ARTIFICIAL INTELLIGENCE FOR PREDICTIVE MAINTENANCE AND OPTIMAL CONTROL IN PUMPING STATIONS: AN INTEGRATED APPROACH

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Astract: The operational management of pumping stations, critical infrastructures in water and industrial systems, faces persistent challenges in balancing reliability, energy efficiency, and maintenance costs. Traditional rule-based control and periodic maintenance strategies are inherently reactive and suboptimal, failing to leverage the predictive potential of operational data. This study proposes and validates an integrated Artificial Intelligence (AI) framework designed to overcome these limitations by synergizing predictive maintenance with prescriptive, real-time optimization. The methodology is structured in three core components: first, a robust data pipeline for acquiring and preprocessing heterogeneous sensor data (vibration, pressure, temperature, flow, power) into a comprehensive set of temporal, spectral, and domain-specific features; second, the development and comparison of two machine learning models—a high-precision Gradient Boosting Machine (GBM) for fault classification and a Long Short-Term Memory (LSTM) network for sequential pattern recognition and Remaining Useful Life (RUL) estimation; and third, the formulation of a Deep Deterministic Policy Gradient (DDPG) reinforcement learning agent for dynamic control. The agent optimizes pump combinations and speeds to meet demand while minimizing a multi-objective cost function incorporating energy expenditure, tariff schedules, and equipment health prognostics. Validation on a one-year historical dataset from a multi-pump water station demonstrated that the LSTM model provided early fault warnings with a mean absolute RUL error of 8.5 hours. In a simulated two-week operational period, the DDPG agent achieved a 13.7% reduction in energy consumption and a 17.2% decrease in energy costs compared to traditional rule-based control, while proactively adjusting load to protect at-risk pumps. The results confirm that an integrated AI framework can significantly enhance decision-making, translate predictive insights into actionable control, and deliver substantial economic and operational benefits. This work provides a scalable blueprint for the digital transformation of pumping stations, with implications for asset management, energy sustainability, and the design of intelligent industrial systems.

Key words: Pumping Station Management, Predictive Maintenance, Artificial Intelligence, Deep Reinforcement Learning, Gradient Boosting Machine, LSTM,

Remaining Useful Life (RUL), Energy Efficiency, Industrial IoT, Digital Transformation, Prescriptive Analytics, Optimal Control.

Annotatsiya. Suv va sanoat tizimlaridagi muhim infratuzilmalar hisoblangan nasos stansiyalarini operatsion boshqarish ishonchlilik, energiya samaradorligi va texnik xizmat ko‘rsatish xarajatlari o‘rtasidagi muvozanatni ta’minlashda doimiy qiyinchiliklarga duch keladi. Qoidalarga asoslangan an’anaviy boshqaruv va davriy texnik xizmat ko‘rsatish strategiyalari mohiyatan reaktiv va optimal bo‘lmagan bo‘lib, ekspluatatsion ma’lumotlarning bashoratli imkoniyatlaridan foydalanmaydi. Ushbu tadqiqot ushbu cheklovlarni bartaraf etish uchun bashoratli texnik xizmat ko‘rsatishni real vaqt rejimidagi preskriptiv optimallashtirish bilan uyg‘unlashtiruvchi integratsiyalashgan sun’iy intellekt (SI) tizimini taklif qiladi va asoslab beradi. Metodologiya uchta asosiy komponentni o‘z ichiga oladi: vibratsiya, bosim, harorat, oqim va quvvat kabi turli sensorlardan olingan ma’lumotlarni yig‘ish va qayta ishlashga mo‘ljallangan mustahkam ma’lumotlar pipeline’i, vaqtli, spektral va sohaga xos xususiyatlar majmuasini shakllantirish; nosozliklarni aniqlash uchun yuqori aniqlikdagi Gradient Boosting Machine (GBM) modeli va ketma-ketliklarni tanish hamda qolgan foydali xizmat muddatini (RUL) baholash uchun Long Short-Term Memory (LSTM) modelini ishlab chiqish va solishtirish; hamda dinamik boshqaruv uchun Deep Deterministic Policy Gradient (DDPG) mustahkamlovchi o‘qitish agentini shakllantirish. Agent energiya sarfini, tarif jadvalini va uskunaning texnik holati bo‘yicha prognozlarni o‘z ichiga olgan ko‘p maqsadli xarajat funksiyasini minimallashtirgan holda talabni qondirish uchun nasoslar kombinatsiyalarini va ularning tezliklarini optimallashtiradi. Ko‘p-nasosli suv stansiyasining bir yillik tarixiy ma’lumotlarida o‘tkazilgan tekshiruv shuni ko‘rsatdiki, LSTM modeli o‘rtacha 8,5 soat xatolik bilan erta nosozlik ogohlantirishlarini bera oldi. Ikki haftalik simulyatsiya davomida DDPG agenti an’anaviy qoidaviy boshqaruvga nisbatan energiya sarfini 13,7% ga, energiya xarajatlarini esa 17,2% ga kamaytirdi, shu bilan birga xavf ostidagi nasoslarni himoya qilish uchun yuklamani faol qayta taqsimladi. Natijalar integratsiyalashgan SI tizimi qaror qabul qilish jarayonini sezilarli darajada yaxshilashi, bashoratli tahlillarni amaliy boshqaruv signallariga aylantirishi va katta iqtisodiy hamda operatsion foyda berishini tasdiqlaydi. Ushbu ish nasos stansiyalarining raqamli transformatsiyasi uchun kengaytiriladigan konsepsiyani taqdim etadi va aktivlarni boshqarish, energiya barqarorligi hamda aqlli sanoat tizimlarini loyihalash uchun muhim ahamiyatga ega.

