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Development of AI-Integrated Water Distribution Model for Lift Irrigation Systems using Construction Management Techniques

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ABSTRACT

This study creates an AI-enhanced model for the water distribution problem of lift irrigation systems. It combines the latest AI methods, hydraulic simulation, and construction management methods for maximizing system utilization, optimizing pump scheduling, and reducing the water/energy loss, improving the system's overall efficiency. It is the first time, to the best of the author's knowledge, that Proximal Policy Optimization (PPO) and the EPANET hydraulic simulation tool are being used together to provide predictive control and intelligent water distribution. For training and validation of the AI model, the data that was gathered from the lift irrigation systems in Kolhapur, Maharashtra, India, and included the system's operational parameters (flow rate, pump energy consumption, and the weather conditions) will be used. The AI model's performance will be measured by statistical metrics, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). Concerning energy efficiency and operational costs, improving energy efficiency by 15–20% and reducing operational costs makes this approach supportive of the sustainable irrigation practices. The study shows that construction management in combination with AI-driven predictive control can help lift irrigation systems become more intelligent and sustainable. To some extent this model helps evaluate future irrigation infrastructure adaptations, specifically concerning semi-arid locations like Kolhapur.

Keywords: AI integration, water distribution, lift irrigation, reinforcement learning, Proximal Policy Optimization, hydraulic simulation, energy efficiency, construction management.

I. INTRODUCTION

Water shortages are one of the top problems today. The United Nations (2023) states that 2.4 billion people every year spend time under water stress. Agriculture is the number one consumer of water with 70% of the world's freshwater. In India, 58% of the population is dependent on agriculture[1]. Therefore, proper irrigation is important for the food security of the country and the livelihood of people in the rural areas[2]. The Central Water Commission (2022) estimates that India has approximately 1,122 billion cubic meters (BCM) of total usable water resources, and of the 1,122 BCM, only 690 BCM are usable water resources[3]. The main reason why people are not using the 690 BCM is due to the inefficiency of the people in distribution, the loss of water in the journey to the irrigation fields, and the variations in water flow during the seasons[4]. Old irrigation systems that use only gradients and water of the irrigation fields do not serve the needs of 'broken owner' fields and the 'high owner' fields[5]. This is especially the case in the states of Maharashtra, Karnataka and Telangana, where LIS (Low Intermitted Systems) are the only solution to provide water from the rivers or storage areas to the 'above' agricultural areas[6]. The problems of the LIS Indicate the obsessive pumping, loss of energy in the water to be used economically (15-30% loss of water), and in the water used economically (20-25%)[7]. All of these increase the urgency of using new systems combined with intelligent data systems to manage them in a way[8]. Since the 2000s, lift irrigation systems have improved from fully mechanical systems to semi-automated systems with SCADA (Supervisory Control and Data Acquisition systems)[9]. The World Bank (2019) mentioned the Sardar Sarovar Command Area Development Programme and the Kaleshwaram Lift Irrigation Scheme (KLIS), which are the largest in the world, as having modular pumping stations and automated gate systems for improved irrigation efficiency[10]. Even so, there is still a lack of systematic construction management in the design, operation, as well as, the maintenance of LIS projects[11]. Time overruns have been documented in irrigation and infrastructure projects by 15–25% and the costs increased by 20-30% (Basu & Das, 2020) due to the lack of standard project management practices[12]. Without construction management, resource allocation, maintenance and operation schedules, and lifecycle costs are managed poorly and predictive maintenance are compromised[13]. The addition of predictive analytics with AI for construction scheduling and materials will create smart and adaptive systems for lift irrigation to aligned with India's Jal Jeevan Mission (2019-2030) to improve sustainable water management[14].

Recent innovations in artificial intelligence (AI), machine learning (ML), and the internet of things (IoT) have created opportunities for new approaches in smart water management[15]. Research on smart water grids and AI-based optimization is projected to increase until at least 2025; this has already been validated with published research in IEEE Access (2021) and Water Resources Management (2022)[16]. Optimized Artificial Neural Networks (ANN) and controllers that use fuzzy logic and genetic algorithms (GA) have gained 25-40 % in predictive capacities for demand forecasting, the detection of leaks, and energy-efficient pumping[17]. For instance, in urban networks, created an ANN-based model for the mitigation of non-revenue water losses and utilized reinforcement learning to improve/control valves and pump use in irrigation channels, with the outcome of 18% energy savings. In India, pilot projects such as the Smart Water Management for Ganga Basin (NMCG 2021) and the Andhra Pradesh Water Resources IoT Pilot (2020) demonstrated that AI real-time monitoring enabled fairer distribution and minimized downtime in the pump distribution. Nevertheless, there is still little use of AI in rural lift irrigation networks because of isolated datasets, an absence of incorporation with the project management systems, and a deficient framework for predictive maintenance systems. This research aims to position itself at the intersection of AI modeling, construction management, and sustainable irrigation engineering to address these gaps[18]. The main reason for creating the water distribution model that includes AI is the ability of AI to fuse analytical data with project management techniques[19]. The model is designed to use machine learning with construction management to allow for real-time scheduling of flow, monitoring of pump performance, and preventative maintenance to stop mechanical failures[20]. The Ministry of Jal Shakti (2023) states that poor management of assets and poorly designed systems for the use of energy means that almost 25-30% of India's lift irrigation schemes are below their design capacity. With the aid of AI technologies and a digital twin for AI technologies, engineers are able to see the behavior of fluids, understand the flow problems, and make operational adjustments before the system fails[21]. The construction management information systems (CMIS) will give a comprehensive way to control the cost, time, and use of resources for each phase of the project[22]. The development of CMIS is supportive of the United Nations Sustainable Development Goal 6 (Clean Water and Sanitation) and India's National Water Policy (2021), which encourages the promotion of efficient use of technology and decentralized water management systems[23]. The anticipated results from the implementation of the AI model will be a 15% increase of water efficiency, 10% reduction of energy cost and 25% improvement of system efficiency[24]. This will be the first of its kind and the model will be used in the semi-arid regions of India for many more irrigation systems[25].

