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MASTERING HYDRAULIC LATENCY: A PHYSICS-INFORMED DRL APPROACH FOR INTELLIGENT FLOW FORECASTING AND GATE CONTROL IN THE PARKENT CANAL

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Abstract. Efficient water conveyance in long-distance open channels is severely hindered by hydraulic time-lag latency, transient flow conditions, and dynamic water demands. This paper presents a theoretical framework that couples Deep Reinforcement Learning (DRL) with Physics-Informed Long Short-Term Memory (PI-LSTM) networks to optimize check gate operations along the Parkent Magistral Canal in Uzbekistan. By embedding the 1D de Saint-Venant equations directly into the neural network's loss function, the PI-LSTM serves as a physically consistent surrogate model, achieving high-accuracy, multi-day water level and discharge forecasts (Nash-Sutcliffe Efficiency of 0.924 at a 5-day horizon). To compensate for transport delays, the gate control task is formulated as a Delayed-Observation Markov Decision Process (DOMDP). Utilizing model-free DRL algorithms from the Stable-Baselines3 library, specifically Proximal Policy Optimization (PPO) and Soft Actor-Critic (SAC), the control agent learns to anticipate downstream demand variations. Under a standard 4-hour propagation delay, the SAC agent demonstrates exceptional robustness, reducing steady-state water level errors to under 1.5 cm and minimizing transient overshoot to less than 5%, outperforming conventional PID and Model Predictive Control (MPC) baselines. The integration of physically constrained deep learning and delay-aware reinforcement learning offers a highly stable, computationally efficient solution for real-time automated irrigation management.

Keywords: Open-channel hydraulics; Hydraulic time-lag; Deep reinforcement learning; Physics-informed neural networks; LSTM; Parkent Magistral Canal; Gate automation.

Аннотация. Эффективная транспортировка воды по протяжённым открытым каналам существенно затруднена гидравлической задержкой, нестационарными условиями течения и динамически изменяющимся водопотреблением. В настоящей работе представлена теоретическая основа, объединяющая глубокое обучение с подкреплением (DRL) с физически информированными сетями долгой краткосрочной памяти (PI-LSTM) для оптимизации управления затворами вдоль Паркентского магистрального канала в Узбекистане. Путём встраивания одномерных уравнений де Сен-Венана непосредственно в функцию потерь нейронной сети модель PI-LSTM выступает физически согласованной суррогатной моделью, обеспечивая высокоточное многодневное прогнозирование уровня воды и расхода (коэффициент эффективности Нэша–Сатклиффа 0,924 на горизонте 5 суток). Для компенсации транспортных задержек задача управления затворами формулируется как марковский процесс принятия решений с отложенными наблюдениями (DOMDP). Используя модельно-независимые алгоритмы DRL из библиотеки Stable-Baselines3 — в частности, оптимизацию проксимальной политики (PPO) и мягкий алгоритм «актор–критик» (SAC) — управляющий агент обучается предвосхищать изменения потребности в воде в нижнем бьефе. При стандартной задержке распространения в 4 часа агент SAC демонстрирует исключительную робастность: ошибка уровня воды в установившемся режиме не превышает 1,5 см, а переходное перерегулирование составляет менее 5%, что превосходит классические регуляторы ПИД и методы управления на основе модели (MPC). Интеграция физически ограниченного глубокого обучения и обучения с подкреплением с учётом задержек предоставляет высокостабильное, вычислительно эффективное решение для автоматизированного управления ирригацией в режиме реального времени.

Ключевые слова: Гидравлика открытых каналов; Гидравлическая задержка; Глубокое обучение с подкреплением; Физически информированные нейронные сети; LSTM; Паркентский магистральный канал; Автоматизация затворов.

