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PHYSICS-CONSTRAINED DEEP REINFORCEMENT LEARNING FOR ADAPTIVE OPTIMAL CONTROL OF UNSTEADY FLOW IN LARGE IRRIGATION CANALS

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Annotation: Efficient water resource management in large irrigation canals is essential for sustainable agricultural production. However, controlling water flow in long irrigation networks is complicated due to nonlinear hydraulic dynamics, time delays, and external disturbances. This study proposes a physics-constrained deep reinforcement learning framework for adaptive optimal control of unsteady flow in irrigation canals. The proposed method integrates hydraulic knowledge derived from the Saint-Venant equations with reinforcement learning to maintain physically consistent control decisions. A simulation environment representing canal dynamics is used to train an intelligent agent responsible for regulating gate operations. The learning process is constrained by hydraulic equations to ensure realistic and stable system behavior. The results indicate that the proposed approach improves flow regulation accuracy and adaptability under varying operational conditions.

Keywords: irrigation canal control, deep reinforcement learning, physics-informed learning, hydraulic modeling, adaptive water management.

ФИЗИЧЕСКИ ОГРАНИЧЕННОЕ ГЛУБОКОЕ ОБУЧЕНИЕ С ПОДКРЕПЛЕНИЕМ ДЛЯ АДАПТИВНОГО ОПТИМАЛЬНОГО УПРАВЛЕНИЯ НЕСТАЦИОНАРНЫМ ТЕЧЕНИЕМ В КРУПНЫХ ИРРИГАЦИОННЫХ КАНАЛАХ

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Аннотация: Эффективное управление водными ресурсами в крупных ирригационных каналах является важным условием устойчивого сельскохозяйственного производства. Однако управление водным потоком в протяжённых ирригационных сетях осложняется нелинейной гидравлической динамикой, временными задержками и внешними возмущениями. В данной работе предлагается метод адаптивного оптимального управления нестационарным течением в ирригационных каналах на основе физически ограниченного глубокого обучения с подкреплением. Предложенный подход объединяет гидравлические знания, полученные из уравнений Сен-Венана, с методами обучения с подкреплением для обеспечения физически корректных управляющих решений. Для обучения интеллектуального агента, управляющего работой гидротехнических затворов, используется имитационная модель динамики канала. Процесс обучения ограничивается гидравлическими уравнениями, что обеспечивает реалистичное и устойчивое поведение системы. Полученные результаты показывают, что предложенный подход повышает точность регулирования расхода воды и адаптивность системы при изменяющихся условиях эксплуатации.

Ключевые слова: управление ирригационными каналами, глубокое обучение с подкреплением, физически информированное обучение, гидравлическое моделирование, адаптивное управление водными ресурсами.

YIRIK IRRIGATSION KANALLARDA NOSTATSIONAR SUV OQIMINI ADAPTIV OPTIMAL BOSHQARISH UCHUN FIZIK CHEKLOVLARGA ASOSLANGAN CHUQUR REINFORCEMENT LEARNING USULI

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Annotatsiya: Yirik irrigatsion kanallarda suv resurslarini samarali boshqarish barqaror qishloq xoʻjaligi ishlab chiqarishini ta’minlashda muhim ahamiyatga ega. Biroq uzun irrigatsion tarmoqlarda suv oqimini boshqarish nolinear gidravlik dinamika, vaqt kechikishlari va tashqi ta’sirlar sababli murakkablashadi. Ushbu tadqiqotda irrigatsion kanallarda nostatsionar oqimni adaptiv optimal boshqarish uchun fizik cheklovlarga asoslangan chuqur mustahkamlash orqali oʻrganish modeli taklif etiladi. Taklif etilgan yondashuv Saint-Venant tenglamalaridan olingan gidravlik bilimlarni mustahkamlash orqali