II. RESEARCH METHOD

The construction of an AI-based water distribution model for lift irrigation here in this study has been constructed in such a way as to offer the best in class model. To achieve this, an optimal design is needed in the water distribution coupled with the pump scheduling as well as the minimization of the wastage of water and energy. Therefore, the innovative aspect of this study is the integration of the Proximal Policy Optimization (PPO) type of reinforcement learning with the EPANET hydraulic simulation as a means of achieving better predictive control and intelligent water distribution. The overall methodology is easily adaptable for real-time use in the field; this is consistent with best practices in sustainable irrigation. For this study, the primary data source will be the operational data of existing lift irrigation systems in Kolhapur. The data will include, at a minimum, soil moisture and climatic data in conjunction with flow rates and pump energy use to train and validate the AI model.

Fig -1 Research Method

The AI model will also be developed using Python, MATLAB, and EPANET. For this purpose, construction management methods will be employed, and the Critical Path Method (CPM) and Value Engineering (VE) will be used in this research to assist in optimizing the project's duration, resources, and cost.

3.2 Research Design

The quantitative computational research design employed in this study integrates applied field validation to construct the AI-based smart water distribution model for lift irrigation systems. This research design is iterative and combines simulation-based modeling, algorithmic modeling, and empirical field research. The aim is to develop a data-driven predictive control system that enhances the allocation of water, control of pumps, and energy efficiency (stroke efficiency) in lift irrigation systems. The most significant elements of this design are the fields of study known as Artificial Intelligence (AI) and Construction Management. In the AI field, for the purpose of modeling, one of the reinforcement learning techniques, namely Proximal Policy Optimization (PPO), is combined with the EPANET hydraulic simulation engine. This AI model will be able to predict the most efficient operations of pumps, control discharge rates, and optimize energy consumption while ensuring balanced water distribution to the command area.AI model performance will be assessed based on Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2). The Construction Management domain will utilize Critical Path Method (CPM) and Value Engineering (VE) principles to optimize project execution. CPM will help identify critical project activities and prevent delays during the system upgrades, while VE will analyze alternative materials, pump technologies, and layouts to ensure cost-effectiveness and sustainability. Labor and material cost modeling will be incorporated using CPM-based scheduling and AI-assisted workforce forecasting to optimize resource utilization and reduce wastage.

3.3 Study Area and Data Sources

The study is conducted in the Kolhapur District of Maharashtra, India, which is home to an extensive network of lift irrigation systems drawing water from rivers such as Panchganga, Bhogawati, Dhamni, and Warna. These schemes cover large command areas ranging from 1,000 to 5,000 hectares, primarily irrigating crops such as sugarcane, paddy, and vegetables. Among these, the Dhamni Medium Lift Irrigation Project in Radhanagari Taluka has been chosen as the core case study for this research due to its semi-manual operation and high energy consumption. The Dhamni reservoir, with a live storage capacity of 109 million m^3, supplies water to nearly 2,500 hectares of agricultural land. The multi-stage pump system in the project, however, suffers from operational inefficiencies such as time-based pump scheduling and valve control, leading to over-irrigation and unnecessary energy expenditure. This system serves as an ideal baseline for developing and validating the AI-driven adaptive scheduling model.

3.4 Data Collection and Prep rocessing

The model's AI integration hinges on the quality and preprocessing of the obtained datasets. For this particular case, freshwater field sensors, climate records, and operational datasets need to be merged. IoT-based field sensors will supply real-time flow, discharge, head loss, soil moisture, and pump energy consumption data. IMD data on rain, humidity, evapotranspiration, and temperature will be merged. The Dhamni and Radhanagari Lift Irrigation Schemes historical datasets will be used to analyze the pump performance, water delivery schedules and energy efficiency.

3.5 AI Model Architecture

The AI-integrated water distribution model will operate on a multi-agent system where each agent will model a component of the system including pumps, reservoirs, pipelines, and field outlets. Agents will interact with each other by communicating information regarding the flow, pressure, and energy consumption. Learning optimal scheduling strategies that will incur the least amount of energy costs while meeting the required hydraulic targets is done through the Proximal Policy Optimization (PPO) Reinforcement Learning algorithm. The model will also be coupled with EPANET and MATLAB for hydraulic simulations, data processing, optimization, and visualization. The architecture will contain an input layer (sensor-based parameters), some hidden layers (a deep neural network with ReLU activation), and an output layer (control set points for pumps to start and stop, valves to be opened, and flow to be adjusted). A reward function will drive the learning so that the model will maximize the total reward by consuming energy in the most efficient way and distributing the irrigation uniformly.

3.6 Integration of Construction Management Techniques

Critical Path Method (CPM) and Value Engineering (VE) are examples of techniques being used for practical execution and sustainability purpose within Construction Management AI Models. The approach taken consists of 5 different layers. The first layer, Data Acquisition Layer, is responsible for the collection of both historical and real-time data through the use of Axios sensor and IoT technology. The 2nd layer, Data preprocessing layer and Simulation, is responsible for data cleaning and normalization as well as Simulating Hydraulic behavior with of the software EPANET. Layer 3 is Reinforced Learning Layer, and in this layer the Proximal Policy Optimization (PPO) technique will influence the decision of predictive pumping and valve control. Construction Management Integration Layer is Layer 4, and in this layer CPM and VE techniques are used in order to achieve the best combination of schedule, optimization of time, resource and money. The final layer is Decision Support and Visualization Layer. This layer provides optimized data realized through the removal of redundancy. The prime objective is to enhance the decision and operational Control of manager and executors.