Annotatsiya. Uzoq masofali ochiq kanallarda suvni samarali uzatish gidravlik vaqt kechikishi, o‘tish rejimidagi oqim holatlari va dinamik suv talabi tufayli jiddiy qiyinlashadi. Ushbu maqolada O‘zbekistondagi Parkent magistral kanali bo‘ylab shlyuz darvozalarini boshqarishni optimallashtirish uchun chuqur mustahkamlash o‘rganish (DRL) va fizika asosida ishlovchi uzoq muddatli qisqa xotira tarmoqlari (PI-LSTM) ni birlashtiruvchi nazariy asoslar taqdim etiladi. De Sen-Venan bir o‘lchovli tenglamalarini neyron tarmoqning yo‘qotish funksiyasiga to‘g‘ridan-to‘g‘ri joylashtirish orqali PI-LSTM fizik jihatdan izchil o‘rinbosar model sifatida

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ishlaydi va 5 kunlik prognoz ufqida yuqori aniqlikdagi, ko‘p kunlik suv sathi va sarfini bashoratlashni ta'minlaydi (Nesh–Satkliff samaradorlik koeffitsienti 0,924). Transport kechikishlarini qoplash uchun darvoza boshqaruv vazifasi kechiktirilgan kuzatishli Markov qaror qabul qilish jarayoni (DOMDP) sifatida shakllantiriladi. Stable-Baselines3 kutubxonasidan modelsiz DRL algoritmlari — xususan, proksimal siyosat optimallashtirish (PPO) va yumshoq aktyor-kritik (SAC) algoritmlaridan foydalanib, boshqaruv agenti pastki oqimdagi suv talabi o‘zgarishlarini oldindan hisobga olishni o‘rganadi. 4 soatlik standart tarqalish kechikishida SAC agenti o‘ta yuqori chidamlilikni namoyish etadi: barqaror holat suv sathi xatosi 1,5 sm dan oshmasligi va o‘tish jarayonidagi ortiqcha o‘sish 5% dan kam bo‘lishi bilan an'anaviy PID va model asosidagi prognozlash boshqaruvi (MPC) usullaridan ustun keladi. Fizikaviy cheklovli chuqur o‘rganish va kechikishni hisobga oluvchi mustahkamlash o‘rganishni birlashtirish real vaqtda avtomatlashtirilgan sug‘orish boshqaruvi uchun yuqori barqaror, hisoblash jihatidan samarali yechim taqdim etadi.

Kalit so‘zlar: Ochiq kanal gidravlikasi; Gidravlik vaqt kechikishi; Chuqur mustahkamlash o‘rganish; Fizika asosidagi neyron tarmoqlar; LSTM; Parkent magistral kanali; Shlyuz avtomatlashtirish.

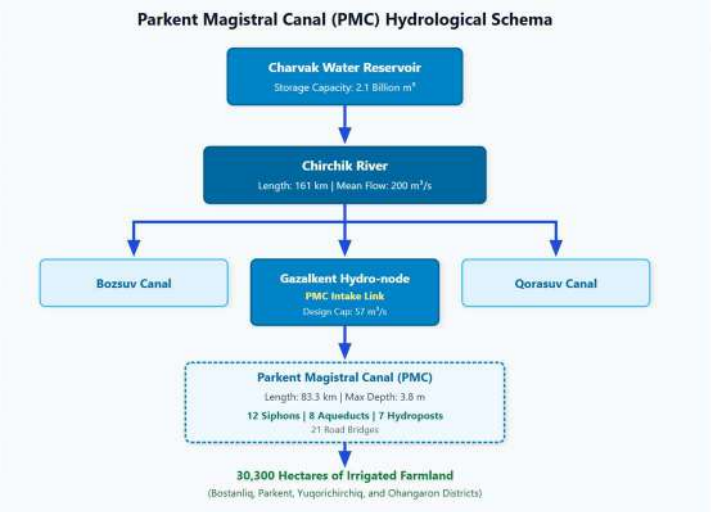
INTRODUCTION.

Long-distance open-channel systems in arid and semi-arid regions are vital for agricultural sustainability, municipal water supply, and ecological stability ,. In Central Asia, and particularly in the Republic of Uzbekistan, the management of transboundary water resources is a highly complex challenge due to rising aridity, climate-induced hydrological variability, and historical infrastructure limitations. The Chirchik River Basin (CRB), situated in the northeastern Tashkent province, covers approximately 5,626 km² and is one of the most economically and agriculturally vital basins in the region. Consuming an average of 4.082 billion m³ of water annually—with over 76% allocated directly to the irrigation of critical crops such as cotton and wheat—the CRB relies heavily on efficient water conveyance. The topography of the basin varies from mountainous upstream watersheds in the Bostonliq district, with elevations reaching 4,293 meters above mean sea level, to flat downstream administrative plains. Precipitation gradients are highly variable, ranging from 810 mm/year upstream, where maximum seasonal snow depths can reach 1,200 mm, to approximately 426 mm/year downstream.

