

PAPER

A Data-Driven Framework for Sensor-based Anomaly Analysis and Predictive Microclimate Control in Small-scale Potato Storage

Gulmira Baenova¹  (✉),
Madina Serikova¹ ,
Aruna Animish Pavate² 

¹L.N. Gumilyov Eurasian
National University,
Astana, Kazakhstan

²Thakur College of Engineering
and Technology, Mumbai,
Maharashtra, India

baenova_gm@enu.kz

ABSTRACT

Postharvest losses during potato storage remain a serious problem, especially for small-scale storage facilities with limited automation, monitoring, and energy resources. This paper proposes a data-driven cyber-physical framework for sensor-based microclimate analysis and predictive management of small-scale potato storage facilities. The framework defines the integration of a physics-informed digital twin, a safe reinforcement learning controller formulated as a constrained Markov decision process (CMDP), and a multi-sensor anomaly detection module operating on multidimensional time-series sensor data. The proposed approach is aimed at analyzing microclimate dynamics, detecting abnormal changes in temperature, humidity, and gas composition, and supporting prediction-oriented control decisions under technological and energy constraints. The digital twin is intended to serve as a simulation environment for training and future evaluation of predictive control strategies without risk to stored products. The control formulation explicitly represents the trade-off between energy consumption and storage quality while considering constraints on temperature, relative humidity, oxygen, carbon dioxide, and spoilage-related gas indicators. A set of forecasting-oriented validation scenarios is defined, including normal operation, hypoxia, early biodegradation, sensor failures, and energy-constrained storage conditions. The work forms a methodological basis for subsequent quantitative simulation, sensor data analysis, and experimental validation on real potato storage facilities.

KEYWORDS

sensor data analysis, microclimate forecasting, anomaly detection, predictive control, digital twin, safe reinforcement learning, potato storage, cyber-physical system

1 INTRODUCTION

Postharvest losses of agricultural products remain a significant problem, especially for small-scale potato storage facilities. Potatoes are usually stored for several months

Baenova, G., Serikova, M., Pavate, A. A. (2026). A Data-Driven Framework for Sensor-based Anomaly Analysis and Predictive Microclimate Control in Small-scale Potato Storage. *IETI Transactions on Data Analysis and Forecasting (iTDAF)*, 4(3), pp. 17–33. <https://doi.org/10.3991/itdaf.v4i3.61867>

Article submitted 2026-04-07. Revision uploaded 2026-07-02. Final acceptance 2026-07-02.

© 2026 by the authors of this article. Published under CC-BY.

in conditions close to the limits of the microclimate, in which even minor deviations in temperature, humidity, or gas composition can lead to deterioration in product quality and economic losses [1]. At the same time, maintaining stable storage conditions is complicated by the need to balance energy consumption and product quality.

In recent years, digital technologies for monitoring and controlling the microclimate have been actively developing, including IoT sensors, SCADA systems, and data analysis platforms [2]. However, most practical solutions are still based on rule-based strategies and PID controllers operating relative to fixed settings. Such systems, as a rule, do not take into account the multi-criteria nature of the storage task and do not adapt well to changing external conditions.

At the same time, the development of data-driven approaches, including digital twins, reinforcement learning, and anomaly detection methods, opens up new opportunities for adaptive and predictive management of storage systems. These methods make it possible to process data in real time, identify deviations at an early stage, and make decisions under conditions of uncertainty [3].

Despite the progress made, the use of such approaches in small-scale agricultural storage remains limited. Most of the existing solutions are focused on large industrial facilities, while integrated architectures combining physical modeling, intelligent control, and anomaly diagnostics have not been sufficiently developed for small and medium-sized storage facilities.

To solve these problems, a cyber-physical framework for microclimate management of a small-scale potato storage facility is proposed. The proposed approach combines a physically grounded digital twin, safe reinforcement learning using the constrained Markov decision process (CMDP), and a multisensory anomaly detection module.

The main contribution of this study lies in the methodological integration and formalization of a cyber-physical framework that combines physics-informed digital twin modeling, CMDP-based safe reinforcement learning, and anomaly-aware monitoring for small-scale potato storage. The proposed approach forms the basis for subsequent quantitative simulation and experimental validation on real storage facilities.

2 RELATED WORKS

To better understand the current state of research and identify the existing methodological gaps, this section reviews recent studies related to microclimate control in storage facilities, digital twin technologies, reinforcement learning in energy systems, and anomaly detection in IoT-enabled cold chains.

2.1 Microclimate management in vegetable and potato storage rooms

Traditional microclimate management in vegetable and potato storage facilities is mainly based on rule-based strategies and PID controls implemented in a SCADA or PLC environment. Such systems typically use a limited number of temperature and humidity sensors, while ventilation and refrigeration equipment operate according to pre-set values. Recent research has focused on improving temperature and humidity control, optimizing ventilation parameters, and increasing the spatial uniformity of the storage microclimate. When storing potatoes, heat and mass transfer models emphasize the importance of respiration, evaporation, and airflow distribution processes for predicting weight loss and deterioration during long-term storage.

However, most existing systems are designed to maintain environmental parameters within acceptable limits, rather than explicitly optimizing the relationship between energy consumption and product quality. Formal formulations of storage control as a constrained multi-objective optimization problem remain relatively rare.

The study presented in [4] describes an automated microclimate management system for fruit and vegetable storage facilities, including temperature, humidity, and CO₂ sensors, as well as ventilation and cooling actuators. Their work emphasized the role of thermal modeling and active ventilation in maintaining storage quality. In another study [5], the distribution of temperature and humidity in potato storage rooms was studied, and it was shown that CFD-based analysis can help optimize ventilation and environmental control.