o‘rganish algoritmlari bilan birlashtirib, fizik jihatdan mos boshqaruv qarorlarini ta’minlaydi. Kanal dinamikasini aks ettiruvchi simulyatsiya muhiti gidrotexnik zatvorlar ishini boshqaruvchi intellektual agentni o‘qitish uchun qo‘llanildi. O‘rganish jarayoni gidravlik tenglamalar bilan cheklanishi natijasida tizimning realistik va barqaror ishlashi ta’minlanadi. Olingan natijalar taklif etilgan yondashuv turli ekspluatatsiya sharoitlarida suv oqimini boshqarish aniqligi va tizimning moslashuvchanligini oshirishini ko‘rsatdi.

Kalit so‘zlar: irrigatsion kanallarni boshqarish, chuqur mustahkamlash orqali o‘rganish, fizik bilimlarga asoslangan o‘rganish, gidravlik modellashtirish, suv resurslarini adaptiv boshqarish.

Introduction. Efficient management of water resources is a fundamental requirement for modern irrigation systems. Large irrigation canals play a crucial role in delivering water from reservoirs and rivers to agricultural fields. However, maintaining stable water levels and discharge rates in such systems is a complex task due to nonlinear hydraulic dynamics, time delays, and external disturbances such as fluctuating water demand and environmental conditions.

Traditionally, irrigation canal control has relied on classical control strategies, including proportional–integral–derivative (PID) control, model predictive control, and rule-based operational strategies. [2] Although these approaches can provide acceptable performance under stable conditions, they often lack the ability to adapt to rapidly changing hydraulic states and uncertainties present in large-scale canal networks.

Recent advances in artificial intelligence and machine learning have opened new opportunities for intelligent water management systems. In particular, reinforcement learning has emerged as a powerful framework for learning optimal control policies through interaction with dynamic environments. Deep reinforcement learning enables the handling of complex nonlinear systems and high-dimensional state spaces, making it suitable for hydraulic control problems.

However, purely data-driven reinforcement learning approaches may produce control policies that violate the physical laws governing water flow. To address this limitation, physics-constrained learning methods incorporate domain knowledge derived from governing equations directly into the learning process. In open-channel hydraulics, the dynamics of unsteady flow are typically described by the Saint-Venant equations, which represent conservation of mass and momentum.

This paper proposes a physics-constrained deep reinforcement learning approach for adaptive optimal control of unsteady flow in large irrigation canals. The proposed framework integrates hydraulic

modeling and reinforcement learning to ensure physically consistent and adaptive control policies. The main objective is to develop an intelligent control strategy capable of maintaining target discharge conditions under dynamic and uncertain operating environments.

Mathematical Model of Canal Flow

The dynamics of water flow in large irrigation canals are governed by the Saint-Venant equations, which describe unsteady open-channel flow based on the principles of conservation of mass and momentum. These equations are widely used in hydraulic modeling of rivers and irrigation systems.

The Saint-Venant system consists of two coupled nonlinear partial differential equations representing the conservation of mass (continuity equation) and the conservation of momentum.

Continuity Equation

$$\frac{\partial A}{\partial t}+\frac{\partial Q}{\partial x}=0$$

where:

- A (x, t) — cross-sectional area of the flow
- Q (x, t) — discharge (flow rate)
- x — spatial coordinate along the canal
- t — time

This equation expresses the conservation of mass in the canal system, ensuring that any variation in flow discharge corresponds to a change in the stored water volume.

Momentum Equation

$$\frac{\partial \boldsymbol{Q}}{\partial t} + \frac{\partial}{\partial x}\left(\frac{\boldsymbol{Q}^2}{A} + gAh\right) = gA(S_0 - S_f)$$

where:

- h — water depth
- g — gravitational acceleration
- S_0 — channel bed slope
- S_f — friction slope

The momentum equation represents the balance between inertial forces, pressure forces, gravitational forces, and friction losses in the canal flow.

