RESEARCH ON GREENHOUSE TEMPERATURE AND HUMIDITY PREDICTION MODEL BASED ON ISSA-BILSTM

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基于 ISSA-BILSTM 的温室温湿度预测模型研究

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ABSTRACT

Accurate prediction of greenhouse temperature and humidity variations was essential for optimizing crop growth conditions. To improve prediction accuracy under complex nonlinear environments, this study proposed an Improved Sparrow Search Algorithm–optimized Bidirectional Long Short-Term Memory model (ISSA-BILSTM). By introducing Tent chaotic mapping, an adaptive discoverer ratio mechanism, and a Lévy flight disturbance strategy, the proposed approach enhanced population diversity, balanced global exploration and local exploitation, and improved the convergence stability of hyperparameter optimization. Validation results showed that the proposed model achieved an R^2 of 0.9777 (MAE = 0.0159) for temperature prediction and an R^2 of 0.9762 (MAE = 0.0213) for humidity prediction, outperforming standard BILSTM and SSA-LSTM models. The proposed model enabled accurate short-term prediction of temperature and humidity, providing effective support for intelligent environmental regulation and contributing to reduced energy consumption and production costs.

摘要

准确预测温室温湿度变化对优化作物生长环境至关重要。为提高复杂非线性条件下的预测精度，本文提出改进麻雀算法优化的双向长短期记忆网络模型（ISSA-BILSTM）。通过引入 Tent 混沌映射、自适应发现者比例和 Lévy 飞行扰动策略，增强种群多样性，平衡全局搜索与局部开发，提升超参数优化的收敛稳定性。验证结果表明，该模型温度预测 R^2为 0.9777（MAE=0.0159），湿度预测 R^2为 0.9762（MAE=0.0213），性能优于标准 BILSTM 与 SSA-LSTM。所提模型可实现短期温湿度准确预测，为智能环境调控提供支持，有助于降低能耗与生产成本。

INTRODUCTION

As an important part of modern facility agriculture, greenhouse cultivation can create a suitable climate for crop growth by regulating internal environmental conditions. Therefore, it has been widely applied in China, especially in northern regions *(Fu et al., 2024)*. However, the internal environment of a greenhouse is affected by many factors such as external meteorological changes, structural characteristics, and crop physiological activities, showing strong nonlinear, time-varying, and complex characteristics of multi-factor coupling *(Peng et al., 2017)*. Temperature and humidity are the core environmental parameters affecting crop growth, and they have a direct regulatory effect on photosynthesis, transpiration and nutrient metabolism. Accurate prediction of temperature and humidity change trend is of great significance for realizing intelligent management of greenhouse environment and improving crop yield *(Liu et al., 2024)*.

At present, the research on greenhouse temperature and humidity prediction mainly includes two ideas: mechanism modeling and data-driven modeling. The mechanism model based on physical laws can better describe the dynamic process of energy and material in the greenhouse, and has strong explanatory power. For example, *Esmaeli et al., (2020)*, proposed an optimization framework for solar greenhouse design by combining a dynamic heat model with an optimization algorithm, in which a thermal model considering heat

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storage capacity was developed to predict indoor air temperature and achieve optimal thermal performance; *Chen et al., (2018)* proposed a greenhouse air temperature control method by integrating a particle swarm optimization algorithm with a model predictive control strategy. The simulation results showed that the proposed controller could track the desired greenhouse air temperature trajectory well under disturbance conditions; *Lin et al*., *(2020)*, proposed a hierarchical control strategy for Venlo-type greenhouses and conducted simulations using typical winter meteorological data. Simulation results showed that the hierarchical model predictive control strategy could effectively regulate temperature, relative humidity, and CO_2 concentration while reducing operating costs and keeping CO_2 levels within the required ranges. Although the mechanism model has clear physical significance and good theoretical basis, its practical application and promotion are still difficult due to the complexity of greenhouse system and the difficulty in accurately obtaining parameters *(Hu et al., 2024)*. Similar limitations related to parameter identification complexity and poor adaptability of physical-based greenhouse climate models have also been reported in previous studies *(Li et al., 2024)*.