Despite these achievements, the development of adaptive management strategies that can simultaneously take into account product dynamics, external disturbances, and energy efficiency remains an open research problem.

2.2 Digital twins in buildings, HVAC systems, and food storage systems

The digital twin technology is increasingly being used in building energy management and HVAC systems, where physical and hybrid models are used to reproduce temperature and humidity dynamics, evaluate operational scenarios, and support advanced management strategies.

In the agri-food sector, digital twins are used to model cold chain processes and predict product quality in various environmental conditions. Models of heat and mass transfer have been developed for potatoes and other vegetables, taking into account the processes of respiration, evaporation, and internal moisture transfer. However, in most published studies, digital twins are used primarily for offline analysis or monitoring, rather than as a learning environment for adaptive management.

At the same time, long-term storage of fruits and vegetables requires a balance between energy efficiency and product quality. Recent reviews have highlighted the importance of intelligent detection, monitoring, and control technologies to reduce food waste while limiting energy consumption [6–8].

In general, there is a growing need in the literature for intelligent data storage systems that integrate digital twins not only for monitoring but also for management-oriented modeling and policy optimization.

2.3 Reinforcement learning and safe energy management in energy systems

Reinforcement learning RL has recently gained attention as a control approach for HVAC systems and building energy management. A growing body of research shows that RL-based controllers can reduce energy consumption while maintaining acceptable indoor environmental conditions when compared with conventional PID- or rule-based strategies.

Recent advances in safe reinforcement learning have introduced formulations based on CMDPs, where the control policy is optimized subject to explicit operational constraints. In energy and thermal systems, methods such as Lagrangian relaxation and constrained policy optimization have been proposed to enforce safety requirements, including temperature bounds and energy consumption limits.

Despite significant progress in the development of energy management systems, the use of RL—and especially safe RL—for agricultural product storage systems after

harvest remains limited. Most of the studies are devoted to standard ventilation and air conditioning indicators and clearly do not take into account the biophysical dynamics of stored agricultural products or the long seasonal periods characteristic of crop storage.

2.4 Anomaly detection in IoT-enabled cold chain systems

The rapid adoption of IoT sensors in logistics and storage infrastructures has stimulated research on anomaly detection methods for identifying deviations in temperature, humidity, and equipment behavior at an early stage. Common approaches include one-class SVM, Isolation Forest, autoencoders, and multivariate time-series analysis.

In agri-food applications, anomaly detection is increasingly used to identify abnormal storage conditions associated with product spoilage. However, in most existing studies it is treated as a monitoring or diagnostic tool rather than as an integrated part of the control architecture.

Recent IoT-based cold-storage systems demonstrate the transition toward cyber-physical infrastructures that combine sensing, automation, and data analytics [9–11]. Nevertheless, the interaction between anomaly detection modules and intelligent control strategies—such as safe-mode switching or RL policy adaptation—remains insufficiently explored.

2.5 Gaps in research

The reviewed literature reveals several important gaps. First, most storage systems still rely on conventional rule-based or PID control. Second, digital twins are mainly used for monitoring and offline analysis rather than as integrated components of adaptive control systems. Third, safe reinforcement learning has progressed significantly in building energy management but is still rarely applied to agricultural storage. Finally, anomaly detection modules are typically implemented as standalone monitoring tools and are only weakly connected to decision-making mechanisms.

Therefore, the integration of a physics-informed digital twin, safe reinforcement learning formulated as a CMDP problem, and anomaly detection within a unified management architecture for small-scale potato storage remains insufficiently studied and requires further methodological development.

3 RESEARCH METHODOLOGY

Based on the research gaps identified in Section 2, this study proposes an integrated methodological framework for intelligent microclimate management in small-scale potato storage facilities. The framework defines the interaction between a physics-based digital storage twin, a safe reinforcement learning controller formulated as a CMDP, and an anomaly detection module operating on multidimensional sensor data streams. Within the proposed framework, the digital twin is considered a future simulation environment for reproducing heat, humidity, gas transfer, and product–environment interaction processes. Such an environment can be used in subsequent studies for safe training and evaluation of control strategies without risk to stored products. The microclimate control problem is formulated as a constrained decision-making task, in which the control policy is intended to balance energy consumption and product quality while satisfying technological constraints on temperature, humidity, and gas composition.

3.1 The general architecture of the proposed framework

The architecture of the proposed intelligent storage management system is based on three closely interrelated components. The first component is a proposed digital twin model of the storage chamber, which is intended to reproduce the main thermodynamic and gas-dynamic processes occurring inside the storage.

The second component is a safe reinforcement learning controller developed within the framework of a CMDP. This development makes it possible to optimize management policy in relation to a variety of goals, including energy efficiency and microclimate stability, while ensuring compliance with technological safety requirements.

The third component is the anomaly detection module, which analyzes multidimensional time series generated by distributed sensors installed in the storage. This module is designed to detect abnormal operating conditions such as equipment malfunctions, abnormal temperature gradients, or unexpected changes in gas concentration. The detected anomalies can be used to adapt the management policy or switch to a safe mode of operation. The integration of these three components forms a unified cyber-physical architecture for intelligent storage management. Simulation-based digital twins are also used in agricultural warehouse systems to model operational processes and support decision-making, including optimizing storage, processing, and logistics [12]. The general structure of the proposed system is shown in Figure 1.

