MULTIMODAL SCENARIO CONTROL METHOD FOR LOW-TEMPERATURE GRAIN STORAGE BASED ON THE ADABELIEF ALGORITHM
/
基于 Adabelief 算法的低温粮食储存多模态场景控制方法

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ABSTRACT
To address the issues of slow convergence in traditional methods, this study integrates adaptive gradient correction with a belief update mechanism based on the AdaBelief algorithm, and proposes a multimodal scenario control model for low-temperature grain storage. Experimental results indicate that the proposed model can maintain the grain storage temperature at approximately 12°C under various environmental conditions, and the average conductivity of wheat, rice, corn, and soybean is kept below 45 µs.cm^{-1}. These findings demonstrate that the proposed model significantly improves the level of intelligent control in low-temperature grain storage systems and provides a novel approach for the precise regulation of grain storage environments.

摘要
为解决传统方法收敛速度慢的问题，本研究通过 AdaBelief 算法将自适应梯度校正与信念更新机制相结合，提出了一种低温粮食储存的多模态场景控制模型。实验结果表明，在各种环境条件下，所提出的模型可以将粮食储存温度保持在约 12° C，小麦、水稻、玉米和大豆的平均电导率保持在 45 µs.cm^{-1} 以下。这些发现表明，所提出的模型显著提高了低温粮食储存系统的智能控制水平，并为粮食储存环境的精确调节提供了一种新方法。

INTRODUCTION
By keeping the grain temperature below 15°C, it effectively suppresses insect reproduction and microbial metabolism, while slowing down the deterioration of grain quality (*Zhao et al., 2023*). As a major grain-producing and consuming country, China faces challenges in storage practices due to the high energy consumption of traditional mechanical ventilation and grain cooling systems (*Cao et al., 2022; Chang et al., 2023*). Therefore, applying intelligent technologies to precisely regulate grain temperature has opened up new possibilities for low-temperature grain storage (*Ren et al., 2023*). Early studies primarily used the Proportional-Integral-Derivative (PID) controller and fuzzy logic to adjust ventilation parameters. However, these methods rely heavily on manual parameter tuning and have limited adaptability (*Li et al., 2023*). Recently, intelligent control methods based on multimodal data integration have gained attention. However, these models may cause information loss due to their reliance on single-modality data (*Tsanousa et al., 2022*). The AdaBelief algorithm provides a promising solution by building a multimodal deep reinforcement learning framework that improves convergence stability under complex conditions (*Hamzaoui et al., 2024*). The AdaBelief algorithm improves the convergence efficiency and control accuracy of the model in non-stationary environments by adaptively adjusting the learning rate, and is suitable for dynamic control scenarios of multivariate and multimodal data in low-temperature grain storage. *Guan L. et al. (2024)* put forward a deep learning training model that combined weight prediction with gradient optimization which uses the AdaBelief algorithm along with five other models to verify forward and backward propagation based on the update rules of the optimizers. *Yang et al. (2023)* introduced the AdaBelief optimizer into adversarial sample generation to address the problem of inaccurate outputs caused by adversarial attacks on deep neural networks. They also proposed a fast gradient method based on AdaBelief to optimize the convergence process of deep neural networks. *Zhou et al. (2023)* introduced beliefs based on a fast adaptive revocable argumentation framework to examine whether the AdaBelief algorithm could further improve convergence speed without compromising generalization ability.

Wang et al. (2025) used AdaBelief algorithm to solve the step size selection problem in intelligent algorithms, and combined it with mean square projection function. The experimental results showed that this method has good performance in neural network training.

The development of low-temperature grain storage methods has matured in both theory and practice and has been widely applied in real-world grain storage. *Ngoma et al. (2024)* analyzed the composition of two types of storage bags for post-harvest grain storage and compared the changes in grain quality after storage. *Zhao et al. (2023)* analyzed green grain storage technologies popular worldwide in response to increasing demand for healthy food and global efforts to protect the environment. They noted that low-temperature storage technology adapts to local climates by modifying temperature-controlled warehouses to seal grain and reduce metabolic changes. *Ji et al. (2025)* have designed a method that combines quantitative analysis algorithms to improve the quality of low-temperature grain storage. Experimental results show that the proposed method can effectively improve the storage effect of wheat grain quality. Paim de Oliveira and his pattern (2025) established a mathematical model algorithm to improve the quality of grain storage at different temperatures. The results showed that the proposed method can effectively provide grain storage quality.

In summary, existing studies have made progress in low-temperature grain storage technologies, but still face limitations in prediction performance and intelligence. The AdaBelief algorithm can support intelligent prediction and enable real-time and comprehensive monitoring under varying conditions. Therefore, this study introduces a multimodal scenario control model for low-temperature grain storage based on the AdaBelief algorithm, aiming to ensure food safety. The innovation of this study lies in combining AdaBelief with multimodal deep reinforcement learning, designing a cross-modal interaction mechanism, and constructing a multimodal model that supports optimization of both energy consumption and temperature control accuracy.

MATERIALS AND METHODS

Design of low-temperature grain storage method based on AdaBelief algorithm

AdaBelief is an optimization algorithm designed for deep learning, with the core idea of balancing convergence speed and generalization performance by dynamically adjusting the gradient update step size. Its adaptive learning ability has shown significant advantages in the field of low-temperature grain storage. Therefore, the study adopts the AdaBelief algorithm to identify abnormal data, quickly locate anomalies, and trigger warnings.

The AdaBelief algorithm is shown in Equation (1) (*Muthubalaji et al., 2024*).

$$\begin{cases} t \leftarrow t+1 \\ g_t \leftarrow \nabla \theta_t f_t(\theta_{t-1}) \\ m_t \leftarrow \beta_1 m_{t-1} + (1-\beta_1) g_t \\ s_t \leftarrow \beta_2 v_{t-1} + (1-\beta_2)(g_t - m_t)^2 \end{cases} \tag{1}$$

In Equation (1), t represents the current iteration count. $f_t(\theta_t)$ represents the loss function to be minimized during the t-th optimization. θ_t refers to the parameters of the loss function. g_t denotes the gradient of $f_t(\theta_{t-1})$ with respect to θ_t. m_t is the predicted value of the gradient. s_t represents the exponential moving average of $(g_t - m_t)^2$. ∇ is the partial derivative operator. β_1 and β_2 are smoothing parameters. v_t is the exponential moving average of g_t^2. α and ε are values close to zero to ensure the validity of the expression and correct the bias.