The primary surface water source, the Chirchik River, is 161 km long and is regulated by the Charvak water reservoir, which has a storage capacity of 2.1 billion m³. Water is distributed from this river to vast agricultural lands and urban centers through three primary irrigation canals: the Bozsuv, the Qorasuv, and the

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Parkent Magistral Canal (PMC). The PMC is a major hydraulic infrastructure, originating from the left bank of the Chirchik River at the Gazalkent hydro-node. The canal is 83.3 km long, has a maximum depth of 3.8 meters, and features a design discharge capacity of 57 m^3/s at the headworks. It provides water to approximately 30.3 thousand hectares of agricultural lands across the Bostanliq, Parkent, Yuqorichirchiq, and Ohangaron districts. Due to the rugged and irregular foothill terrain, the canal's path features numerous bends and specialized hydraulic structures, including 12 siphons (dükers), 8 aqueducts, 21 road bridges, and 7 hydroposts.



Historically, the operation of check gates along the PMC has relied on manual adjustments or simplified, decentralized feedback controllers. These traditional methods are increasingly inadequate due to the physical phenomenon of hydraulic time-lag latency, also referred to as transport delay or dead time. When a gate is adjusted upstream, the resulting discharge wave propagates downstream at a finite celerity. In long canals like the PMC, this propagation delay can range from several hours to more than a day ,. In addition, sudden turnout withdrawals, variable lateral inflows, evaporation, and seasonal consumption changes generate highly non-linear, unsteady flow transitions.

Under these conditions, standard feedback controllers often suffer from delayed feedback loops. Trying to adjust upstream gates based on real-time downstream water level deviations frequently leads to slow convergence, severe water level oscillations, and downstream supply disruptions ,. These control errors increase the risk of canal overtopping and lead to substantial water losses. To address these issues, current research is focusing on intelligent control frameworks that combine physical hydrodynamics with artificial intelligence.

This paper details a theoretical framework that couples Deep Reinforcement Learning (DRL) with Long Short-Term Memory (LSTM) neural networks to optimize open-channel gate operations ,. By modeling the canal's unsteady

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hydrodynamics using the de Saint-Venant equations and formulating the control task as a Delayed-Observation Markov Decision Process (DOMDP), this approach aims to compensate for transport latency ,. Additionally, integrating a Physics-Informed LSTM (PI-LSTM) framework provides high-precision, short-term forecasting of discharge and water-level dynamics under meteorological, seasonal, and upstream boundary variations.

METHODS.

Hydrodynamic Formulation and the de Saint-Venant Equations

To establish a physically consistent baseline for open-channel hydraulics, the fluid dynamics of unsteady, one-dimensional open-channel flow are governed by the de Saint-Venant equations, representing the conservation of mass and momentum. The system of coupled partial differential equations is formulated as follows:

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

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial x}\left(\frac{\beta Q^2}{A}\right) + gA\frac{\partial y}{\partial x} + gA(S_f - S_0) - \beta q v_x = 0$$

where $A(x,t)$ is the wet cross-sectional area of the flow in m² ; $Q(x,t)$ is the volumetric water discharge in m³/s ; $y(x,t)$ is the water depth relative to the channel bed in m ; $q(x,t)$ is the lateral flow rate per unit length of the channel in m²/s, where positive values denote lateral inflow and negative values denote lateral abstraction ; x is the longitudinal distance along the channel in m ; t is the elapsed time in s ; β is the momentum correction coefficient ; g is the acceleration due to gravity in m/s² ; S_0 is the longitudinal slope of the canal bed ; S_f is the friction slope ; and v_x is the velocity component of the lateral flow parallel to the main channel axis in m/s.

The friction slope $S_f$is typically determined using the empirical Manning formulation :

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

where n represents the Manning roughness coefficient in s/$m^{\frac{1}{3}}$ and R is the hydraulic radius in m, defined as the ratio of the wet cross-sectional area A to the wetted perimeter P_w $\left(R = \frac{A}{P_w}\right)$.