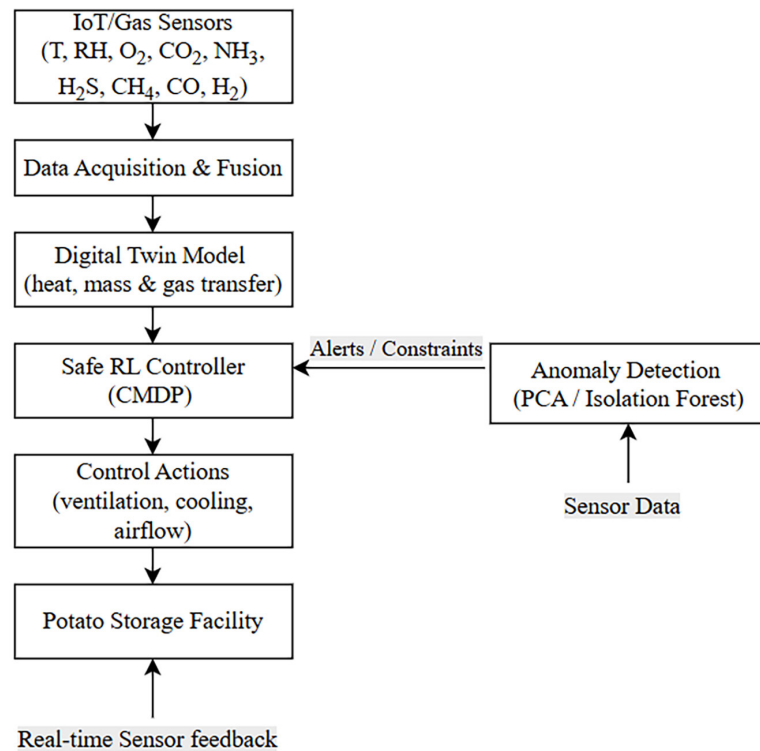


Fig. 1. Architecture of the proposed intelligent microclimate management framework for small-scale potato storage facilities

As shown in Figure 1, the proposed framework defines the integration of sensor monitoring, a digital twin, a safe RL controller, and an anomaly detection module within a single cyber-physical architecture. The proposed platform is designed to be compatible with existing automation infrastructures based on SCADA or PLC and provide a scalable and reproducible solution applicable to small and medium-sized agricultural warehouses.

This architecture is consistent with modern IoT-oriented cold chain systems, where distributed sensor networks and real-time data flows serve as the basis for intelligent monitoring and management decision support.

3.2 The model of the control object and the digital twin

The physical behavior of the storage system is presented using a model with concentrated parameters, which reflects the main processes of heat and mass transfer occurring inside the storage chamber. The object of control considered in this study is a potato storage facility with mechanical ventilation, with a capacity of 30–50 tons, corresponding to an internal volume of about 80–150 m³. Such storage facilities are typical for small and medium-sized rural farms.

To build a digital twin, a simplified dynamic model is used that describes the evolution of several key state variables characterizing the storage environment. The state vector includes the following components:

- average air temperature in the chamber $T_{air}(t)$;
- temperature of the potato mound $T_{prod}(t)$;
- relative humidity $\phi(t)$;
- concentration of carbon dioxide (CO_2) $Cco_2(t)$;
- external climatic parameters $w(t)$ (temperature, humidity, seasonal profiles).

The dynamics of the system are determined by related heat and mass balance equations describing the interaction between the stored product, the ambient air, and the ventilation system. In particular, the model takes into account the heat exchange between air and the mass of the product, the production of metabolic heat as a result of product respiration, moisture exchange caused by evaporation and ventilation processes, as well as the accumulation and removal of carbon dioxide associated with respiration and airflow. A similar approach to thermochemical modeling has been applied in digital twin systems for industrial thermal systems, where transient and stationary models are combined to represent the dynamics of heat and mass transfer [13].

In a compact continuous-time form, the dynamics of the storage environment can be represented as follows:

$$\dot{x}(t) = f(x(t), u(t), \omega(t); \theta) \quad (1)$$

where $\dot{x}(t)$ is the state vector of the storage environment,
 $u(t)$ is the control actions (ventilation, inflow mode, cooling capacity),
 $\omega(t)$ denotes external disturbances,
 θ represents model parameters.

The state vector includes air temperature, product temperature, relative humidity, CO_2 concentration, and other gas-related variables when gas monitoring is considered. The control vector includes ventilation intensity, air recirculation ratio, and cooling or heating power. External disturbances include outdoor temperature, outdoor humidity, seasonal conditions, and variations in product respiration intensity.

For implementation in the digital twin, the continuous model is discretized with a fixed sampling time step Δt . The resulting state-transition model is written as:

$$x_{t+1} = F(x_t, u_t, \omega_t, \theta) + \varepsilon_t \quad (2)$$

where x_t is the state at time step t ,
 u_t – the applied control action,
 ω_t – the external disturbance vector,
 θ is the set of model parameters,

and ε_t denotes modeling uncertainty and measurement noise. This discrete transition model provides the basis for formulating the microclimate management task as a constrained Markov decision process.

3.3 Problem statement as a constrained Markov decision-making process CMDP

The task of microclimate management is formulated as a CMDP, which makes it possible to optimize the control strategy in the presence of obvious technological limitations [14]. CMDP can be defined using the tuple

$$M = S, A, P, R, C, \gamma, \quad (3)$$

where S is the state space,
 A – action space,
 $P(s_{t+1}|s_t, a_t)$ indicates the dynamics of the transition,
 $R(s_t, a_t)$ is the reward function,
 $C = \{c_i(s_t, a_t)\}$ – constraint functions,
 $\gamma \in (0, 1)$ is the discount factor.

The state of the system at time t is given by the vector

$$s_t = [T_{air,t}, T_{prod,t}, \varphi_t, Cco_{2,t}, \varphi_{out,t}, d_t] \quad (4)$$

where $T_{air,t}$ – air temperature,
 $T_{prod,t}$ – is the temperature of the potato mound,
 φ_t – is the relative humidity,
 $Cco_{2,t}$ – is the concentration of carbon dioxide,
 $\varphi_{out,t}$ – external humidity,
 d_t – represents contextual variables such as time of day and storage stage.

