multiple predictive algorithms, including Random Forest and XGBoost for nonlinear ensemble learning, Support Vector Regression for kernel-based regression, and LSTM and GRU networks for temporal degradation learning. The proposed FW-AON extends these methods by combining temporal feature extraction, adaptive attention, wash-history information, and nonlinear fouling-state estimation within a unified architecture. The diagnostic stage separates clean and fouled operating states while the regression stage forecasts future compressor-efficiency decline and fouling progression over operating hours. These predictions are then translated into maintenance decisions rather than being treated as isolated model outputs. As shown on the monitoring displays, the framework estimates the current fouling condition, predicts future efficiency, and recommends an appropriate water-wash intervention window. This prediction-to-decision linkage supports the broader objective of the study by reducing unnecessary washing, minimizing maintenance cost and freshwater consumption, lowering wastewater generation, recovering compressor efficiency, and improving the reliability and sustainability of gas turbine power generation.

➢ *Multi-Objective Optimization of Maintenance Scheduling, Water Use, and Wastewater Generation*

Optimization of compressor washing is intrinsically multi-objective because minimizing fouling does not necessarily minimize lifecycle cost or environmental burden. Very frequent washing can maintain relatively high compressor cleanliness yet increase water consumption, cleaning-system utilization, intervention frequency, and, for offline procedures, outage-related generation losses. Conversely, excessively long intervals reduce wash expenditure but permit larger efficiency, output, and fuel penalties as presented in table 1. Musa et al. (2022) demonstrated this nonlinearity by evaluating online washing across gas turbines of substantially different capacities and incorporating washing-liquid consumption, equipment economics, and electricity value into a genetic-algorithm optimization framework. Their results showed that the economically preferred interval was not simply the most frequent feasible wash schedule, reinforcing the need to identify a compromise solution rather than maximize one performance indicator. This insight directly motivates the multi-objective decision layer of FW-AON. The present study broadens that optimization space to incorporate freshwater demand and wastewater generation alongside maintenance and energy variables. Chen et al. (2020) showed at energy-system scale that robust planning must explicitly represent conflicts among energy supply, water consumption, resource availability, cost, and environmental constraints under uncertainty. Applied to compressor maintenance, the decision vector includes wash interval, wash type, expected fouling severity at intervention, water requirement, wastewater quantity, outage duration, recovered efficiency, and avoided fuel expenditure. FW-AON therefore seeks Pareto-efficient solutions rather than a single unconstrained minimum-cost schedule. The expected graphical analysis maps maintenance cost against efficiency recovery, water consumption against recovered output, and wastewater generation against wash frequency, while three-dimensional response surfaces can represent the joint influence of fouling severity, washing interval, and recovery efficiency. Such comparisons permit identification of operating regions where additional washing produces diminishing thermodynamic benefit but disproportionately increases water and effluent burden, thereby integrating economic and environmental sustainability directly into compressor maintenance planning.

Table 1 Summary of Multi-Objective Optimization of Maintenance Scheduling, Water Use, and Wastewater Generation

Optimization Dimension	**Main Decision Variable**	**Key Performance Indicator**	**Relevance to FW-AON Framework**
Maintenance scheduling	Compressor water-wash interval and intervention timing	Maintenance cost, downtime, avoided production loss	Determines the optimal point at which predicted fouling justifies washing without causing premature maintenance or excessive degradation.
Water-use optimization	Wash-water volume and washing frequency	Water consumption per wash, water-use intensity	Minimizes unnecessary demineralized-water demand while maintaining acceptable compressor cleaning effectiveness and efficiency recovery.
Wastewater management	Volume of wash effluent generated and treatment requirement	Wastewater volume, wastewater reduction percentage	Reduces the environmental burden associated with contaminated compressor wash effluent and supports treatment, reuse, or controlled disposal planning.
Integrated sustainability optimization	Combined maintenance, energy, water, wastewater, and recovery objectives	Pareto-optimal cost, efficiency recovery, fuel saving, water reduction, wastewater reduction	Enables FW-AON to identify a balanced operating solution that jointly improves compressor performance, maintenance economics, and environmental sustainability.

- ***Research Gap in Integrated Fouling Prediction, Water-Wash Optimization, and Sustainable Wastewater Management***

Existing literature provides substantial knowledge on individual elements of compressor degradation management, yet a pronounced systems-integration gap remains. Gas-turbine prognostic research has concentrated primarily on detecting deterioration and forecasting future performance. For example, Tsoutsanis and Meskin (2017) developed a derivative-driven window-based prognostic methodology capable of tracking compressor-fouling evolution under dynamic gas-turbine operating modes. Such work establishes the technical feasibility of degradation forecasting but does not, by itself, resolve how a prediction should be converted into a washing decision when fuel penalties, electricity revenue, shutdown cost, wash-water requirement, wastewater treatment, and environmental objectives interact. Conversely, washing-optimization studies frequently emphasize maintenance economics and recovered performance but may treat the volume and environmental consequences of generated wash effluent as external considerations. The literature therefore tends to separate fouling diagnosis, degradation forecasting, washing optimization, and environmental management into sequential rather than mathematically coupled decision problems.

A similar fragmentation exists in wastewater research. Nakkasunchi et al. (2021) found that water and wastewater optimization tools commonly address energy benchmarking, treatment efficiency, renewable integration, or resource recovery, while highlighting the need for more integrated optimization platforms. The specific linkage between gas-turbine compressor degradation and the wastewater generated by maintenance interventions remains comparatively underdeveloped. FW-AON addresses this gap by combining four previously separated functions: temporal fouling-state estimation, future degradation prediction, anticipated water-wash recovery, and multi-objective maintenance optimization. Operational sensor data are therefore connected directly to decisions concerning wash timing, maintenance expenditure, lost production, freshwater consumption, and wastewater volume. The resulting comparative framework also evaluates FW-AON against Random Forest, XGBoost, SVR, LSTM, GRU, and fixed-interval maintenance. This integrated formulation enables the study's results to determine not merely which algorithm predicts fouling most accurately, but whether superior prediction produces measurable improvements in compressor efficiency retention, power recovery, fuel use, maintenance planning, water productivity, wastewater reduction, and overall sustainable power-plant infrastructure performance.

III. SYSTEM MODEL DESCRIPTION

- *Gas Turbine Compressor Performance, Fouling, and Water-Washing System Model*

The gas turbine compressor was modelled using corrected thermodynamic and operational variables so that deterioration attributable to compressor fouling could be separated from variations caused by ambient temperature, atmospheric pressure, relative humidity, and load demand. This distinction is essential because raw compressor measurements may change significantly even when component condition remains unchanged. Data-driven gas turbine performance modelling has shown that appropriate normalization of operational variables enables reliable estimation of compressor and overall engine performance under varying operating conditions (Liu & Karimi, 2020).