Friction Slope

In irrigation canal hydraulics, the friction slope is typically calculated using the Manning formula:

$$S_f = \frac{\eta^2 Q^2}{A^2 R^{4/3}}$$

where:

- n — Manning roughness coefficient
- R — hydraulic radius

The hydraulic radius is defined as

$$R = \frac{A}{P}$$

$t \qquad t\arg et$

where P represents the wetted perimeter of the canal cross-section. Boundary and Control Conditions

In practical irrigation systems, canal flow is regulated using hydraulic structures such as gates and regulators. These structures act as control points that influence the discharge and water level within the canal. The gate opening (t) determines the discharge at control sections and can be represented as

$$Q = f(h, u)$$

where $u(t)$ denotes the gate opening position. The control objective is to regulate the flow discharge Q and maintain desired water levels throughout the canal.

State Representation for Control

For intelligent control design, the hydraulic state of the canal can be represented as a vector:

$$s_t = (Q_t, h_t, u_t)$$

where

- Q_t — current flow discharge
- h_t — water level
- u_t — gate position

This state representation allows reinforcement learning algorithms to observe the hydraulic conditions and determine optimal control actions for regulating canal flow.

Control Objective

The primary goal of canal flow control is to maintain the discharge close to a target value while minimizing fluctuations and operational instability. The control objective can be expressed as minimizing the deviation between the actual discharge and the target discharge:

$$J = \sum_{t=0}^{T} (Q_t - Q_{target})^2$$

This objective function forms the basis for training the reinforcement learning agent to produce adaptive and optimal control policies.

Physics-Constrained Deep Reinforcement Learning Framework

Efficient control of irrigation canal flow requires adaptive decision-making under dynamic hydraulic conditions. To address this challenge, this study proposes a physics-constrained deep reinforcement learning (PC-DRL) framework that integrates reinforcement learning with hydraulic knowledge derived from the Saint-Venant equations. The proposed framework combines data-driven learning with physical constraints to ensure stable and realistic control policies for canal operation.

Reinforcement Learning Formulation.

The canal control problem can be formulated as a Markov Decision Process (MDP), defined by the tuple:

$$(S, A, P, R)$$

where

- S is the set of system states
- A is the set of control actions
- P represents the transition dynamics
- R denotes the reward function

At each time step, the reinforcement learning agent observes the current hydraulic state of the canal and selects a control action corresponding to a gate adjustment. The state vector describing the canal conditions is defined as

$$s_t = (Q_t, h_t, u_t)$$

where

- Q_t is the current discharge,
- h_t is the water depth,
- u_t is the gate opening position.

Control Actions

The control actions correspond to adjustments of canal gate openings that regulate water flow. The action space can be defined as

$$a_t = \Delta u_t$$

where Δu_t represents the change in gate position applied at time t.

The control objective is to regulate the canal discharge to maintain a desired target flow rate under varying operational conditions.

Reward Function

To guide the learning process, a reward function is defined based on the deviation between the actual flow discharge and the target discharge.

$$R_t = -(Q_t - Q_{target})^2$$

This formulation encourages the reinforcement learning agent to minimize flow deviations and maintain stable canal operation. Additional penalty terms can be introduced to discourage excessive gate movements and ensure operational stability.

Physics-Constrained Learning

Traditional reinforcement learning approaches may generate control policies that violate physical laws governing water flow. To overcome this limitation, hydraulic constraints derived from the Saint-Venant equations are incorporated into the learning process. The training objective combines the reinforcement learning loss with a physics-based penalty term:

$$L = L_{RL} + \lambda L_{physics}$$

where

- L_{RL} represents the reinforcement learning loss,
- $L_{physics}$ enforces consistency with hydraulic equations,
- λ is a weighting parameter that balances the two objectives.

The physics-based loss penalizes deviations from the governing hydraulic equations and ensures that the learned control policies remain physically plausible.