The action vector is defined as

$$a_t = [u_t^{vent}, u_t^{damper}, u_t^{cool}] \quad (5)$$

including:

u_t^{vent} – ventilation intensity,
 u_t^{damper} – degree of air recirculation,
 u_t^{cool} – cooling or heating capacity.

The dynamics of the transition is determined by the digital twin model:

$$s_{t+1} = F(s_t, a_t, \omega_t, \theta) + \varepsilon_t \quad (6)$$

where F is the discrete-time transition function of the digital twin;
 θ is the set of model parameters;
 ε_t denotes modeling uncertainty and measurement noise;

This representation makes it possible to consider external disturbances and uncertainty in sensor measurements and model approximation

The reward function reflects the trade-off between storage quality, energy consumption, and control stability:

$$R(s_t, a_t) = -\alpha_T e_T(t) - \alpha_\varphi e_\varphi(t) - \alpha_{CO_2} e_{CO_2}(t) - \alpha_E E_t - \alpha_{\Delta u} \|a_t - a_{t-1}\|^2 \quad (7)$$

where $e_T(t)$, $e_\varphi(t)$, $e_{CO_2}(t)$ are penalties for deviations of temperature, relative humidity, and CO₂ concentration from the target technological ranges:

E_t is energy consumption;

$\|a_t - a_{t-1}\|^2$ penalizes abrupt changes in control actions;

α_T , α_φ , α_{CO_2} , α_E , and $\alpha_{\Delta u}$ are non-negative weighting coefficients.

For practical implementation, the main constraint functions can be expressed as:

$$c_1(s_t, a_t) = \max(0, T_{air,t} - T_{max}) + \max(0, T_{min} - T_{air,t}) \quad (8)$$

$$c_2(s_t, a_t) = \max(0, \varphi_t - \varphi_{max}) + \max(0, \varphi_{min} - \varphi_t) \quad (9)$$

$$c_3(s_t, a_t) = \max(0, C_{CO_2,t} - C_{CO_2,max}) \quad (10)$$

$$c_4(s_t, a_t) = \max(0, Risk_{cond,t} - Risk_{cond,max}) \quad (11)$$

$$c_5(s_t, a_t) = \max(0, Risk_{dry,t} - Risk_{dry,max}) \quad (12)$$

where c_1 represents temperature-limit violations, c_2 represents relative-humidity-limit violations, c_3 represents excessive CO₂ concentration, c_4 represents condensation risk, and c_5 represents overdrying risk. These constraints are used to penalize unsafe operating conditions and to keep the control policy within technological safety boundaries

Thus, the CMDP formulation allows the controller to search for a management policy that balances energy efficiency and storage quality while explicitly accounting for technological limitations and uncertainty.

3.4 The algorithm of safe learning

To solve the problem formulated in the form of CMDP, the safe reinforcement learning approach is used, based on relaxation of constraints using Lagrange multipliers. Relaxation of constraints makes it possible to transform rigid technological requirements into punitive functions, which makes the management task more flexible and suitable for reinforcement learning methods. In this approach, optimization is carried out not only according to the reward function but also taking into account the limitations imposed on the state of the system and control actions. To do this, we introduce a Lagrangian of the following form:

$$\mathcal{L}(\pi, \lambda) = \mathbb{E}[R(\pi)] - \sum_i \lambda_i (\mathbb{E}[C_i(\pi)] - d_i) \quad (13)$$

where

π – management strategy;

λ_i – Lagrange multipliers, adaptively updated during the learning process;

$\mathbb{E}[R(\pi)]$ – the expected value of the total reward;
 $\mathbb{E}[C_i(\pi)]$ – the expected accumulated value of the i th constraint;
 d_i – acceptable threshold values.

The basic algorithm can be used:

- PPO-Lagrangian,
- Constrained Policy Optimization CPO,
- or a similar algorithm that ensures compliance with restrictions.

During the learning process, the strategy π is updated in order to maximize the Lagrangian, while the multipliers λ_i are adaptively adjusted, increasing the penalty for violating constraints [15]. This mechanism allows you to find a balance between optimizing the objective function and meeting technological requirements.

From a practical point of view, modern safe RL methods such as PPO with Lagrangian relaxation PPO-Lagrangian or Constrained Policy Optimization CPO can be used as the basic algorithm to ensure stable learning and control compliance with constraints.

3.5 Anomaly detection module

To increase the reliability and stability of the control system, an anomaly detection module is integrated into the architecture, based on the analysis of multidimensional time series coming from a distributed network of sensors [16].

The proposed approach uses dimensionality reduction and deviation detection methods, including principal component analysis PCA or autoencoders, as well as single-class classification algorithms such as One-class SVM and Isolation Forest. These methods allow you to identify hidden anomalies in the behavior of the system without the need for labeled data.

The anomaly detection module is designed to identify atypical operating modes of the system, including the formation of abnormal temperature zones inside the storage and deviations of CO_2 concentration from acceptable values, as well as potential signs of equipment failures or incorrect operation of actuators.

Unlike traditional monitoring systems, the module in question is integrated into the control loop and interacts with the RL agent. In particular, the anomaly detection results can be used to switch the system to a safe mode of operation, temporarily limit the permissible set of actions of the RL agent, or adjust the management strategy.

Thus, the anomaly detection module acts as an additional level of safety, ensuring the system's resilience to uncertainties, measurement noise, and emergency situations.

3.6 Implementation assumptions and reproducibility parameters

To improve the reproducibility of the proposed framework, this subsection summarizes the main implementation assumptions that can be used in subsequent simulation-based validation. Since the present study focuses on the methodological formulation of the cyber-physical framework, the parameters listed below should be interpreted as baseline settings for future numerical experiments rather than as optimized values obtained from completed training.