The compressor pressure ratio is expressed as:

$$\pi_c = \frac{P_2}{P_1} \tag{1}$$

Where π_c shows the compressor pressure ratio, P_1 represents the absolute compressor inlet pressure, and P_2 denotes the absolute compressor discharge pressure.

To compensate for variations in atmospheric conditions, corrected compressor mass flow is defined as:

$$\dot{m}_{corr} = \dot{m}_a \frac{\sqrt{T_1/T_{ref}}}{P_1/P_{ref}} \tag{2}$$

Where $\dot{m}_{corr}$ represents corrected compressor air mass flow, $\dot{m}_a$ shows actual air mass flow, T_1 represents compressor inlet temperature, T_{ref} represents reference temperature, P_1 captures inlet pressure, and P_{ref} represents reference pressure.

Compressor isentropic efficiency is evaluated as:

$$\eta_c = \frac{T_{2s} - T_1}{T_2 - T_1} = \frac{\pi_c^{(\gamma-1)/\gamma} - 1}{T_2/T_1 - 1} \tag{3}$$

Where η_c represents compressor isentropic efficiency, T_{2s} shows theoretical isentropic discharge temperature, T_2 captures actual compressor discharge temperature, and γ denotes the specific heat ratio of air.

The plant heat rate is calculated from:

$$HR = \frac{3600\dot{m}_f LHV}{P_e} \tag{4}$$

Where HR represents heat rate in kJ/kWh, $\dot{m}_f$ captures fuel mass flow rate, LHV represents fuel lower heating value, and P_e shows electrical power output.

A dimensionless fouling index was developed from deterioration in corrected airflow and compressor efficiency:

$$FI_t = \alpha\left(1 - \frac{\dot{m}_{corr,t}}{\dot{m}_{corr,0}}\right) + (1-\alpha)\left(1 - \frac{\eta_{c,t}}{\eta_{c,0}}\right) \tag{5}$$

Where FI_t represents the fouling index at time t, $\dot{m}_{corr,t}$ represents corrected mass flow at time t, $\dot{m}_{corr,0}$ shows clean-condition corrected mass flow, $\eta_{c,t}$ denotes current compressor efficiency, $\eta_{c,0}$ captures clean-condition efficiency, and α represents a weighting coefficient between 0 and 1.

Water-wash recovery effectiveness is expressed as:

$$R_\eta = \frac{\eta_{post} - \eta_{pre}}{\eta_{c,0} - \eta_{pre}} \times 100 \tag{6}$$

Where R_η shows the percentage of recoverable compressor efficiency restored, η_{pre} denotes pre-wash efficiency, and η_{post} shows post-wash efficiency.

Wastewater generation is estimated through the liquid balance:

$$V_{ww} = V_w + V_c - V_{ev} - V_h \tag{7}$$

Where V_{ww} denotes wastewater volume, V_w shows wash-water volume, V_c captures cleaning-agent liquid volume where applicable, V_{ev} represents evaporative and aerosol losses, and V_h represents liquid retained within the washing system. These equations provide the physical basis for the degradation, recovery, fuel-use, water-use, and wastewater analyses presented subsequently.

- *Development of the Fouling–Wash Adaptive Optimization Network (FW-AON)*

The proposed *Fouling–Wash Adaptive Optimization Network (FW-AON)* was developed as an integrated temporal prediction and maintenance optimization framework. Unlike conventional models that terminate at fouling classification or degradation prediction, FW-AON converts predicted compressor deterioration directly into a water-washing decision. Its principal input variables include compressor inlet temperature, ambient humidity, particulate concentration, compressor pressure ratio, corrected mass flow, compressor efficiency, fuel flow, exhaust temperature, generator output, accumulated operating hours, previous water-wash events, wash-water consumption, and wastewater generation. Predictive compressor-washing studies have demonstrated that temporal deep-learning models are suitable for forecasting progressive gas turbine fouling before maintenance optimization (Chen et al., 2022).

Each input feature is standardized using:

$$z_{j,t} = \frac{x_{j,t} - \mu_j}{\sigma_j} \tag{8}$$

Where $x_{j,t}$ represents the value of feature j at time t, μ_j shows its training-set mean, σ_j denotes its standard deviation, and $z_{j,t}$ represents the normalized feature.

Temporal information is extracted from an observation window of length L, after which an adaptive attention mechanism assigns greater importance to time steps containing stronger degradation information:

$$a_k = \frac{\exp[q^T \tanh(W_a h_k + b_a)]}{\sum_{r=t-L+1}^{t} \exp[q^T \tanh(W_a h_r + b_a)]} \quad (9)$$

And

$$c_t = \sum_{k=t-L+1}^{t} a_k h_k \quad (10)$$

Where a_k shows the attention coefficient at time k, h_k represents the hidden temporal state, W_a shows the attention weight matrix, b_a represents the bias vector, q captures a trainable context vector, and c_t shows the aggregated temporal representation.

The estimated fouling condition is:

$$\widehat{FI}_t = \sigma(W_F c_t + b_F) \quad (11)$$

Where $\widehat{FI}_t$ is predicted fouling severity, W_F and b_F capture trainable parameters, and $\sigma(\cdot)$ represents the sigmoid activation function.

Future compressor degradation is predicted over a forecasting horizon H:

$$\widehat{FI}_{t+h} = g_\theta(c_t, h), \qquad h = 1,2, \dots, H \quad (12)$$

Where g_θ represents the trained degradation forecasting function and h represents forecast lead time.

Expected washing recovery is modelled as:

$$\hat{R}_w = f_\phi(\widehat{FI}_{t+\tau}, V_w, M_w, X_{env}) \quad (13)$$

Where $\hat{R}_w$ represents predicted performance recovery, τ represents the candidate wash interval, V_w shows wash-water volume, M_w represents online or offline wash mode, and X_{env} contains environmental variables.

FW-AON training minimizes the composite loss:

$$\mathcal{L} = \lambda_1 MSE_{FI} + \lambda_2 MSE_\eta + \lambda_3 MSE_P + \lambda_4 MSE_{ww} \quad (14)$$

Where MSE_{FI}, MSE_η, MSE_P, and MSE_{ww} represent mean squared errors for fouling severity, compressor efficiency, power output, and wastewater prediction, respectively, while λ_1 to λ_4 show loss-weighting parameters.

