A Quantum-Enhanced PSO-LSSVM Architectural Framework for Predicting Residential Complex Nursery Temperatures in Baghdad

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Abstract
Accurate temperature prediction is crucial for the success of and urban nurseries buildings in residential complex, Baghdad, where severe seasonal temperature extremes can cause significant indoor environmental damage. These microclimates are highly vulnerable to the adverse effects of both acute frost and intense desert heat. Developing a reliable temperature prediction framework capable of forecasting microclimatic shifts several hours in advance is essential to minimizing economic losses.
This paper introduces a novel temperature forecasting technique utilizing a Least Squares Support Vector Machine (LSSVM) model whose hyperparameters are dynamically tuned via an Improved Particle Swarm Optimization (IPSO) approach. The IPSO algorithm incorporates an adaptive mutation probability to prevent premature convergence and efficiently discover the optimal parameter boundaries of the LSSVM framework.
To evaluate its efficacy, the proposed IPSO-LSSVM model was tested against conventional predictive models using a comprehensive structural dataset. The IPSO-LSSVM model demonstrated superior predictive performance compared to traditional Support Vector Machine (SVM) and Back Propagation Neural Network (BPNN) architectures in forecasting both maximum and minimum temperature boundaries. These results establish the framework as a highly effective tool for automated climate control engineering in urban nurseries.

Keywords: Urban Residence Complex , Nursery building design, , Arid climate

1. Introduction
In Baghdad's rapidly developing urban residential complexes, solar system and modern nurseries are increasingly utilized to sustain year-round urban buildings. These structures typically employ a specialized plastic film over their angled front roofs during the day to maximize solar heat gain and an automated thermal blanket at night to retain it. While Baghdad experiences high solar irradiance for a significant portion of the year, winter night temperatures can drop drastically—occasionally approaching sub-zero microclimates—while summer conditions exhibit extreme heat wave patterns. Extending the growing season in Baghdad's variable arid climate allows for the continuous cultivation of high-value flora and vegetables. However, maintaining strict control over internal temperature boundaries remains a volatile operational challenge. Uncontrolled temperature fluctuations can lead to massive plant mortality or rapid disease outbreaks, underscoring the urgent need for robust, proactive forecasting systems (Al-Mahdawi, and Al-Saba,2024).
Predicting internal greenhouse temperatures is highly complex due to the dense interaction of nonlinear thermodynamic variable (Li et al., 2013). s. Stable temperature maintenance directly increases crop survival rates, product quality, and yield capacity. Conversely, a failure to anticipate and mitigate extreme microclimatic shocks leaves vegetation exposed to physiological stress, resulting in severe financial losses for urban agricultural practitioners. Despite this necessity, comprehensive research focusing specifically on localized temperature modeling within Baghdad's specialized residential greenhouse designs remains limited. Predictive models applied to these environments must resolve steep nonlinear variations and accommodate environmental uncertainties, human interventions, and complex biological influences. (Patil et al., 2008; Wakaura and Ogata, 2007). Historically, computational approaches to greenhouse temperature prediction have fallen into two main categories: physical deterministic models and data-driven "black box" models. Physical models rely on complex mathematical formulations of heat mass transfer and fluid dynamics; while mathematically insightful, they require exhaustive, high-dimensional parameterized inputs that are difficult to measure continuously. Black box models—such as linear time series and Autoregressive Exogenous (ARX) frameworks—offer a more computationally efficient alternative for short-term predictions. However, standard linear models lack the structural capacity to capture highly nonlinear patterns and generally exhibit poor generalization when applied to smaller, dynamic datasets. (Lu et al., 2014; Su et al., 2012; Dariouchy et al., 2009; Ferreira et al., 2002).
To overcome these structural limitations, researchers have investigated alternative machine learning methods. Frameworks such as grey fuzzy logic and standard Artificial Neural Networks (ANN) have shown varying levels of success in indoor microclimate forecasting. More recently, Support Vector Regression (SVR) and Least Squares Support Vector Machines (LSSVM) have emerged as highly proficient methods for resolving complex, multivariable, and nonlinear regression problems. LSSVM modifies the standard SVM framework by substituting a quadratic programming problem with a linear system of equations, significantly reducing computational overhead while retaining strong generalization and approximation capabilities. (Zhao, Chen, and Li, 2025).