The considered storage object is a small-scale potato storage facility with a product capacity of approximately 30–50 tons and an internal chamber volume of

about 80–150 m³. The digital twin may be simulated over a long-term storage horizon of up to 180 days with a fixed sampling step of 10–15 minutes. The state vector includes air temperature, product temperature, relative humidity, CO₂ concentration, external climatic variables, and contextual information such as time of day and storage stage. The action vector includes ventilation intensity, air recirculation ratio, and cooling or heating power.

For the safe RL controller, a continuous-action policy can be implemented using an actor-critic architecture. As a baseline configuration for future validation, both actor and critic networks may contain two fully connected hidden layers with 64–128 neurons per layer and nonlinear activation functions. The policy output represents normalized control actions, which are then mapped to admissible actuator ranges. For future implementation, training may be performed in the digital twin environment using PPO-Lagrangian or another safe RL algorithm suitable for constrained Markov decision processes.

The reward function is constructed as a weighted sum of several components: penalty for deviation of temperature, humidity, and gas composition from target ranges; energy consumption penalty; and penalty for abrupt changes in control actions. The weighting coefficients should be selected according to the storage management priorities. For example, higher weights can be assigned to product-quality and constraint-violation terms during critical storage stages, whereas energy-related weights can be increased under energy-limited operating conditions. In future validation, sensitivity analysis should be performed to assess the influence of these coefficients on the trade-off between energy consumption and storage stability.

The training procedure can be organized in several stages. First, the digital twin would be calibrated using historical or experimentally measured storage data. Second, the RL agent would be trained under normal aerobic storage conditions. Third, the trained policy would be evaluated under disturbed scenarios, including hypoxia, early biodegradation, sensor drift, and limited energy availability. Finally, the safe RL controller would be compared with rule-based control, PID regulation, and, where applicable, simplified MPC under identical initial conditions and external disturbances.

For anomaly detection, unsupervised methods such as PCA-based monitoring, Isolation Forest, One-Class SVM, or autoencoder-based reconstruction error can be applied to multidimensional sensor streams. Thresholds for anomaly detection should be determined using baseline data corresponding to normal storage operation. In particular, the anomaly threshold can be selected as a high quantile of the anomaly score distribution obtained under normal conditions, for example, the 95th or 99th percentile, depending on the required balance between false alarms and missed detections. The resulting anomaly signal can be used to restrict the action space of the RL controller, trigger safe-mode operation, or request operator inspection.

3.7 Protocol for future evaluation

The proposed framework is conceptually assessed using a set of predefined simulation scenarios and performance indicators designed for subsequent numerical verification in a calibrated digital twin environment. Since the present study focuses on the development of a cyber-physical architecture and a formal formulation of the management problem, the evaluation procedure is described as a protocol for future quantification, rather than as a completed experimental verification.

The protocol is designed to compare the proposed safe RL-based control strategy with baseline strategies, including rule-based control, classical PID regulation, and a simplified model predictive control MPC scheme [17]. All strategies should be

evaluated under the same initial conditions, external climatic influences, and storage-stage assumptions.

The following key metrics are suggested for subsequent evaluation:

- total energy consumption of the system during the storage period;
- the fraction of time during which the microclimate parameters exceed the permissible technological ranges;
- an integral indicator of the risk of loss of product quality based on accumulated deviations in temperature, humidity, and CO concentration;
- control stability, characterized by smoothness of control actions and absence of sudden fluctuations.

Additionally, as part of the subsequent validation, it is expected to analyze the potential ability of the proposed control strategy to support a compromise between energy consumption and storage quality, as well as the system's resistance to external disturbances and abnormal situations.

4 PROPOSED SIMULATION SCENARIOS FOR FUTURE VALIDATION

4.1 General formulation of the proposed validation study

The proposed validation study is designed to assess the potential effectiveness of the proposed architecture, which includes a digital microclimate twin, a safe RL controller, a multi-sensor gas analysis subsystem, and an anomaly detection module.

The future simulation study is planned to be conducted in a calibrated digital twin environment over a 180-day storage horizon with a sampling step of 10–15 minutes. Input variables would include temperature, relative humidity, and gas composition parameters, including CO_2 , NH_3 , H_2S , CH_4 , CO , and H_2 , obtained from the sensor subsystem or generated within the simulation environment.

For future comparative evaluation, the proposed RL-based control strategy is intended to be compared with baseline strategies, including rule-based control, PID regulation, and, where applicable, simplified model predictive control. All strategies should be evaluated under identical initial conditions, external disturbances, and storage-stage assumptions.

4.2 The scenario of normal aerobic storage

This scenario simulates standard storage conditions with stable aerobic respiration of products and a gradual decrease in ambient temperature [18]. The oxygen concentration is maintained at a level close to atmospheric, and CO_2 remains within acceptable limits; there are no gas markers of degradation.

Energy consumption, temperature and humidity stability, CO_2 levels, and control stability would be evaluated. The main focus would be on assessing whether the RL-based control strategy can reduce excessive energy use without violating storage conditions.

4.3 Hypoxia and anaerobic activity scenario

This scenario reflects conditions of insufficient ventilation, accompanied by a decrease in O_2 concentration and an increase in CO_2 . Additionally, the appearance of CH_4 and H_2 as markers of fermentation, as well as the growth of NH_3 , is modeled [19].

The speed of detection of the transition to an anaerobic regime, the correctness of ventilation enhancement, compliance with CMDP restrictions, and prevention of the accumulation of putrefactive gases would be analyzed.