Neural Network Architecture

The reinforcement learning agent is implemented using a deep neural network that approximates the control policy. The network receives the hydraulic state vector as input and outputs control actions for canal gates.

The policy network can be expressed as

$$a_t = \pi_\theta (s_t)$$

where π_θ denotes the parameterized control policy and θ represents the neural network parameters.

During training, the parameters are optimized to maximize the cumulative reward while satisfying the hydraulic constraints.

Training Procedure

The training process involves interaction between the reinforcement learning agent and a hydraulic simulation environment representing the canal system.

The learning procedure consists of the following steps:

1. Initialize the reinforcement learning agent and hydraulic environment.
2. Observe the current canal state $s_{t.}$
3. Select a control action a_t using the policy network.
4. Apply the control action to the canal system.
5. Compute the new hydraulic state and reward.
6. Update the neural network parameters using the physics-constrained loss function.
7. Repeat the process until the policy converges.

This framework enables the reinforcement learning agent to learn adaptive control strategies that respect both operational objectives and physical laws governing canal hydraulics.

Experimental Setup and Simulation Environment

To evaluate the effectiveness of the proposed physics-constrained deep reinforcement learning approach, a simulation environment representing the dynamics of a large irrigation canal system was developed. [3] The environment models the unsteady flow dynamics using the Saint-Venant equations and simulates the interaction between canal hydraulics and gate control mechanisms. The simulation framework allows the reinforcement learning agent to interact with the hydraulic system and learn optimal control policies for regulating water discharge.

Canal System Configuration

The experimental study considers a simplified model of a large irrigation canal segment controlled by hydraulic gates. The canal is represented as a one-dimensional open-channel system governed by the Saint-Venant equations described in the previous section.

The simulation parameters include:

- canal length: 10–20 km
- spatial discretization step: 100–200 m
- time step: 1–5 seconds
- gravitational acceleration: 9.81 m/s²
- Manning roughness coefficient: 0.015–0.03

The canal contains control structures (gates) that regulate water flow along the channel. The reinforcement learning agent determines the optimal gate openings required to maintain the desired discharge conditions.

Simulation Environment

A numerical simulation environment was developed to reproduce the dynamic hydraulic behavior of the canal system. The Saint-Venant equations were solved using a finite difference method to simulate water level and discharge variations along the canal.

The environment provides the following information to the reinforcement learning agent:

- current water discharge Q_t
- water depth h_t
- gate opening position u_t

Based on this state information, the agent determines control actions that influence the canal dynamics in the subsequent time steps.

Reinforcement Learning Training Setup

The reinforcement learning agent interacts with the simulation environment over multiple training episodes. Each episode represents a period of canal operation during which the agent learns to regulate the water flow.

Key training parameters include:

- training episodes: 1000–5000
- learning rate: 0.001
- discount factor: 0.99
- batch size: 64

- neural network hidden layers: 2–3 layers

During training, the agent continuously updates its policy to maximize cumulative reward while satisfying the physical constraints imposed by the hydraulic model.