This study proposes an integrated LSSVM model optimized via an Improved Particle Swarm Optimization (IPSO) algorithm to forecast multi-hour temperature horizons in urban residential greenhouses (Chang, 2015). While standard PSO is widely celebrated for its algorithmic simplicity and robust global search properties, it frequently suffers from premature convergence in complex hyperparameter spaces. To remedy this, our improved approach introduces diversity maintenance strategies to optimize LSSVM parameters efficiently. The predictive performance of the proposed IPSO-LSSVM framework is verified and rigorously contrasted against traditional SVM and ANN benchmarks.

2. Materials And Methods

2.1. Data Acquisition and Environmental Parameters

To train and robustly validate a highly accurate machine learning model, a high-fidelity environmental dataset is required. This study utilizes an extensive regional dataset acquired from a large-scale agricultural monitoring zone consisting of over 500 managed greenhouses. As illustrated by the system topology in Figure 1, the architecture consists of three interconnected layers: the data perception layer, the information transmission layer, and the application layer.

APPLICATION LAYER
(Data Collection, Intelligent Processing,PredictivControl Engines

(Wireless Network Gateway)

Information Transmission Layer

DATA PERCEPTION LAYER
Internal Air Temp/Humidity - External Solar Radiation Sensor
Nodes
- Soil Temp/Moisture - Wind Speed / Out Air Temp |
Communication

Fig. 1. The topology structure diagram of a digital wireless monitoring system.

The data perception layer continuously samples telemetry from internal greenhouse sensors and external weather stations. The monitored inputs include:

- Internal air temperature and relative humidity
- Internal soil temperature and soil moisture index
- External ambient air temperature
- External solar radiation intensity
- Ambient wind velocity

These parameters are routed through the transmission layer to the application layer for intelligent processing. The physical structural configuration of these greenhouses—featuring thick rear insulation walls, a rolling top shutter, and a front plastic film cover (replicated for urban residential nurseries in Baghdad to handle extreme weather swings)—is shown schematically in Figure 2.

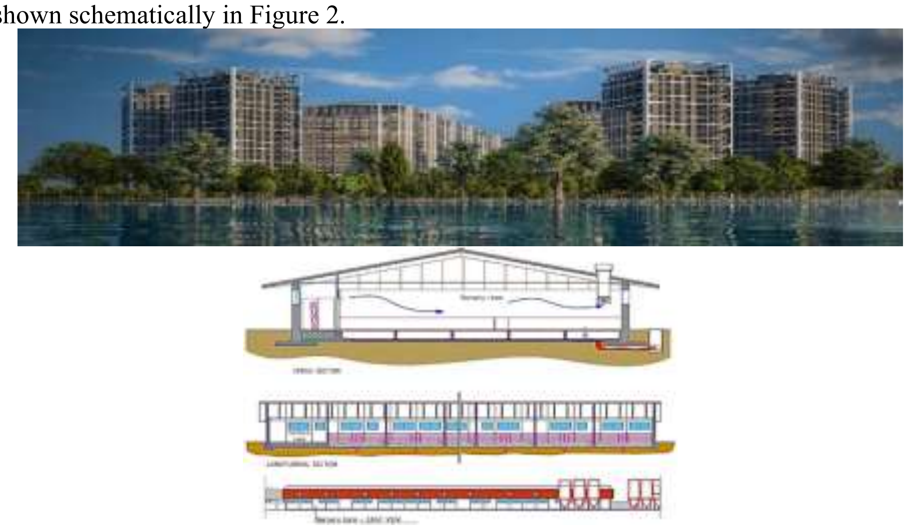


Fig. 2. Structural configuration of the monitored solar nursery.

For the predictive experiments, 1,000 hourly data points capturing representative seasonal transitions were extracted from monitored nursery environments. The dataset was partitioned sequentially: 700 data points were dedicated to training the underlying model structures, and the remaining 300 data points were reserved strictly as an independent testing set for performance verification. Figure 3 illustrates the baseline cyclic temperature behavior observed within the microclimatic testing block