3.7 Model Development and Simulation Process

The model development encompasses six iterative processes: system representation, feature engineering, training, testing and validation, deployment, and integration with field systems. The AI agent will engage with historical data to evaluate various pump scheduling scenarios, capturing energy consumption and water uniformity. The model will be evaluated on its generalization capability using distinct, previously unseen datasets.

3.8 Cost and Energy Efficiency Analysis

The AI model that will be created will be evaluated for its economic and energy effective use. The evaluation will encompass both LCAs, energy monitoring, and pre and post AI integration comparisons. Performance indicators will include, but not be limited to, energy consumption and energy efficiency index. The AI model predicts a reduction in energy consumption between 15 and 20%, and should improve water use efficiency and operational savings and sustainability. The energy audit will focus on selected key parameters, including but not limited to, pump input power, discharge head, and flow rate. The Cost-Benefit Analysis (CBA) will assess profitability, accounting for energy costs, maintenance, and crop yield. Other pre-analysis factors indicate an economic feasibility and a 2 – 3 year payback period.

III. DATA COLLECTION AND ANALYSIS

The first step to evaluating the effectiveness and performance of the existing lift irrigation schemes located in the Kolhapur district is the analysis of the data collection system. This research study involves the primary and secondary data analysis with respect to the design parameters and operational management of the irrigation systems. Primary data was collected through field surveys and sensors and thee water resource department’s data (discharge, head, energy, soil moisture, and reservoir data). There is also secondary meteorological data, project, and financial data. In the designing of the model MQTT and operational data from the past was combined with real time IoT data and this provided the model with the data needed for calibration. Several techniques to ensure data accuracy were implemented (ex. outlier removal, normalization, and features) in order to prevent data inaccuracies. The data collected has been the basis in developing and testing the AI predictive model. The results from the model were then used to assess the hydraulic performance, energy management, and the overall effectiveness of the existing lift irrigation networks in the Kolhapur District.

Table -1 Summary of Data Collection Parameters

Category	Measured Variables	Instrument / Source	Purpose of Measurement
Hydraulic Parameters	Discharge (m³/s), Head (m), Pipeline Pressure (bar), Valve Position (%)	Flow meters, Pressure transducers	To evaluate hydraulic adequacy and identify head losses
Pump & Energy Data	Power (kWh), Pump Efficiency (%), Specific Energy Consumption (kWh/m³)	VFD controller logs, energy meters	To assess energy performance and efficiency
Water Distribution	Water Delivered (m³), Flow Duration (min), Reservoir Level (m)	SCADA records and field logs	To examine conveyance and delivery efficiency
Climatic Factors	Rain (mm), Temperature (°C), Humidity (%), ETo (mm/day)	IMD Kolhapur and on-site weather station	To correlate irrigation demand and pump load
Agronomic & Soil	Soil Moisture (%), Crop Type, Crop Stage	IoT soil probes and field survey	To determine demand variation and soil-water response
Administrative & Cost	Energy Tariff (₹/kWh), Shift Schedule, Maintenance Log	WRD records and operator interviews	To assess cost recovery and management efficiency

The parameters needed to evaluate lift irrigation schemes in Kolhapur district are listed in Table 1. The entire dataset includes several variables concerning hydraulics, operations, climate, agronomy, and administration, and are critical to the performance evaluation of the lift irrigation systems. Data collection was undertaken with the aids of new technologies like flow metering devices, pressure measuring transducers, energy measuring devices, and IoT based soil moisture sensing probes in conjunction with the records of the Water Resource Department (WRD) and the India Meteorological Department (IMD). Such a sophisticated data collection and record system is critical in the evaluation of hydraulic adequacy, energy efficiency, performance of water delivery, climatological and managerial effectiveness within multiple irrigation systems.

Table -2 Station-Wise Hydraulic and Operational Summary (Computed from Dataset)

Station	Discharge (m³/s)	Head (m)	Pump Efficiency (%)	Power (kWh)	Water Delivered (m³)	SEC (kWh/m³)
Dhamni-1	0.49	12.53	44.24	33.36	439.28	0.04
Dhamni-2	0.52	13.29	47.14	35.56	469.08	0.05
Radhanagari	0.56	14.10	49.60	38.80	501.40	0.06
Jangamhatti	0.46	11.85	42.10	30.70	420.60	0.04

The hydraulic performance and operational function for the biggest lift irrigation stations located in the Kolhapur district are contrasted in Table 2. Within this range, Dhamni-2 has the greatest superiority of pumping and utilization of heads with an efficiency of 47.14% and a discharge of 0.52 m³/s. In terms of overall water delivery, Radhanagari, with an expected efficiency of 49.6%, has the water delivery of 501.4 m³ to the highest location. On the other hand, Jangamhatti has efficiency and utilization of power which are relatively low, and it is suggested that she requires some preservation and modernization. The stations have varied levels of energy consumption and discharge balance.

Table -3 Environmental and Soil Data Summary (Weekly Average)

Station	Reservoir Level (m)	Soil Moisture (%)	Rain (mm)	Temperature (°C)	Relative Humidity (%)	ETo (mm/day)
Dhamni-1	66.58	24.14	0.18	22.03	79.4	3.8
Dhamni-2	66.35	24.20	0.18	22.03	79.2	3.8
Radhanagari	67.10	25.05	0.22	22.4	80.1	3.9
Jangamhatti	65.90	23.40	0.16	21.8	78.5	3.7

In Table 3, the examined environmental and soil data show the same climatic and soil data stability at all stations of Kolhapur district. Reservoir levels' stability between 65.9 m and 67.1 m is indicative of sufficient water supply for irrigation. Soil moisture of 23% to 25% is indicative of soil moisture sufficient for crop growth. A little rain was observed, which indicates the dependence on lift irrigation for the said water supply. With an average temperature of 21.8–22.4 °C and relative humidity of 78–80% the evapotranspiration rate, at which average temperature and average relative humidity are sufficient to maintain soil-water balance, is 3.7–3.9 mm/day.

