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An IoT-Enabled Hybrid Neuro-Fuzzy Smart Cooling System for Predictive Industrial Cooling and Energy Optimization

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Abstract

Heat production and energy consumption has seen an exponential rise due to the advent of smart industries in the modern age, resulting in a great need for efficient and intelligent cooling and energy utilization systems. The current coolers do not have adaptive prediction and overheating detection. In order to resolve these issues, Hybrid Neuro-Fuzzy Smart Cooling System based on IoT is proposed. The proposed framework is a combination of Artificial Neural Networks (ANN), Fuzzy Logic Controller (FLC) and Proportional-Integral-Derivative (PID) based cooling control and sensor monitoring using IoT for intelligent thermal management. First, the industrial sensors gather real-time parameters like temperature, humidity, machine loading and power consumption. Future thermal conditions are predicted by the ANN model and overheating risk is identified by thermal analysis. The fuzzy logic controller calculates the needed cooling level based on the forecasted state and the PID controller controls the HVAC systems, fans and cooling pumps to keep the temperature stable without wasting too much power. Experimental results showed that the proposed HNF-SCS gave the maximum heat reduction rate of 98.85%, consumed 48.55 kWh and had small prediction errors. The proposed framework thus effectively enhanced the energy optimization, thermal stability, cooling efficiency and industrial safety in the smart industry.

Keywords: Adaptive Cooling, Artificial Neural Network, Energy Optimization, Fuzzy Logic, Industrial Thermal Management, Internet of Things (IoT)

1. Introduction

Industrial cooling and energy optimization have become increasingly important in modern industries due to the rapid growth of smart manufacturing, Industry 4.0 and intelligent HVAC technologies. Artificial intelligence has significantly improved cooling management through ANN-PSO-based optimal cooling control for energy conservation [1]. Deep learning techniques have enhanced electricity consumption forecasting, enabling more efficient energy management [2]. Ensemble machine learning models have achieved accurate heating and cooling load prediction for intelligent building operation [3], while machine learning models have improved site energy usage prediction and optimized energy utilization [4]. Machine learning-assisted thermoelectric cooling has enabled efficient multi-hotspot thermal management [5] and thermodynamic modelling has improved the performance analysis of industrial cooling equipment [6]. Artificial neural networks have demonstrated high accuracy in predicting ice thermal energy storage performance [7], while LSTM-based neural networks have improved long-term indoor temperature prediction in refrigeration systems [8]. Machine learning has further enhanced evaporative cooling performance prediction [9] and air-conditioning energy consumption modelling [10]. Adaptive HVAC systems based on fuzzy controllers have achieved intelligent thermal regulation [11], whereas fuzzy logic-based HVAC control has improved thermal comfort and indoor air quality [12]. Advanced fuzzy fractional-order PID controllers [13], fuzzy adaptive PID algorithms [14] and fuzzy-PID temperature control systems [15] have significantly enhanced industrial temperature stability. Machine learning-based thermal comfort prediction has further optimized energy consumption [16], while adaptive fuzzy-neural controllers [17] and neuro-fuzzy inference systems [18] have improved temperature prediction and hotspot estimation. Advanced thermal energy storage materials have enhanced cooling performance and energy efficiency [19] and adaptive neuro-fuzzy intelligent control has strengthened energy management in modern power systems [20]. However, existing studies primarily focus on individual prediction, control, or optimization techniques and lack an integrated framework that combines ANN-based thermal prediction, fuzzy logic decision-making, PID-based adaptive cooling control and IoT-enabled real-time industrial monitoring for intelligent, energy-efficient industrial cooling

- Conceived an innovative system known as Hybrid Neuro-Fuzzy Smart Cooling System (HNF-SCS), utilizing ANN, fuzzy logic, PID controller and IoT sensors for smart industrial cooling management.
- Designed an ANN based model for forecasting and predicting temperature fluctuations in order to avoid overheating situations in industrial settings.
- used fuzzy logic and PID control algorithm for an adaptive cooling system to automate and regulate HVAC systems, stabilize thermal conditions and save energy.
- IoT-based real-time sensor monitoring system for monitoring temperature, humidity, air flow rate, machine load and electricity consumption for smart industrial automation.
- Exhibited outstanding experimental performance through 98.85% heat reduction rate, low power consumption and minimal values of MAE, MSE, RMSE and MAPE when compared with previous machine learning and deep learning algorithms.