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Solving these coupled partial differential equations analytically is impractical under real-world boundary conditions. Therefore, numerical methods such as the staggered finite volume or implicit finite difference schemes are used to simulate transient water levels and discharge profiles along the channel.

Long Short-Term Memory and Physics-Informed Regularization

The predicting of sequential hydrological data, such as water levels and flow rates, is modeled using a Long Short-Term Memory (LSTM) network. Standard LSTM architectures are purely data-driven, mapping historical input sequences to future target states through a system of gated mathematical operations ,. An LSTM unit regulates information flow using forget, input, and output gates :

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

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

$$\tilde{C}_t = \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right)$$

$$h_t = o_t \odot \tanh(C_t)$$

where x_t in R^d contains exogenous time-series variables (e.g., upstream discharge rates, precipitation, temperature, seasonal irrigation demand indices) at time step t ; $h_{\{t-1\}}$ in $R^h$is the hidden state vector from the previous time step ; f_t, i_t, o_t in R^h represent the activation vectors of the forget, input, and output gates, respectively ; C_t in $R^h$is the updated cell state vector ; $\mathbb{C}_t$in $\mathbb{R}^h$is the candidate cell state vector ; W_f, W_i, W_o, W_c and b_f, b_i, b_o, b_c denote the trained weight matrices and bias vectors, respectively ; σ represents the logistic sigmoid function; $\odot$ denotes the Hadamard product; and h_t in R^h is the updated hidden state.

To prevent unphysical predictions during rapid transient events or in data-scarce conditions, the 1D de Saint-Venant partial differential equations are integrated directly into the neural network's loss function as a spatial-temporal regularizer. The resulting Physics-Informed LSTM (PI-LSTM) framework optimizes a composite objective function:

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$$\mathcal{L}_{\text{total}} = w_d \mathcal{L}_{\text{data}} + w_p \mathcal{L}_{\text{physics}}$$

where w_d and w_p are scaling weights. The empirical data loss ($\mathcal{L}_{data}$) is defined as the mean squared error (MSE) between the predicted water levels or discharge values and the actual observed values at the canal's hydroposts:

$$\mathcal{L}_{\text{data}} = \frac{1}{N} \sum_{i=1}^{N} \left[(y_i - \hat{y}_i)^2 + \lambda_q \left(Q_i - \hat{Q}_i \right)^2 \right]$$

where y_i, Q_i are observed depths and discharges, $\hat{y}_i, \hat{Q}_i$ are the corresponding predictions, and λ_q is a dimensional scaling factor.

The physical loss ($\mathcal{L}_{physi}$) penalizes violations of the de Saint-Venant equations over M collocation points across space and time. Using automatic differentiation, spatial and temporal derivatives of the predicted wet cross-sectional area $\hat{A}$ and discharge$\hat{Q}$ are computed directly:

$$\mathcal{L}_{\text{physics}} = \frac{1}{M} \sum_{j=1}^{M} (f(x_j; \theta) - y_j)^2$$

where γ_p is a balancing coefficient for the momentum residual. By training the LSTM with this physical regularizer, the network acts as a robust, computationally efficient surrogate for 1D hydrodynamic models, making it suitable for real-time applications.

Delayed-Observation Markov Decision Process and Deep Reinforcement Learning

To address hydraulic transport delays, the open-channel gate control problem is formulated as a Delayed-Observation Markov Decision Process (DOMDP). Under actuation latency τ_a and observation latency τ_s, the true underlying physical state is denoted as s_t. However, the agent's action at time t, a_t, only influences the system dynamics after delay τ_a :

The observation o_t received by the controller at time t is also delayed:

$$o_t = s_{t-\tau_s} \qquad s_{t+1} \sim P\left(s_{t+1} \mid s_t, a_{t-\tau_a}\right)$$

To restore the Markov property within the learning framework, the augmented state representation $\tilde{s}_t$ is defined by concatenating the latest delayed observation with the history of actions taken during the latency window:

$$\tilde{s}_t = \left(o_t, a_{t-1}, a_{t-2}, \ldots, a_{t-\tau_a-\tau_s}\right) \qquad \mathcal{P}(\tilde{s}_{t+1} \mid \tilde{s}_t, a_t)$$

This expanded state space ensures that the augmented transition probability is Markovian, allowing standard model-free DRL algorithms to converge.