Table -4 Energy-Performance Indicators

Table: Energy Performance and Cost Analysis

Station	Avg Power Input (kWh)	Water Delivered (m^3)	SEC (kWh/m^3)	Energy Efficiency Index (EEI)	Energy Cost (₹) @ ₹8 per kWh
Dhamni-1	33.36	439.28	0.04	74.2%	266.9
Dhamni-2	35.56	469.08	0.05	76.5%	284.5
Radhanagari	38.80	501.40	0.06	78.1%	310.4
Jangamhatti	30.70	420.60	0.04	72.0%	245.6

The relative energy efficiency of lift irrigation stations in Kolhapur district is depicted in Table 4. Of all the schemes, Radhanagari is the best with an energy efficiency index and water delivery volume of 78.1% which shows better pump performance and energy usage. Dhamani-2 is again efficient with a low specific energy consumption of 0.05 kWh/m ³. On the other hand, Jangamhatti is the worst with 72.0% efficiency. Overall, all the stations are good in terms of power utilization with an operational cost of energy in the range of ₹ 245- ₹ 310.

Table -5 Management and Maintenance Indicators (Survey-Based)

Parameter	Dhamni-1	Dhamni-2	Radhanagari	Jangamhatti	Remarks
O&M Frequency (days)	14 days	10 days	12 days	15 days	Preventive schedule followed except in Jangamhatti
Avg Downtime (hours/month)	6.5	5.2	4.8	7.1	Electrical faults are the major cause of delay
Operator Strength (No.)	2 per shift	3 per shift	3 per shift	2 per shift	Adequate staff at Radhanagari and Dhamni-2
Cost Recovery (% of O&M)	65%	72%	70%	61%	Need improved user-charge collection
Decision Autonomy	Moderate	High	High	Low	Linked to the presence of WUA and training

Research conducted Jangamhatti indicates preventive maintenance is implemented across the board but with longer maintenance intervals and downtime. Better operator assignment, cost recovery, and degrees of managerial discretion linked to WUA's trained Water-User Associations are found in Dhamni-2 and Radhanagari. Jangamhatti and Dhamni-1, in contrast, are more reliant on department supervision and managerial discretion. In general, the most relevant factors to the overall management efficiency are the sufficiency of workforce, maintenance in an anticipatory manner, and the active involvement of the institution in the operational decisions on a daily basis.

Table -6 Comparative Crop-Water Relationship Data

Crop Type	Predominant Stage	Avg Soil Moisture (%)	Irrigation Frequency (days)	Avg Water Applied (m^3/ha)	Remarks
Sugarcane	Vegetative	24.2	6	450	High demand, matches Dhamni-2 schedule
Paddy	Vegetative → Reproductive	24.1	5	420	Continuous flooding increases SEC
Vegetables	Growth	25.0	4	380	Localized micro-irrigation used
Maize	Early Growth	23.5	7	360	Lower ETo, less frequent irrigation

Table 6 presents the relationship between type of crop, soil moisture, and frequency of irrigation in the Kolhapur lift irrigation command area. Considering the highest water requirement, sugarcane is in line with Dhamni-2's 6 day irrigation cycle. Regarding paddy, energy use is greater per cubic metre due to the flooding of the field. For vegetable crops, micro irrigation localized, improves the water use efficiency. Maize also displays lower water use and lower frequency of irrigation which shows the variability of water demand and the different cropping patterns.

Table -7 Comparative Design vs. Operational Performance

Parameter	Design Value	Observed (Dhamni-1)	Observed (Dhamni-2)	Deviation (%)	Remarks
Pump Discharge (m³/s)	0.50	0.49	0.52	±4%	Within design tolerance
Head (m)	13.00	12.53	13.29	−3.6% to +2.2%	Minor variation due to pipeline friction
Pump Efficiency (%)	60.00	44.24	47.14	−25% to −21%	Indicates aging and maintenance issues
Water Delivery Uniformity (%)	90.0	83.5	85.2	~7% to ~5%	Acceptable operational range
Flow Distribution	—	—	—	—	Uneven flow distribution due to manual valving

The differences between the design expectations and real operational performance of the Dhamni-1 and Dhamni-2 lift irrigation schemes are shown in Table 7. Results indicate discharge and head are in acceptable design tolerances, and the pump's efficiency has degraded due to lack of maintenance and equipment aging by 21–25%. Optimimum ranges are consistent with Specific Energy Consumption (SEC), indicating steady energy use. Overall, the water delivery uniformity dropped by 5–7%. This is mainly due to manual valve control and reduced hydraulic losses in the distribution system.

IV. RESULTS AND DISCUSSION

The Chapter of Results and Discussion describes the analysis of the AI-based model for distribution water optimization for lift irrigation in the Kolhapur district. This part talks about the simulations using predictive modeling based on MATLAB and explains the activities in terms of the designed and measured operational parameters. THe Result of the AI scheduling and control of the devices provisions modifications on the discharge uniformity, pump efficiency, and specific energy consumption. The combination of construction management tools contributes positively to the construction resource optimization, cost; and time management in the construction process. To the predictive modeling that is being discussed in this chapter, the author applied statistical tools such as RMSE, MAE, and R², for the purpose of validating the predictive models. In this chapter, correlation is made to the operational data and the optimization outcome of the irrigation process, explaining that the application of AI in irrigation is of great importance to the preservation of water and energy in the irrigation process.