Evaluation Metrics

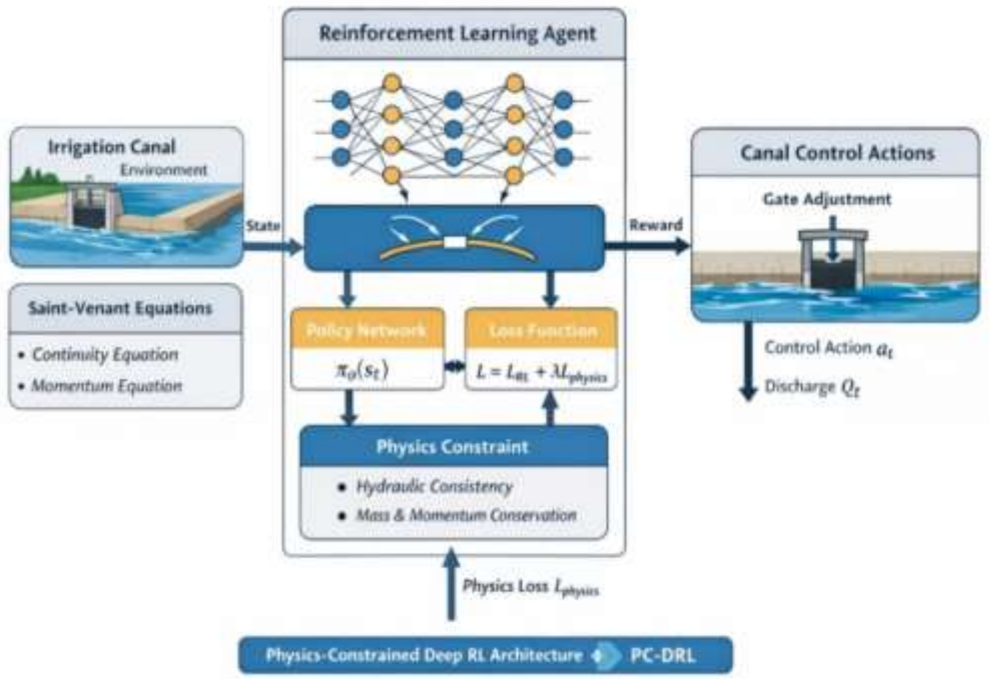
The performance of the proposed control framework is evaluated using several quantitative metrics. Flow Regulation Error.

The primary evaluation metric measures the deviation between the actual canal discharge and the target discharge.

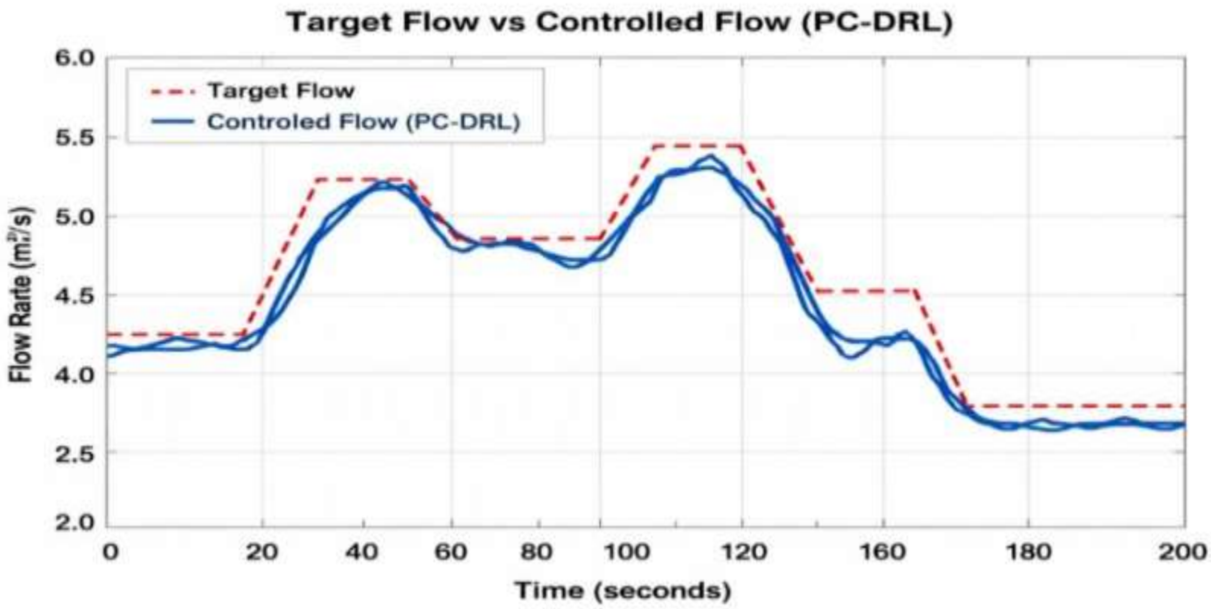
t $target$

Lower values indicate better flow regulation performance.