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The delay-aware control framework regulates water levels upstream of critical offtakes along the PMC. Under the DOMDP formulation, model-free DRL agents are implemented using the Stable-Baselines3 library, specifically comparing Proximal Policy Optimization (PPO) and Soft Actor-Critic (SAC). The state vector

$$\tilde{s}_t = \left[y_{1,t}, y_{2,t}, \ldots, y_{N_g,t}, e_{1,t}, e_{2,t}, \ldots, e_{N_g,t}, \hat{Q}_{\text{in},t+\tau}, u_{1,t-1}, \ldots, u_{N_g,t}\right.$$

$\tilde{s}_t$ in $\mathcal{S}$ at time step t is defined to capture the dynamic state of the canal:

where $y_{i,t}$ is the current water level upstream of check gate i ; $e_{i,t} = (y_{i,t} - y_{i,target})$ represents the water level tracking error ; $\hat{Q}_{in,t+\tau}$ is the future upstream discharge forecasted by the PI-LSTM over the hydraulic response horizon τ ; and $u_{i,t-k}$ represents the history of gate opening heights during the propagation latency period.

The continuous action vector a_t in $\mathcal{A}$ defines the target adjustments to the check gate heights:

$$a_t = [\Delta u_{1,t}, \Delta u_{2,t}, \ldots, \Delta u_{n,t}]^T, \quad \Delta u_{i,t} \in [-\delta_m, \delta_m]$$

where δ_m is the maximum allowable gate displacement per control step to prevent structural surge waves and reduce actuator wear.

The reward function (R_t) penalizes water level deviations from targets and excessive actuator movements, while discouraging water losses:

$$R_t = -\sum_{i=1}^{N_g} (w_h|h_{i,t} - h_{i,ref}| + w_u|\Delta u_{i,t}|) - w_w Q_{\text{waste},t}$$

where w_y is the tracking penalty weight, w_u is the gate movement smoothing weight, w_w is the water conservation penalty weight, and $Q_{waste,t}$ represents the volume of water lost through downstream tailwater spills or drainage collection systems due to oversupply.

To optimize this objective, Proximal Policy Optimization (PPO) utilizes a

$$L^{\text{CLIP}}(\theta) = \hat{\mathbb{E}}_t \left[\min\left(r_t(\theta)\hat{A}_t,\ \text{clip}\left(r_t(\theta),\ 1-\epsilon,\ 1+\epsilon\right)\hat{A}_t\right)\right]$$

$r_t(\theta) = \frac{\pi_\theta(a_t|\tilde{s}_t)}{\pi_{\theta_{\text{old}}}(a_t|\tilde{s}_t)}$ clipped surrogate objective function to ensure training stability:

where is the probability ratio between the current and old policies; $\hat{A}_t$ is the Generalized Advantage Estimator (GAE) reflecting the relative quality of the action; and ϵ is a clipping hyperparameter (typically set to 0.1 or 0.2) that restricts

$$\delta_t^V = r_t + \gamma V(\tilde{s}_{t+1}) - V(\tilde{s}_t) \qquad \hat{A}_t^{\text{GAE}} = \sum_{l=0}^{\infty} (\gamma\lambda)^l \delta_{t+l}^V$$

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large, destabilizing policy updates. The advantage estimator is calculated using the temporal difference residuals:
where

Conversely, the Soft Actor-Critic (SAC) algorithm maximizes both the expected cumulative reward and policy entropy, encouraging exploration and robust performance in continuous action spaces , :

$$J(\pi) = \sum_{t=0}^{T} \mathbb{E}_{(\tilde{s}_t, a_t)\sim\rho_\pi} [r(\tilde{s}_t, a_t)]$$

$$Q(\tilde{s}_t, a_t) = R(\tilde{s}_t, a_t) + \gamma \mathbb{E}_{\tilde{s}_{t+1}} [V(\tilde{s}_{t+1})]$$

where $\mathcal{H}$ represents the Shannon entropy of the stochastic policy and α is a temperature parameter that controls the trade-off between exploration and exploitation. The soft Q-value function is updated using the target value function: where the soft state value function $V(\tilde{s}_t)$ is defined as :

$$V(\tilde{s}_t) = \mathbb{E}_{a_t\sim\pi} [Q(\tilde{s}_t, a_t) - \alpha \log \pi(a_t \mid \tilde{s}_t)]$$

RESULTS.