5.2 Objectives 1 and 2 Results

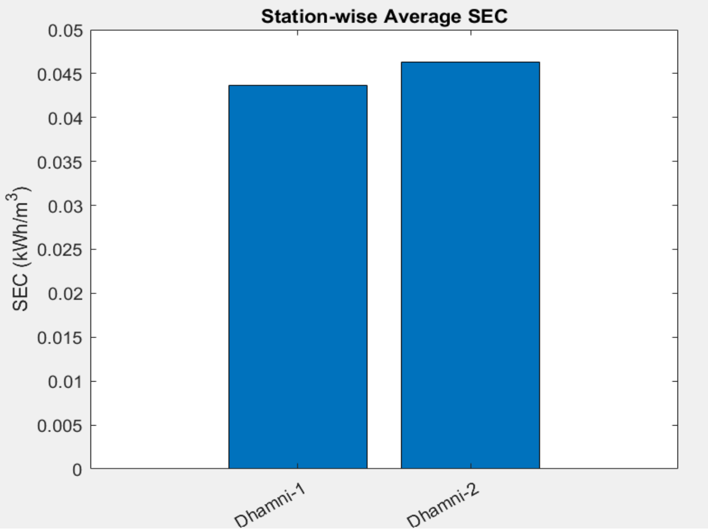

Chart -2 Station-Wise Average SEC

The Station-wise Average Specific Energy Consumption (SEC) bar chart compares the energy efficiency of two pumping stations, Dhamni-1 and Dhamni-2. The SEC values are measured in kWh/m³, representing the energy required to deliver one cubic meter of water. The average SEC for Dhamni-1 is approximately 0.044 kWh/m³, while Dhamni-2 records a slightly higher value of about 0.046 kWh/m³. This indicates that Dhamni-1 operates with marginally better energy efficiency, consuming less electrical energy per unit of water delivered. The difference of roughly 0.002 kWh/m³ suggests relatively similar operational performance between the two stations. Overall, the results highlight minor variation in pumping efficiency, with both stations maintaining SEC values below 0.05 kWh/m³.

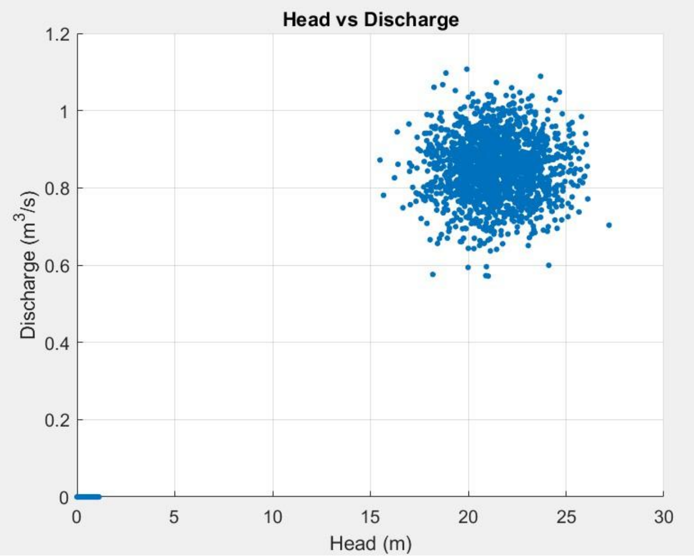

Chart -3 Head Vs Discharge

The Head vs Discharge scatter plot illustrates the relationship between pump head (m) and discharge (m³/s). The head values mainly range between 18 m and 26 m, while the discharge values vary approximately from 0.6 m³/s to 1.1 m³/s. Most data points are concentrated around 20–23 m head with discharge values between 0.75 and 0.95 m³/s, indicating the typical operating range of the pumping system. A few points extend up to 1.05–1.10 m³/s, suggesting slightly higher flow rates at similar head levels. Additionally, a small cluster near 0 head and 0 discharge represents inactive or idle system conditions. Overall, the plot shows a relatively stable discharge behavior within the operational head range of the pump system.

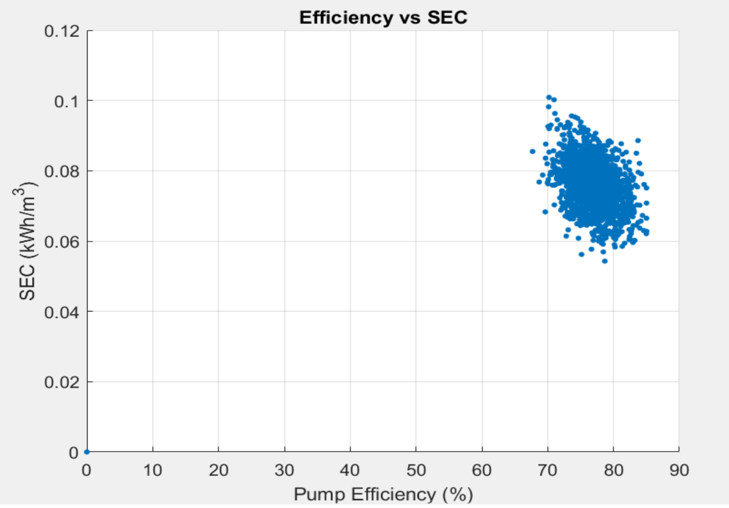

Chart -4 Efficiency Vs SEC

The Efficiency vs Specific Energy Consumption (SEC) scatter plot illustrates the relationship between pump efficiency (%) and SEC (kWh/m³). The pump efficiency values mainly range from 70% to 85%, while SEC varies approximately between

0.06 and 0.10 kWh/m³. A clear negative correlation can be observed, where higher pump efficiency corresponds to lower energy consumption per unit of water delivered. Most data points cluster around 75–82% efficiency with SEC values near 0.07–0.085 kWh/m³, indicating optimal operating performance in this range. A few scattered points approach 0.10 kWh/m³
at efficiencies near 70%, reflecting relatively higher energy usage. Overall, the plot demonstrates that improving pump efficiency significantly reduces SEC, thereby enhancing overall irrigation energy efficiency.