The optimum washing interval is determined from:

$$\tau^* = \underset{\tau \in \Omega}{\operatorname{argmin}} \big[w_1 \tilde{C}_m + w_2 \tilde{C}_f + w_3 \tilde{C}_d + w_4 \tilde{V}_w + w_5 \tilde{V}_{ww} - w_6 \tilde{R}_w \big] \quad (15)$$

Where τ^* denotes the optimal wash interval, Ω shows the feasible set of washing intervals, C_m represents maintenance cost, C_f represents fouling-related fuel cost, C_d denotes downtime cost, V_w shows wash-water consumption, V_{ww} represents wastewater generation, R_w represents expected recovery, and w_1 to w_6 capture decision weights. Tildes indicate normalized quantities. This formulation enables FW-AON to balance operational recovery against economic and environmental consequences.

➢ *Benchmark Algorithms and Experimental Framework*

The predictive and decision-making capability of FW-AON was benchmarked against Random Forest (RF), XGBoost, Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) models. These algorithms were selected because they represent different modelling philosophies: ensemble decision trees, gradient boosting, kernel-based nonlinear regression, and recurrent deep-learning architectures. All algorithms received identical thermodynamic, environmental, operational, fouling, water-wash, and wastewater variables to ensure that performance differences arose from modelling capability rather than unequal data availability. Gas turbine studies have demonstrated that machine-learning models can reproduce nonlinear relationships between gas-path measurements and component performance when properly trained on operational data (Liu & Karimi, 2020).

For Random Forest, the predicted fouling index is:

$$\widehat{FI}^{RF}(x) = \frac{1}{B} \sum_{b=1}^{B} T_b(x) \quad (16)$$

Where B captures the total number of regression trees, $T_b(x)$ represents the output from tree b, and x shows the predictor vector.

The XGBoost objective function is:

$$\mathcal{L}_{XGB} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \left[\gamma T_k + \frac{\lambda}{2} \| w_k \|^2 \right] \quad (17)$$

Where $l(y_i, \hat{y}_i)$ shows the prediction loss, K capture the number of boosting trees, T_k denotes the number of leaves in tree k, w_k contains leaf weights, γ penalizes excessive tree complexity, and λ controls regularization.

SVR estimates the degradation function as:

$$f(x) = w^T \phi(x) + b \quad (18)$$

Where w shows the model-weight vector, $\phi(x)$ transforms the inputs into a nonlinear feature space, and b

represents the intercept. A radial basis function kernel is appropriate for nonlinear fouling behaviour.

For LSTM, temporal memory is governed by:

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{19}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{20}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_C[h_{t-1}, x_t] + b_C) \tag{21}$$

$$h_t = o_t \odot \tanh(C_t) \tag{22}$$

Where f_t, i_t, and o_t represent the forget, input, and output gates, C_t shows cell memory, h_t denotes the hidden state, W and b denote trainable weights and biases, and $\odot$ denotes element-wise multiplication.

The GRU formulation is:

$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \tag{23}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \tag{24}$$

$$\tilde{h}_t = \tanh[W_h x_t + U_h(r_t \odot h_{t-1})] \tag{25}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{26}$$

Where z_t captures the update gate, r_t shows the reset gate, and $\tilde{h}_t$ denotes the candidate hidden state.

The dataset is partitioned chronologically into *60% training, 20% validation, and 20% testing* before temporal windows are generated. Chronological splitting is used instead of random shuffling to prevent future measurements from leaking into model training. Hyperparameters are optimized using the validation set, while final comparison is conducted exclusively on the untouched test dataset.

- *Performance Evaluation, Maintenance, and Sustainability Metrics*

The proposed framework is evaluated at three interconnected levels: *prediction performance, maintenance effectiveness, and sustainability performance.* This approach is required because a fouling-prediction algorithm may produce low statistical error without necessarily producing superior maintenance decisions. Compressor wash optimization should therefore consider not only model accuracy but also recovered efficiency, production availability, fuel savings, washing cost, water consumption, and wastewater generation (Hanachi et al., 2018).

The coefficient of determination is calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{27}$$

Where y_i represents the measured value, $\hat{y}_i$ denotes the predicted value, $\bar{y}$ shows the mean measured value, and n represents the number of observations.

Root mean square error is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{28}$$

Mean absolute error is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{29}$$

Mean absolute percentage error is:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{30}$$

Where MAPE is used only for response variables whose measured values remain sufficiently above zero.

Fouling-detection performance is evaluated using:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{31}$$

$$Precision = \frac{TP}{TP + FP} \tag{32}$$

$$Recall = \frac{TP}{TP + FN} \tag{33}$$

$$F_1 = \frac{2(Precision)(Recall)}{Precision + Recall} \tag{34}$$

Where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

Compressor efficiency and power recovery following water washing are quantified as:

$$\Delta\eta_c = \frac{\eta_{post} - \eta_{pre}}{\eta_{pre}} \times 100 \tag{35}$$

$$\Delta P = \frac{P_{post} - P_{pre}}{P_{pre}} \times 100 \tag{36}$$

Where $\Delta\eta_c$ shows percentage compressor-efficiency recovery and ΔP denotes percentage power-output recovery.

Heat-rate improvement is:

$$HR_{red} = \frac{HR_{pre} - HR_{post}}{HR_{pre}} \times 100 \tag{37}$$

Where HR_{pre} and HR_{post} show heat rates before and after washing.

Fuel saving over an evaluation period is:

$$FS = \left(\dot{m}_{f,base} - \dot{m}_{f,FW}\right)t \quad (38)$$

Where FS shows total fuel saved, $\dot{m}_{f,base}$ is baseline fuel-flow rate, $\dot{m}_{f,FW}$ is fuel-flow rate under FW-AON scheduling, and t is operating duration.

Total maintenance-related cost is defined as:

$$C_{tot} = C_{wash} + C_{maint} + C_{fuel} + C_{down} + C_{water} + C_{ww} \quad (39)$$

Where C_{wash} denotes washing cost, C_{maint} shows maintenance cost, C_{fuel} represents incremental fuel cost caused by fouling, C_{down} represents downtime cost, C_{water} captures water-supply cost, and C_{ww} denotes wastewater treatment or disposal cost.

Water-use intensity is:

$$WUI = \frac{V_w}{E_{rec}} \quad (40)$$

Where WUI shows wash-water consumption per unit of recovered electrical energy, V_w denotes wash-water volume, and E_{rec} represents electrical energy recovered because of washing.

Wastewater reduction is quantified by:

$$WWR = \left(1 - \frac{V_{ww,FW}}{V_{ww,base}}\right) \times 100 \quad (41)$$

Where $V_{ww,FW}$ represents wastewater generated under FW-AON scheduling and $V_{ww,base}$ shows wastewater generated under the conventional maintenance strategy.

Maintenance-decision effectiveness is:

$$MDE = \frac{C_{tot,base} - C_{tot,FW}}{C_{tot,base}} \times 100 \quad (42)$$

Where $C_{tot,base}$ represents total cost under the conventional strategy and $C_{tot,FW}$ is total cost under FW-AON.