The estimated value after deviation correction is shown in formula (2).

$$\begin{cases} \hat{m}_t \leftarrow \hat{m}_t / (1-\beta_1) \\ \hat{s}_t \leftarrow (s_t + \varepsilon) / (1-\beta_2) \end{cases} \tag{2}$$

In Equation (2), $\hat{m}_t$ represents the first-order moment estimation after deviation correction. $\hat{s}_t$ represents the second-order moment estimation after deviation correction. The update for θ_t in the AdaBelief algorithm is given in Equation (3).

$$\theta_t \leftarrow \theta_{t-1} - \alpha \hat{m}_t / \sqrt{\hat{s}_t + \varepsilon} \tag{3}$$

AdaBelief has high accuracy in tasks such as image classification and language modeling, and its application to low-temperature grain storage can more accurately monitor the status of grains. The process of intelligent control for low-temperature grain storage is shown in Figure 1.

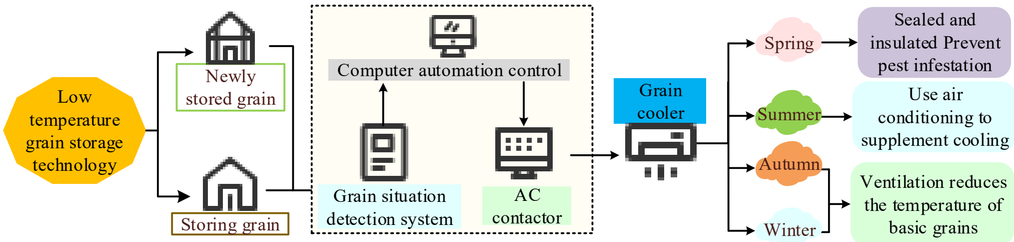


Fig. 1 – Flowchart of the low-temperature grain storage process
(*Icon source from: https://iconpark.oceanengine.com/home*)

As illustrated in Figure 1, the system acquires real-time key parameters, including temperature, relative humidity, and pest activity, and transmits the data to the automatic control system to regulate the operation of the grain cooling unit. The cooling system applies season-specific control strategies to adapt to varying environmental conditions. Various external interferences may affect the accuracy of AdaBelief in low-temperature environments. Therefore, Programmable Logic Controller (PLC) technology is applied in this field (*Li et al., 2023*). PLC is an industrial automation control device that can achieve equipment control or production process management, with high reliability, flexibility, and compatibility, and is suitable for complex industrial environments. In the control system, PLC generates the final control instructions by comprehensively calculating multiple input signals, as shown in equation (4).

$$U = \partial E_1 + (1-\partial)E_2, \partial \in [0,1] \tag{4}$$

In Equation (4), U denotes the control value. E represents the temperature parameter of the storage. ∂ is the configuration weight coefficient. PLC programming enables the calculation of the temperature sensor data's change rate, as shown in Equation (5).

$$R_{i,j} = \frac{T_{i,j} - T_{i,j-1}}{\Delta t} \tag{5}$$

In Equation (5), $R_{i,j}$ represents the temperature change rate of the i-th sensor at the j-th sampling time. $T_{i,j}$ represents the temperature value. $T_{i,j-1}$ represents the temperature value measured by the same sensor at the previous sampling moment. Δt represents the time interval. In practical applications, the performance of PLC algorithms is constrained by various real-world factors. To address this issue, this study employed a PID controller with an adaptive mechanism. The PID-PLC architecture is formed by embedding the PID algorithm into the PLC. The principle of the PID-PLC control system is shown in Figure 2.

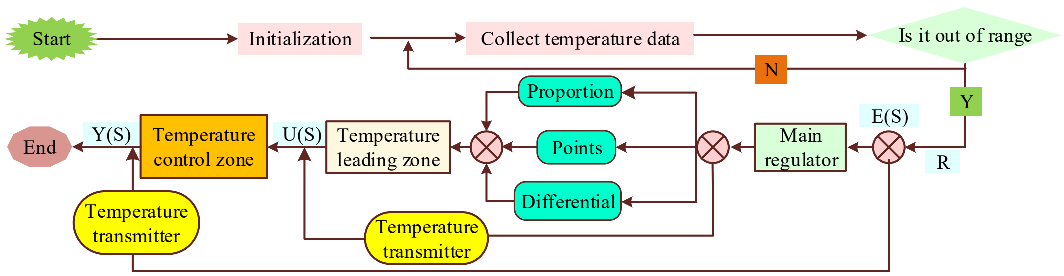


Fig. 2 – Principle diagram of the PID-PLC control system
(Source from: author self-drawn)

As shown in Figure 2, the collected data is initialized by the PID controller, which checks whether the values exceed predefined thresholds. The results pass through the temperature pre-control and temperature regulation zones to adjust the temperature.

The PID controller calculates the control error $E(S)$ from the setpoint $R(S)$ and the actual output $Y(S)$, as shown in Equation (6).

$$E(S) = R(S) - Y(S) \tag{6}$$

The control rule formed by the linear combination is expressed in Equation (7).

$$U(S) = K_P[E(S) + \frac{1}{T_I}\int E(S)dS + \frac{T_D dE(S)}{dS}] \tag{7}$$

In Equation (7), K_p is the proportional gain, T_I is the integral time constant, and T_D is the derivative time constant.

PID-PLC collects real-time temperature data from various points inside the grain pile and feeds this information back to the controller while also supplying reliable data to AdaBelief, allowing it to adjust the temperature dynamically. Therefore, this study combines the PID-PLC algorithm with AdaBelief to develop the AdaBelief-PID-PLC hybrid algorithm, and its process is shown in Figure 3.