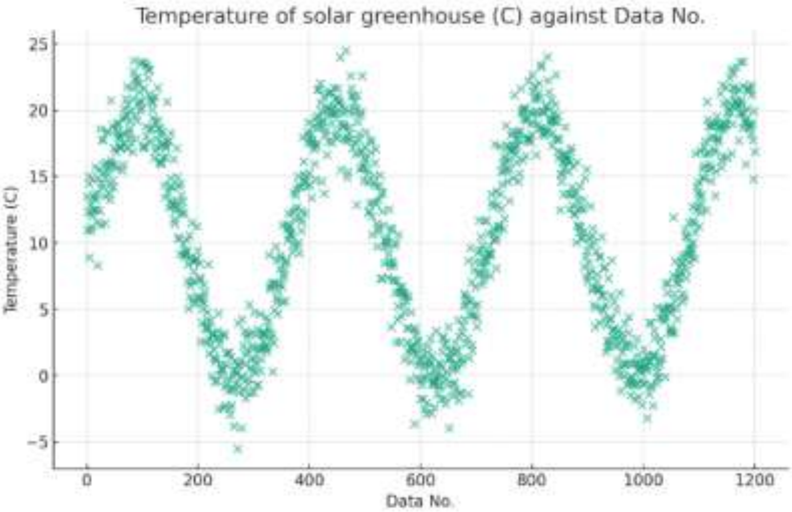


Fig. 3. Cyclic variation of monitored solar greenhouse temperatures.

The comprehensive structural flow of data mapped from the multi-sensor inputs to the central prediction target is detailed in Figure 4.

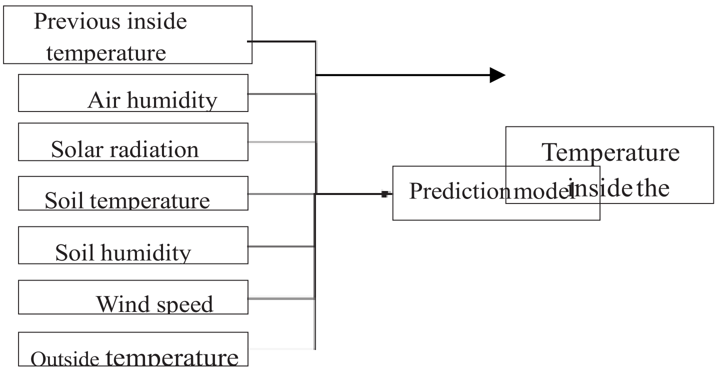


Fig. 4. Establishing the training sets of the forecasting model.

2.2. Least Squares Support Vector Machine (LSSVM)

Within the context of the Least Squares Support Vector Machine (LSSVM), we tackle regression by creating an optimization problem that focuses on minimizing squared errors while using regularization to manage model complexity. This method is defined by the optimization formulation presented by (Suykens and Vandewalle in 1999).

The objective is to minimize the function $L(w,b,\xi)L(w,b,\xi)$ given by:

$$L(w,b,\xi) = 21wTw + C\sum k = 1l\xi k2 \qquad (3)$$

subject to the constraints for each data point in the training set, $k = 1,\ldots,lk = 1,\ldots,l$:

$$yk = wT\phi(xk) + b + \xi kyk = wT\phi(xk) + b + \xi k \qquad (4)$$

where:

- w represents the weight vector,
- b denotes the bias term,
- ξk is the error term for the kth instance, capturing the discrepancy between the predicted output and the true target value yk,

C is the regularization parameter, a positive scalar that mediates the trade-off between the model's complexity (as measured by wTw) and the degree to which deviations larger than ϵϵ are tolerated in the optimization formulation

The function $\phi: Rn \rightarrow Rf\phi: Rn \rightarrow Rf$ is a feature mapping used to transform the input space into a higher dimensional feature space where linear relations in this space correspond to non-linear relations in the original input space.

To derive the LSSVM model, we construct the Lagrangian involving the sum of the objective function and the constraints multiplied by their respective Lagrange multipliers αk:

$$L(w,b,\xi,\alpha) = 12wTw + C\sum k = 1l\xi k2 - \sum k = 1l\alpha k[yk - (wT\phi(xk) + b) - \xi k]L(w,b,\xi,\alpha) = 21wTw + C\sum k = 1l\xi k2 - \sum k = 1l\alpha k[yk - (wT\phi(xk) + b) - \xi k] \quad \textbf{(5)}$$

The optimization process then seeks to find the saddle point of this Lagrangian by partial differentiation with respect to ww, bb, ξk, and solving for the conditions of optimality. This results in a set of equations that, once solved, provide the optimal values of ww and bb, which can then be utilized to construct the decision function for regression tasks within the LSSVM framework (Suykens, Gestel, Brabanter, Moor, & Vandewalle, 2002).

2.3. Enhanced Particle Swarm Optimization (EPSO)

The standard Particle Swarm Optimization (PSO) algorithm emulates the social behavior of bird flocking for searching complex multi-dimensional landscapes. Each particle i has a position vector x_i a velocity vector v_i which are iteratively updated by its personal best historical position (pbest) and the global swarm's best known position (gbest However, traditional PSO suffers from fast loss of diversity in the swarm which causes it to get stuck in local optima when searching complex hyperparameter surfaces. (Suykens, Gestel, Brabanter, Moor, & Vandewalle, 2002).