Finally, multi-objective sustainability performance is represented as:

$$\min \mathbf{F}(\tau) = [C_{tot}(\tau), V_w(\tau), V_{ww}(\tau), HR(\tau), -P_e(\tau)] \quad (43)$$

Where $\mathbf{F}(\tau)$ represents the multi-objective optimization vector and τ shows the candidate washing interval. The negative sign before P_e converts the maximization of electrical output into an equivalent minimization objective. Equation (43) supports the Pareto-front analysis in the results section, allowing identification of wash schedules for which further gains in efficiency or power output would require disproportionate increases in cost, freshwater consumption, or wastewater generation.

IV. DISCUSSION OF RESULTS

- *Compressor Fouling Characteristics and Operational Performance Degradation*

Compressor fouling produced a progressive deterioration in the principal gas-path and plant-performance variables used by the FW-AON framework. Relative to the clean reference state, compressor isentropic efficiency decreased from 88.4% to 82.7%, while corrected air mass flow declined from 510 to 481 kg/s and pressure ratio fell from 15.8 to 15.1. These aerodynamic losses propagated to the plant level, reducing electrical output from 150.0 to 138.2 MW. At the same time, heat rate increased from 10,050 to 10,780 kJ/kWh and fuel flow rose from 8.42 to 8.79 kg/s. The combined pattern is consistent with progressive flow-path restriction and increasing compressor work as deposits accumulate. These results establish the physical degradation trajectory subsequently used by FW-AON and the benchmark algorithms to estimate fouling severity and determine when water washing becomes technically and economically justified.

Table 2 Compressor Fouling-Induced Operational Performance Degradation

Performance Metric	Clean Condition	Fouled Condition	Relative Change (%)
Compressor isentropic efficiency (%)	88.40	82.70	-6.45
Corrected air mass flow (kg/s)	510.00	481.00	-5.69
Compressor pressure ratio	15.80	15.10	-4.43
Electrical power output (MW)	150.00	138.20	-7.87
Heat rate (kJ/kWh)	10,050.00	10,780.00	+7.26
Fuel mass flow rate (kg/s)	8.42	8.79	+4.39

Table 2 indicates that fouling simultaneously reduces aerodynamic and electrical performance while increasing the energy required for electricity generation. The 7.87% decline in power output is the largest adverse operational change, while the 7.26% increase in heat rate confirms deterioration in overall plant conversion efficiency. The reduction in corrected airflow and pressure ratio further demonstrates that the degradation originates principally from compressor flow-path contamination rather than from an isolated generator-side effect.

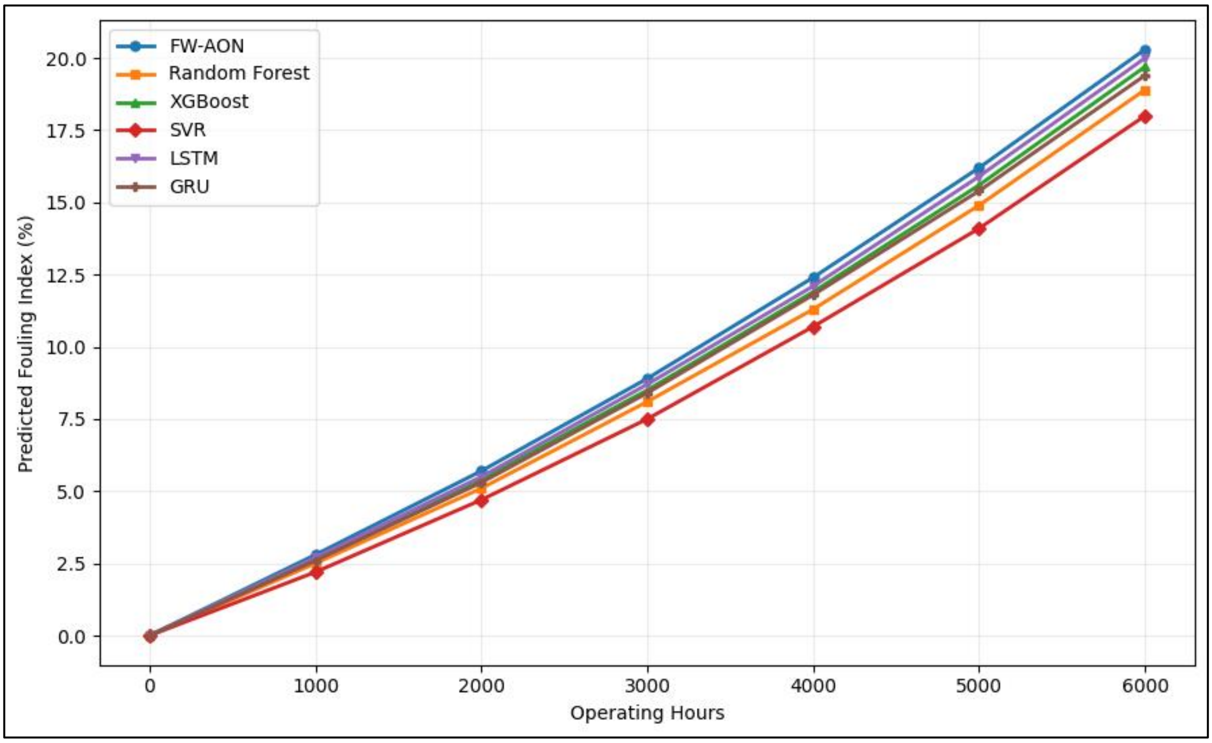

Fig 4 Comparative fouling-index trajectories predicted by FW-AON, Random Forest, XGBoost, SVR, LSTM, and GRU.

Figure 4 compares the predicted fouling trajectories of FW-AON, Random Forest, XGBoost, SVR, LSTM, and GRU over 6,000 operating hours. All models indicate monotonic deterioration, but their sensitivity to progressive fouling differs. At 2,000 h, FW-AON predicts a fouling index of 5.7%, compared with 5.5% for LSTM, 5.4% for XGBoost, 5.3% for GRU, 5.1% for Random Forest, and 4.7% for SVR. The separation becomes more pronounced as degradation accumulates. At 4,000 h, FW-AON reaches 12.4%, whereas LSTM, XGBoost, GRU, Random Forest, and SVR predict 12.1%, 11.9%, 11.8%, 11.3%, and 10.7%, respectively. By 6,000 h, the corresponding values are 20.3%, 20.0%, 19.7%, 19.4%, 18.9%, and 18.0%. The greater sensitivity of FW-AON reflects its integration of temporal operating history, environmental exposure, wash history, and nonlinear fouling-state estimation. This is important because underestimation of advanced fouling can delay water washing and increase heat-rate and fuel penalties.