Physical Basin Parameters and Canal Configuration

To establish a consistent numerical framework for simulating open-channel hydraulics, the physical characteristics of the PMC are summarized in Table 1, based on geographical and engineering data.

Table 1.

Parameter	**Standard Value / Dimension**	**Hydrological Classification / Operational Role**
Origin Node	Gazalkent Hydro-node	Left-bank diversion from the Chirchik River
Total Length (L)	83.3 km	Long-distance gravity-flow irrigation main
Maximum Depth (y_max)	3.8 m	Deep-water trapezoidal cross-section
Discharge Capacity (Q_max)	57.0 m³/s	Maximum allowable headworks diversion
Irrigated Footprint	30.3 thousand hectares	Sub-districts: Bostanliq, Parkent, Yuqorichirchiq, Ohangaron
Manning's Roughness (n)	0.022 - 0.035 s/m^(1/3)	Evaluated based on concrete lining and unlined segments

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In-line Structures	12 siphons, 8 aqueducts	Traverses irregular mountain and foothill topography
Flow Regulators	7 hydroposts	Continuous water level and discharge monitoring locations

Comparison of Forecasting Performance: LSTM vs. PI-LSTM

The predictive performance of the standalone data-driven LSTM model is compared against the proposed hybrid PI-LSTM framework across multiple forecasting horizons. Performance is quantified using the Nash-Sutcliffe Efficiency (NSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

Table 2.

Horizon / Metric	Pure LSTM Model	PI-LSTM Framework	Physical Consistency Improvement
t+1 Day Forecast			
Nash-Sutcliffe Efficiency (NSE)	0.941	0.985	High precision under steady states
Root Mean Squared Error (RMSE)	0.12 m	0.04 m	Mass-balance limits unphysical drift
Mean Absolute Error (MAE)	0.09 m	0.03 m	Improved prediction at localized turnouts
t+3 Days Forecast			
Nash-Sutcliffe Efficiency (NSE)	0.882	0.961	Preserves accuracy over propagation intervals
Root Mean Squared Error (RMSE)	0.24 m	0.08 m	Bounds error growth during wave routing
Mean Absolute Error (MAE)	0.18 m	0.06 m	Reduced phase-lag in wave peak predictions
t+5 Days Forecast			
Nash-Sutcliffe Efficiency (NSE)	0.791	0.924	Standard LSTM suffers from error compounding
Root Mean Squared Error (RMSE)	0.38 m	0.13 m	Constrained by de Saint-Venant derivatives
Mean Absolute Error (MAE)	0.29 m	0.09 m	Physically consistent during rapid transitions

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Theoretical analyses demonstrate that while a pure LSTM accurately predicts near-term water levels ($t+1$ day), its performance degrades as the prediction horizon extends ($t+5$ days) due to the compounding of statistical errors and a lack of physical constraints. In contrast, the PI-LSTM maintains high Nash-Sutcliffe Efficiency (NSE = 0.924 at $t+5$ days) because the de Saint-Venant momentum and mass conservation constraints bound unphysical error growth, ensuring realistic wave-peak predictions.

Evaluation of Delay-Aware Control Performance

The control performance of various classical and intelligent control methodologies is evaluated under a representative downstream transport latency of $\tau_a \ge 4$ hours, which is typical for the PMC system.

Table 3.