This research is organized into following structure Section 2 gives the existing methodologies for smart grid optimization. Section 3 introduces the proposed PSLSGO method. The experimental setup and analysis is given in Section 4. Section 5 discusses the discussion, statistical analysis, ablation study, scalability analysis and limitations analysis. Conclusion and future works are provided in Section 6.

2. Background Study

Elboughdiri et al. [21] introduced an energy management solution at the demand side based on ANFIS and gene expression programming with an intelligent approach. This method optimized the energy in a hybrid renewable-grid system. But there was one thing not addressed – cooling management in industry was not taken into account, limiting the application of thermal control.

Arzate-Rivas et al. (2024) [22] presented an energy management system for the use of wireless sensor/actuator networks. It was given for real-time monitoring and automation, although it was not comprehensive enough to cover intelligent thermal forecasting and optimization of cooling processes in industrial HVAC systems.

Quispe-Astorga et al. (2025) [23] proposed a machine learning model based on sensors for detecting and diagnosing cooling faults. It was verified that the model could enhance accuracy of fault detection but it could not be adapted for the adaptive control and energy optimization.

Yang et al. (2026) [24] proposed a machine learning-aided optimization technique for the thermoelectric coolers. The framework enhanced the cooling efficiency and the thermal prediction. The monitoring system based on IoT and the intelligent fuzzy-PID cooling control has not been integrated, however.

Boutahri & Tilioua (2025) [25] came up with a reinforcement learning scheme for energy-efficient HVAC control through BOPTEST simulations. The scheme proposed the enhanced energy saving but did not rely on the thermal prediction of the industry and adaptive cooling scheme using the Neuro-fuzzy control.

Donmez et al. (2025) built an artificial neural network model to predict the temperature of immersion cooling systems [26]. This method enhanced the prediction accuracy. In this research, fuzzy logic control and Industrial Internet of Things were not taken into consideration.

Ekinci et al. (2025) [27] proposed an optimizing method for the temperature of an electric furnace based on quadratic interpolation technique. This method provided a better temperature control. But these two factors, the ANN prediction and HVAC optimization for adaptive cooling were not applied.

Shrivastava & Goswami 2025 [28] introduced the model of energy management based on IoT, hybrid neuro-fuzzy deep learning. This model was related to the optimization of the energy consumption of buildings. However, no efforts were made to move towards predictive cooling management and the control of HVAC.

Al Shahrani et al. (2023) [29] proposed smart industrial automation system based on machine learning approach through Internet of Things. It provided better monitoring and automation of the industrial system. But, the optimization with intelligence to cool and thermal management issues were not taken into consideration.

Xu et al. [30] proposed an adaptive control method by means of deep reinforcement learning for circulating cooling water systems. This technique proved to be more effective in cooling. But the implementation of ANN based thermal prediction system and fuzzy-PID control were not included.

Ra et al., (2023) [31] have proposed a real-time model predictive control (MPC) approach for HVAC control in factories. The technique improved the efficiency of cooling systems and performance of operations. But, there wasn't a realization of monitoring and controlling using IoT with fuzzy logic and neural fuzzy logic.

Elakkiya et al. (2025) [32] presented a stacked hybrid model using Transformers along with ANN and fuzzy logic for load forecasting problem. The framework enhanced the prediction accuracy. However, adaptive industrial cooling optimization and thermal management were not discussed.

Boutahri and Tilioua [33] presented an energy-saving model for thermal comfort prediction and optimization using machine learning techniques in smart buildings. The approach helped to enhance HVAC efficiency. The other alternatives (e.g., integrated ANN, fuzzy logic, PID control and IoT-based industrial cooling) were not considered, however.