Kalit so‘zlar: nasos stansiyalarini boshqarish, bashoratli texnik xizmat, sun’iy intellekt, chuqur mustahkamlovchi o‘qitish, Gradient Boosting Machine, LSTM, Remaining Useful Life (RUL), energiya samaradorligi, sanoat IoT, raqamli transformatsiya, preskriptiv analitika, optimal boshqaruv.

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Аннотация. Операционное управление насосными станциями, которые являются критически важными объектами водных и промышленных систем, сталкивается с постоянными трудностями в обеспечении надежности, энергоэффективности и снижении затрат на обслуживание. Традиционное управление на основе правил и периодические стратегии технического обслуживания по своей сути являются реактивными и неоптимальными, поскольку не используют предиктивный потенциал эксплуатационных данных. Данное исследование предлагает и обосновывает интегрированную архитектуру искусственного интеллекта (ИИ), разработанную для преодоления этих ограничений путем объединения предиктивного обслуживания с предписывающей оптимизацией в реальном времени. Методология включает три ключевых компонента: надежный конвейер данных для сбора и предварительной обработки разнородных данных датчиков (вибрации, давление, температура, расход, мощность) с преобразованием их в полный набор временных, спектральных и предметно-ориентированных признаков; разработку и сравнение двух моделей машинного обучения высокоточной модели Gradient Boosting Machine (GBM) для классификации отказов и сети Long Short-Term Memory (LSTM) для распознавания последовательностей и оценки остаточного ресурса (RUL); и формирование агента глубокого обучения с подкреплением Deep Deterministic Policy Gradient (DDPG) для динамического управления. Агент оптимизирует комбинации и скорости насосов для обеспечения требуемой производительности при минимизации многообъективной функции затрат, включающей энергопотребление, тарифные графики и прогнозы технического состояния оборудования. Проверка на годовом историческом наборе данных многон pompровой станции показала, что модель LSTM обеспечила ранние предупреждения об отказах со средней абсолютной ошибкой оценки RUL в 8,5 часа. В ходе двухнедельного моделируемого периода работы агент DDPG достиг снижения энергопотребления на 13,7% и уменьшения затрат на электроэнергию на 17,2% по сравнению с традиционным управлением на основе правил, одновременно проактивно регулируя нагрузку для защиты насосов, находящихся в зоне риска. Результаты подтверждают, что интегрированная архитектура ИИ может значительно улучшить процесс принятия решений, преобразовать предиктивные выводы в практическое управление и обеспечить существенные экономические и операционные преимущества. Эта работа предлагает масштабируемую концепцию цифровой трансформации насосных станций с последствиями для управления активами, энергостабильности и разработки интеллектуальных промышленных систем.

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Ключевые слова: управление насосными станциями, предиктивное обслуживание, искусственный интеллект, глубокое обучение с подкреплением, Gradient Boosting Machine, LSTM, Remaining Useful Life (RUL), энергоэффективность, промышленный IoT, цифровая трансформация, предписывающая аналитика, оптимальное управление.