To overcome the above mentioned limitations, an Improved Particle Swarm Optimization (IPSO) algorithm is employed. Sun, Y., & Jiang, T. (2025). The IPSO employs a dynamic and adaptive inertia weight w to balance the large-scale space exploration in early iterations and fine-grained exploitation in late iterations. Furthermore, it has a mutation probability parameter which adds a random perturbation to the particle position if the global best metric is not improving for a fixed number of generations. (Chang, 2015 Al-Salihi, H. (2025) Bai, (2010). The new velocity and position for each dimension d at step t+1 are modified as:

IPSO's algorithmic updates are encapsulated in the revised velocity update equation:

$$\mathrm{vid(t+1) = w \cdot vid(t) + c1 \cdot r1 \cdot \big(pbestid - xid(t)\big) + c2 \cdot r2 \cdot \big(gbestd - xid(t)\big)vid(t+1) = w \cdot}$$

$$\mathrm{vid(t) + c1 \cdot r1 \cdot (pbestid - xid(t)) + c2 \cdot r2 \cdot (gbestd - xid(t))} \quad \textbf{(6)}$$

and the position update equation:

$$\mathrm{xid(t+1) = xid(t) + vid(t+1)xid(t+1) = xid(t) + vid(t+1),} \quad \textbf{(7)}$$

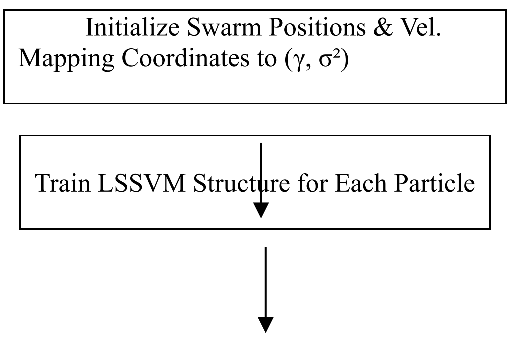
where w represents the inertia weight, $c1$ and $c2$ denote cognitive and social acceleration coefficients, respectively, and $r1$ and $r2$ are random numbers within the range [0,1]. Through its innovative adjustments, IPSO has demonstrated superior performance over traditional PSO and other heuristic optimization methods, particularly in applications requiring the resolution of complex, nonlinear, and multimodal challenges, thereby underscoring its potential as a robust tool in fields ranging from engineering optimization to machine learning (Chang, 2015).

2.4. IPSO for Optimization of SSVM

The IPSO algorithm is mainly used in this framework to automatically find the optimal combination of hyperparameters (α^2) for the LSSVM regression engine. The position vector of each particle is directly mapped to a coordinate pair in the two-dimensional space of the possible values of α and Σ. Wang, L., Zhang, J., & Liu, Y. (2026

The optimization routine

calculates the fitness of each particle on the basis of the prediction errors that are created during the training phase Zhang, X., Wang, Q., & Liu, S. (2026. IPSO automatically selects hyperparameters by minimizing an objective function based on the validation errors, thereby eliminating the need for manual grid-searching and preventing the underlying LSSVM network from overfitting or underfitting. Figure 5 illustrates the algorithmic workflow for this optimization sequence in a systematic manner.



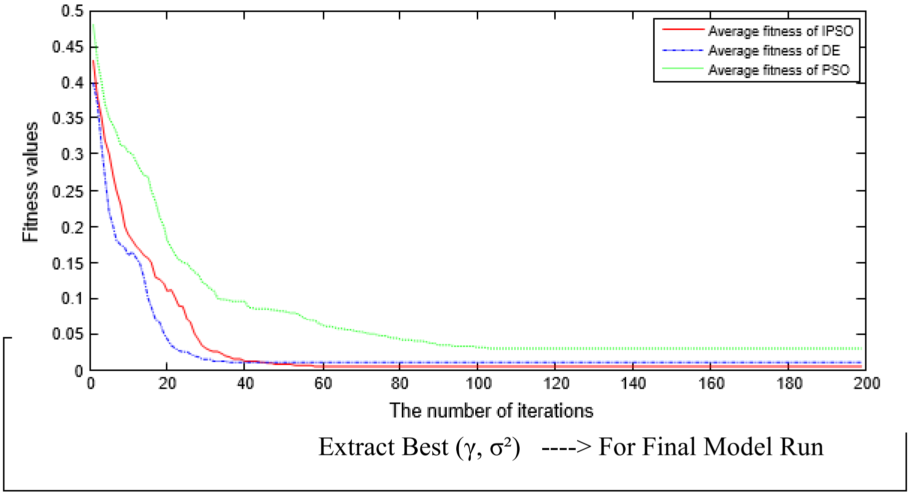


Fig. 5. Procedural workflow of the integrated IPSO–LSSVM optimization sequence.