In contrast, the data-driven method avoids the tedious physical modeling process by directly analyzing the relationship between environmental variables for modeling. Recent studies have demonstrated that data-driven modeling approaches can effectively capture nonlinear relationships among greenhouse environmental variables and improve prediction accuracy under complex operating conditions *(Liang et al., 2025)*. It is characterized by simple modeling and strong adaptability, so it has been widely used in the field of greenhouse environment prediction *(Guo et al., 2024)*. *Zhang et al., (2025)*, proposed an ISSA-LSTM model by using an improved sparrow search algorithm (ISSA) to optimize the hyperparameters of the long short-term memory (LSTM) network, thereby achieving accurate prediction of temperature and humidity in a double-spore mushroom greenhouse; *Zhang et al., (2021)*, established an Elman neural network prediction model to accurately forecast greenhouse temperature, humidity, and CO_2 concentration. Although traditional data-driven models have certain predictive capabilities, their performance remains limited when dealing with complex nonlinear greenhouse environments with strong multi-variable coupling *(Xu et al., 2017)*.

With the rapid development of artificial intelligence technology, neural network model has become an important means to predict greenhouse environmental factors by virtue of its powerful nonlinear fitting ability and adaptive characteristics. *Ullah et al., (2020)*, reported that prediction accuracy was significantly improved by combining an artificial neural network with a Kalman filter method. *Qu et al., (2011),* proposed an RBF-PID control method that integrates a radial basis function (RBF) neural network with a conventional PID controller, enabling adaptive control strategies according to crop growth requirements in greenhouses. Previous studies have shown that neural networks exhibit superior performance in processing high-dimensional and strongly nonlinear data *(Xue et al., 2020).*

To address the above challenges, this study proposes an enhanced hybrid prediction model that integrates an Improved Sparrow Search Algorithm (ISSA) with a Bidirectional Long Short-Term Memory (BILSTM) network for greenhouse temperature and humidity forecasting. Compared with conventional LSTM-based models, the BILSTM structure enables bidirectional learning of temporal dependencies, which is particularly suitable for greenhouse environments characterized by strong coupling, time-varying dynamics, and nonlinear interactions among multiple environmental factors. Meanwhile, the proposed ISSA introduces Tent chaotic mapping for population initialization, an adaptive discoverer ratio mechanism, and a Lévy flight-based disturbance strategy to effectively optimize key BILSTM hyperparameters, thereby improving convergence stability and global search capability. By combining these advantages, the proposed ISSA-BILSTM model is able to capture complex temporal patterns in short-term (30-minute) greenhouse environmental data and achieve higher prediction accuracy and robustness, providing reliable support for intelligent greenhouse environmental regulation.

MATERIALS AND METHODS

Overview of test site

The experimental site of this study is located in the greenhouse of Luzang Plateau Seed Research Institute, Zhufeng Modern Agricultural Science and Technology Innovation Expo Park, Shigatze City, Tibet (89.253°E, 29.119°N). The greenhouse measures approximately 150.0 m in length and 20.0 m in width. The experimental data, collected over a 90-day period from January 13,2025, to April 13,2025, with a 30 min time interval and 24 h continuous collection, comprised a total of 4321 data points. Based on the experimental data, the dataset was divided into training, test, and validation sets in an 8:1:1 ratio to develop a greenhouse temperature and humidity prediction model. The experimental greenhouse and surrounding environment are shown in Figure 1.

Fig. 1 - Photograph of the experimental greenhouse at Luzang Plateau Seed Research Institute

Data acquisition and preprocessing

The outdoor environmental factors were collected by VMS-QXZN-* Agricultural Small weather station produced by Shandong Weiming's Technology Co., LTD. The collected parameters included total solar radiation, atmospheric temperature, atmospheric humidity, wind speed, wind direction and CO_2. The collection of indoor environmental factors, including concentration, atmospheric pressure, and UV levels, uses the light, temperature, and humidity transmitter and soil moisture, temperature, and conductivity sensors produced by Shandong Jian da Ren Ke Electronic Technology Co., Ltd. The technical parameters of each sensor are listed in Table 1. The collected parameters include air temperature, air humidity, soil temperature, soil moisture, soil conductivity, and light intensity. A total of five sensor groups is evenly distributed throughout the greenhouse, and the average measurement from these five groups serves as the data for indoor environmental factors. The greenhouse data collection system is illustrated in Figure 2, The actual placement of the sensors is shown in Figure 3.