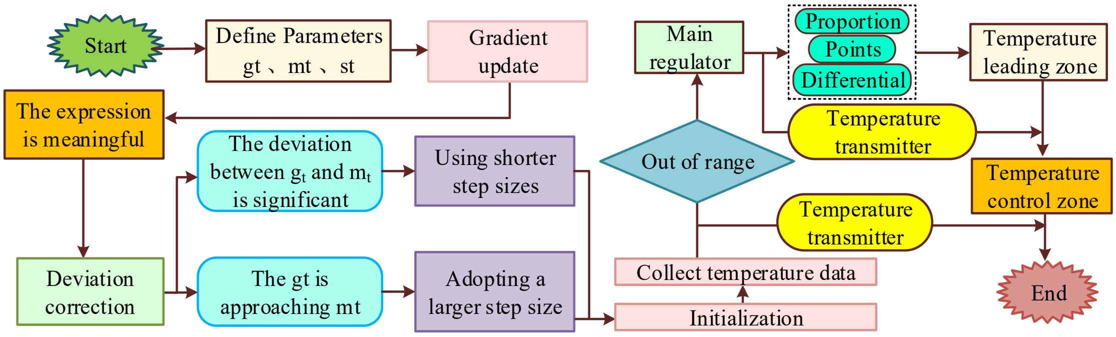


Fig. 3 – Flowchart of the AdaBelief-PID-PLC algorithm
(Source from: author self-drawn)

In Figure 3, AdaBelief first defines parameters and then updates gradients. After that, it passes through the PID system. The main control module outputs commands based on optimized parameters, regulates the power of cooling equipment, and adjusts temperature through proportional, integral.

Low-temperature grain storage model combining CNN-RNN-Transformer and AdaBelief-PID-PLC

Although the AdaBelief PID PLC algorithm can monitor grain conditions in real-time and dynamically adjust warehouse temperatures, the deep application of intelligent control systems also brings potential risks to data and network security. It is crucial to build an intelligent security framework that can resist external influences (*Muthubalaji et al., 2024*). Therefore, this study introduces the Transformer algorithm to optimize the model. The core advantage of Transformer lies in its ability to handle long sequence text and avoid the problem of vanishing gradients in long sequences.

The Transformer algorithm is shown in Equation (8).

$$Attention(Q,K,V)=soft\max(\frac{QK^T}{\sqrt{d_K}})V \tag{8}$$

In Equation (8), Q represents the query vector, K denotes the key vector, V indicates the value vector, and d_K is the dimension of the key vector K. The supplementary equation is shown in Equation (9).

$$\begin{cases} MultiHead(Q,K,V)=Concat(head1,...,headh)WO \\ headi=Attention(QW_i^W,KW_i^K,VW_i^V) \end{cases} \tag{9}$$

However, Transformer has weak local feature extraction capabilities and struggles to focus on local details. Convolutional Neural Network combined with Recurrent Neural Network (CNN-RNN) is good at extracting local features and enhances overall model performance, allowing for more comprehensive information processing (*Li et al., 2023; Guo et al., 2024*). The convolutional layer in CNN performs local convolution on input signals using the same kernel and a sigmoid activation function within the filter to extract features. The convolution process is shown in Equation (10).

$$(I*C)(z,a)=\sum_M\sum_n I(M,n)\bullet K(z-M,a-n) \tag{10}$$

In Equation (10), I denotes the input image, C is the convolutional layer, M and n are the sliding window indices of the kernel on the input matrix, z represents the coordinate position in the output feature map, and a is the corresponding index of the convolution result. The pooling layer in CNN serves as a downsampling layer, which can reduce the size of the feature map. Max pooling retains the most prominent features by selecting the maximum value in the window, as shown in Equation (11).

$$L=\max(x_1,x_2,...,x_n) \tag{11}$$

In Equation (11), L denotes the output value after pooling, and x represents the set of features within the pooling window. The CNN-RNN algorithm optimizes the Transformer algorithm and forms the CNN-RNN-Transformer algorithm. Its process is shown in Figure 4.

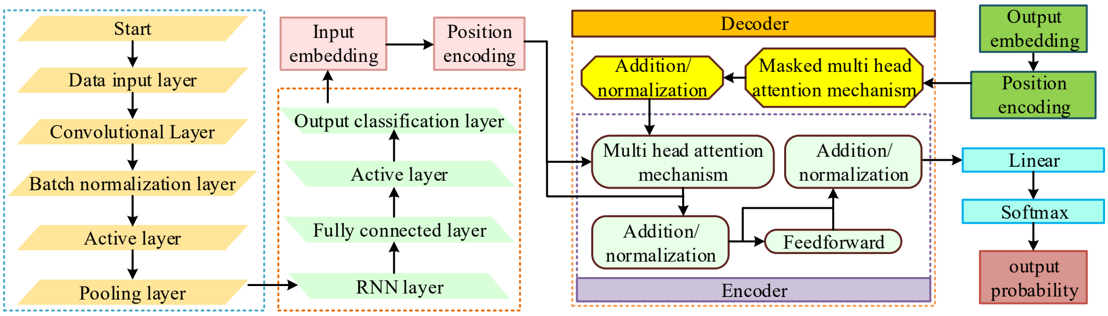


Fig. 4 – Flow chart of the CNN-RNN-Transformer algorithm
(Source from: author self-drawn)

As shown in Figure 4, the data enters the convolutional layer for automatic local feature extraction, followed by batch normalization. The activation layer introduces nonlinearity to prevent overfitting. The pooling layer then reduces data dimensionality. The data proceeds to the RNN layer to capture time-varying patterns and long-term dependencies of the features. It then goes through a fully connected layer and another activation layer. The final data processed by CNN-RNN is input into the Transformer algorithm. It is embedded, position-encoded, and enters the encoder, where it passes through multi-head attention, a feed-forward network, and normalization, followed by Linear and Softmax layers to output probabilities. The RNN is described by Equation (12).

$$\zeta_{\psi} = \tan\zeta(\xi_{\zeta\zeta}\zeta_{\psi-1} + \xi_{\omega\zeta}\omega_{\psi} + \upsilon_{\zeta}) \tag{12}$$

In Equation (12), ζ_{ψ} denotes the hidden state at a specific time, $\zeta_{\zeta\zeta}$ is the weight matrix from one hidden state to the next, $\zeta_{\psi-1}$ indicates the previous time step, $\zeta_{\omega\zeta}$ is the weight matrix from input to the hidden layer, ω_{ψ} is the input data at a specific time, υ_{ζ} is the bias term of the hidden layer, and $\tan\zeta$ is the activation function. This study proposes a multimodal scenario control model for low-temperature grain storage based on CNN-RNN-Transformer and AdaBelief-PID-PLC. Its operational process is shown in Figure 5.