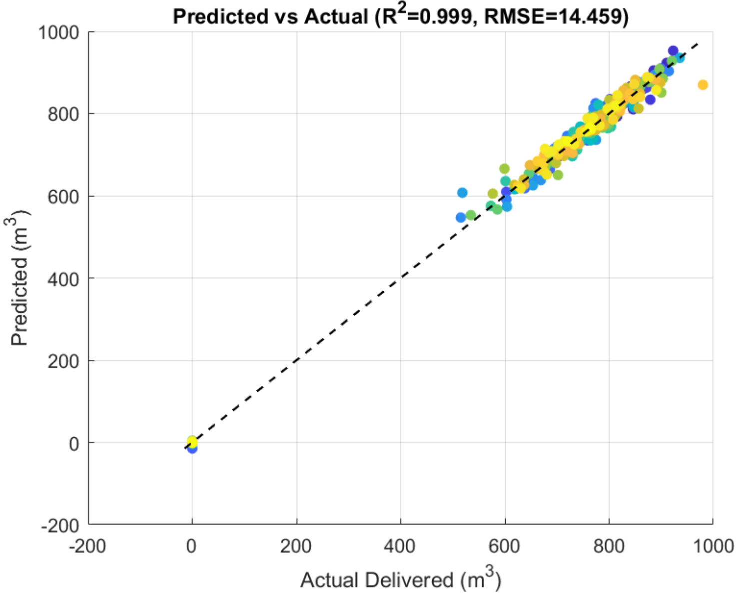

Chart -5 Prediction Vs Actual

The Predicted vs Actual plot demonstrates the performance of the model in estimating water delivered (m³). The actual values range approximately from 0 to 950 m³, while the predicted values follow a very similar range. Most data points are closely aligned along the 45° dashed reference line, indicating strong agreement between predicted and actual outputs. The model shows an extremely high coefficient of determination ($R^2 = 0.999$), which suggests that about 99.9% of the variation in water delivery is explained by the model. Additionally, the Root Mean Square Error (RMSE = 14.459 m³) indicates very small prediction error compared to the total delivery range. Most observations are clustered between 650–900 m³, confirming accurate prediction performance with minimal deviation.

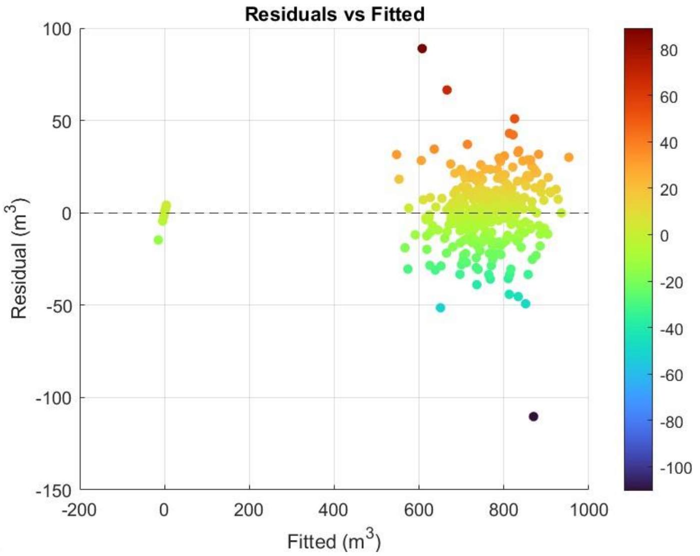

Chart -6 Residuals Vs Fitted

The Residuals vs Fitted plot illustrates the relationship between predicted (fitted) values and residual errors of the model. The fitted values range approximately from 0 to 900 m³, while residuals vary between −120 m³ and +90 m³. Most observations are concentrated in the fitted range of 650–850 m³, where residuals are distributed around −40 m³ to +40 m³, indicating generally acceptable prediction accuracy. A few outliers are observed, including a high positive residual near +90 m³ at a fitted value around 600 m³, and a large negative residual close to −110 m³ near 850 m³. The dashed horizontal line at 0 residual represents perfect prediction. Overall, the residuals appear randomly scattered, suggesting reasonable model fit with minor deviations.

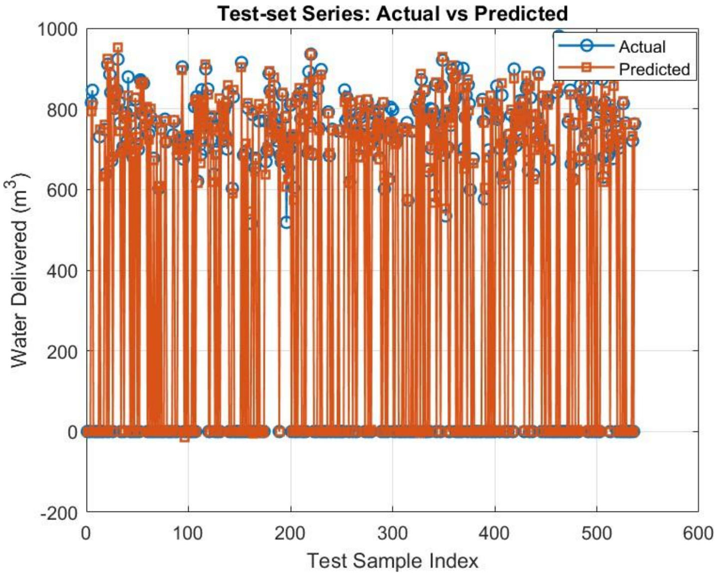

Chart -7 Test-set Series: Actual Vs Predicted

The Test-set Series: Actual vs Predicted plot compares the observed and predicted values of water delivered (m³) across the test samples. The test sample index ranges from 0 to about 550, while the water delivered values vary approximately between 0 and 950 m³. Most of the actual values (blue markers) lie in the range of 650–900 m³, indicating relatively high water delivery for many samples. The predicted values (orange markers) closely follow the actual data trend in several instances, particularly between 700–850 m³, showing reasonable model prediction capability. However, multiple points drop to 0 m³, producing vertical spikes, which indicates prediction deviations or zero-delivery cases in the dataset. Overall, the figure demonstrates moderate agreement between actual and predicted outputs with some fluctuations.