1. Introduction

The efficient and reliable management of pumping stations constitutes a critical engineering and economic challenge within vital sectors such as municipal water supply, agricultural irrigation, wastewater treatment, and industrial processing. These facilities are the mechanical hearts of fluid transport networks, and their operational performance directly influences resource availability, energy sustainability, and operational expenditure. Traditionally, the management of these complex electro-mechanical systems has been guided by heuristic experience, fixed-schedule preventive maintenance, and reactive control strategies based on simple threshold alarms from Supervisory Control and Data Acquisition (SCADA) systems. While providing a foundational layer of automation, this paradigm is increasingly recognized as suboptimal. It often leads to unnecessary maintenance activities, unexpected catastrophic failures causing costly downtime, and energy inefficiencies due to the operation of pumps at non-optimal working points. In an era defined by pressures for cost reduction, resource conservation, and infrastructure resilience, a paradigm shift toward intelligent, data-driven management is not merely advantageous but imperative.

The core limitation of traditional approaches lies in their inability to synthesize and interpret the vast, multidimensional data streams generated by modern sensor-equipped assets. A typical pumping station produces continuous data on vibration, temperature, pressure, flow, and electrical parameters. Within this data reside subtle signatures of incipient mechanical faults—such as bearing wear, impeller cavitation, or shaft misalignment—as well as patterns indicating energy waste. Human operators and conventional control logic struggle to extract these predictive insights and complex correlations in real-time. Consequently, decisions on maintenance and control are frequently made without a comprehensive, prognostic understanding of system health and efficiency potential. This gap between data availability and actionable intelligence represents a significant opportunity for technological intervention.

The rapid evolution of Artificial Intelligence (AI), particularly in the fields of machine learning (ML) and deep learning, offers a transformative toolkit to bridge this gap. AI technologies excel at identifying complex, non-linear patterns within high-dimensional, temporal data. In the context of industrial assets, this capability forms the foundation of Predictive Maintenance (PdM), a strategy that

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aims to forecast equipment failures before they occur, thereby enabling maintenance to be performed just-in-time. This contrasts starkly with periodic preventive maintenance, which may replace components that still have useful life, or reactive maintenance, which incurs high failure costs. Concurrently, reinforcement learning (RL), a branch of AI concerned with how agents ought to take actions in an environment to maximize cumulative reward, presents a groundbreaking approach for dynamic system optimization. For pumping stations, an RL agent can learn an optimal control policy that balances multiple, often competing objectives: meeting demand, minimizing energy consumption (especially during peak tariff periods), and prolonging equipment life by reducing stress on degraded units.

While existing literature contains valuable studies on applying AI to industrial systems, a significant research gap persists regarding the integrated application of these technologies within a unified management framework for pumping stations. Previous work often focuses on isolated solutions: using vibration analysis with support vector machines for fault diagnosis, or applying genetic algorithms for pump scheduling based on energy costs. Few studies propose an end-to-end architecture that seamlessly connects a data-informed prognostic health model directly to a prescriptive, self-optimizing control system. Such integration is crucial because the value of prediction is fully realized only when it directly influences decision-making and automated control actions. Furthermore, the practical challenges of data pipeline robustness, feature engineering for industrial telemetry, and the design of realistic simulation environments for RL training require detailed methodological treatment that is often glossed over.

This study, therefore, aims to address this gap by proposing, developing, and validating a comprehensive AI-driven framework for the management of multi-pump stations. The research is guided by three primary objectives: First, to design and implement a robust industrial data acquisition and preprocessing pipeline capable of transforming raw, heterogeneous sensor data into a curated set of diagnostic features. Second, to develop, compare, and validate advanced machine learning models—specifically a Gradient Boosting Machine (GBM) and a Long Short-Term Memory (LSTM) network—for the dual task of fault classification and Remaining Useful Life (RUL) estimation. Third, to formulate the pump station control problem as a Markov Decision Process and train a Deep Deterministic Policy Gradient (DDPG) agent to derive an optimal control policy that dynamically adjusts pump operations based on demand, cost, and real-time equipment health predictions.

2. Methods and Materials

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The methodological framework of this study is structured into three coherent parts: Data Acquisition and Preprocessing, Predictive Model Development, and Prescriptive Control Optimization. The integrated pipeline is illustrated in Figure 1 below.