➢ *Comparative Predictive Performance of FW-AON and Benchmark Algorithms*

The predictive capability of FW-AON was evaluated against LSTM, XGBoost, GRU, Random Forest, and SVR using the common test dataset defined in Section 3.3. As shown in Table 4.2, FW-AON produced the strongest overall predictive performance, attaining an R2R^2 of 98.2%, fouling-detection accuracy of 97.8%, and F1-score of 97.1%. LSTM provided the closest benchmark response with corresponding values of 96.8%, 95.9%, and 95.4%, whereas SVR recorded the lowest values of 93.6%, 92.6%, and 91.8%. XGBoost and GRU remained competitive but showed weaker combined regression and classification performance than FW-AON. Random Forest exhibited greater deterioration in classification effectiveness. These results indicate that integrating temporal degradation history, nonlinear fouling-state estimation, environmental variables, and compressor wash history improves FW-AON's ability to distinguish genuine fouling progression from normal gas-turbine operational variability.

Table 3 Comparative Predictive Performance of FW-AON and Benchmark Algorithms

Algorithm	**R2R^2 (%)**	**Fouling-Detection Accuracy (%)**	**F1-Score (%)**
FW-AON	**98.2**	**97.8**	**97.1**
LSTM	96.8	95.9	95.4
XGBoost	96.1	95.1	94.6
GRU	95.7	94.7	94.1
Random Forest	94.8	93.9	93.2
SVR	93.6	92.6	91.8

The three metrics provide complementary evidence of predictive quality. R2R^2 measures the proportion of compressor-fouling variation explained by each algorithm, while detection accuracy evaluates correct classification of fouled and normal operating states. The F1-score additionally balances false-positive and false-negative fouling decisions, which is important because either unnecessary washing or delayed intervention can adversely affect maintenance economics. FW-AON exceeds the nearest LSTM benchmark by 1.4 percentage points in R2R^2, 1.9 points in accuracy, and 1.7 points in F1-score. The gap relative to SVR increases to 4.6, 5.2, and 5.3 percentage points, respectively. Thus, FW-AON provides the most consistent combination of regression accuracy and operationally meaningful fouling detection.

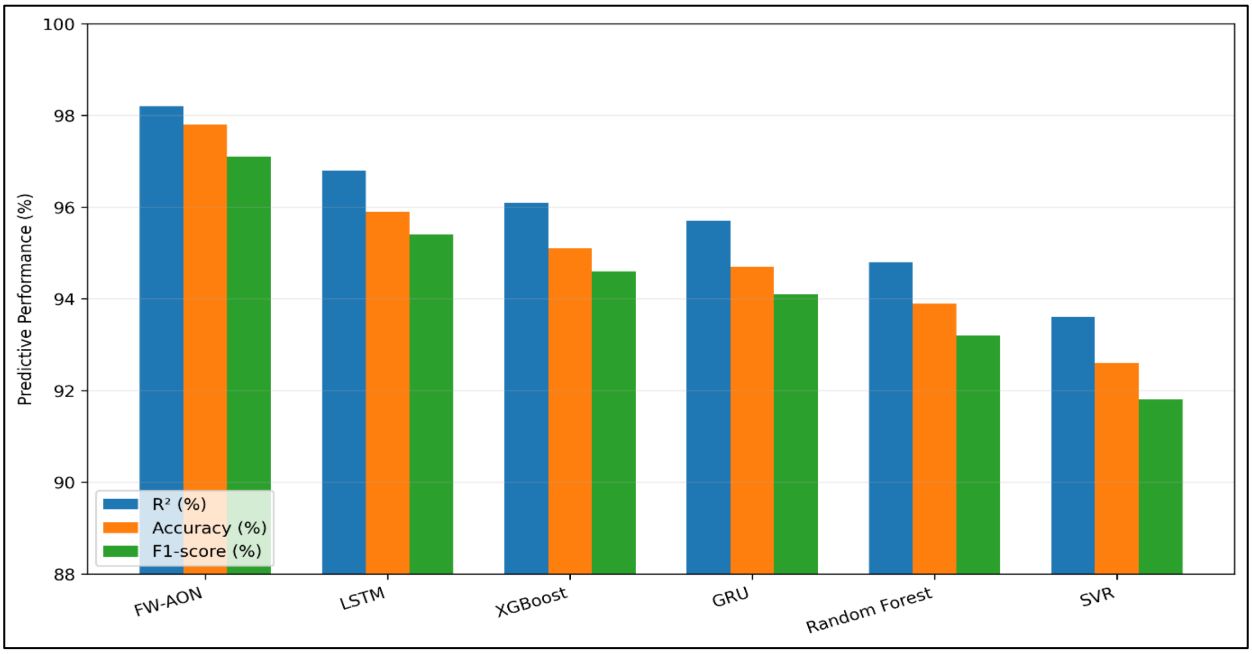

Fig 5 Comparative predictive performance of FW-AON, LSTM, XGBoost, GRU, Random Forest, and SVR.

Figure 5 shows a clear performance hierarchy across the six algorithms. FW-AON records the highest values across all three plotted metrics, with R2R^2, accuracy, and F1-score reaching 98.2%, 97.8%, and 97.1%, respectively. LSTM follows at 96.8%, 95.9%, and 95.4%, indicating that recurrent temporal learning captures much of the compressor degradation pattern but remains less effective than the adaptive FW-AON architecture. XGBoost achieves 96.1% R2R^2, 95.1% accuracy, and 94.6% F1-score, while GRU produces 95.7%, 94.7%, and 94.1%. Random Forest declines to 94.8%, 93.9%, and 93.2%. SVR gives the lowest values at 93.6%, 92.6%, and 91.8%. The progressively widening separation demonstrates that FW-AON benefits from combining temporal feature extraction, environmental information, wash history, and nonlinear fouling estimation. Its stronger F1-score is especially important because reliable fouling classification reduces both premature washing and delayed maintenance interventions.

- *Optimization of Compressor Water-Washing and Maintenance Scheduling*

The FW-AON framework produced a longer and more economically favorable compressor water-washing interval than the benchmark algorithms while retaining superior predicted performance recovery. As summarized in Table 4, FW-AON recommended a mean intervention interval of 3,380 h, compared with 3,137 h for LSTM and progressively shorter intervals for XGBoost, GRU, Random Forest, and SVR. The optimized FW-AON schedule was associated with a 6.1% compressor-efficiency recovery and a 14.8% reduction in total maintenance-related cost. LSTM achieved 5.8% efficiency recovery and 12.9% cost reduction, while SVR produced the lowest corresponding improvements of 4.8% and 8.1%. The results indicate that FW-AON better distinguishes economically significant fouling from transient operating variability, thereby reducing premature washing while preventing excessive compressor deterioration, fuel penalties, and avoidable production losses.