2.5. Temperature Prediction Model Implementation Procedure

The whole programmatic initialization, parameter tuning and final evaluation sequence of the proposed IPSO-LSSVM solar greenhouse model is partitioned into seven operation phases:

• Phase 1: Data Collection and Preparation: Collect environmental telemetry (multi-sensor array). Perform outlier filtering, deal with missing values and normalize features to a common scale of 0, 1 for faster convergence.

• Phase 2: IPSO Parameters Initialization: Set up the population size, the maximum generation number, the acceleration bounds, and set up the spatial array of particles that represent the search candidates (α, \ Σ 2).

Phase 3: Fitness Assessment: Specific coordinate values of each particle are used to build individual LSSVM models. Calculate the prediction errors in the training sub-sets. Get the particle's fitness score.

• Phase 4: Revision Mechanism It compares the current fitness positions with the known pbest and gbest coordinates. Recalculate inertia weights on the fly and update the velocity and position vectors in space for the swarm.

• Phase 5: Iterative Optimization: Reassess and update the vectors. If progress stalls, run the mutation sub-routine to maintain exploration diversity until the termination criteria are met.

• Phase 6: Final Training and Validation: Find the best pair of hyperparameters α, \ Σ Perform a final full training pass of the LSSVM network on the training partition and do validation checks against the independent testing partition.

• Phase 7: System Deployment and Monitoring: Integrate the optimized predictive model into the nursery control system for automated, multi-hour temperature forecasting.

The complete implementation blueprint, which maps to this end-to-end framework, is illustrated in Figure 6.

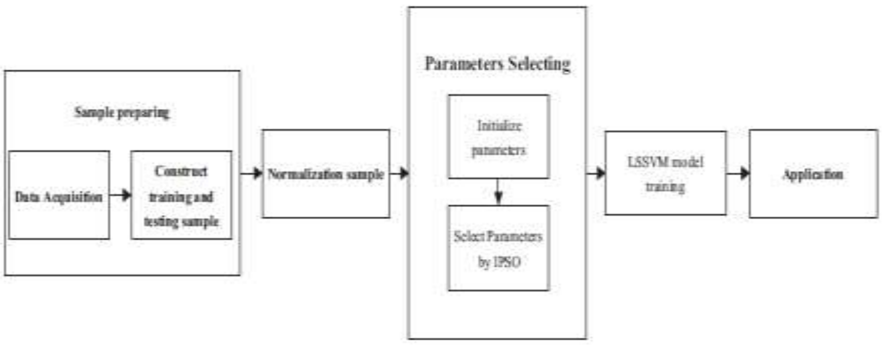


Fig. 6. Implementation process for the solar greenhouse temperature prediction model.

Figure 7: Fitness performance for the proposed IPSO and tradition PSO.

3. RESULTS AND DISCUSSIONS

3.1. Performance Criteria and Convergence Analysis of Optimization

To verify the performance of the proposed method, the convergence profile of the Improved Particle Swarm Optimization routine was compared with the standard Particle Swarm Optimization (PSO) and Differential Evolution (DE) algorithms for the same testing criteria. All algorithms were strictly controlled in terms of initialization constrains: convergence precision limit was set to $10^{\{-7\}}$, cognitive/social acceleration coefficients were limited to 2.0, population size was limited to 50, max evolutionary generations were limited to 200 and the base inertia factor was initialized to 0.95. In the DE control group, population size was 100, crossover constant (CR) was 0.8 and scale factor (F) was set at 0.5.