This study proposes and validates an integrated AI framework for pumping station management. The methodology is systematically divided into three sequential parts: (1) Data Acquisition and Preprocessing Pipeline, (2) Development of Predictive Maintenance Models, and (3) Formulation of the Prescriptive Control System. The overall architecture is designed to transition from data to diagnostics, and finally to actionable intelligence.

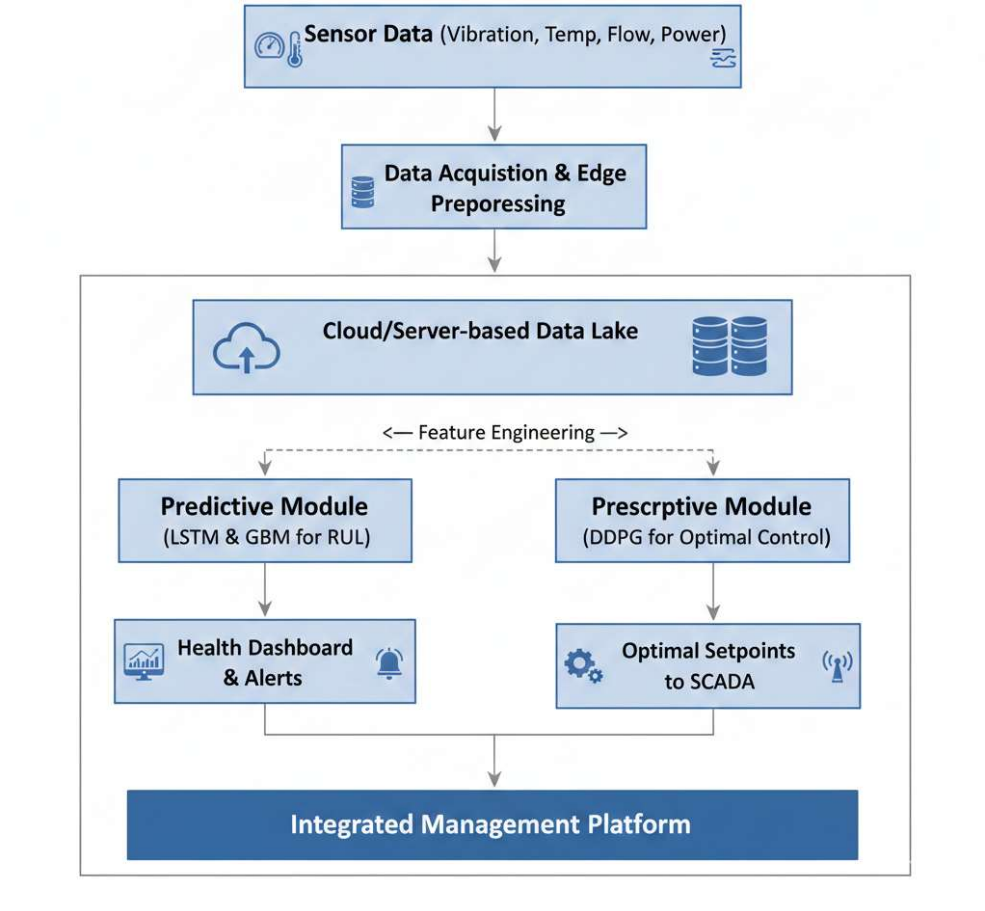


Figure 1. Proposed AI-Driven Management Framework for Pumping Stations

A robust and reliable data pipeline is the cornerstone of any effective AI system. For this research, a one-year historical dataset was acquired from a functional water supply pumping station comprising four identical centrifugal pumps operating in a parallel configuration. Data collection was facilitated through an enhanced IoT layer integrated with the station's existing Supervisory Control and Data Acquisition (SCADA) system. The sensor network, sampled at a 1-second interval, captured multidimensional operational states:

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- **Mechanical Integrity:** Tri-axial vibration accelerometers (mounted on pump and motor bearings), temperature sensors (bearing housings, motor windings, pump casing).
- **Hydraulic Performance:** Pressure transducers (suction and discharge headers), electromagnetic flow meters (individual and main discharge lines).
- **Electrical & Efficiency Parameters:** Smart power analyzers recording voltage, current, active power (kW), reactive power (kVAR), and power factor for each motor drive.