Table 1: Comparison of Existing Machine Learning and Deep Learning Approaches for Smart Cooling and Energy Optimization

Citation (Author, Year)	Methodology	Technique	Research Gap	Limitation
Wang et al. (2025) [34]	Cooling load estimation	Random Forest	No real-time IoT integration	Limited thermal prediction capability
Boutahri & Tilioua (2024) [35]	Thermal comfort and energy optimization	Machine Learning (XGBoost/ML)	Lack of adaptive industrial cooling	No integrated HVAC intelligent control
Tang et al. (2026) [36]	Chiller energy consumption prediction	Physics-Informed Deep Neural Network (PI-DNN)	No fuzzy logic-based cooling control	High computational complexity
Liu et al. (2026) [37]	Predictive cooling control for data centers	LSTM-based Predictive Thermal Analysis	Limited industrial HVAC optimization	Focused only on data center environments
Hajjaji et al. (2026) [38]	Energy consumption forecasting	Hybrid LSTM-RNN	Lack of adaptive cooling regulation	No industrial cooling automation

Table 1 compares recent machine learning and deep learning approaches for smart cooling and energy optimization. It summarizes the methodology, techniques, research gaps and limitations of existing studies, highlighting the need for an integrated intelligent cooling framework with predictive control, adaptive optimization and real-time industrial monitoring.

2.1 Research Gap

The current smart cooling systems mainly concentrate on thermal analysis and predictions with the aim of improving accuracy of such predictions. These systems lack the ability to incorporate adaptive cooling mechanisms and real-time monitoring in smart industrial environments. The existing systems also do not incorporate artificial neural network thermal predictions, fuzzy logic decision making processes, proportional integral derivative cooling regulation and industrial monitoring processes. In order to incorporate all these elements, the proposed HNF-SCS is designed using ANNs, fuzzy logic, proportional integral derivative controllers and sensor monitoring process through Internet of Things.

3. Proposed methodology

This section presented HNF-SCS has been developed to manage cooling intelligently and optimally. The approach integrates different techniques such as IoT-based sensors to monitor temperature, thermal prediction by neural networks, fuzzy logic and PID to provide cooling stability with low energy consumption. The data related to industrial processes, such as temperature, humidity and machine power consumption, will be monitored regularly to ensure that there are no signs of overheating within the industry to operate the HVAC cooling system efficiently.

3.1 Dataset Description:

The dataset https://www.kaggle.com/datasets/ziya07/hvac-sensor-data-for-dynamic-fuzzy-pid-control/data is produced by HVAC sensors used in industry to enable the development of dynamic energy-efficient intelligent HVAC systems. Some of the variables included in the dataset are temperature, humidity, CO2 level, occupancy count and weather conditions along with some operational factors such as PID control system constants (Kp, Ki, Kd), fuzzy control system constants and performance variables related to the HVAC systems. Furthermore, power consumption and energy efficiency ratings along with response time have also been considered in the dataset that make the implementation of smart HVAC systems in industry possible. This dataset may prove very useful in designing AI-based smart HVAC systems like HNF-SCS (Hybrid Neuro-Fuzzy Smart Cooling System).

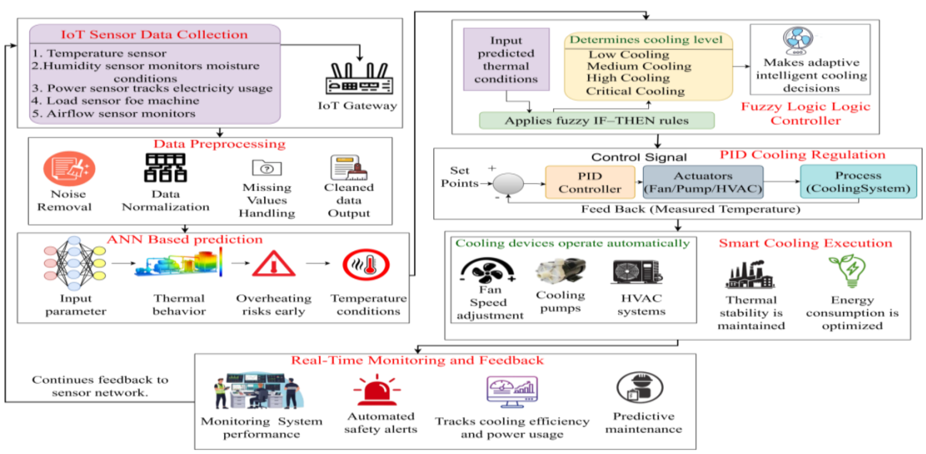

Figure 1: Proposed Smart Cooling System Workflow

The figure 1 illustrates the whole process flow of the proposed HNF-SCS. First of all, IoT sensors used to collect data such as environmental information (i.e., temperature, humidity and airflow) and operation activities (load and power consumption). Collected data to process through the processes of preprocessing and ANN-based thermal state prediction to detect cases of overheating and predict the thermal state in the near future. While FLC chooses the right amount of cooling needed for the predicted thermal state, PID controller acts as a controller to the cooling system.