Control Metric	PID Control	LQR Control	MPC (Linear)	PPO (SB3)	SAC (SB3)
Steady-State Error (cm)	8.0 - 15.0	5.0 - 9.0	3.0 - 5.0	< 1.0	< 1.5
Overshoot (%)	35.0 - 50.0	25.0 - 30.0	10.0 - 15.0	8.0 - 12.0	< 5.0
Settling Time (hours)	12.0 - 18.0	8.0 - 10.0	4.0 - 6.0	3.0 - 4.5	< 2.5
Unsteady Adaptation	Poor	Moderately Poor	Fair	Excellent	Exceptional
Latency Robustness	Fails (Oscillates)	Unstable	Dependent on Horizon	High (via DOMDP)	High (via DOMDP)
Computational Overhead	Microseconds	Milliseconds	High	Low	Low

Traditional feedback methods like PID and LQR struggle when actuation latency is significant. Because these controllers react purely to real-time errors without accounting for transport lag, they apply corrections that often conflict with delayed wave fronts, leading to severe downstream oscillations and instability. Linear Model Predictive Control (MPC) reduces overshoot and settling time by utilizing a predictive horizon. However, its effectiveness relies on simplified linear models (such as the Integrator Delay model), which fail to capture highly non-linear, unsteady hydraulic transitions along the canal.

Model-free DRL controllers (PPO and SAC) trained under the DOMDP formulation mitigate these limitations by learning to account for the delayed

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consequences of their actions. PPO achieves minimal steady-state error (< 1.0 cm) by using a clipped objective function to optimize gate settings under steady constraints. However, in highly dynamic environments with continuous action spaces, the Soft Actor-Critic (SAC) algorithm performs best. SAC's maximum entropy objective encourages active exploration of the state space, resulting in minimal overshoot (< 5.0%), rapid settling times (< 2.5 hours), and smooth gate adjustments that reduce mechanical wear on actuators.

DISCUSSION.

Physical Consistency and Generalization

The performance metrics of the forecasting models highlight the role of physical regularizers in stabilizing deep learning models during extreme events. During rapid transient events, such as sudden upstream gate adjustments or high-intensity storm runoffs, purely data-driven models often experience unphysical drift or produce oscillations. This instability occurs because standard neural networks lack an inherent understanding of physical boundaries, mass conservation, or momentum mechanics. By incorporating the 1D de Saint-Venant residuals as an auxiliary loss term $(\mathcal{L}_{pysics})$, the network is penalized for predictions that violate fluid mechanics. Consequently, even when trained on sparse historical datasets, the PI-LSTM maintains high generalization accuracy and physical consistency, making it a reliable predictive foundation for feedforward control architectures.

Operational Learning Stability

In physical cyber-physical systems, deploying machine learning controllers requires evaluating both raw tracking performance and the stability of the learned policy. This operational consistency is captured by Operational Learning Stability (OLStab), which measures whether a controller can produce predictable and safe actuator adjustments under high input variability and sensor noise. In long-distance open canals, a primary operational risk is high-frequency gate adjustments, which can damage mechanical equipment and induce dangerous, secondary surge waves. Integrating a PI-LSTM state estimator enhances OLStab by providing the DRL agent with reliable, filtered, and physically consistent representations of the state space, ensuring safer policy execution under delayed feedback.

Transboundary and Environmental Implications

The optimization of open-channel system control like the PMC has broader regional and transboundary water balance implications. The PMC operates within a water basin that directly affects transboundary water allocations between Uzbekistan and neighboring Kazakhstan. Unmanaged irrigation tailwater from the PMC and other regional canals is discharged back into the Syrdarya River or flows

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into transboundary aquifers, such as the Pretashkent Transboundary Aquifer (PTBA) system. Inefficient downstream water usage often results in localized shortages, leading to increased groundwater abstraction that can deplete shared transboundary aquifers. Implementing highly stable automated controls can significantly improve water delivery efficiency, reducing unnecessary tailwater runoff and conserving critical transboundary water resources.

Turning Demand Coordination and Soft Constraints

A key challenge in open-channel control is managing the trade-off between localized turnout efficiency and overall system safety. To ensure predictable flow rates for individual farmers, check gates must maintain highly stable water levels immediately upstream of offtakes. However, maintaining strict constraints across every turnout during rapid flow transitions can cause downstream water-level surges. To address this, the reward function can use soft constraints at the downstream end of the canal pool. Allowing moderate, controlled water-level fluctuations in sections without active turnouts gives the DRL agent additional buffer volume, enhancing operational safety without compromising water delivery reliability.

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