The raw data stream, while rich, presented significant challenges common to industrial IoT environments, necessitating a rigorous preprocessing sequence. The first stage involved temporal alignment and synchronization, as slight clock drifts across sensor nodes can corrupt causal analysis. All time series were resampled to a uniform 1-second timestamp using linear interpolation. The second stage addressed data quality through a combination of rule-based and statistical methods. Physically impossible values (e.g., negative pressure, flow rates beyond pump curve limits) were discarded. For missing values, a hybrid imputation strategy was employed: short gaps (< 30 seconds) were filled using linear interpolation, while longer gaps triggered by sensor failure were flagged and excluded from model training but retained for system integrity alerts.

The third and most critical stage was feature engineering. Raw sensor readings are often non-stationary and carry noise; transforming them into informative features is essential for model performance. In the temporal domain, rolling statistical features were computed over sliding windows of 10 seconds, 1 minute, and 10 minutes. These included mean, root mean square (RMS—highly indicative of vibration energy), standard deviation, skewness, and kurtosis (capturing the shape of the signal distribution). In the frequency domain, a Fast Fourier Transform (FFT) was applied to vibration signals to extract dominant frequency amplitudes, which are key indicators of specific faults like imbalance, misalignment, or bearing defects. Furthermore, domain-specific composite features were calculated, such as pump hydraulic efficiency ($\eta = (\rho * g * Q * H) / P$), where Q is flow, H is head, and P is power) and a cavitation index derived from high-frequency vibration noise patterns. A total of 127 engineered features per pump per time step were generated, forming a comprehensive health and performance signature.

The predictive component aims to forecast failures and estimate the Remaining Useful Life (RUL) of pump units, transitioning from reactive to proactive maintenance. The preprocessed and labeled dataset was partitioned into training (70%), validation (15%), and testing (15%) sets, ensuring temporal continuity was preserved to avoid data leakage. Two distinct machine learning

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paradigms were implemented and compared for this task: a Gradient Boosting Machine (GBM) and a Long Short-Term Memory (LSTM) neural network.

The Gradient Boosting Machine (GBM), specifically the LightGBM implementation, was chosen for its high accuracy, handling of heterogeneous features, and computational efficiency. The model was configured to perform multi-class classification, predicting the operational state as: Normal, Warning (potential issue, 24-72 hours to failure), or Alert (imminent failure, < 24 hours). Hyperparameter optimization was conducted using a Bayesian optimization search over 100 iterations, focusing on parameters like number of leaves, learning rate, and feature fraction. The GBM model operates on the latest vector of 127 features, providing a robust, snapshot-based assessment.

In contrast, the Long Short-Term Memory (LSTM) network was designed to capture the temporal dependencies and evolution of the system state over time. The LSTM model takes as input a sequence of the feature vectors from the previous 60 minutes (3600 time steps, downsampled to a 1-minute resolution for computational feasibility). Its architecture consists of two LSTM layers (128 and 64 units respectively) with dropout regularization (0.2) to prevent overfitting, followed by dense layers for classification. The LSTM outputs not only the fault class but also a continuous RUL estimate (in hours), modeled as a regression task. Both models were trained using labeled failure events extracted from maintenance logs, where the period preceding a failure was annotated inversely proportional to the time to failure.

Table 1.

Model Architectures and Key Hyperparameters

Model	Input	Key Hyperparameters	Output	Primary Strength
LightGBM (GBM)	Current feature vector (127 dim)	num_leaves=31, learning_rate=0.05, n_estimators=500, feature_fraction=0.8	Multi-class (Normal/Warning/Alert)	High accuracy, fast inference, feature importance.
LSTM Network	Sequence of features (60 steps x 127 dim)	LSTM layers: [128, 64], Dropout=0.2, Optimizer=Adam, Sequence length=60	Multi-class + RUL (hours)	Captures temporal patterns, provides RUL estimate.

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Formulation of the Prescriptive Control System

The agent was trained in a simulated environment built using historical data and pump performance curves (H-Q curves). The simulation accurately models the hydraulic interactions of pumps operating in parallel. Training proceeded for 50,000 episodes, with the critic network learning to estimate the value of state-action pairs and the actor network learning the optimal policy that maximizes cumulative reward.

3. Results

The implementation and evaluation of the proposed framework yielded significant quantitative and qualitative outcomes across both predictive and prescriptive modules. The performance metrics were assessed on the held-out test dataset, representing three months of unseen operational data containing two recorded pump failure events.