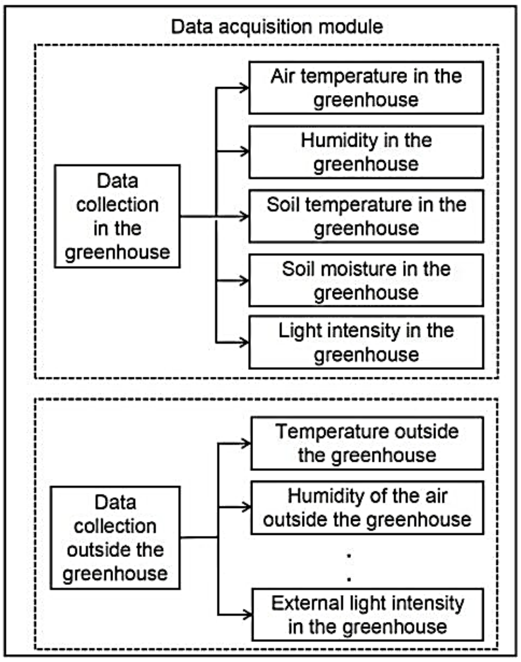


Fig. 2 - Greenhouse Data Collection System

Table 1

Sensor parameters

name	model	accuracy	range
Air temperature sensor	RS-GZ-*	±0.2 ℃	-40-125 ℃
Air humidity sensor	RS-GZ-*	±3% RH	0-100% RH
Soil temperature sensor	RS-ECTH-*-TR-1	±0.5 ℃	-40-80 ℃
Soil moisture sensor	RS-ECTH-*-TR-1	±2 %RH	0-100 %RH
Light intensity sensor	RS-GZ-*	±4% Lux	0-200000 Lux
Wind direction sensor	VMS-QXZN-*	±3°	0-360°
Wind speed sensor	VMS-QXZN-*	±0.3	0-60$m\cdot s^{-1}$
CO_2 sensor	VMS-QXZN-*	±5	0-1000 ppm

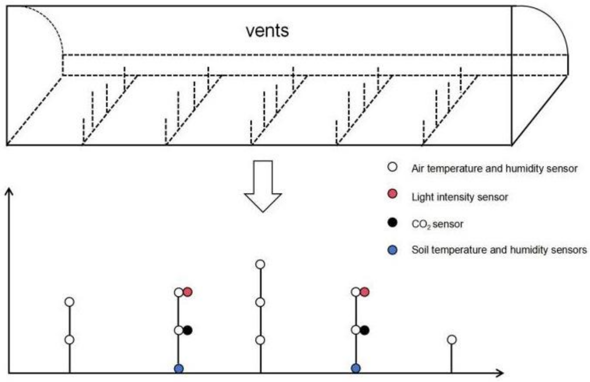


Fig. 3 - Schematic diagram of sensor layout in the greenhouse

Missing data processing/data filling

In the long-term operation of the greenhouse environment monitoring system, the data recording often has missing values due to sensor failure, communication interruption, power supply instability and other factors, which adversely affects the accuracy of the subsequent prediction model *(Wang et al., 2024).* In order to ensure the integrity of experimental data and the stability of model training, this study fills in the missing data by linear interpolation. The calculation formula is as follows:

$$x_{a+i} = x_a + \frac{i(x_{a+j}-x_a)}{j}(0<i<j) \tag{1}$$

where x_{a+i} Indicates the current missing value of $a+i$, x_a and x_{a+j} represent the raw data at time a and $a+j$, respectively.

Normalization processing

In the modeling of greenhouse environmental data, variables such as temperature, humidity, and light intensity often have different scales and numerical ranges. If these unprocessed data are directly fed into the model, certain features may dominate during training, affecting the model's learning efficiency. Therefore, data normalization is a crucial step to ensure the model's stability and prediction accuracy *(Wang et al., 2018).* Before modeling, the collected data is normalized. After completing the model training and predictive analysis, the data is restored to its original scale using inverse normalization. This study employs the Min-Max normalization method, which linearly maps each feature value to the [0,1] interval. This method is simple and effective, preserving the distribution characteristics of the original data, making it suitable for most neural network models. The formula for this calculation is as follows.

$$x' = \frac{x-x_{min}}{x_{max}-x_{min}} \tag{2}$$

Here x' represents the normalized value, and x is the environmental data within the sample dataset x', x_{min} and x_{max} represent the minimum and maximum values of the data belonging to the sample before normalization.