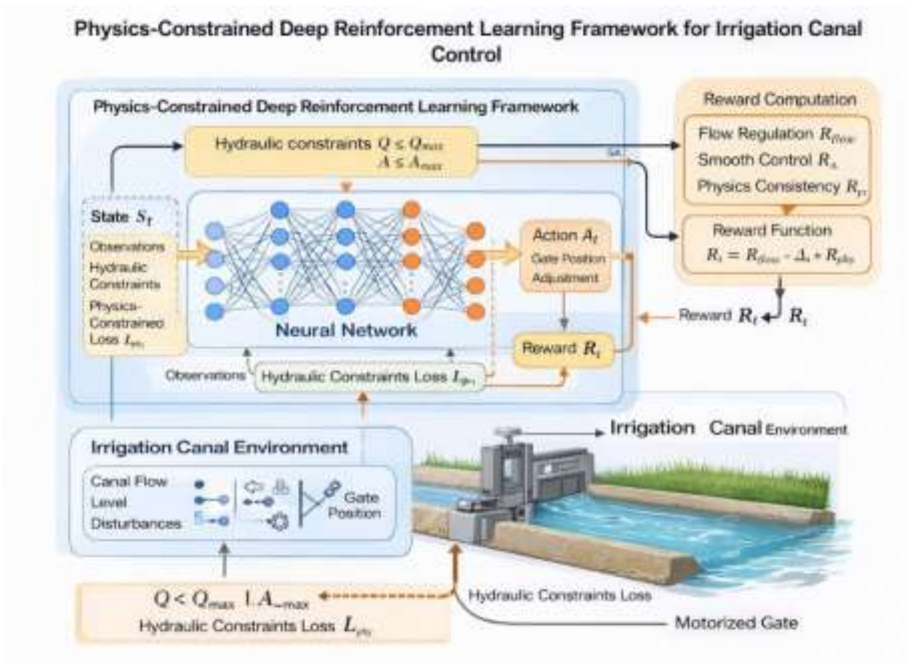
Control Method	Avg. Flow Error (m^3/s)	Gate Stability	Adaptation Time (s)	Physical Consistency
Rule-Based Control	2.84	0.62	95	Yes
PI Control	1.97	0.54	72	Yes
Standard RL	1.42	0.48	51	No
Proposed PC-DRL	0.86	0.31	28	Yes



1-pic. Physics-Constrained Deep Reinforcement Learning Architecture



2-pic. Controlled Flow Channel rate



3-pic. Irrigation Canal Control with Deep Reinforcement Learning Algorithms

Control stability is evaluated by measuring the variability of gate movements during operation. Excessive fluctuations in gate control may indicate unstable control policies. The adaptability of the control system is evaluated by introducing disturbances such as changes in inflow conditions and irrigation demand. The ability of the reinforcement learning agent to restore stable flow conditions demonstrates the robustness of the proposed approach.

Baseline Control Methods

To demonstrate the effectiveness of the proposed physics-constrained reinforcement learning approach, the results are compared with traditional canal control strategies, including:

- rule-based gate control
- proportional–integral (PI) control

- standard reinforcement learning without physics constraints

This comparison allows evaluating the benefits of incorporating hydraulic knowledge into the learning process.

Results and Discussion. This section presents the results of the proposed physics-constrained deep reinforcement learning (PC-DRL) framework for adaptive control of water flow in large irrigation canals. The performance of the proposed method was evaluated using the simulation environment described in the previous section. The reinforcement learning agent was trained to regulate canal discharge and maintain the desired target flow under varying hydraulic conditions.