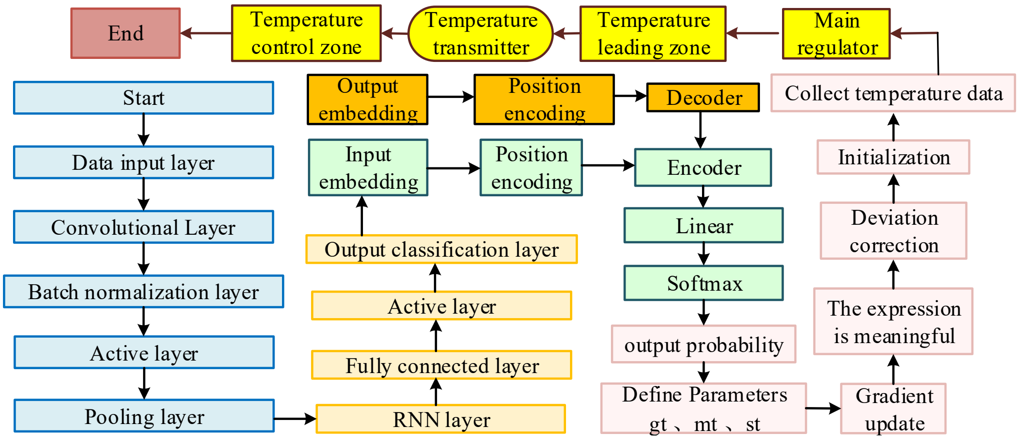


Fig. 5 – Multimodal scenario control process of the grain storage model based on CNN-RNN-Transformer and AdaBelief-PID-PLC
(Source from: author self-drawn)

As shown in Figure 5, the model processes the data with the Transformer algorithm optimized by CNN-RNN. It then defines parameters in the AdaBelief algorithm and performs gradient updates. The collected data is filtered by the PID system. If the data meets the range requirements, PLC inputs it into the control system to define a dynamic temperature control curve. The main control module outputs instructions based on optimized parameters to adjust cooling device power. It then controls temperature using proportional, integral, and derivative computations through the temperature pre-control and control zones.

RESULTS

Validation of the improved AdaBelief algorithm

To evaluate the accuracy of the AdaBelief-PID-PLC algorithm, the study compared it with Adam-PID, fuzzy adaptive PID, and SGD-PID models. The experiments ran on a system with Windows 10 version, Linux 5.15.133 operating system, Python 3.10.12 as the programming language, NVIDIA RTX3080 graphics card, and 10GB memory.

To ensure the authenticity and reliability of the experiments, the Fashion-MNIST dataset and a shallow silo grain cooling low-temperature storage dataset were selected for testing and training. The same learning rate and iteration count were applied across all models. The study tested the accuracy and loss rates of the temporal convolutional network optimized with attention mechanism under AdaBelief-PID-PLC, Adam-PID, fuzzy adaptive PID, and SGD-PID. The results are shown in Figure 6.

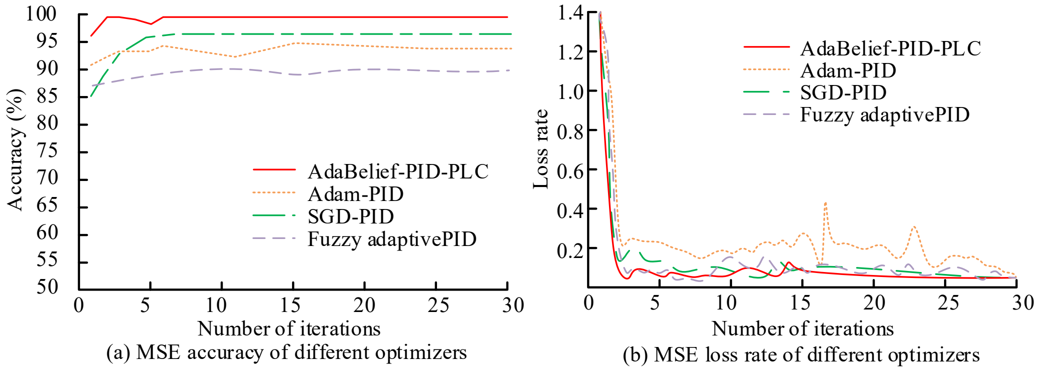


Fig. 6 – Temperature control results over one year
(Source from: author self-drawn)

Figure 6(a) shows that AdaBelief-PID-PLC achieved a high accuracy of 99.8%, which was significantly higher than the other models, with very small fluctuations throughout the process. It should be pointed out that the 99.8% accuracy was measured on the Fashion MNIST standard image classification dataset, which mainly verifies the algorithm's excellent feature learning and convergence ability in ideal and stable data environments. However, in more challenging practical multimodal control scenarios for low-temperature grain storage, the evaluation of system performance needs to comprehensively consider multiple indicators such as temperature control accuracy, energy consumption, and stability. Moreover, factors such as sensor errors in actual environments, local temperature and humidity anomalies caused by food impurities, and complex external climate disturbances can introduce data noise and uncertainty, leading to a decrease in the accuracy of algorithms compared to ideal datasets. Adam-PID's accuracy steadily increased from 85% to 95%. SGD-PID's accuracy gradually rose from 80% to 90%. Fuzzy adaptive PID fluctuated around 85%. Figure 6(b) shows that the loss value of AdaBelief-PID-PLC quickly dropped from 1.4 to below 0.15 and remained stable, indicating the highest optimization efficiency among the four algorithms. Adam-PID's loss quickly decreased from 1.4 to 0.2. SGD-PID started at a loss of 1.4, dropped to 0.15, then rose slightly and fluctuated around 0.2, slowly declining after 20 iterations. Fuzzy adaptive PID's loss decreased slowly from 1.4, with large fluctuations and slower convergence compared to the other three models. In summary, AdaBelief-PID-PLC outperformed other models in accuracy and loss metrics, demonstrating good accuracy and convergence. To further verify the effectiveness of AdaBelief-PID-PLC, the study compared prediction errors on the test set across different optimizers. The results appear in Figure 7.