Pearson correlation analysis

In the process of data modeling, variables may exhibit multicollinearity or redundant features, which can impact the model's predictive performance. The temperature and humidity in greenhouses are influenced by numerous factors. To identify the key variables closely related to these conditions, this study employs Pearson correlation analysis. The relationship between these variables is indicated by the correlation coefficient r, which ranges from -1 to 1. When |r| is between 0.8 and 1, the relationship is highly significant; between 0.6 and 0.8, it is strong; between 0.4 and 0.6, it is moderate; between 0.2 and 0.4, it is weak; and when |r| is 0, it is very weak *(Fourati et al., 2007).* The formula is as follows.

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\bullet\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{3}$$

where x_i and y_i are the i-th observations of the variables X and Y, $\bar{x}$ and $\bar{y}$ are the average values of the variables X and Y, and n is the total number of observations

After data preprocessing, the Pearson correlation coefficient was applied to analyze the relationships between environmental factors inside and outside the greenhouse. The dependent variables in the Pearson correlation analysis were the current air temperature (Y1) and air relative humidity (Y2) inside the greenhouse, while the independent variables were the environmental factors measured 30 minutes earlier (X1–X11). The environmental factors outside the greenhouse included wind speed (X1), wind direction (X2), outdoor air temperature (X3), outdoor air relative humidity (X4), outdoor CO_2 concentration (X5), and outdoor light intensity (X6). The environmental factors inside the greenhouse included soil temperature (X7), soil moisture (X8), indoor light intensity (X9), air temperature (X10), and air relative humidity (X11). The correlation analysis results between greenhouse air temperature and relative humidity and the other environmental variables are presented in Table 2.

Table 2

Environmental factor correlation test

relativity	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
Y1	0.22	0.05	0.44	0.29	0.23	0.54	0.80	0.05	0.46	0.99	0.78
Y2	0.13	0.03	0.21	0.33	0.12	0.42	0.64	0.43	0.47	0.78	0.99

After the calculation of correlation coefficient, this study further tested the significance of each value by using the two-sided t-test to determine whether the correlation was significant at a given confidence level. The specific formula is as follows.

$$t = r_{xy}\sqrt{\frac{n-2}{1-r_{xy}{}^{2}}} \tag{4}$$

where r_{xy} represents the sample correlation coefficient, and n is the sample size.

A p-value threshold of 0.05 was adopted as the criterion for statistical significance. Variables exhibiting moderate correlations with greenhouse air temperature and relative humidity ($|r|> 0.4$ and $p <0.05$) were selected as input variables for the subsequent modeling stage. Based on this criterion, the environmental factors influencing air temperature inside the greenhouse were identified as outdoor air temperature, outdoor light intensity, indoor soil temperature, indoor light intensity, indoor air temperature, and indoor air relative humidity, resulting in a total of six input variables. Similarly, the environmental factors influencing air relative humidity inside the greenhouse included outdoor light intensity, indoor soil temperature, indoor soil moisture, indoor light intensity, indoor air temperature, and indoor air relative humidity, also yielding six input variables.

Model construction

Bidirectional long short-term memory network

Long Short-Term Memory (LSTM) networks are a widely used type of recurrent neural network (RNN) architecture, well-suited for time series modeling tasks due to their ability to capture long-term dependencies. However, traditional LSTM networks can only process data in the forward temporal direction, limiting their capacity to capture bidirectional dependencies within the input sequence *(Luo et al., 2022)*. To address this limitation, this study employs the Bidirectional Long Short-Term Memory (BILSTM) network, which simultaneously trains both forward and backward LSTM subnetworks. This dual-directional structure enables the model to effectively extract both past and future contextual features from the sequence, thereby enhancing its representation capability for complex temporal data.

The BILSTM architecture typically consists of an input layer, a forward LSTM hidden layer, a backward LSTM hidden layer, a concatenation layer, and an output layer. The output of the BILSTM is influenced not only by the current input but also by future time steps, making it particularly suitable for greenhouse multi-parameter prediction tasks characterized by strong temporal dependencies *(Liang et al., 2025).* The architecture of the BILSTM network is illustrated in Figure 4.