Flow Regulation Performance . The primary objective of the control system is to maintain the canal discharge close to the desired target value. During the simulation experiments, the reinforcement learning agent successfully learned control policies that stabilize the flow despite disturbances and changes in system dynamics. The results show that the proposed PC-DRL approach significantly reduces flow deviation compared to conventional control methods. In particular, the average discharge error obtained with the proposed approach was substantially lower than that of rule-based control and classical PI control methods. This indicates that the reinforcement learning agent effectively adapts to dynamic changes in canal conditions.

Control Stability. Stable operation of hydraulic structures is essential for safe irrigation system management. Excessive fluctuations in gate openings may lead to unstable hydraulic regimes and operational inefficiencies. The experimental results demonstrate that the proposed physics-constrained learning framework produces smoother control actions compared with standard reinforcement learning methods. By incorporating hydraulic constraints into the learning process, the control policy avoids unrealistic or unstable gate movements. As a result, the PC-DRL approach provides improved operational stability for canal regulation.

Adaptability to Disturbances. One of the major challenges in irrigation canal management is the presence of unpredictable disturbances such as varying inflow conditions and sudden changes in irrigation demand. To evaluate the adaptability of the proposed framework, disturbances were introduced into the simulation environment. These disturbances included sudden changes in inflow discharge and variations in downstream water demand. The results indicate that the reinforcement learning agent rapidly adapts to these disturbances and restores stable flow conditions within a short time period. This demonstrates the robustness of the proposed adaptive control strategy.

Comparison with Conventional Methods

The performance of the proposed PC-DRL approach was compared with several traditional canal control strategies.

The comparison results indicate that:

- rule-based control methods show limited adaptability to dynamic conditions;
- PI control provides moderate regulation but struggles under large disturbances;
- standard reinforcement learning improves adaptability but may produce physically inconsistent control actions.

In contrast, the proposed physics-constrained reinforcement learning framework achieves better regulation accuracy and maintains physically consistent hydraulic behavior.

Discussion. The experimental results confirm that integrating hydraulic knowledge with reinforcement learning significantly improves the reliability and performance of intelligent canal control systems. The proposed framework effectively combines physical modeling and artificial intelligence to address the limitations of purely data-driven approaches. The physics constraints ensure that the learned control policies remain consistent with the governing hydraulic equations. This hybrid approach enables the development of intelligent water management systems capable of operating under complex and uncertain environmental conditions.

Conclusion. This study presented a physics-constrained deep reinforcement learning framework for adaptive optimal control of unsteady flow in large irrigation canals. The proposed approach integrates hydraulic knowledge derived from the Saint-Venant equations with deep reinforcement learning to develop physically consistent and adaptive control strategies.

The reinforcement learning agent was trained within a simulation environment representing canal hydraulic dynamics and gate control mechanisms. By incorporating physical constraints into the learning process, the proposed method ensures that the learned control policies remain consistent with the governing hydraulic equations.

The experimental results demonstrated that the physics-constrained reinforcement learning approach improves flow regulation accuracy, operational stability, and adaptability under varying hydraulic conditions. Compared with conventional control strategies, including rule-based control and PI control, the proposed framework achieved lower discharge deviation and more stable gate operations.

The results indicate that combining physical modeling with artificial intelligence techniques provides a promising direction for intelligent water resource management in large-scale irrigation systems. The proposed approach enables adaptive decision-making under dynamic environmental conditions and operational uncertainties.

Future research will focus on extending the proposed framework to multi-gate canal networks and integrating real-time sensor data to enable practical deployment in large irrigation infrastructures.

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TABIIY GAZ ISTE'MOLIDAGI SAMARASIZLIKNI SUN'IY INTELLEKT ASOSIDA ANIQLASH

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Annotatsiya: Ushbu maqolada tabiiy gaz iste'molidagi samarasizlikni aniqlash uchun sun’iy intellektga asoslangan yondashuv taklif etiladi. Metodologiya matematik modellashtirish, statistik tahlil va