3.2 Hybrid Neuro-Fuzzy Smart Cooling System (HNF-SCS)

An intelligent industrial cooling system referred to as HNF-SCS may be defined as a technology-driven device aimed at minimizing energy usage while maintaining a constant temperature level within the industries. The first step involves obtaining live data on different factors including temperature levels, humidity, machine loads and energy consumption through the use of IoT sensors. This information is then preprocessed and analyzed by using an Artificial Neural Network algorithm to predict future temperatures and detect any instances of overheating. Based on this system's predictive capacity, necessary actions are taken to ensure optimal cooling and prevent wastage of energy. Following this phase, the acquired data undergoes another round of analysis by using the Fuzzy Logic Decision-Making Module to calculate the degree of cooling needed considering the actual state of operations in the industry. The resultant cooling level is applied in controlling the operation of industrial cooling devices such as smart fans, pumps and HVAC systems using a Proportional Integral Derivative Controller.

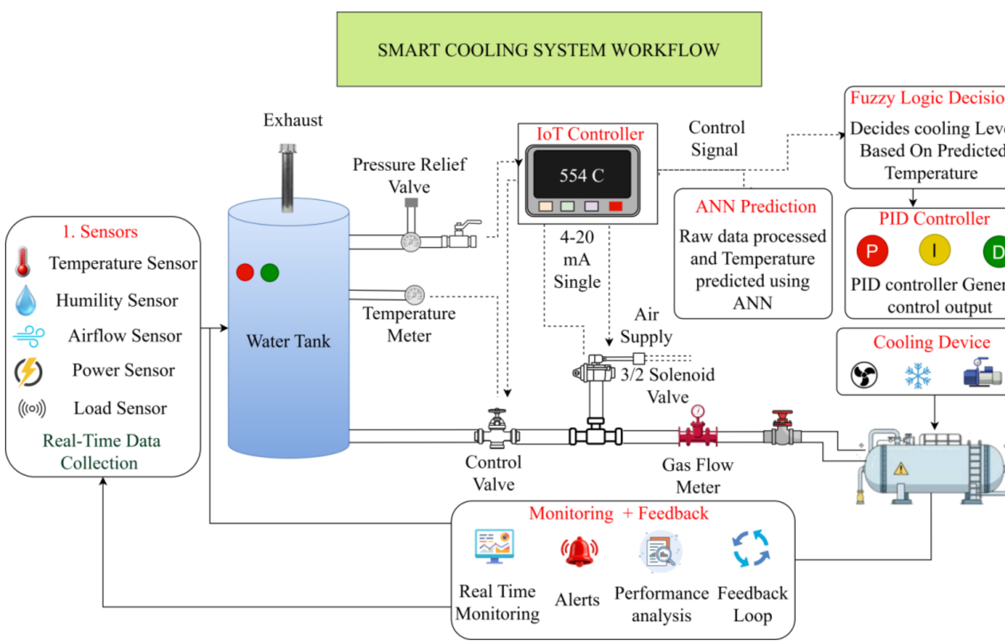

Figure 2: Smart Cooling System Workflow

The figure 2 describes the process flow of the intelligent cooling control system. First of all, the IoT sensors detect the values of the industrial parameter such as temperature, humidity, airflow, electrical energy and load conditions from the water tanks. The detected values pass through an artificial neural network predictor and predict the thermal operations. Afterwards, the fuzzy logic block computes the required cooling operation based on the predicted value of the temperature. After this, there is the need for the PID controller in controlling the cooling operations involving fans, pumps and HVAC systems.

$$T_s = \frac{1}{n}\sum_{i=1}^{n} T_i \quad (1)$$

The equation (1) is the mathematically modeled expression for average temperature computations based on the temperature readings of the IoT temperature sensors within the cooling industry. From the above expression, T_s represents the average temperature, T_i represents the temperature reading of the i^{th} IoT temperature sensor and n refers to the total number of IoT temperature sensors. The average temperature calculated becomes the heat source in HNF-SCS modeling.