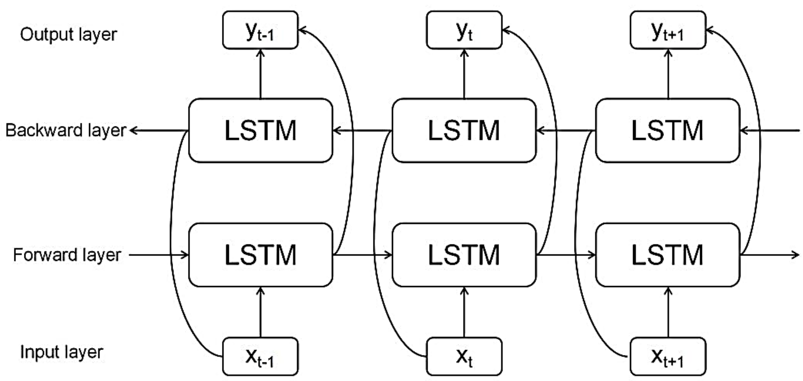


Fig. 4 - BILSTM network structure diagram

Improved Sparrow Search Algorithm

The Sparrow Search Algorithm (SSA) is an emerging swarm intelligence optimization method that has been widely applied in various fields such as function optimization, feature selection, and control parameter tuning, owing to its simple structure, few parameters, and strong global search capability. However, in practical applications, SSA still exhibits certain limitations, primarily including uneven initial population distribution, a tendency to fall into local optima, and a lack of exploration ability in the later stages of the search process.

To address these issues, this study proposes an Improved Sparrow Search Algorithm (ISSA), which is employed to optimize key hyperparameters of the BILSTM neural network *(Li et al., 2024)*. In terms of improvement strategies, considering that the random initialization of individual positions in the original SSA may lead to insufficient coverage of the search space and thereby impair global exploration ability, this paper adopts the Tent chaotic map to replace the traditional uniform random initialization method. The Tent map is characterized by good ergodicity and sensitivity to initial conditions, enabling the generation of a more evenly distributed initial population. This enhances the diversity and coverage of the solution space in the early search stage. The sparrow population is thus initialized using the Tent map, as shown in the following equation (5):

$$z_{i+1} = \begin{cases} \frac{z_i}{u} & 0 \le z_i \le u \\ \frac{1-z_i}{1-u} & u \le z_i \le 1 \end{cases} \tag{5}$$

Here z_i denotes the initial value of the population, and u represents the chaotic control parameter.

Secondly, to enhance the adaptability of the algorithm across different stages of the iteration process, this study introduces an adaptive discoverer ratio adjustment mechanism based on the current number of iterations. In the early stages of optimization, maintaining a relatively high proportion of discoverers facilitates broader exploration of the search space. Conversely, in the later stages, gradually reducing the discoverer ratio improves local search accuracy and accelerates convergence, thereby effectively addressing the convergence instability observed in the original SSA. This adaptive strategy is formulated as shown in Equation (6).

$$p(t) = p_{max} - (p_{max} - p_{min}) \cdot \left(\frac{t}{T}\right)^{\gamma} \tag{6}$$

Here $p(t)$ denotes the proportion of discoverers at the t-th iteration, while p_{max} and p_{min} represent the maximum and minimum discoverer ratios, respectively. T is the maximum number of iterations, and γ is the adjustment factor.

Furthermore, to enhance the ability of individuals to escape from local optima, this study incorporates the Lévy flight mechanism into the position update formula for joiners. Lévy flight is a type of random walk characterized by long jumps, with step lengths following a power-law distribution. This property enables individuals to perform long-range exploratory moves, thereby improving the exploration capability and enhancing the algorithm's global optimization performance. The incorporation of this strategy has demonstrated strong escape capability in multi modal function optimization experiments, contributing to improved overall search efficiency. The updated position formula is given in Equation (7).

$$X_i^{t+1} = X_i^t + \alpha \cdot L\acute{e}vy(\lambda) \tag{7}$$

Here X_t^i denotes the current position of the t-th individual in the i-th generation, and X_t^{i+1} represents its updated position. The parameter α is a step size scaling factor used to control the magnitude of the jump, typically set to a small value. The parameter λ is usually selected within the range (1,2].

ISSA-BILSTM fusion model

To enhance the accuracy and robustness of greenhouse environmental parameter prediction, this study integrates the Improved Sparrow Search Algorithm (ISSA) with a Bidirectional Long Short-Term Memory (BILSTM) network, constructing the ISSA-BILSTM model. This hybrid model leverages the temporal modeling capability of BILSTM and the global optimization strength of ISSA, making it suited for short-term forecasting tasks in highland greenhouses characterized by complex multi-factor coupling environments.

