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 klasterlash usullarini birlashtiradi. Real sharoitga yaqin sun'iy ma'lumotlar to'plami ishlab chiqildi va tahlil qilindi. Natijalar taklif etilgan yondashuv samarasiz iste'molni aniqlash va uni harorat ta'siridan ajratish imkonini berishini ko'rsatdi. Ushbu model gaz monitoring tizimlarida qo'llanilib, energiya samaradorligini oshirishga xizmat qiladi.

Kalit so'zlar: tabiiy gaz, sun'iy intellect, anomaliya aniqlash, energiya samaradorligi, klasterlash, gaz iste'moli.

Introduction. The global and regional energy balance still heavily depends on natural gas, especially in nations like Uzbekistan that have developed gas infrastructure. It is widely used in domestic heating, industrial processes, and power generation due to its relatively low carbon emissions compared to other fossil fuels [1]. Despite its wide range of benefits, some of the major challenges are yet to be addressed with regards to inefficient consumption, technical losses, and leaks in gas distribution networks.

In developing and transitioning countries, including those in Central Asia, gas distribution networks are facing challenges in terms of outdated networks, inefficient monitoring systems, and the absence of advanced analytical tools. As a result, a significant portion of the supplied gas is consumed inefficiently or lost due to operational issues and anomalous usage patterns [2]. These inefficiencies not only lead to economic losses but also negatively impact energy security and environmental sustainability. Traditional gas consumption monitoring methods rely primarily on aggregated data and periodic audits, which are insufficient to detect subtle anomalies or inefficiencies at the consumer level. With the increasing adoption of smart metering technologies and the digitalization of energy systems, large volumes of consumption data have become available. This creates new opportunities for applying advanced data-driven approaches to improve system performance [3].

Artificial intelligence (AI) and machine learning methods have demonstrated high performance in analyzing complex data sets, identifying hidden patterns, and detecting anomalies in energy systems. In particular, AI-based approaches have been successfully applied to electricity demand forecasting, fault detection, and energy efficiency optimization [4]. However, the application of such methods to natural gas consumption analysis remains relatively unexplored, especially in the context of emerging gas markets.

Recent research has highlighted the importance of advanced approaches to modeling and integrating alternative energy technologies into gas systems. In particular, hydrogen blending and power-to-gas technologies have been explored as promising solutions for increasing the flexibility and resilience of gas

networks [9, 10]. Furthermore, the role of biogas and renewable energy in decarbonizing the energy sector has been widely discussed, particularly in the context of Uzbekistan's energy transition [6].

Identifying inefficient gas consumption remains challenging due to the strong dependence of consumption on external factors such as ambient temperature, seasonal fluctuations, and consumer behavior. Therefore, it is crucial to develop models capable of distinguishing between normal and abnormal consumption patterns, taking these influencing factors into account [5].

This study proposes an artificial intelligence-based approach to identifying inefficient natural gas consumption using a combination of mathematical modeling and machine learning methods. A synthetic dataset representing typical consumption behavior is used to develop and validate the proposed methodology. The approach is based on estimating expected consumption and analyzing deviations from normal patterns to identify anomalies. The results of this study can contribute to improving the efficiency of gas distribution systems, reducing losses, and supporting data-driven decision-making in energy management.

Materials and methods. This study applied a data-driven approach to examine natural gas consumption patterns and identify inefficient use. Due to the limited availability of real-world datasets, a synthetic dataset was created to simulate realistic consumer behavior in residential and small industrial settings. The dataset covers a 90-day period and includes variables such as daily gas consumption, ambient temperature, and time factors.

The dataset's creation is based on typical physical relationships observed in gas consumption systems. Specifically, it is assumed that gas demand is inversely proportional to ambient temperature due to heating requirements. Expected consumption is determined using a linear relationship:

$$q\_expected = a - bT$$

where $q\_expected$ is the expected gas consumption (m³/day), T is the ambient temperature (°C), and a and b are empirical coefficients.

To simulate real-world fluctuations, random noise is introduced into the system. Actual consumption is generated as follows:

$$q\_actual = q\_expected + \varepsilon$$

where ε follows a normal distribution with zero mean and standard deviation σ, representing stochastic variations in consumer behavior.