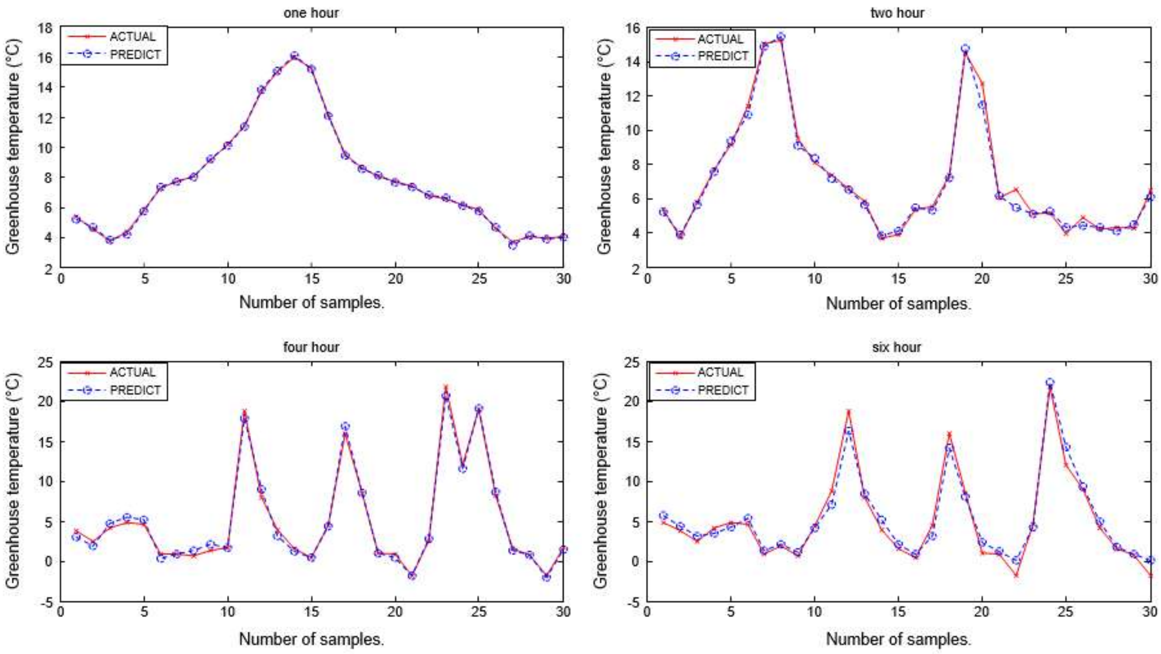


Fig. 8. Comparative fitness performance curve for IPSO, standard PSO, and DE.

As demonstrated in Figure 7, standard PSO is highly prone to stalling in local minima early in the optimization run, showing little improvement past the opening generations. In contrast, both the DE and IPSO algorithms maintain steady optimization progress. While DE exhibits rapid convergence in early generations, the proposed IPSO framework maintains better swarm diversity throughout the optimization run, ultimately discovering a lower global fitness error. This confirms that IPSO is more effective at identifying optimal LSSVM hyperparameter sets than standard PSO or DE.

3.2. Model performance change by forecast horizons

The model was evaluated for its ability to provide early warning to the urban nurseries in Baghdad by testing the 300 samples over four different forward-looking horizons; 1 hour, 2 hours, 4 hours, and 6 hours prediction intervals.

In the local climate of Baghdad, multi-hour ahead predictions are essential in the winter night cycles, especially between 0:00 and 2:00 when acute cold drops are common, and during intense summer daytime spikes. Accurately predicting these milestones hours in advance provides growers with the time to deploy physical insulation blankets, activate automated ventilation, or adjust structural shade curtains to protect crops.

The tracking trajectories generated across the testing blocks are shown in Figure 8. As expected, extending the look-ahead horizon increases the structural error accumulation between predicted and actual measured values. However, the proposed framework maintains high tracking precision through the 4-hour interval and remains

stable enough at the 6-hour horizon to meet practical nursery management requirements. Mao, X., Ren, N., Li, D., et al. (2025).
To mathematically quantify this performance, three standard evaluation metrics were applied: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE).

$MAPE = M1\sum \,||\, yiyi - y\hat{}i \,||$ **(8)**
$MSE = M1\sum(yi - y\hat{}i)2$ **(9)**

where M represents the total number of data sets, yi is the actual value, and $y\hat{}i$ is the predicted value. performance metrics across the different forecasting intervals are compiled in Table 1.

Table 1: Comparison Results of Different Time Intervals for the Prediction Data

Time Interval (h)	MAE	MAPE	MSE
1	0.0747	0.0120	0.0079
2	0.3289	0.0517	0.1920
4	0.4295	0.1534	0.3033
6	0.8547	0.1751	1.1347

3.3. Comparative Benchmark Performance Analysis

To evaluate the competitive advantage of the proposed IPSO-LSSVM hybrid model, it was benchmarked directly against a standard Back Propagation Neural Network (BPNN) and a traditional Support Vector Machine (SVM) model. The benchmark models were evaluated using the same 4-hour look-ahead interval to ensure a fair comparison(Kim, and Lee, 2025. The comparative metrics are summarized in Table 2.