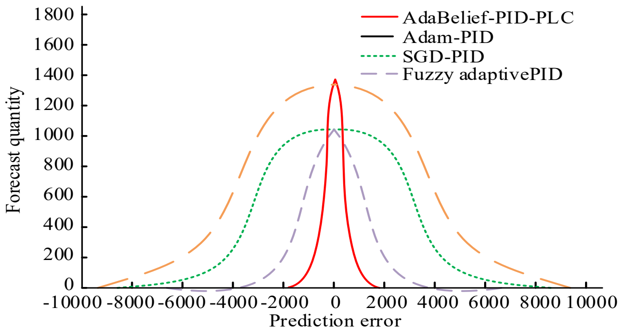


Fig. 7 –Prediction error distribution on test set
(Source from: author self-drawn)

As shown in Fig.7, AdaBelief-PID-PLC had the largest number of small-error prediction samples, while the count of prediction samples with errors exceeding 2000 MW approached zero. The fuzzy adaptive PID showed larger prediction errors and performed worse than the other models in training. Meanwhile, AdaBelief-PID-PLC ran significantly faster than Adam-PID and SGD-PID in each iteration, reducing single computation time by 24.8% and 6.9%, respectively. The study's algorithm not only surpassed traditional methods in prediction accuracy but also improved computational speed, enhancing load forecasting efficiency.

Overall, AdaBelief-PID-PLC showed faster convergence, better stability, clear accuracy advantages, and stronger normalization ability. The study then compared the prediction results of the proposed algorithm with fuzzy adaptive PID, Adam-PID, and SGD-PID under the improved framework against real values, as shown in Fig.8.

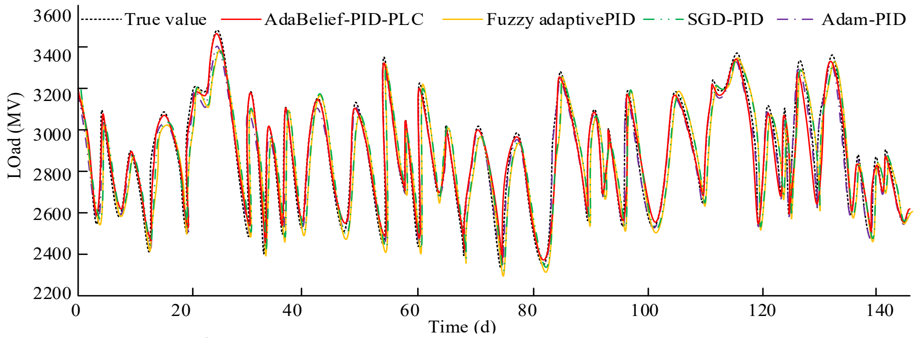


Fig. 8 – Comparison between predicted values and real values
(Source from: author self-drawn)

As shown in Figure 8, the proposed algorithm's predictions were closer to the real values, indicating obvious performance advantages and smaller load prediction errors. In contrast, fuzzy adaptive PID, Adam-PID, and SGD-PID had visible gaps compared to real values. In summary, the proposed algorithm achieved breakthroughs in key metrics such as accuracy and loss. It not only exceeded similar models in prediction precision but also exhibited excellent convergence properties. The algorithm featured faster parameter optimization, a more stable training process, and unique advantages in data normalization, confirming its effectiveness.

Analysis of the multimodal scenario control model for low-temperature grain storage

After confirming the feasibility of the AdaBelief-PID-PLC model for low-temperature grain storage, this study aimed to ensure its stable performance in multimodal control scenarios. The study recorded the temperature control results of the proposed model across different periods of the year. The model was compared with the PROFIBUS-based low-temperature grain storage model, the fuzzy adaptive PID low-temperature grain storage model, and the Liquefied Natural Gas (LNG) cold energy low-temperature grain storage model. The results are shown in Fig.9.

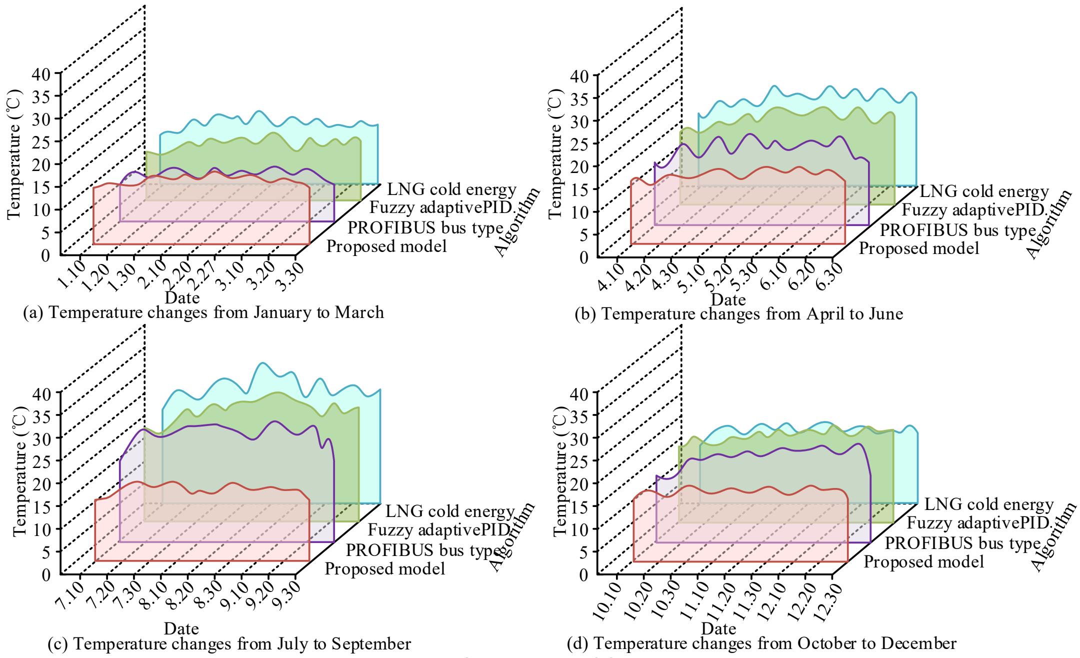
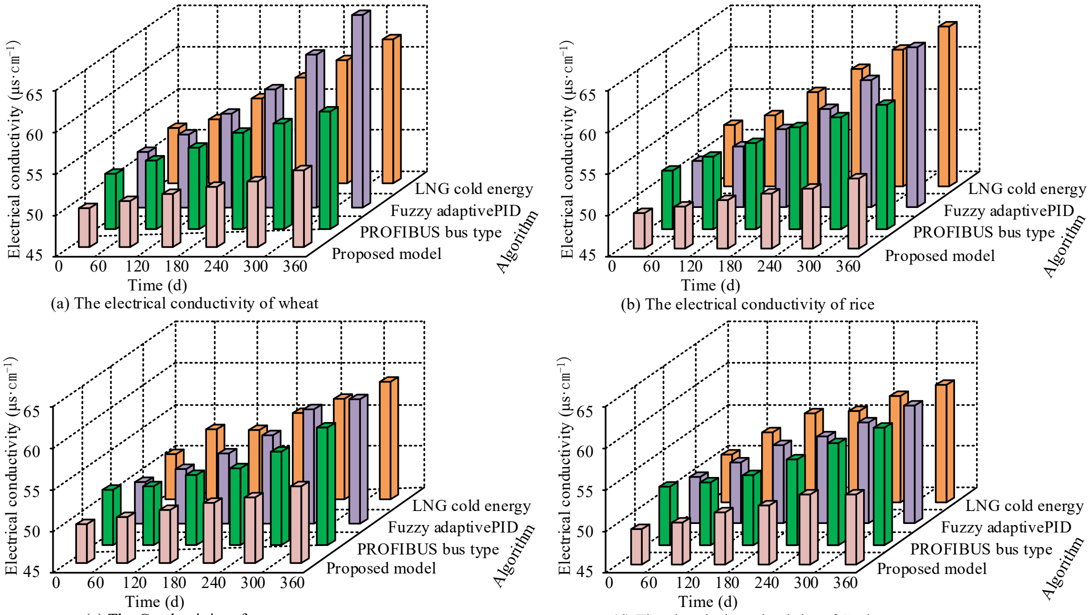