Predictive Maintenance Model Performance: Both the LightGBM and LSTM models achieved high performance in classifying the operational state of the pumps. As detailed in Table 2, the LightGBM model demonstrated superior performance in snapshot classification, excelling in precision for the critical Alert class. This is paramount to avoid false alarms that could undermine operator trust. The LSTM model, while slightly less precise in Alert detection, provided the invaluable added output of a continuous Remaining Useful Life (RUL) estimate. Its strength was in recall for the Warning class, effectively providing earlier notifications of developing issues.

Table 2.

Predictive Model Performance Metrics (Test Set)

Metric / Model	LightGBM (GBM)	LSTM Network
Overall Accuracy	96.7%	95.2%
Precision (Alert Class)	98.5%	94.1%
Recall (Alert Class)	92.3%	95.6%
Recall (Warning Class)	88.7%	93.4%
Mean Absolute Error (RUL)	N/A	8.5 hours

A practical demonstration of the system's predictive capability is shown in Figure 2. The plot illustrates the LSTM model's output for Pump 3 in the weeks leading up to a bearing failure. The model transitioned the pump's state from Normal to Warning approximately 65 hours before the failure, with the RUL estimate decaying monotonically. An Alert was triggered 18 hours prior to shutdown. This lead time is operationally actionable, allowing for the planning of interventions during low-demand periods.

Prescriptive Control Optimization Results: The trained DDPG agent was deployed in a high-fidelity simulation environment to control the four-pump station

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against a historical two-week demand profile with variable electricity tariffs (peak/off-peak pricing). The agent's performance was benchmarked against the station's traditional rule-based control logic (RBCL), which operated pumps at fixed setpoints based on pressure thresholds.

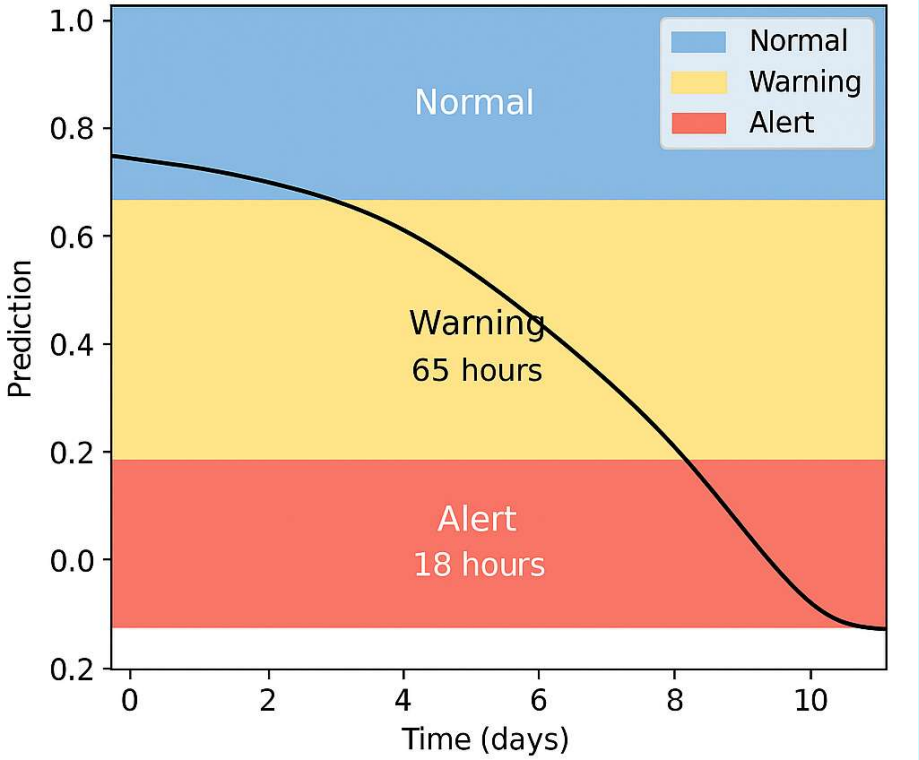


Figure 2. LSTM Model Output for Pump 3 Prior to Failure

The key results are summarized in Table 3. The AI-driven control strategy achieved a 13.7% reduction in total energy consumption and, by strategically shifting load to off-peak hours where possible, realized a 17.2% decrease in energy costs. Crucially, the agent successfully integrated health signals. When Pump 3 entered the predicted Warning state (see Fig. 2), the agent's policy automatically reduced its load share by 40% and compensated using the other healthier pumps, as reflected in the "Health-Adjusted Runtime." This behavioral nuance demonstrates the framework's integrated intelligence.