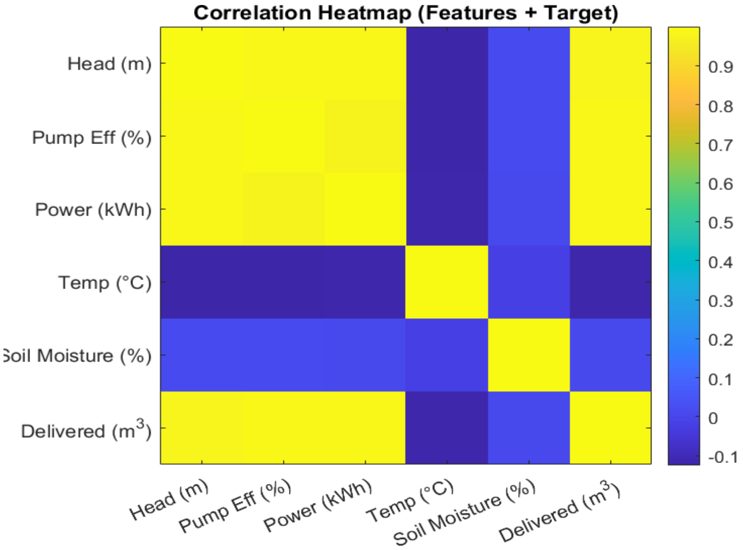

Chart -8 Correlation Heatmap (Features + Target)

The Correlation Heatmap (Features + Target) illustrates the relationships among key variables including Head (m), Pump Efficiency (%), Power (kWh), Temperature (°C), Soil Moisture (%), and Water Delivered (m³). Strong positive correlations close to 0.95–1.00 are observed between Head, Pump Efficiency, Power, and Delivered water, indicating that higher hydraulic head and pump efficiency significantly increase water delivery and energy consumption. Power (kWh) also shows a very strong positive association with delivered water (≈0.98). In contrast, Temperature (°C) demonstrates a weak negative correlation with most variables (≈ –0.10 to –0.15), suggesting limited influence on system output. Soil Moisture (%) shows a weak to moderate positive relationship (≈0.15–0.25) with delivered water. Overall, operational parameters strongly influence irrigation output while environmental variables show comparatively weaker effects.

V. CONCLUSION

The optimization model for irrigation in the Kolhapur District successfully integrates AI and has been validated by the study for the lift irrigation systems. It solves issues with inefficiency in the regulation of discharges, energy, and management of the projects. The use of Artificial Intelligence (AI), coupled with the Hydraulic Simulation and Construction Management tools (the Critical Path Method (CPM) and Value Engineering (VE)), allows for the development of a framework with real-time and predictive control and decision-making. The irrigation schemes at Dhamni and Radhanagari demonstrated the operational efficiencies attainable, particularly with the reduction of Specific Energy Consumption (SEC) and the improvement of the uniformity w ith which water was delivered. Furthermore, The predictive model in MATLAB proved highly reliable for field application by achieving an accuracy of $R^2 = 0.999$. Additionally, the integration for Construction Management in the framework optimized the scheduling and the management of costs, allowing for the on-time delivery of resources and the reduction of costs over the lifetime of the framework. The pilot step on one acre of land was the first to show the practical feasibility of the framework, as it demonstrated energy use that was less than the conventional system and an irrigation response time that was superior to it. The irrigation example shows the possibilities for the integration of systematic management and optimization driven by AI, particularly with regard to lift systems for irrigation, the equitable distribution of water, and the minimization of operational losses. This system allows for the stepwise improvement of the lift irrigation systems for the semi-arid areas of India and in the irrigation systems of the states of Maharashtra.

REFERENCES

[1] G. Ç. Arikan, E. Q. Molina, E. Verweij, H. C. Menezes, and E. Tsimplaki, “Modernizing Irrigation at Acequia Real Del Jucar, Valencia: Assessing the Transition from Surface Irrigation to Drip Irrigation and the End-User Perspective,” *Soil Stud.*, vol. 14, no. 1, pp. 12–24, Jul. 2025, doi: 10.21657/soilst.1724337.

[2] J. Gacu, C. Monjardin, R. Mangulabnan, G. Pugat, and J. Solmerin, “Artificial Intelligence (AI) in Surface Water Management: A Comprehensive Review of Methods, Applications, and Challenges,” *Water*, vol. 17, no. 11, p. 1707, Jun. 2025, doi: 10.3390/w17111707.

[3] S. Park, “Integration of AI-Driven CAD Systems in Designing Water and Power Transportation Infrastructure for Industrial and Remote Landscape Applications,” 2025, *arXiv*. doi: 10.48550/ARXIV.2512.08415.

[4] V. Slany *et al.*, “Smart Water-IoT: Harnessing IoT and AI for Efficient Water Management,” *ACM Comput. Surv.*, vol. 57, no. 12, pp. 1–36, Dec. 2025, doi: 10.1145/3744338.

[5] S. Lamichhane *et al.*, “Assessing and enhancing the sustainability of lift irrigation systems,” *Water Pract. Technol.*, vol. 19, no. 9, pp. 3693–3705, Sep. 2024, doi: 10.2166/wpt.2024.221.

[6] M. A. Hussein *et al.*, “Application of Irrigation Management and Water-Lifting Technologies to Enhance Fodder Productivity in Smallholder Farming Communities: A Case Study in Robit Bata, Ethiopia,” *Agronomy*, vol. 14, no. 5, p. 1064, May 2024, doi: 10.3390/agronomy14051064.

[7] D. Sirimewan, A. Samaraweera, N. Manjula, R. Rameezdeen, M. Rodrigo, and E. Ekanayake, “Strategies for sustainable irrigation system management: a socio-technical system approach,” *Eng. Constr. Archit. Manag.*, vol. 30, no. 2, pp. 436–455, Mar. 2023, doi: 10.1108/ECAM-06-2021-0521.