Table 4 Comparative Optimization of Compressor Water-Washing and Maintenance Scheduling

Algorithm	Mean Recommended Wash Interval (h)	Compressor Efficiency Recovery (%)	Maintenance Cost Reduction (%)
FW-AON	**3,380**	**6.1**	**14.8**
LSTM	3,137	5.8	12.9
XGBoost	2,969	5.6	11.7
GRU	2,837	5.4	10.8
Random Forest	2,669	5.1	9.4
SVR	2,537	4.8	8.1

FW-AON extends the average wash interval by approximately 243 h relative to LSTM and 843 h relative to SVR while simultaneously providing the highest compressor-efficiency recovery and maintenance-cost reduction. This indicates that the proposed framework does not achieve lower maintenance frequency simply by delaying intervention. Instead, it identifies an operating window where the accumulated performance loss is sufficiently large to justify washing while remaining below the region where prolonged fouling would impose excessive heat-rate, fuel-consumption, and power-output penalties. The progressive shortening of recommended intervals from FW-AON through SVR also demonstrates how less effective degradation forecasting can increase the probability of premature maintenance intervention.

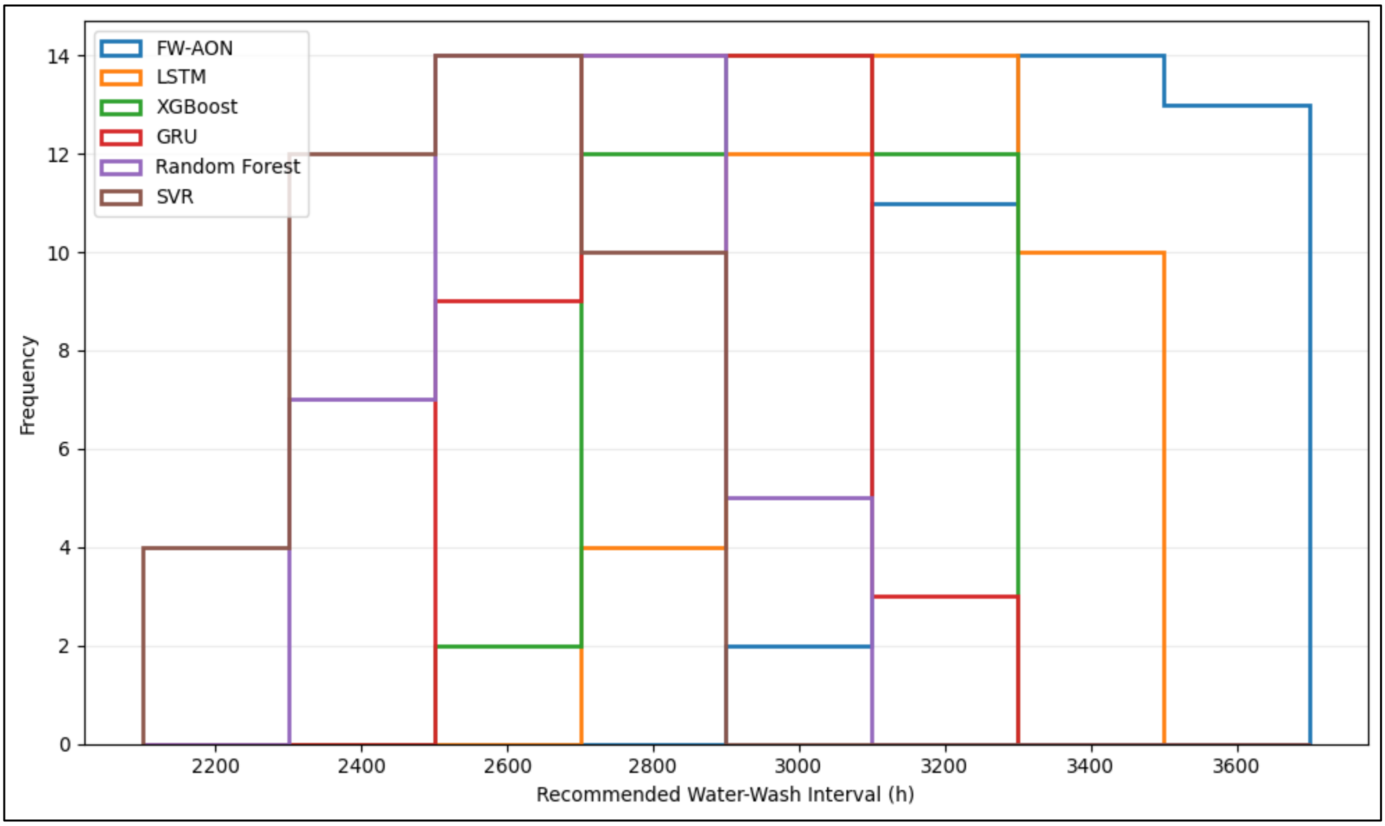

Fig 6 Distribution of compressor water-wash intervals recommended by FW-AON and benchmark algorithms.

Figure 6 demonstrates substantial differences in maintenance scheduling across the six algorithms. FW-AON recommendations are concentrated toward longer intervals, with 14 of 40 test windows falling between 3,300 and 3,500 h and another 13 between 3,500 and 3,700 h. LSTM peaks at 14 observations between 3,100 and 3,300 h, whereas XGBoost records its highest frequency of 14 observations between 2,900 and 3,100 h. GRU produces two dominant regions, each containing 14 observations between 2,700–2,900 h and 2,900–3,100 h. Random Forest shifts further toward premature intervention, with 14 observations in both the 2,500–2,700 h and 2,700–2,900 h ranges. SVR is the most conservative scheduler, recording 14 observations between 2,500 and 2,700 h and none above 2,900 h. The rightward FW-AON distribution indicates greater confidence in distinguishing tolerable fouling progression from the point at which efficiency loss, fuel penalty, and maintenance economics justify washing.

FW-AON identified a mean optimal water-wash interval of approximately 3,380 h, compared with 2,537–3,137 h for the benchmark algorithms, while providing 6.1% compressor-efficiency recovery and 14.8% maintenance-cost reduction.

- *Water, Wastewater, Economic, and Sustainability Performance*

The sustainability assessment demonstrated that the maintenance strategy selected by FW-AON produced the strongest combined reduction in water demand, wastewater burden, and maintenance-related expenditure. Table 4.4 shows that FW-AON reduced wash-water use by 22.6%, wastewater generation by 24.3%, and maintenance cost by 14.8%. LSTM achieved corresponding reductions of 17.9%, 19.6%, and 12.9%, while XGBoost and GRU produced intermediate improvements. Random Forest and SVR yielded progressively weaker sustainability outcomes, with SVR providing only 9.8% water-use reduction, 11.2% wastewater reduction, and 8.1% maintenance-cost reduction. The stronger FW-AON outcome results from linking predicted fouling severity to the technically justified wash interval rather than applying premature interventions. This reduces unnecessary cleaning cycles, limits freshwater withdrawal and effluent generation, and preserves the economic benefit of recovered compressor efficiency, power output, and reduced fuel consumption.