The model architecture consists of three main components: input feature construction, the ISSA optimization module, and the BILSTM prediction module. The input features include six environmental variables. These features are structured into time series using a sliding time window to serve as the model's input. The BILSTM network is responsible for learning the temporal dependencies among the variables and outputs the predicted air temperature and humidity for the next 30 minutes.

To improve model performance, ISSA is employed to optimize critical BILSTM hyperparameters, such as the number of hidden units, learning rate, and time steps.

During the optimization process, the algorithm first utilizes Tent chaotic mapping to initialize the population, enhancing the uniformity of initial solution distribution. Subsequently, the adaptive discoverer ratio adjustment and Lévy flight mechanism are applied to strengthen the search capability of the algorithm. The flowchart of the algorithm is shown in Figure 5.

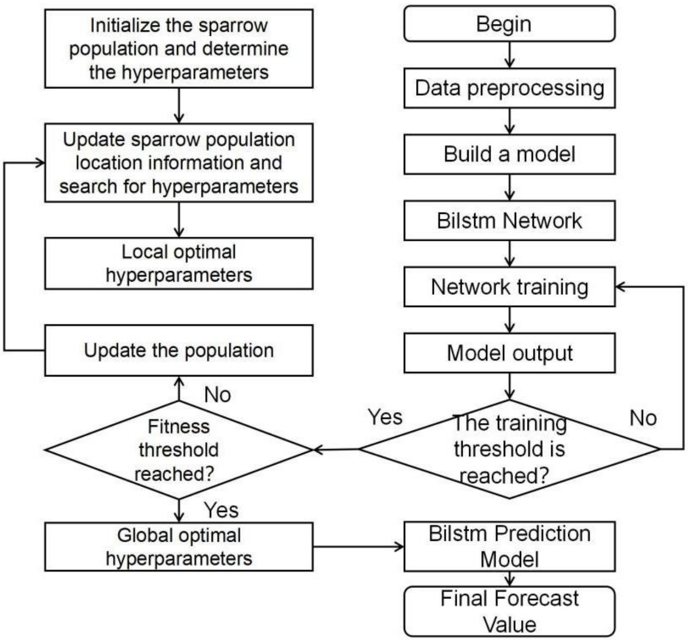


Fig. 5 - The prediction process of the ISSA-BILSTM model

To verify the relative optimality of the ISSA-BILSTM model, aims to eliminate the impact of different factor data scales. In the same operating environment, the BP neural network, BILSTM, and SSA-LSTM models are used with the same input parameters. The advantages of the ISSA-BILSTM neural network model in parameter optimization are verified through comparative experiments. The specific steps are as follows:

(1) Initialize the key parameters of the ISSA algorithm, including population size, maximum number of iterations, proportions of discoverers and joiners, adaptive control functions, and Lévy flight factors. Simultaneously, encode the BILSTM network's hyperparameters to be optimized—such as the number of hidden neurons, learning rate, and time steps—into continuous real-valued vectors that correspond to the positions of sparrow individuals.

(2) For each individual representing a specific hyperparameter configuration, train the corresponding BILSTM model and compute the mean squared error (MSE) between the predicted results and true values on the validation set, which serves as the fitness evaluation metric.

(3) Rank the population from best to worst according to fitness values, and divide individuals proportionally into discoverers (40%), joiners (40%), and sentinels (20%) to enable cooperative optimization through differentiated strategies. Following the ISSA update rules, discoverers perform global guided searches to explore promising regions; joiners introduce Lévy flight mechanisms to conduct jump-based perturbation searches, enhancing diversity; vigilantes adjust their positions based on alert-response mechanisms to improve the algorithm's robustness and convergence speed.

(4) Following the ISSA update rules, discoverers perform global guided search to explore promising regions; joiners incorporate the Lévy flight mechanism to conduct jump perturbations that increase population diversity; sentinels adjust their positions based on an alarm response mechanism to enhance algorithm robustness and convergence speed.

(5) Update the fitness values of all individuals, and if a better solution is found, update the global best position and its corresponding hyperparameter configuration to ensure continuous improvement during optimization.