4.4 Early biodegradation scenario

This scenario simulates the initial stages of decomposition with local growth of NH_3 and the appearance of H_2S and CO with minimal changes in temperature and humidity.

The time of detection of deviations, the transition of the system to safe mode, and the effectiveness of localization of the risk zone due to adaptive management would be analyzed [20]. Of particular importance is the ability to detect degradation in the gas profile before the appearance of temperature anomalies.

4.5 Failure scenario or systematic displacement of sensor readings

This scenario simulates abnormal situations associated with incorrect operation of the sensor subsystem and data transmission channels. It is aimed at assessing the architecture's resilience to distorted measurements and failures of IoT infrastructure elements.

The scenario reproduces typical types of measurement degradation and failures: temperature drift of electrochemical sensors, noise emissions in CO_2 readings, false positive signals over the NH_3 channel, as well as partial loss of communication of the microcontroller unit. Such violations lead to outliers, offsets, and omissions in data streams, which can negatively affect management decision-making.

In this scenario, the ability of the system to correctly process incorrect input data would be evaluated due to the mechanisms of combining sensory information, data fusion, and filtering signals. The problem of systematic measurement bias is especially relevant for IoT sensors, since parameter drift can accumulate over time and lead to a steady distortion of the observed state of the system [21].

In particular, the algorithms' resistance to noise and bias, the correctness of false alarm suppression, and the behavior of the RL controller in the presence of distorted observations would be analyzed.

Special attention would be paid to the proportion of false switching of control modes and the ability of the system to maintain stable operation without exceeding permissible technological limits.

4.6 Energy limitation scenario

The scenario considers the conditions of limited energy resources, under which restrictions are imposed on the total ventilation and cooling capacity.

The ability of the system to reallocate priorities between storage quality and energy consumption, as well as the stability of the microclimate with limited resources, would be analyzed [22]. Special attention would be paid to compliance with CMDP restrictions.

4.7 Complex scenario of unfavorable conditions

This scenario combines several unfavorable factors and is used for a comprehensive assessment of the stability of the proposed control architecture in conditions of

multiple disturbances. This statement is consistent with modern research in the field of digital twins and intelligent energy systems, where the stability of architecture would be assessed under the simultaneous influence of several external and internal disturbances [23].

The scenario simultaneously simulates an external temperature increase, an increase in CO_2 concentration, the appearance of gas degradation markers in particular, NH_3 , as well as the introduction of restrictions on available energy resources.

In this scenario, the ability of the entire system to maintain operability and stability is assessed under the simultaneous influence of several adverse factors. Special attention would be paid to the coordination between the RL controller and the anomaly detection module, as well as the dynamics of Lagrange multipliers, reflecting the system's adaptation to stricter restrictions.

Management efficiency would be assessed by the degree to which parameters are kept within acceptable ranges and the balance between energy consumption and storage quality is maintained.

5 PROPOSED EVALUATION METRICS

For a comprehensive future assessment of the effectiveness of the proposed management system, in addition to standard indicators of energy consumption and microclimate stability, an expanded set of gas analytical metrics is being introduced to take into account the biochemical processes occurring in stored products. This approach is consistent with modern research in the field of food storage and quality, where, along with temperature and humidity, monitoring of O_2 , CO_2 , NH_3 and other gas parameters as indicators of the state of the product and the storage environment is becoming increasingly important [24].

To make the proposed validation protocol more explicit, Table 1 summarizes the relationship between the proposed scenarios, simulated disturbances, evaluation focus, and expected outputs for future quantitative validation.

Table 1. Proposed validation scenarios and expected evaluation outputs

Scenario	Main Simulated Disturbance	Main Evaluation Focus	Expected Output for Future Validation
Normal aerobic storage	Stable respiration and seasonal cooling	Energy use, temperature, and humidity stability	Energy consumption profile; fraction of time within technological limits
Hypoxia and anaerobic activity	O_2 decrease, CO_2 increase, and CH_4 and H_2 appearance	Detection of anaerobic transition and ventilation response	Detection latency; CO_2 accumulation rate; constraint violations
Early biodegradation	Local increase in NH_3 , H_2S , and CO	Early anomaly detection and safe-mode activation	NH_3 detection latency; anomaly score; safe-mode switching event
Sensor failure or drift	Sensor noise, bias, missing data	Robustness to incorrect measurements	False alarm rate; missed anomaly cases; stability of control actions
Energy limitation	Restricted ventilation and cooling capacity	Energy-quality trade-off and constraint compliance	Energy use under constraint; temperature and humidity violations
Complex unfavorable conditions	Combined external warming, CO_2 increase, degradation markers, and energy limits	Overall resilience of the architecture	Stability indicators; constraint violations; controller response under multiple disturbances

Table 1 does not present completed experimental results; rather, it defines the structure of the future simulation-based validation and specifies which outputs should be analyzed for each scenario.

The proposed indicators are focused on identifying early signs of degradation and assessing storage quality based on multidimensional sensory data.

In particular, the following metrics are proposed for future validation:

- O_2 stability index is an indicator of oxygen concentration stability that characterizes the maintenance of an aerobic storage regime;
- CO_2 accumulation rate – the rate of accumulation of carbon dioxide, reflecting the intensity of respiratory processes and ventilation efficiency;
- NH_3 detection latency – the detection time of ammonia as an indicator of the initial stage of decomposition;
- H_2S peak value – the maximum value of the hydrogen sulfide concentration, which characterizes the depth of the rotting processes;
- Fermentation risk score is an integral indicator of fermentation risk calculated based on concentrations of CH_4 and H_2 ;
- The Composite Spoilage Index is a generalized indicator of product degradation that takes into account the cumulative effect of gas markers and microclimate deviations.