Table 5 Comparative Water, Wastewater, and Economic Performance of FW-AON and Benchmark Algorithms

Algorithm	Wash-Water Reduction (%)	Wastewater Reduction (%)	Maintenance-Cost Reduction (%)
FW-AON	**22.6**	**24.3**	**14.8**
LSTM	17.9	19.6	12.9
XGBoost	15.8	17.1	11.7
GRU	14.6	15.9	10.8
Random Forest	12.1	13.5	9.4
SVR	9.8	11.2	8.1

Table 5 demonstrates that the sustainability advantage of FW-AON extends beyond predictive accuracy. Relative to LSTM, FW-AON provides an additional 4.7 percentage points of wash-water reduction, 4.7 percentage points of wastewater reduction, and 1.9 percentage points of maintenance-cost reduction. The differences become substantially larger relative to SVR, reaching 12.8, 13.1, and 6.7 percentage points, respectively. These improvements are consistent with the longer condition-responsive washing interval identified in Section 4.3. Fewer unnecessary washing events reduce demineralized-water demand and the corresponding contaminated effluent stream, while more accurate identification of economically significant fouling prevents excessive delay that would otherwise increase fuel consumption, heat rate, and generation losses.

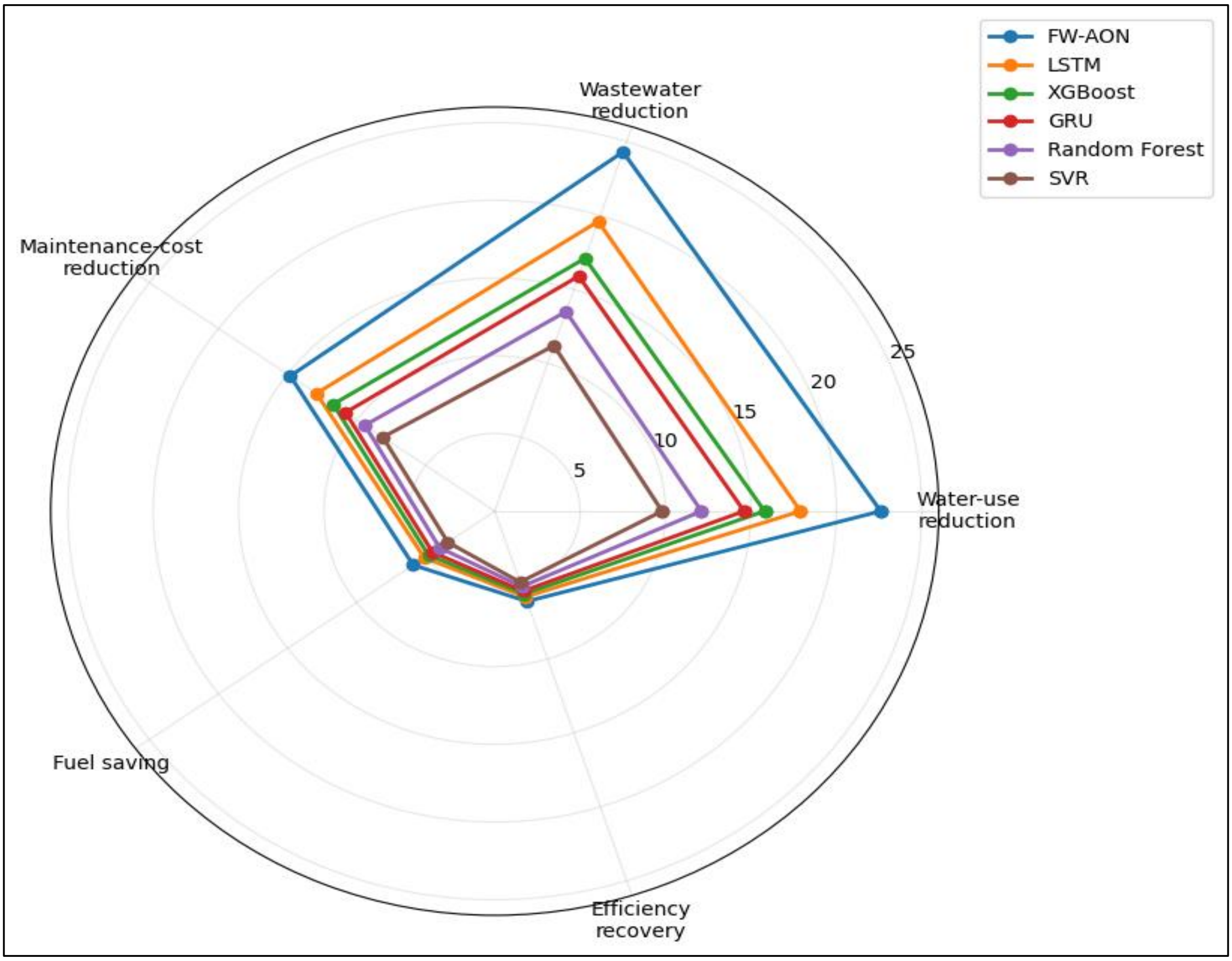

Fig 7 Multi-Criteria Sustainability Comparison of FW-AON and Benchmark Algorithms.

Figure 7 compares the six algorithms across five sustainability dimensions and shows that FW-AON forms the widest performance envelope. It achieves 22.6% wash-water reduction and 24.3% wastewater reduction, compared with 17.9% and 19.6% for LSTM, 15.8% and 17.1% for XGBoost, and 14.6% and 15.9% for GRU. Random Forest falls to 12.1% and 13.5%, while SVR records 9.8% and 11.2%. FW-AON also produces the highest maintenance-cost reduction of 14.8%, fuel saving of 5.9%, and compressor-efficiency recovery of 6.1%. LSTM follows with 12.9%, 5.1%, and 5.8%, whereas SVR produces only 8.1%, 3.4%, and 4.8%. The consistent outward position of the FW-AON trace indicates that longer condition-responsive wash intervals do not compromise performance recovery. Instead, the framework simultaneously improves resource productivity, reduces wash effluent, lowers fouling-related operating expenditure, and preserves thermodynamic recovery. This represents the intended Pareto behavior of the multi-objective formulation, where economic and environmental objectives are optimized jointly.

FW-AON reduced wash-water consumption by 22.6%, wastewater generation by 24.3%, and maintenance-related cost by 14.8%, while achieving 5.9% fuel saving and 6.1% compressor-efficiency recovery.