Fig. 9 –Temperature control performance of four models throughout the year
(Source from: author self-drawn)

As shown in Figure 9, the CNN-RNN-Transformer combined with the AdaBelief-PID-PLC model achieved better temperature control than the other three models throughout various time periods. It maintained the warehouse temperature around 12°C with minimal fluctuation, demonstrating that it was not affected by ambient temperature and performed well in all seasons.

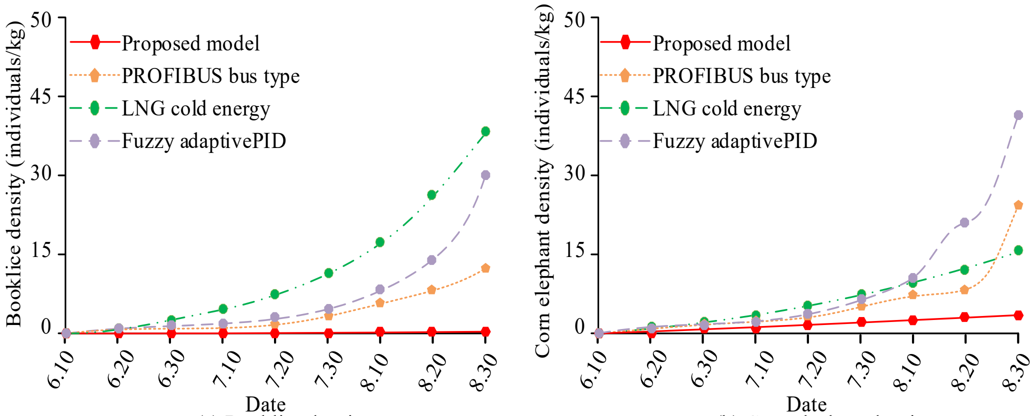
The LNG cold energy model was affected by seasonal changes, with an average temperature of 25°C in spring, 33°C in summer, 28°C in autumn, and 15°C in winter. Both the PROFIBUS-based model and the fuzzy adaptive PID model also showed susceptibility to weather changes and failed to maintain a stable temperature like the proposed model. To evaluate the model's performance on different grain types, randomly selected grains were soaked in water and their leachate conductivity was measured. A higher conductivity value indicated greater damage to cell membranes and faster electrolyte diffusion. The conductivity of grains stored under the proposed model was compared with those stored under the PROFIBUS-based, fuzzy adaptive PID, and LNG cold energy models. The results are shown in Figure 10.



(a) The electrical conductivity of wheat
(b) The electrical conductivity of rice
(c) The Conductivity of corn
(d) The electrical conductivity of Soybean

Fig. 10 – Conductivity of different grains under four storage models
(Source from: author self-drawn)

As shown in Fig.10, the grains stored using the proposed model showed the lowest conductivity across all types. The average conductivity for wheat, rice, corn, and soybeans under this model remained below 45 μs·cm^{-1}. For rice, the average conductivity values under the PROFIBUS-based model, fuzzy adaptive PID model, and LNG cold energy model were 59 μs·cm^{-1}, 65 μs·cm^{-1}, and 62 μs·cm^{-1}, respectively. For corn, the PROFIBUS-based model achieved a relatively good result with values below 55 μs·cm^{-1}, while the average conductivity for soybeans reached 59 μs·cm^{-1}. Both the fuzzy adaptive PID model and the LNG cold energy model yielded conductivity values over 55 μs·cm^{-1} for stored corn and soybeans. In summary, the proposed model preserved different grain types effectively and demonstrated general applicability to various storage needs. To further assess how the proposed model addressed pest problems in grain storage, the study conducted a comparative analysis with the PROFIBUS-based model, the fuzzy adaptive PID model, and the LNG cold energy model. The results are shown in Fig.11.