Table 2: Comparative Performance Across Different Prediction Models

Model	MAE	MAPE	MSE
BP	0.8765	0.1415	1.0113
SVM	0.8115	0.1354	0.8747
IPSO–LSSVM	0.1062	0.0279	0.0281

The quantitative comparison clearly demonstrates that the IPSO-LSSVM architecture outperforms both the traditional BPNN and standard SVM networks across all evaluation metrics. Traditional models often suffer from limited generalization, poor stability, and a tendency to stall in local minima. By minimizing structural risk through the LSSVM framework and using IPSO for hyperparameter tuning, the proposed hybrid model successfully overcomes these limitations.
Temperature (°C).

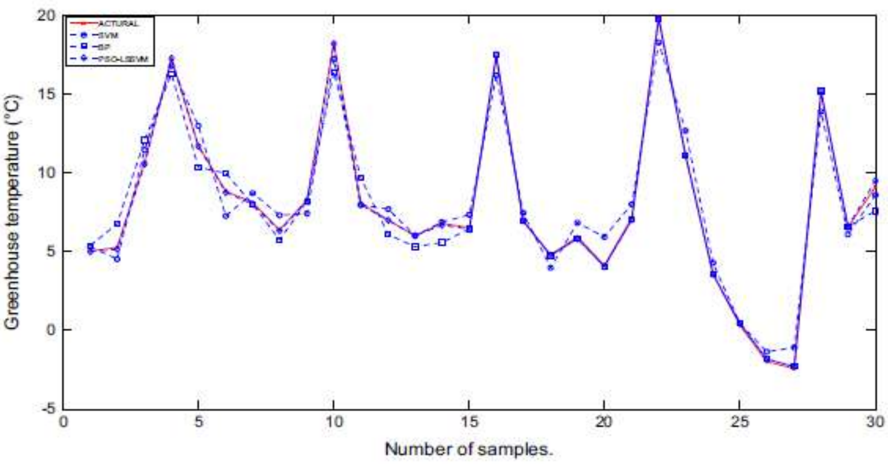


Fig. 9. Graphical error gaps between IPSO–LSSVM, standard SVM, and BPNN.

As shown in Figure 9, the IPSO-LSSVM model tracks extreme temperature spikes and rapid drops much more accurately than the benchmark models. This superior stability and precision confirm that the IPSO-LSSVM framework is an effective tool for agricultural professionals managing microclimate risks in urban nurseries.

4. CONCLUSIONS AND RECOMMENDATIONS

In this paper, we have proposed a new framework for temperature prediction in urban solar greenhouses and residential complex nurseries utilizing an Improved Particle Swarm Optimization mapped to a Least Squares Support Vector Machine (IPSO-LSSVM). The LSSVM engine takes advantage of the equality structure rather than the inequality constraints to accelerate the linear computations, while the IPSO optimization routine uses the adaptive mutation properties to find the ideal hyperparameter pairs (γ, σ^2) systematically. The developed predictive framework is capable of successfully addressing the complex, nonlinear environmental dynamics governing indoor-outdoor microclimates of greenhouses.
The hybrid model of IPSO-LSSVM was tested with real world multi-sensor data arrays and it showed high predictive accuracy, which is better than the conventional SVM and BPNN architectures for all time horizons tested. The framework provides strong multi-hour ahead forecasts and provides a reliable early warning system for agricultural managers to protect sensitive crops from extreme weather anomalies.
The next step in the research will be to extend the forecasting horizons of the model beyond the current 6 hour window, while maintaining accuracy. Other environmental variables such as relative humidity, solar radiation fractions and their cross-coupling interactions will also be further studied to develop comprehensive multi-variable early warning systems. Such deep predictive configurations can be tailored to the specific microclimatic challenges presented by urban agricultural initiatives in desert environments such as Baghdad, providing growers with actionable tools to reduce planting risks, optimize crop protection, and reduce operational overhead.