V. CONCLUSIONS AND RECOMMENDATIONS

- *Conclusions on Compressor Fouling Prediction and FW-AON Performance*

The study established that compressor fouling produces a measurable and progressive deterioration in gas-turbine aerodynamic and thermodynamic performance. Across the evaluated operating period, compressor isentropic efficiency declined from 88.4% to 82.7%, corrected air mass flow decreased from 510 to 481 kg/s, and compressor pressure ratio reduced from 15.8 to

15.1. These changes propagated to plant-level performance, where electrical power output fell from 150.0 MW to 138.2 MW while heat rate increased from 10,050 to 10,780 kJ/kWh and fuel flow rose from 8.42 to 8.79 kg/s. The results confirm that fouling is not adequately represented by a single operating variable and should instead be treated as a multivariable degradation process involving airflow restriction, efficiency loss, increased compressor work, and higher fuel intensity.

The proposed FW-AON framework demonstrated superior predictive performance because it combined temporal operating history, environmental conditions, nonlinear fouling-state estimation, and previous wash information within a unified architecture. FW-AON achieved an R2R^2 of 98.2%, fouling-detection accuracy of 97.8%, and F1-score of 97.1%, outperforming LSTM, XGBoost, GRU, Random Forest, and SVR. The strongest competing model, LSTM, achieved 96.8%, 95.9%, and 95.4%, respectively, while SVR produced the lowest results. This performance advantage indicates that incorporating temporal attention and maintenance-history information improves separation of genuine compressor deterioration from load and ambient-condition variations. Consequently, FW-AON provides a more technically reliable basis for predicting progressive fouling and identifying when degradation has become sufficiently significant to justify water-washing intervention.

- *Conclusions on Water-Wash Optimization, Efficiency Recovery, and Maintenance Planning*

The water-wash optimization results demonstrate that maintenance effectiveness depends on determining when compressor deterioration becomes technically and economically significant rather than simply washing at fixed calendar or operating-hour intervals. FW-AON identified a mean optimal wash interval of approximately 3,380 operating hours, compared with 3,137 h for LSTM, 2,969 h for XGBoost, 2,837 h for GRU, 2,669 h for Random Forest, and 2,537 h for SVR. The longer FW-AON interval did not represent deferred maintenance at the expense of equipment condition. Instead, it reflected improved confidence in differentiating tolerable fouling progression from degradation requiring intervention, thereby avoiding premature compressor washing.

At the selected interval, FW-AON achieved 6.1% compressor-efficiency recovery and a 14.8% reduction in maintenance-related cost. These results exceeded the 5.8% efficiency recovery and 12.9% maintenance-cost reduction obtained with LSTM and substantially outperformed the SVR strategy, which achieved 4.8% and 8.1%, respectively. The findings show that improved degradation prediction can be translated into more effective maintenance decisions when prediction is directly connected to thermodynamic recovery, fuel penalties, downtime, and washing expenditure. The approach also limits unnecessary start-stop cycles and production interruptions associated with premature offline washing. From a maintenance-planning perspective, FW-AON therefore provides a shift from scheduled cleaning toward condition-responsive intervention. Plant operators can use predicted fouling severity and projected performance loss to plan wash windows around generation demand, maintenance manpower, water availability, and production constraints. This creates a more defensible basis for balancing equipment health, plant availability, fuel efficiency, and maintenance expenditure.

- *Recommendations for Sustainable Wash-Water and Wastewater Management in Power Plants*

Compressor water-washing programmes should be managed as both maintenance and resource-efficiency processes. The findings show that FW-AON-based scheduling can reduce wash-water consumption by 22.6% and wastewater generation by 24.3% while simultaneously maintaining strong compressor-performance recovery. Power plants should therefore replace routine high-frequency washing with condition-responsive scheduling based on quantified fouling severity, expected efficiency recovery, water requirement, and predicted wastewater burden. Wash authorization should include a defined technical trigger based on corrected airflow, compressor efficiency, predicted fouling index, and expected economic recovery rather than operating hours alone. Wash-water consumption should also be monitored at individual-event level. Each washing record should include demineralized-water volume, cleaning-agent quantity, wash duration, pre- and post-wash compressor condition, effluent volume, and recovery in efficiency and power output. These data can be converted into indicators such as litres of wash water per percentage point of efficiency recovered and wastewater generated per recovered megawatt-hour. Such indicators allow maintenance teams to identify inefficient washing practices and detect deteriorating cleaning effectiveness.

Wastewater from compressor washing should be collected through controlled drainage rather than discharged directly to the environment. Depending on contaminant characteristics, treatment should address suspended solids, oil residues, dissolved salts, detergent constituents, and metallic particulates. Where water quality permits, treated effluent should be evaluated for non-potable reuse applications such as dust suppression, preliminary equipment washing, or other approved industrial uses. Power plants should additionally establish site-specific water and wastewater targets within maintenance performance dashboards so that compressor reliability decisions are evaluated simultaneously against operational, economic, and environmental performance requirements.

- *Recommendations for Industrial Deployment, Digital-Twin Integration, and Future Research*

Industrial deployment of FW-AON should begin with integration into the existing distributed control system, historian, computerized maintenance management system, and environmental monitoring platform. Real-time compressor inlet conditions, discharge pressure, corrected airflow, compressor efficiency, exhaust temperature, fuel flow, electrical output, ambient humidity, particulate loading, operating hours, and washing history should be streamed automatically into the predictive architecture. The FW-AON output should not function as an autonomous maintenance command during initial deployment. Instead, it should provide operators and maintenance engineers with fouling severity, forecast degradation trajectory, expected time to economically justified washing, predicted recovery, water requirement, wastewater volume, and cost implications within a decision-support dashboard.

A digital-twin implementation would further strengthen the framework by maintaining a continuously updated virtual representation of compressor condition. The digital twin could simulate alternative wash dates and quantify their effects on efficiency, power output, heat rate, fuel consumption, downtime, water demand, and wastewater generation before maintenance is authorized. This would allow operators to evaluate scenarios such as washing during low-demand periods, postponing intervention during water scarcity, or selecting online rather than offline washing where technically appropriate. Future research should validate FW-AON using extended multi-season and multi-unit operating datasets covering varying climates, particulate concentrations, fuel conditions, compressor designs, and filtration systems. Additional work should incorporate uncertainty quantification, explainable-AI methods, remaining-useful-performance estimation, and dynamic electricity-price signals. The optimization framework should also be expanded to include wastewater contaminant concentration, treatment energy, carbon intensity, water scarcity indices, and lifecycle environmental cost. Ultimately, integrating FW-AON with plant-wide digital twins could enable coordinated optimization of compressor cleanliness, turbine performance, maintenance scheduling, resource consumption, and environmental compliance across sustainable power-generation infrastructure.

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