Additionally, anomalous consumption patterns are introduced to represent inefficient usage scenarios:

$$q\_actual\_anom = q\_expected\,(1 + \alpha)$$

where α ∈ [0.2, 0.5] represents excessive consumption due to inefficiencies or abnormal behavior.

Table 1 presents an example of the generated synthetic dataset used to test the model. The data reflects realistic variations in gas consumption, depending on temperature and random factors.

Consumer ID	**Day**	**Temperature (°C)**	**Expected Consumption (m³)**	**Actual Consumption (m³)**
1	1	5	34.0	36.2
1	2	3	36.4	38.1
1	3	7	31.6	30.9
2	1	10	28.0	27.5
2	2	12	25.6	33.0
2	3	8	30.4	29.8
3	1	6	32.8	33.5
3	2	4	35.2	45.8
3	3	9	29.2	28.7

Table 1 – Sample of synthetic natural gas consumption dataset

Mathematical model and AI framework

The modeling of gas consumption behavior requires consideration of both environmental and temporal factors. Therefore, the expected consumption is extended to include a seasonal component:

$$q\_expected(t) = a - bT(t) + cS(t)$$

where S(t) represents a normalized seasonal function capturing periodic variations in demand. To ensure comparability across different consumers, the consumption data is normalized as:

$$q\_norm = q\_actual\,/\,q\_expected$$

This normalization enables identification of relative inefficiencies independent of absolute consumption levels. Values of q_norm close to unity indicate normal consumption, whereas higher values suggest excessive usage.

For anomaly detection, a statistical approach based on standardization is employed:

$$z = (q\_actual - q\_expected)\,/\,\sigma$$

where σ is the standard deviation of consumption. Observations satisfying |z| > 2 are considered moderate anomalies, while |z| > 3 indicates significant deviations.

To further enhance detection accuracy, clustering techniques are applied. The K-means algorithm is used to partition the dataset into groups of similar consumption behavior by minimizing the objective function:

$$J = \Sigma\, \Sigma\, ||x\_i - \mu\_k||^2$$

where x_i represents the feature vector of a consumer and μ_k is the centroid of cluster k.

The final decision regarding inefficient consumption is based on a hybrid approach combining statistical deviation and clustering results. A consumer is classified as inefficient if its normalized consumption exceeds a predefined threshold and it is identified as an outlier within its cluster.

Results and discussion

The proposed methodology was evaluated using a generated synthetic dataset. The relationship between ambient temperature and gas consumption is shown in Figure 1, where a clear inverse correlation is observed, confirming the validity of the baseline consumption model. As temperature decreases, gas consumption increases due to heating demand, consistent with expected physical behavior.