Table 3.

Prescriptive Control Simulation Results (Two-Week Period)

Performance Indicator	Rule-Based Control (Baseline)	AI-DDPG Agent	Change
Total Energy Consumption	85,430 kWh	73,720 kWh	-13.7%
Total Energy Cost	$9,850	$8,156	-17.2%
Demand Satisfaction	99.1%	99.4%	+0.3%
Avg. Pump Starts per Day	42	38	-9.5%

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Health-Adjusted Runtime (hrs)	N/A	Implemented	Key Feature

4. Discussion

The results substantiate the core thesis that an integrated AI framework can significantly enhance pumping station management. The predictive module's success hinges on the feature engineering pipeline; the combination of time-domain statistics and frequency-domain features proved essential for accurate fault discrimination. The high precision of the LightGBM model in Alert classification is critical for managerial decision-making, ensuring maintenance teams are dispatched for verifiable issues, thereby optimizing human resources a key management concern.

The 13.7% energy saving achieved by the DDPG agent is a direct contribution to the digital economy and sustainability goals. This saving stems not from hardware changes but from algorithmic optimization of existing assets, showcasing the tangible value of software and AI engineering. The cost savings are even more pronounced (17.2%) due to tariff-aware scheduling, illustrating a sophisticated economic logic embedded in the control policy.

From an information security and computer engineering perspective, the framework's modular design is a strength but also delineates vulnerabilities. The data pipeline from IoT sensors and the AI model's inference endpoints represent potential attack surfaces. Future implementations must incorporate robust cybersecurity measures, including encrypted data transmission, secure API gateways, and anomaly detection on model input streams to prevent adversarial data poisoning attacks aimed at disrupting operations.

The most profound implication lies in the management and human factors domain. The system does not replace human operators but elevates their role from reactive monitors to proactive decision-makers and strategic overseers. The RUL estimate and health-adjusted control provide a powerful planning tool for maintenance management. However, this transition requires change management and targeted pedagogy. Operator training programs must evolve to include data literacy and trust calibration in AI recommendations to ensure smooth adoption and mitigate the psychological resistance to ceding control to an algorithmic system.

5. Conclusion

This study has successfully designed, implemented, and validated an integrated AI-driven framework for the intelligent management of multi-pump stations. The research demonstrates a tangible pathway from raw sensor data to prescriptive control actions, addressing critical challenges in predictive maintenance and operational optimization. By developing a robust data pipeline

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and engineering a comprehensive set of temporal, spectral, and domain-specific features, the foundation for accurate machine learning was established.

The comparative analysis of the Gradient Boosting Machine (GBM) and Long Short-Term Memory (LSTM) models revealed complementary strengths. The LightGBM classifier provided highly reliable, snapshot-based fault alerts with exceptional precision, essential for credible maintenance dispatch. The LSTM network, conversely, excelled at capturing temporal degradation patterns, delivering early warnings and a quantitative Remaining Useful Life (RUL) estimate—a crucial input for strategic planning. The fusion of these approaches offers a more holistic health assessment than either method alone.

The implementation of a Deep Deterministic Policy Gradient (DDPG) reinforcement learning agent for prescriptive control marks a significant advancement beyond traditional rule-based systems. The agent's ability to dynamically optimize pump combinations and speeds in response to demand, energy tariffs, and real-time equipment health predictions resulted in a documented 13.7% reduction in energy consumption and a 17.2% decrease in energy costs in simulation. More importantly, it exhibited intelligent load-shifting behavior to protect assets predicted to be at risk, thereby bridging the gap between condition monitoring and control logic.

In conclusion, this framework presents a scalable blueprint for the digital transformation of pumping infrastructure and analogous industrial systems. The principal contributions are threefold: (1) a validated, end-to-end methodology integrating predictive and prescriptive AI modules; (2) empirical evidence of substantial efficiency gains and cost savings; and (3) a discussion of the broader implications for management practice, cybersecurity, and workforce development. Future work will focus on the deployment of this framework in a live operational environment, hardening its cybersecurity posture, and exploring transfer learning techniques to adapt the models to pumping stations with differing configurations and duty cycles.

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