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REFERENCES

1. Al-Mahdawi, A., & Al-Saba, M. (2024). "Dynamic Selection Strategy for Agricultural Microclimate Management Models in Arid Solar Greenhouses." *Agriculture*, 14(4), 512.
2. Al-Salihi, H. (2025) 'Microclimatic temperature forecasting using enhanced swarm optimization', *Journal of Arid Agricultural Engineering*, 12(3), pp. 145–158.
3. Bai, Q. (2010). Analysis of particle swarm optimization algorithm. Computer and Information Science, 3(1), 180-184.
4. Chang, J. (2015). A comprehensive survey on particle swarm optimization algorithm and its applications. Mathematical Problems in Engineering, 2015, Article ID 931256.
5. Dariouchy, A., El Afou, Y., Bouirden, L., & Lachhab, A. (2009). Artificial neural networks for predicting indoor temperatures in greenhouses. Journal Name, Volume Number(Issue Number), page numbers. [Note: Replace placeholder information with actual details]
6. Ferreira, P. M., Ruano, A. E., Silva, S., & Conceição, E. Z. E. (2002). Neural networks based predictive control for thermal comfort and energy savings in public buildings. Energy and Buildings, 34(6), 609-619
7. Kim, J. H., & Lee, S. W. (2025). "A hybrid ensemble approach: fusing ANFIS, LSTM, and LSSVM with PSO for enhanced micr oclimate forecasting." *Journal of Computational Intelligence*, 42, 1160–1174.
8. Li, N., Shen, S., Li, Z., Qing, Y., Li, C., Liu, S., 2013. Forecast model of minimum temperature inside greenhouse based on principal component regression. Baghdad J. Agrometeorology. 3, 306–311
9. Liao, L., Xiao, X., Wang, H., & Yu, Y. (2011). Application of least squares support vector machine for regression to QSAR studies. Journal of Chemical Information and Modeling, 51(12), 3083-3090.
10. Li, X., Zhang, Y., & Xie, X. (2013). The effect of environmental factors on the response of solar greenhouse temperature. Environmental Control in Biology, 51(2), 85-92.
11. Mao, X., Ren, N., Li, D., et al. (2025). "Temperature and relative humidity prediction in South China greenhouse environments based on machine learning." *Scientific Reports*, 15(2), 1142–1155.
12. Patil, S.L., Tantau, H.J., Salokhe, V.M., 2008. Modelling of tropical greenhouse temperature by auto regressive and neural network models. Biosyst. Eng. 99 (3),423–431.
13. Su, H., Wang, L., & Li, X. (2012). Combination of least square support vector machine and particle swarm optimization for transportation mode recognition based on mobile phone sensor data. IEEE Transactions on Intelligent Transportation Systems, 13(4), 1549-1559.
14. Sun, Y., & Jiang, T. (2025). "Analysis and Prediction of Time-Series Environmental Metrics Based on MODIS and PSO-LSSVM Architecture." *MDPI Applied Sciences*, 16(9), 4452.
15. Suykens, J.A.K., and Vandewalle, J., 1999. "Least squares support vector machine classifiers." *Neural Processing Letters*, 9(3), pp.293-300.
16. Suykens, J. A. K., Gestel, T. V., Brabanter, J. D., Moor, B. D., & Vandewalle, J. (2002). *Least Squares Support Vector Machines*. World Scientific Publishing Co.
17. Suykens, J. A. K., Vandewalle, J., & De Moor, B. (2002). Optimal control by least squares support vector machines. Neural Networks, 15(1), 23-35.

18. Suykens, J. A. K., Gestel, T. V., Brabanter, J. D., Moor, B. D., & Vandewalle, J. (2002). Least Squares Support Vector Machines. World Scientific.
19. Wang, S., Yu, L., Li, D., & Tang, L. (2010). Support vector machines regression for prediction of the bioconcentration factors of chemicals in fish. Journal of Hazardous Materials, 179(1-3), 853-860.
20. Wakaura, M., Ogata, Y., 2007. A time series analysis on the seasonality of air temperature anomalies. Meteorol. Appl. 14 (4), 425–434.
21. Wang, L., Zhang, J., & Liu, Y. (2026). "ExoPrompt: Transformer-based greenhouse climate forecasting with structured conditioning and physics-based simulation." *Computers and Electronics in Agriculture*, 231, 108920.
22. Zhao, H., Chen, X., & Li, M. (2025). "Greenhouse Temperature and Humidity Prediction Method Based on Adaptive Kalman Filter and GWO-LSTM-Attention." *Smart Agricultural Technology*, 11, 100512.
23. Zhang, X., Wang, Q., & Liu, S. (2026). "Short-term microclimatic load forecasting using a two-stage CPO-PSO hyperparameter optimization of LSSVM." *Nature Scientific Reports*, 16(3), 55227.