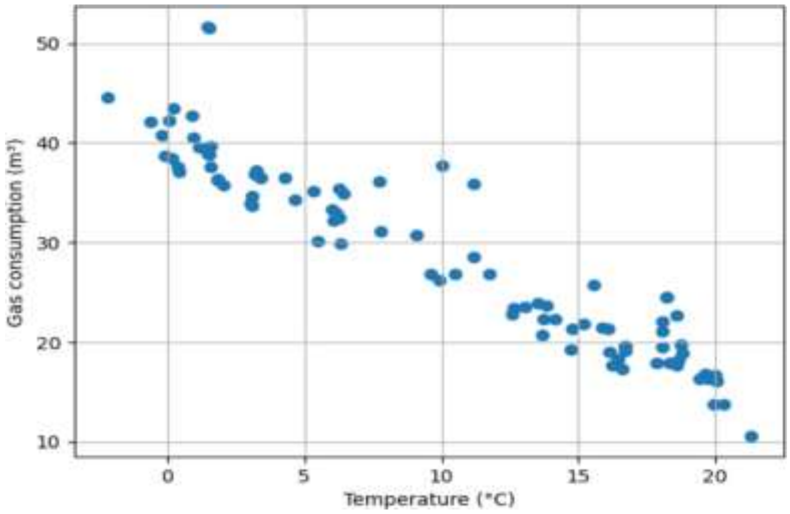
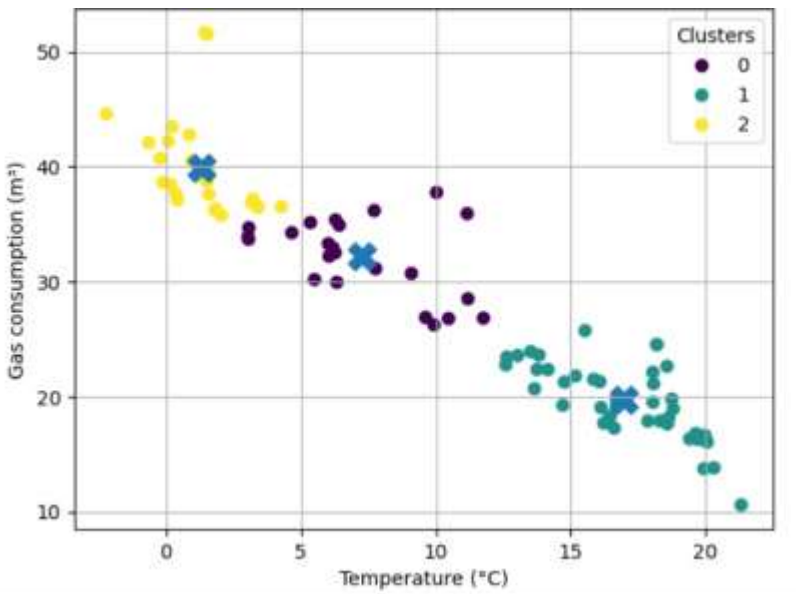


Figure 1 –Temperature vs gas consumption.

After applying normalization, the majority of observations fall within the range $q\_norm \approx 0.9 - 1.1$, indicating that the model accurately represents typical consumption patterns. However, a subset of

observations exhibits elevated values exceeding $q\_\{norm\} > 1.3$, which are classified as inefficient consumption.

The statistical anomaly detection results show that 6.67% of observations correspond to moderate anomalies ($|z| > 2|z| > 2\,|z| > 2$), while 3.33% of observations are classified as significant anomalies ($|z| > 3|z| > 3\,|z| > 3$). Additionally, inefficient consumption based on normalized values accounts



for 6.67% of the dataset. These anomalies are associated with irregular consumption behavior, including excessive gas usage under moderate temperature conditions and deviations from expected trends.

Figure 2 – Clustering of gas consumption patterns.

The clustering results presented in Figure 2 demonstrate the effectiveness of the K-means algorithm in identifying various consumption patterns. The dataset is divided into three clusters corresponding to different behavioral profiles, including temperature-dependent consumption, relatively stable usage, and highly variable consumption patterns. It is observed that most anomalous observations are concentrated in the cluster with the highest variability, indicating a strong relationship between irregular consumption and inefficiency.

Overall, the results confirm that the combined use of normalization, statistical anomaly detection, and clustering provides a robust framework for identifying inefficient gas consumption. The proposed methodology reduces the number of false positives associated with temperature fluctuations and improves the reliability of anomaly identification. From a practical perspective, the developed approach enables early detection of inefficient consumption, identification of anomalous usage patterns, and supports data-driven decision making in gas distribution systems.

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МОДИФИЦИРОВАННАЯ МОДЕЛЬ ПЕРОНА–МАЛИКА С ЭНТРОПИЙНОЙ АДАПТАЦИЕЙ ДЛЯ ФИЛЬТРАЦИИ СПЕКЛ-ШУМА В УЛЬТРАЗВУКОВЫХ ИЗОБРАЖЕНИЯХ СЕРДЦА

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Аннотация: В данной статье исследуется проблема снижения спекл-шума в ультразвуковых (ЭхоКГ) изображениях — ключевой вызов, существенно влияющий на точность диагностической интерпретации и автоматической сегментации. Предложена энтропийно-адаптивная модификация классической модели анизотропной диффузии Перона–Малика, в которой коэффициент диффузии управляется локальными статистическими дескрипторами (энтропией и дисперсией) для каждого