(a) Booklice density
(b) Corn elephant density

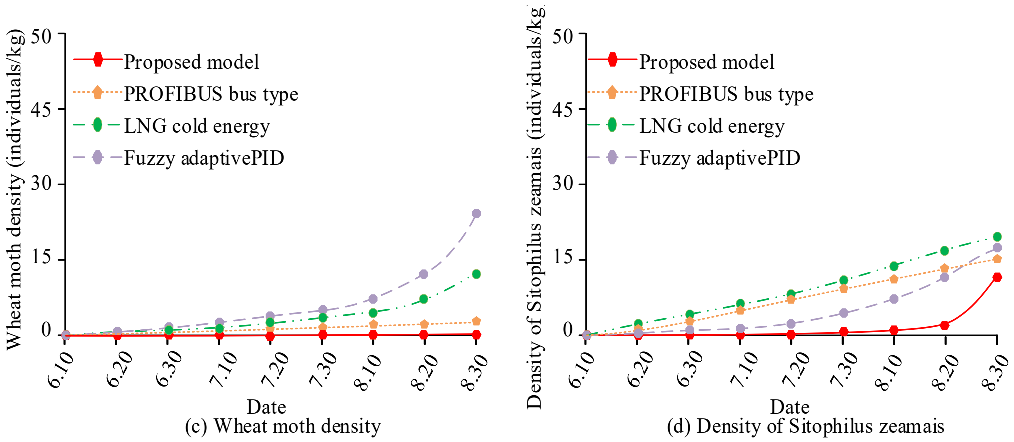


Fig. 11 – Pest control performance of four models across different grain pests
(Source from: author self-drawn)

As shown in Figure 11(a), for Rhizopertha dominica density control, the fuzzy adaptive PID and LNG cold energy models exhibited a significant upward trend over time, indicating increasing pest density. In contrast, the proposed model maintained a steady, low-density curve. The PROFIBUS-based model initially showed good control but gradually increased in the later stages. In Figure 11(b), regarding Sitophilus zeamais, the fuzzy adaptive PID model showed a sharp rise in the later period, the PROFIBUS-based model increased gradually, and the LNG cold energy model showed a steady increase. The model based on the AdaBelief algorithm consistently maintained an extremely low density, showing outstanding control. Figure 11(c) illustrated that for Ephestia kuehniella, both the fuzzy adaptive PID and LNG cold energy models displayed noticeable increases in the later stages, while the PROFIBUS-based model and the proposed model maintained low levels throughout. In Figure 11(d), for Sitophilus oryzae, the LNG cold energy model continued to rise, the PROFIBUS-based model showed gradual growth, and the fuzzy adaptive PID model exhibited a slight increase. The proposed model remained stable in the early phase and showed only a slight increase later, still staying at a relatively low level. Overall, the proposed model effectively suppressed pest density and performed well in controlling multiple types of grain pests.

CONCLUSIONS

This study addresses the key challenges of multimodal data coupling complexity and insufficient dynamic adaptability of control strategies in low-temperature grain storage systems. A collaborative control model is proposed that integrates a CNN-RNN-Transformer multimodal feature extraction framework with an AdaBelief-PID-PLC intelligent control strategy. The proposed method innovatively embeds the AdaBelief optimizer into the PID-PLC control architecture, enabling adaptive parameter adjustment through dynamic gradient correction and a belief update mechanism. Breaking through the limitations of the traditional single modal, a cross-modal interaction module is designed. The global attention mechanism of Transformer is utilized to integrate spatio-temporal features, combined with the local detail capture ability of CNN-RNN, significantly improving the fusion efficiency of multi-source data. Meanwhile, a three-level closed-loop system of "feature extraction - parameter optimization - execution control" is constructed.

The experimental results show that the prediction accuracy of the model is as high as 99.8%, mainly due to the effective filtering of gradient noise by the confidence update mechanism of the AdaBelief algorithm. But this only represents the strong performance of the model under ideal data conditions, and its stability in the complex noise environment of actual grain warehouses still needs long-term observation. Meanwhile, the parallel computing capability of the Transformer avoids gradient vanishing during long sequence training, ensuring the stability of temperature control in complex environments.

The convergence speed of the research method has increased by 24.8%, which is attributed to the AdaBelief adaptive step size strategy significantly accelerating the parameter optimization process. Combined with the multimodal feature complementarity mechanism, it avoids information loss in single-modal models. The research method performed better than the other three types of comparison models in temperature control throughout the year in all seasons, and could precisely maintain the temperature of the grain silo around 12℃. This proves the effectiveness of the closed-loop system of "feature extraction parameter optimization execution control" proposed by the research institute.

The experimental indicators accurately demonstrated the superiority of the research method in the three key performances of accuracy, efficiency and generalization ability. Compared with traditional models and comparative models, the research method can better stably control the temperature of grains under the influence of different environments, different grains, and different pests, providing a replicable technical solution for the construction of smart grain depots. However, the experimental data in this study mainly comes from simulated environments and some measured datasets, and the long-term reliability in real large-scale grain warehouses needs to be verified. Moreover, multimodal data fusion still relies on preset weights and lacks cross modal adaptive interaction capabilities. Therefore, in future research, the system should be further deployed in actual grain warehouses in different regions for long-term validation, exploring adaptive fusion methods based on attention mechanisms to enhance cross modal interaction capabilities, and introducing anomaly detection and digital twin technology to improve system fault tolerance and robustness.

REFERENCES

[1] Cao, H., Duncan, O., & Millar, A.H. (2022). The molecular basis of cereal grain proteostasis. *Essays in Biochemistry*, Vol. 66(2), pp. 243-253. https://doi.org/10.1042/EBC20210041

[2] Chang, H., Park, Y., Kim, J.H., Park, S., Kim, B.G., Moon, J. (2023). Data-driven designs and multi-scale simulations of enhanced ion transport in low-temperature operation for lithium-ion batteries. *Korean Journal of Chemical Engineering,* Vol. 40(3), pp. 539-547. https://doi.org/10.1007/s11814-022-1364-0

[3] Ghorbani, B., Zendehboudi, S., Saady, N.M.C., Duan, X., & Albayati, T.M. (2023). Strategies to improve the performance of hydrogen storage systems by liquefaction methods: a comprehensive review. *ACS omega*, Vol. 8(21), pp. 18358-18399. https://doi.org/10.1021/acsomega.3c01072

[4] Guan, L., Li, D., Shi, Y., & Meng, J. (2024). XGrad: Boosting Gradient-Based Optimizers With Weight Prediction (XGrad：通过权重预测提升基于梯度的优化器). *IEEE Trans Pattern Anal Mach Intell*, Vol. 46(10), pp. 6731-6747, Changsha/China. https://doi.org/10.1109/TPAMI.2024.3387399

[5] Guo, Y.J., Yin, R., Zhang, Q. (2024). MRI‐based kinetic heterogeneity evaluation in the accurate access of axillary lymph node status in breast cancer using a hybrid CNN‐RNN model (基于 MRI 的动力学异质性评估在乳腺癌腋窝淋巴结状态准确评估中的应用, 采用混合卷积神经网络-递归神经网络 CNN-RNN 模型). *Journal of Magnetic Resonance Imaging*, Vol. 60(4), pp. 1352-1364, Tianjin/China. https://doi.org/10.1002/jmri.29225