The use of these metrics makes it possible to move from a traditional assessment based primarily on temperature and humidity parameters to a more informative analysis of the product condition, taking into account hidden biochemical processes.

6 DISCUSSION

The integration of Internet of Things technologies ensures continuous monitoring and increased visibility of the system, which is a prerequisite for reliable monitoring of the microclimate in cold storage facilities. However, the transformation of sensory data flows into effective control actions remains a challenging task requiring a combination of physically sound models and intelligent control methods.

The proposed framework is expected to facilitate the transition from reactive control strategies to more adaptive and proactive approaches through a combination of digital twinning, safe reinforcement learning, and anomaly-based monitoring. At the same time, this advantage at the current stage is considered a methodologically sound assumption that requires further confirmation through quantitative modeling and experimental verification.

Of particular importance is the integration of an anomaly detection module based on the analysis of multidimensional sensory data. Unlike traditional systems that focus primarily on temperature and humidity parameters, the proposed approach creates the prerequisites for detecting early signs of biodegradation, even while maintaining formally acceptable microclimate conditions. The practical significance of this approach is particularly noticeable for potato storage facilities, where storage diseases can develop locally and lead to the formation of spoilage foci, followed by increased production losses [25]. It is known that the progression of certain forms of rot increases under unfavorable gas conditions, including oxygen deficiency, and is sometimes accompanied by characteristic signs such as an ammonia odor. This further supports the relevance of extended gas analytical monitoring as an addition to standard temperature and humidity monitoring.

At the same time, a number of limitations should be noted. The presented model is based on lumped equations and does not take into account spatial heterogeneity within the storage. In addition, this paper does not present quantitative results

of modeling or experimental application, so evaluating the effectiveness of the proposed architecture is considered a direction for further research.

7 CONCLUSION

The paper proposes a methodological framework for intelligent microclimate management in a small-scale potato storage facility, combining a physically grounded digital twin, safe reinforcement learning in the CMDP setting, and a multisensory gas analytical monitoring system.

Unlike traditional rule-based and PID strategies, the proposed approach formalizes the storage task as a multi-criteria optimization task with explicit consideration of technological limitations in temperature, humidity, and gas composition. The use of safe RL in the framework of the proposed formulation is focused on taking into account the compromise between product quality and energy consumption over a long storage horizon.

The key contribution of the work is the integration of a multisensor anomaly detection module based on the analysis of concentrations of CO_2 , NH_3 , H_2S , CH_4 and other markers of biodegradation. This creates the methodological prerequisites for future investigation of early detection and control adaptation before severe quality deterioration occurs.

The proposed architecture is designed for use in small and medium-sized enterprises and is compatible with existing SCADA/PLC systems. The developed approach creates the basis for further research aimed at empirical validation of the model on real objects and quantitative assessment of its potential influence on post-harvest losses and energy consumption. The main value of the proposed system is to provide a structured and reproducible framework for integrating digital twin modeling, safe reinforcement learning, and anomaly-based monitoring in the control of small-scale potato storage.

8 REFERENCES

- [1] L. Kitinoja, V. Tokala, and M. Mohammed, "Clean cold-chain development and the critical role," *Agriculture for Development*, vol. 36, pp. 19–25, 2019.
- [2] X. Tang, C. Tan, A. Chen, Z. Li, and R. Shuai, "Design and implementation of temperature and humidity monitoring system for small cold storage of fruit and vegetable based on Arduino," *Journal of Physics: Conference Series*, vol. 1601, p. 062010, 2020. <https://doi.org/10.1088/1742-6596/1601/6/062010>
- [3] S. Kh. Yakubov and R. K. Pirova, "Climate management system in the vegetable storage of perishing agricultural products," *International Journal of Latest Engineering Research and Applications IJLERA*, vol. 6, no. 9, pp. 24–32, 2021.
- [4] A. Isakov, R. Pirova, and F. Sodiqova, "Automatic control system for automatic maintenance of microclimate in vegetable storages," in *E3S Web of Conferences*, vol. 458, 2023, p. 01012. <https://doi.org/10.1051/e3sconf/202345801012>
- [5] Q. Zhen *et al.*, "Research on the temperature and humidity distribution characteristics in potato storage facilities: Experimental analysis and numerical simulation," *Front. Sustain. Food Syst.*, vol. 9, p. 1594791, 2025. <https://doi.org/10.3389/fsufs.2025.1594791>
- [6] D. Onwude, G. Chen, N. Eke-emezie, A. Kabutey, A. Alkhaled, and B. Sturm, "Recent advances in reducing food losses in the supply chain of fresh agricultural produce," *Processes*, vol. 8, no. 11, p. 1431, 2020. <https://doi.org/10.3390/pr8111431>