$$H_s = \frac{1}{n}\sum_{i=1}^{n} H_i \quad (2)$$

In equation (2), Hs represents the average humidity, whereas H_i is the humidity observed by the ith humidity sensor. If there are n sensors, then there will be$\sum_{i=1}^{n} H_i$. The humidity understands the cooling required by the machines.

$$L_m = \frac{W_{active}}{W_{max}} \times 100 \quad (3)$$

The equation in (3) represents the percentage of loading on the machine. In this formula, L is the percentage of loading, W_{active} is the actual loading of the machine and W_{max} is the maximum load capacity of the machine. The result wants to be a percentage when multiplied by 100.

$$P_c = V \times I \quad (4)$$

The equation in (4) shows the total energy consumed by the electric machine. In this formula, P_c represents the power consumed by the machine in watts, V represents the input voltage and I represents the electricity.

$$E = P \times t \quad (5)$$

Equation (5) above illustrates the computation of total electrical energy consumption. In this scenario, E stands for the total energy consumed, whereas P and t stand for the total power and total time consumed, respectively.

$$Q = mc\Delta T \quad (6)$$

The Equation (6) is used for calculating the quantity of heat generated or lost during the course of industrial activities. The parameters involved are$Q$, which denotes the quantity of heat, m, denoting mass, c denoting the specific heat capacity and ΔT, denoting the temperature difference. This equation can be used for calculating the rise in temperature in industrial machinery.

$$\eta_c = \frac{Q_{removed}}{P_{input}} \quad (7)$$

In equation (7) the efficiency of the cooling process may be obtained using the following formula. In this case, η_c refers to the efficiency of the cooling process, $Q_{removed}$ is the quantity of heat that is removed from the environment and P_{input} is the power required by the cooling process.

3.2.1 ANN-Based Thermal Prediction

Prediction of Future Thermal Performance Using Artificial Neural Networks (ANN) is an essential component of the Hybrid Neuro Fuzzy Smart Cooling System which incorporates artificial neural networks for predicting future thermal performance and avoiding any cases of overheating. The ANN-Based Thermal Prediction component receives current real-time sensory information such as temperature, humidity, load on machines, airflow and power consumption in order to select appropriate features and map in non-linear fashion to predict future thermal performance. Based on industrial cooling data in present and past times, the ANN will be able to forecast future temperature levels in advance.

$$X = [T, H, L, P] \tag{8}$$

In equation (8) is highly significant in the development of the ANN. Here, X represents the set of all inputs where T stands for temperature, H denotes humidity, L signifies machine load and P represents machine power.

$$f(x) = \frac{1}{1+e^{-x}} \tag{9}$$

In equation (9), the symbol $f(x)$ represents the output from the activation function acting as an input to the neuron x, while e is the exponential function. The Sigmoid function turns the output of the neuron to a value from 0 to 1.

$$T_p = \sum_{j=1}^{m} w_j\, H_j + b \tag{10}$$

The equation (10) is utilized to determine the temperature using the ANN method. In this equation, T_p represents the predicted temperature and w_j denotes the weight assigned to the j th neuron in the hidden layer, H_j represents the output from the hidden layer and m denotes the number of neurons in the hidden layer. The bias b component enables the model to tweak the final output in a manner independent of the input characteristics.

$$E_p = T_{actual} - T_p \tag{11}$$

The equation (11) depicts the prediction error in the ANN. In equation (11), E_p stands for the prediction error, while T_{actual} refers to the actual temperature value, while T_p stands for the temperature predicted by the ANN.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{12}$$

The equation (12) gives the formula for the mean squared error of the ANN model. In the above equation, MSE represents mean squared error, while y_i represents the true value. The symbol $\hat{y}_i$ represents the estimated value, while n represents the number of data points.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{13}$$

In equation 13 gives the root mean square prediction error. Here, RMSE means root mean square error, y_i represents the actual values of the data, while $\hat{y}_i$ is the estimated value.