[6] Hamzaoui, M., Aidoun, Z., Nesreddine, H., & Tiachacht, S. (2024). Optimisation of a cascade refrigeration system with natural refrigerants, based on nature-inspired algorithms. *Arabian Journal for Science and Engineering*, Vol. 49(5), pp. 7701-7730. https://doi.org/10.1007/s13369-023-08689-6

[7] Ji, W., Osman, R., Ma, J., Jiang, X., Wang, L., Xiao, L., Tang, L., Cao, W., Zhu, Y., Liu, B., & Liu, L. (2025). Improving Process‐Based Modelling to Simulate the Effects of Low‐Temperature Stress During Pre‐Anthesis on the Quality Characteristics of Wheat Grains (改进基于过程的建模方法，以模拟开花前低温应力对小麦籽粒品质特性的影响). *Plant, Cell & Environment*, Vol. 48(2), pp. 1574-1593, Nanjing/China. https://doi.org/10.1111/pce.15217

[8] Li, D., Huang, Y., Guo, C., Wang, H.T., Jia, J.W., & Huang, L. (2023). Low-Carbon Optimization Design for Low-Temperature Granary Roof Insulation in Different Ecological Grain Storage Zones in China (中国不同生态粮食储存区低温粮仓屋顶保温的低碳优化设计). *Sustainability*, Vol. 15(18), pp. 2071-1050, Zhengzhou/China. https://doi.org/10.3390/su151813626

[9] Li, L., Wu, Z., & Zhang, Z. (2023). Anti-Overturning Capability and Fuzzy PID Speed Control for Four-Way Shuttle Vehicles in Processed Grain Storage (防倾覆能力与模糊 PID 速度控制在加工谷物储存中的四向穿梭车应用). *Processes,* Vol. 11(5), pp. 1355-1360, Zhengzhou/China. https://doi.org/10.3390/pr11051355

[10] Muthubalaji, S., Muniyaraj, N.K., Rao, S.P.V.S., Thandapani, K., Mohan, P.R., & Somasundaram, T. (2024). An intelligent big data security framework based on AEFS-KENN algorithms for the detection of cyber-attacks from smart grid systems. *Big Data Mining and Analytics*, Vol. 7(2), pp. 399-418. https://doi.org/10.26599/BDMA.2023.9020022

[11] Ngoma, T.N., Monjerezi, M., Leslie, J.F., Mvumi, B.M., Harvey, J.J., & Matumba, L. (2024). Comparative utility of hermetic and conventional grain storage bags for smallholder farmers: a meta‐analysis. *Journal of the Science of Food and Agriculture*, Vol. 104(2), pp. 561-571. https://doi.org/10.1002/jsfa.12934

[12] Paim de Oliveira, D., Coradi, P.C., Menezes Leal, M., Motta Dolianitis, B., Leone Zabot, G., & Mazoy Lopes, A. (2025). Drying and Storing Grains and Cereals: A Flow Approach in Porous Media and Applications. *Journal of the Science of Food and Agriculture*, Vol. 41(3), pp. 1013-1049. https://doi.org/

[13] Ren, D., Ding, C., & Qian, Q. (2023). Molecular bases of rice grain size and quality for optimized productivity (水稻籽粒大小与品质的分子基础及其对产量优化的影响). *Science Bulletin*, Vol. 68(3), pp. 314-350, Hangzhou/China. https://doi.org/10.1080/87559129.2024.2427773

[14] Ren, Y., Li, X., Mao, D., Xi, Y., & Wang, Z. (2023). Northeast China holds huge wetland soil organic carbon storage: an estimation from 819 soil profiles and random forest algorithm (中国东北地区拥有巨大的湿地土壤有机碳储量：基于 819 个土壤剖面和随机森林算法的估算). *Plant and Soil*, Vol. 490(1), pp. 469-483, Changchun/China. https://doi.org/10.1007/s11104-023-06089-1

[15] Tsanousa, A., Bektsis, E., Kyriakopoulos, C., González, A.G., Leturiondo, U., Gialampoukidis, I., Karakostas, A., Vrochidis, S., & Kompatsiaris, I. (2022). A review of multisensor data fusion solutions in smart manufacturing: Systems and trends. *Sensors*, Vol. 22(5), pp. 1734-1760. https://doi.org/10.3390/s22051734

[16] Wang, G., Fu, T., Zheng, R., Zhao, X., Zhu, J., & Zhang, M. (2025). Adaptive temporal-difference learning via deep neural network function approximation: a non-asymptotic analysis (基于深度神经网络函数逼近的自适应时差学习:非渐近分析). *Complex & Intelligent Systems*, Vol. 11(2), pp. 1-19, Luoyang/China. https://doi.org/10.1007/s40747-024-01757-w

[17] Yang, B., Zhang, H., Li, Z., Zhang, Y., Xu, K., & Wang, J. (2023). Adversarial example generation with AdaBelief optimizer and crop invariance (基于 Adabelief 优化器和裁剪不变性的对抗样本生成). *Applied Intelligence*, Vol. 53(2), pp. 2332-2347, Zhengzhou/China. https://doi.org/10.1007/s10489-022-03469-5

[18] Zhao, Y., Kang, Z., Chen, L., Guo, Y., Mu, Q., Wang, S., Zhao, B., & Feng, C. (2023). Quality classification of kiwifruit under different storage conditions based on deep learning and hyperspectral imaging technology (基于深度学习与高光谱成像技术，不同储存条件下猕猴桃的品质分类). *Journal of Food Measurement and Characterization*, Vol. 17(1), pp. 289-305, Tianjin/China. https://doi.org/10.1007/s11694-022-01554-4

[19] Zhao, Y., Lv, H., & Li, Y. (2023). Grain storage: Theory, technology and equipment (粮食储存：理论、技术与设备). *Foods*, Vol. 12(20), pp. 3792-3795, Zhengzhou/China. https://doi.org/10.3390/foods12203792

[20] Zhou, Y., Huang, K., Cheng, C., Wang, X., Hussain, A., & Liu, X. (2022). FastAdaBelief: improving convergence rate for belief-based adaptive optimizers by exploiting strong convexity. *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 34(9), pp. 6515-6529. https://doi.org/0.1109/TNNLS.2022.3143554