- [7] Ph. Trotter, T. Becker, R. Renaldi, X. Wang, R. Khosla, and G. Walther, "The role of supply chains for the sustainability transformation of global food systems: A large-scale, systematic review of food cold chains," *Journal of Industrial Ecology*, vol. 27, no. 7, pp. 1429–1446, 2023. <https://doi.org/10.1111/jiec.13445>
- [8] T. G. Hoffmann *et al.*, "Challenges and future perspectives in postharvest cold storage: Technological review on sustainable and efficient cold storage of fresh produce," *Food Research International*, vol. 221 (Part 3), 2025. <https://doi.org/10.1016/j.foodres.2025.117406>
- [9] M. Mohammed, K. Riad, and N. Alqahtani, "Design of a smart IoT-based control system for remotely managing cold storage facilities," *Sensors*, vol. 22, no. 13, p. 4680, 2022. <https://doi.org/10.3390/s22134680>
- [10] A. Sher, U. Khan, M. Rafique, A. Ikram, and A. Mazhar, "Development and analysis of a smart cold storage system for fruit warehouses," in *MATEC Web of Conferences*, vol. 398, 2024. <https://doi.org/10.1051/mateconf/202439801027>
- [11] H. Afreen and I. Bajwa, "An IoT-based real-time intelligent monitoring and notification system of cold storage," *IEEE Access*, vol. 9, pp. 38236–38253, 2021. <https://doi.org/10.1109/ACCESS.2021.3056672>
- [12] I. N. Krasnikova, V. L. Simonov, and A. E. Petelin, "Features of development of an agricultural warehouse digital twin," *BIO Web of Conferences*, vol. 83, p. 03004, 2024. <https://doi.org/10.1051/bioconf/20248303004>
- [13] M. Hammerschmid *et al.*, "Thermal Twin 4.0: Digital Support tool for optimizing hazardous waste rotary Kiln incineration plants," *Waste and Biomass Valorization*, vol. 14, pp. 2745–2766, 2023. <https://doi.org/10.1007/s12649-022-02028-w>
- [14] A. Wachi, Sh. Xun, and Y. Sui, "A survey of constraint formulations in safe reinforcement learning," in *Conference: Thirty-Third International Joint Conference on Artificial Intelligence IJCAI-24*, 2024, pp. 8262–8271. <https://doi.org/10.24963/ijcai.2024/913>
- [15] V-H. Bui, S. Das, A. Hussain, G. Hollweg, and W. Su, "A critical review of safe reinforcement learning techniques in smart grid applications," *arXiv preprint arXiv:2409.16256*, 2024. <https://doi.org/10.48550/arXiv.2409.16256>
- [16] A. Chatterjee and B. S. Ahmed, "IoT anomaly detection methods and applications: A survey," *Internet of Things*, vol. 19, p. 100568, 2022. <https://doi.org/10.1016/j.iot.2022.100568>
- [17] Kh. Sayed, B. Abhinandana, R. S. Broujeny, and K. Beddiar, "Reinforcement learning for HVAC control in intelligent buildings: A technical and conceptual review," *Journal of Building Engineering*, vol. 95, p. 110085, 2024. <https://doi.org/10.1016/j.jobbe.2024.110085>
- [18] V. Pedrosa *et al.*, "The relationship between respiration rate and quality parameters of Russet potatoes during long-term storage," *American Journal of Potato Research*, vol. 102, no. 2, 2025. <https://doi.org/10.1007/s12230-025-09977-7>
- [19] H. Lin, Zh. Wei Zh, Ch. Chen, Y. Huang, and J. Zhu, "Early identification of rotten potatoes using an electronic nose based on feature discretization and ensemble convolutional neural network," *Sensors*, vol. 24, no. 10, p. 3105, 2024. <https://doi.org/10.3390/s24103105>
- [20] S. Trilles, S. S. Hammad, and D. Iskandaryan, "Anomaly detection based on artificial intelligence of things: A systematic literature mapping," *Internet of Things*, vol. 25, p. 101063, 2024. <https://doi.org/10.1016/j.iot.2024.101063>
- [21] J. Dong, Z. Li, Zh. Yuanshuo, J. Luo, M. Zhang, and X. Yang, "Real-time fault detection for IIoT facilities using GA-Att-LSTM based on edge-cloud collaboration," *Frontiers in Neurorobotics*, vol. 18, p. 1499703, 2024. <https://doi.org/10.3389/fnbot.2024.1499703>
- [22] F. Guo, S. Ham, D. Kim, and H. Moon, "Deep reinforcement learning control for co-optimizing energy consumption, thermal comfort, and indoor air quality in an office building," *Applied Energy*, vol. 377, p. 124467, 2025. <https://doi.org/10.1016/j.apenergy.2024.124467>

- [23] A. Abdessadak, H. Ghennioui, N. Thirion-Moreau, M. Abraim, B. Elbhiri, and S. Merzouk, "Digital twin technology and artificial intelligence in energy transition: A comprehensive systematic review of applications," *Energy Reports*, vol. 13, pp. 5196–5218, 2025. <https://doi.org/10.1016/j.egy.2025.04.060>
- [24] W. Heo and S. Lim, "A Review on Gas Indicators and Sensors for Smart Food Packaging," *Foods*, vol. 13, no. 19, p. 3047, 2024. <https://doi.org/10.3390/foods13193047>
- [25] B. Olsen, J. Miller, and P. Nolte, "Diagnosis & Management of Potato Storage Diseases," CIS 1131, University of Idaho Extension/Idaho Agricultural Experiment Station, 2006. <https://idahopotato.com/uploads/media/diagnosis-and-management-of-potato-storage-disease.pdf>

9 AUTHORS

Gulmira Baenova is a postdoctoral researcher at the Postdoctoral Department, Turon University, Karshi 180100, Uzbekistan; the Postdoctoral Department, International Engineering and Technology Institute, Hong Kong, China; and the Institute of Digital Sciences and Artificial Intelligence, L.N. Gumilyov Eurasian National University, Astana, Republic of Kazakhstan (E-mail: baenova_gm@enu.kz).

Madina Serikova is a postdoctoral researcher at the Postdoctoral Department, Turon University, Karshi 180100, Uzbekistan; Postdoctoral Department, International Engineering and Technology Institute, Hong Kong, China; Department of State Audit, L.N. Gumilyov Eurasian National University, Astana, Republic of Kazakhstan (E-mail: madinaserikova81@gmail.com).

Dr. Aruna Animish Pavate is a postdoctoral researcher at the Postdoctoral Department, Turon University, Karshi 180100, Uzbekistan; the Postdoctoral Department, International Engineering and Technology Institute, Hong Kong, China; and Thakur College of Engineering and Technology, Mumbai, Maharashtra, India (E-mail: arunaapavate@gmail.com).