(6) Terminate the iteration process once the preset maximum number of iterations is reached or the fitness error meets a predefined threshold, outputting the current global best hyperparameter set as the optimization result.

(7) Reconfigure the BILSTM model using the optimized hyperparameters and evaluate the predictive performance of the model on the test set for validation.

Model evaluation index

To evaluate the predictive performance of the different models, RMSE, MAE and R^2 were selected as evaluation metrics, following *Li et al. (2024)*.

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|R_i - y_i| \quad (8)$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(R_i - y_i)^2} \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(y_i-\bar{y})^2}{\sum_{i=1}^{m}(R_i-\bar{y})^2} \quad (10)$$

where m represents the number of test samples, y_i is the predicted value, R_i is the actual value, and $\bar{y}$ is the mean value.

RESULT AND ANALYSIS

Parameter Settings

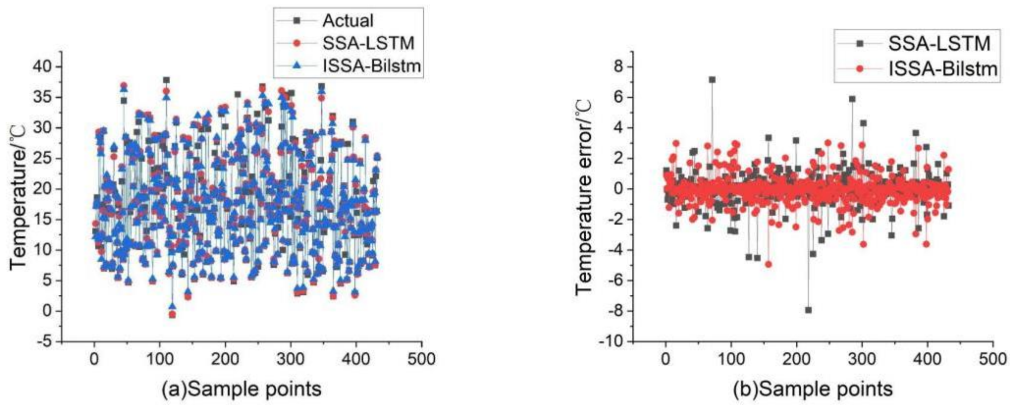
Based on the results of the Pearson correlation analysis, the influencing factors selected for the greenhouse air temperature prediction model were X3, X6, X7, X9, X10, and X11. For the greenhouse air relative humidity prediction model, the selected influencing factors were X6, X7, X8, X9, X10, and X11. To ensure consistency between the number of environmental input variables and the neural network architecture, the air temperature prediction model was constructed with six input neurons and one output neuron, while the air relative humidity prediction model was also constructed with six input neurons and one output neuron.

The optimal hyperparameter configuration obtained through multiple rounds of training and validation is as follows: 10 hidden neurons, a time step of 4, a learning rate of 10^{-3}, a dropout rate of 0.2, a regularization coefficient of 10^{-4}, and a maximum of 500 training iterations. This parameter set demonstrated strong fitting performance and generalization capability in both air temperature and humidity prediction tasks. The main parameter settings for the ISSA are as follows: the initial population size is 30, the proportion of discoverers is 0.2, the proportion of sentinels is 0.1, the safety threshold is set to 0.8, and the maximum number of iterations is 200.

In this study, 4321 sets of greenhouse data were selected for prediction, and BP neural network, BILSTM and SSA-LSTM models were constructed respectively. The training set, test set and verification set were divided in the ratio of 8:1:1. MATLAB was used as the simulation environment.

Forecast results and comparative analysis

Based on the optimized parameters obtained from ISSA, the model's basic settings were configured, and the trained model was subjected to simulation testing. The prediction results were then inverse normalized to realize forecasts of greenhouse air temperature and humidity. To evaluate the performance of the ISSA-BILSTM model in predicting greenhouse temperature and humidity, predictions were conducted under the same operational conditions using BP neural network, BILSTM, and SSA-LSTM models with identical input parameters. Comparative analyses of their prediction performances were carried out. Similar improvements in prediction accuracy obtained by intelligent optimization–based neural network models have also been reported in related greenhouse temperature and humidity prediction studies *(Li et al., 2024)*. The greenhouse temperature and humidity prediction results were shown in Figure 6, and the performance comparison of the four prediction models is summarized in Table 3.