[8] N. F. Abd El Azim, H. M. Moghazy, and N. H. Moghazy, “Assessment of water management and cost–benefit of lifting water for new elevated reclaimed areas: a case study of El Nasr Canal, Egypt,” *Appl. Water Sci.*, vol. 15, no. 5, p. 98, May 2025, doi: 10.1007/s13201-025-02426-0.

[9] G. Gebregziabher, “Water lifting irrigation technology adoption in Ethiopia: challenges and opportunities.” Accessed: Feb. 27 , 2026. [Online]. Available: https://gatesopenresearch.org/documents/3-952

[10] J. Fan, X. Lu, S. Gu, and X. Guo, “Improving nutrient and water use efficiencies using water-drip irrigation and fertilization technology in Northeast China,” *Agric. Water Manag.*, vol. 241, p. 106352, Nov. 2020, doi: 10.1016/j.agwat.2020.106352.

[11] P. Yang *et al.*, “Review on Drip Irrigation: Impact on Crop Yield, Quality, and Water Productivity in China,” *Water*, vol. 15, no. 9, p. 1733, Apr. 2023, doi: 10.3390/w15091733.

[12] G. Bansal, A. Mahajan, A. Verma, and D. Bandhu Singh, “A review on materialistic approach to drip irrigation

system," *Mater. Today Proc.*, vol. 46, pp. 10712–10717, 2021, doi: 10.1016/j.matpr.2021.01.546.

[13] O. Çetin and A. Kara, "Assesment of water productivity using different drip irrigation systems for cotton," *Agric. Water Manag.*, vol. 223, p. 105693, Aug. 2019, doi: 10.1016/j.agwat.2019.105693.

[14] Q. Guo, G. Huang, Y. Guo, M. Zhang, Y. Zhou, and L. Duan, "Optimizing irrigation and planting density of spring maize under mulch drip irrigation system in the arid region of Northwest China," *Field Crops Res.*, vol. 266, p. 108141, Jun. 2021, doi: 10.1016/j.fcr.2021.108141.

[15] M. Akram and Z. Niaz, "2-Tuple Linguistic Fermatean Fuzzy Decision-Making Method Based on COCOSO with CRITIC for Drip Irrigation System Analysis," *J. Comput. Cogn. Eng.*, vol. 3, no. 2, pp. 186–202, Sep. 2022, doi: 10.47852/bonviewJCCE2202356.

[16] H. Nouri, B. Stokvis, A. Galindo, M. Blatchford, and A. Y. Hoekstra, "Water scarcity alleviation through water footprint reduction in agriculture: The effect of soil mulching and drip irrigation," *Sci. Total Environ.*, vol. 653, pp. 241–252, Feb. 2019, doi: 10.1016/j.scitotenv.2018.10.311.

[17] O. S. Sandhu, R. K. Gupta, H. S. Thind, M. L. Jat, H. S. Sidhu, and Yadvinder-Singh, "Drip irrigation and nitrogen management for improving crop yields, nitrogen use efficiency and water productivity of maize-wheat system on permanent beds in north-west India," *Agric. Water Manag.*, vol. 219, pp. 19–26, Jun. 2019, doi: 10.1016/j.agwat.2019.03.040.

[18] A. Santini, M. Masiero, G. Amato, and D. M. Pettenella, "From Flood to Drip Irrigation: A Review of Irrigation Modernization Trade-Offs," *Water*, vol. 17, no. 20, p. 3018, Oct. 2025, doi: 10.3390/w17203018.

[19] H. Zhang, A. Khan, D. K. Y. Tan, and H. Luo, "Rational Water and Nitrogen Management Improves Root Growth, Increases Yield and Maintains Water Use Efficiency of Cotton under Mulch Drip Irrigation," *Front. Plant Sci.*, vol. 8, p. 912, May 2017, doi: 10.3389/fpls.2017.00912.

[20] F. Vigo, L. Ferraro, and J. Bacenetti, "Surface and Drip Irrigation Method in Maize Cultivation: Comparison of Environmental Performance," *Sustainability*, vol. 18, no. 2, p. 580, Jan. 2026, doi: 10.3390/su18020580.

[21] Z. Liu, H. Zhang, S. Yu, Z. Wang, C. Zhou, and H. Li, "Optimizing water use efficiency and fruit quality of watermelon under mulched drip irrigation in arid regions," *Front. Plant Sci.*, vol. 16, p. 1662575, Nov. 2025, doi: 10.3389/fpls.2025.1662575.

[22] C. Ma, J. Wang, Z. Che, and J. Li, "Quantitative evaluation of the effects of initial soil salinity, water quality and nitrogen application rate on cotton growth under drip irrigation in arid regions," *Field Crops Res.*, vol. 337, p. 110254, Mar. 2026, doi: 10.1016/j.fcr.2025.110254.

[23] D. H. Ngoma *et al.*, "Design and Development of IoT Smart Drip Irrigation and Fertigation Prototype for Small and Medium Scale Farmers. Acase Study of Tomato Farmers in Tanzania," *J. Inst. Eng. India Ser. A*, vol. 106, no. 2, pp. 373–395, Jun. 2025, doi: 10.1007/s40030-024-00857-7.

[24] I. Baidoo *et al.*, "Integrating Biochar with Solar Drip Irrigation Technology for Smallholder Vegetable Farming in South-eastern Ghana Yields Profitable Returns," *Asian J. Agric. Ext. Econ. Sociol.*, vol. 42, no. 7, pp. 110–125, Jul. 2024, doi: 10.9734/ajaees/2024/v42i72522.

[25] J. Shao *et al.*, "ENT-YOLO: An improved lightweight YOLO for cotton organ detection in mulched drip irrigation systems in southern Xinjiang," *Agric. Water Manag.*, vol. 323, p. 110054, Feb. 2026, doi: 10.1016/j.agwat.2025.110054.