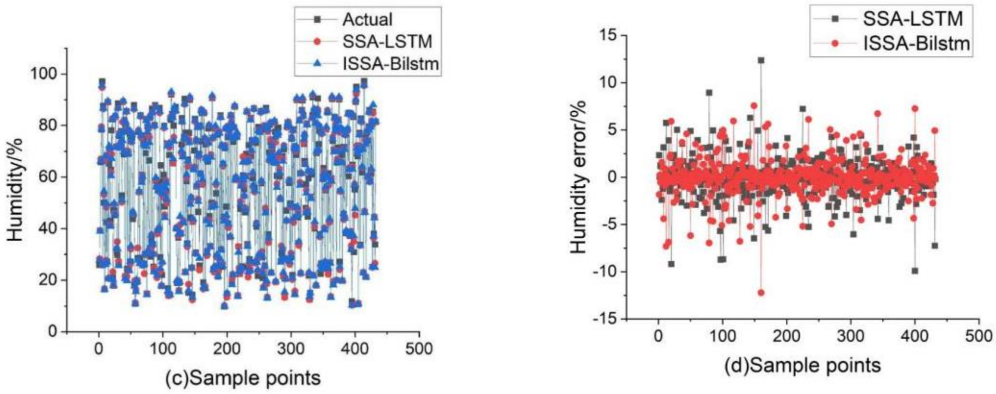


Fig. 6 - Comparison of greenhouse air temperature and humidity prediction results based on ISSA-BILSTM
(a) Air temperature forecast vs. actual value; (b) Comparison of the error of the predicted and actual air temperature values; (c) Comparison chart of predicted and actual air humidity;
(d) Comparison of the error between the predicted and actual air humidity values

In summary, the goodness of fit of BP, BILSTM, SSA-LSTM and ISSA-BILSTM temperature prediction was 88.34%, 90.35%, 94.89% and 97.77%, respectively, and that of humidity prediction was 87.38%, 90.68%, 94.03% and 97.62%. Compared with the other three models, the temperature fitting index of ISSA-BILSTM increased by 9.43%, 7.42% and 2.88%; the humidity prediction fitting degree increased by 10.24%, 6.94% and 3.59%, indicating that the prediction performance of ISSA-BILSTM was the best.

Table 3

Comparison of model predictive evaluation metrics

Environmental factor	Prediction technique	R^2	MAE	RMSE
air temperature	BP	0.8834	0.0294	0.0842
	BILSTM	0.9035	0.0255	0.0642
	SSA-LSTM	0.9489	0.0215	0.0325
	ISSA-BILSTM	0.9777	0.0159	0.0281
air humidity	BP	0.8738	0.0344	0.0854
	BILSTM	0.9068	0.0297	0.0648
	SSA-LSTM	0.9403	0.0254	0.0317
	ISSA-BILSTM	0.9762	0.0213	0.0293

CONCLUSIONS

(1) This study proposes a greenhouse temperature and humidity prediction model based on an improved Sparrow Search Algorithm (ISSA) and Bidirectional Long Short-Term Memory network (BILSTM). Leveraging the global optimization capability of ISSA, the model adaptively tunes the critical hyperparameters of the BILSTM network. By introducing Tent chaotic mapping for population initialization, an adaptive discoverer ratio adjustment mechanism, and a Lévy flight-based perturbation strategy, the proposed approach effectively addresses the limitations of traditional neural networks, such as susceptibility to local optima and slow convergence. As a result, the model demonstrates significantly enhanced robustness and predictive accuracy.

(2) Experimental results show that the proposed model achieves a coefficient of determination of 0.9777 and a root mean square error of 0.0281 in temperature prediction; for humidity prediction, the R^2 reaches 0.9762 with an RMSE of 0.0293. Compared with the BP neural network (R^2 = 0.8834), BILSTM (R^2 = 0.9035), and SSA-LSTM (R^2 =0.9489) models, the ISSA-BILSTM model exhibits superior performance, achieving a balance between computational efficiency, prediction accuracy, and model stability.

(3) The verification results indicate that the ISSA-BILSTM model can accurately forecast short-term (30-minute) trends in air temperature and humidity within highland greenhouses. This capability provides timely decision support for environmental regulation strategies, contributing to reductions in energy consumption and production costs, and promoting the advancement of intelligent management in protected agriculture.

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