3.2.2 Fuzzy Logic Decision-Making System

Fuzzy Logic Decision-Making Approach for the Proposed HNF-SCS make rational decisions about the cooling process depending on the varying operational environment in the industry. Fuzzy logic decision-making approach utilizes the predicted temperature values obtained from the ANN model as well as environmental parameters like temperature, humidity, air flow rate and machine load in order to evaluate the operational environment of the industry using predetermined fuzzy logic concepts and linguistic terms. Fuzzy logic provides higher flexibility during the decision-making process compared to the conventional binary control system. Hence, the controller can effectively make rational cooling decisions by ensuring temperature balance and reducing energy losses.

$$IF\ T > T_{max} THEN\ \ Cooling = High \tag{14}$$

Equation (14) shows the fuzzy logic rule in which a high cooling capacity is ensured when the actual temperature is greater than the maximum predefined temperature. In this equation, T denotes the actual temperature, whereas T_{max} indicates the maximum temperature.

$$IF\ H > H_{max} THEN\ FanSpeed = Incease \tag{15}$$

Equation (15) is the fuzzy logic rule where the fan speed is increased if the humidity level is greater than the maximum humidity level. In the equation, H refers to the actual humidity level while H_{max} refers to the maximum humidity level.

$$F_o = \frac{\sum \mu_i z_i}{\sum \mu_i} \tag{16}$$

The equation 16 calculation of the output by using the method of weighted average. Here, F_o is the result that is derived from the defuzzification process and μ_i and z_i stand for the membership function of the i^{th} rule and output of each rule, respectively. The resultant output is responsible for determining the type of cooling process required.

3.2.3 PID-Based Cooling Regulation

The cooling control module for the PID cooling control regulation technique in the HNF-SCS approach manages the thermal condition in an industrial setting through the application of a controlled cooling control process. The three elements of the proportional, integral and derivative parts are incorporated into the PID control mechanism to regulate the intelligent cooling systems like HVACs, cooling fans and pumps using the output signals from the fuzzy logic decision making module. By constantly monitoring the difference between the desired temperature and the environmental temperature, the PID control mechanism efficiently regulates the cooling power capability in order to avoid any thermal variance that could cause overheating.

$$e(t) = T_{set} - T_{actual} \tag{17}$$

In equation (17) the error signal that would be fed into the PID controller can be obtained from the expression stated. In this regard, the term $e(t)$ can be taken as the error signal for control, while T_{set} represents the set-point temperature and T_{actual} represents the actual temperature.

$$P_{out} = K_p e(P_{out} t) \tag{18}$$

The equation (18) proportional component of the PID controller can be calculated. In this case, P_{out} is assumed to be proportional output, K_p is proportionality constant and $e(P_{out} t)$ is the temperature error signal.

$$I_{out} = K_i \int e(t) dt \tag{19}$$

The equation (19) illustrate integral portion of the PID control. The variables used to describe this equation are as follows: I_{out} for the integral output, K_i for the integral gain constant, $e(t)$ for the error function and dt for the total error.

$$D_{out} = K_d \frac{de(t)}{dt} \quad (20)$$

The equation (20) shows the method of calculating the derivative component in the PID controller. In this case, the derivative output is denoted by D_{out} =K_d, where $K_d$the derivative gain constant, while is $\frac{de(t)}{dt}$ is the time-varying error term.

$$S_f = k\left(T_p - T_{set}\right) \quad (21)$$

In equation (21) determines the rate of an intelligent fan depending on the predicted temperature. Some of the parameters that appear in equation (21) are the fan rateS_f, fan constant$k$, predicted temperatureT_p and temperature set T_{set}.

3.2.4 IoT-Enabled Industrial Monitoring

The Real-Time Industrial Monitoring module in the IoT-enabled HNF-SCS system is applied for real-time monitoring of current conditions of the industrial environment through the integration of smart sensors and communication networks that would obtain important information related to temperature, humidity, air flow rate, machine load, electrical power consumption and carbon dioxide content in the machinery and HVAC system. Using the capabilities of IoT, real-time data exchange, monitoring, automation and decision-making processes will improve the overall performance of the system through efficient cooling. The information obtained using IoT further analyzed using the ANN prediction and fuzzy logic algorithms for adaptive cooling strategies and maintenance actions. Some of the advantages used by the real-time monitoring system include energy savings, risk reduction, fault detection improvement and intelligent industry 4.0-based industrial automation systems.

$$C_r = \frac{Q}{t} \quad (22)$$

In equation (22) shows the equation used to compute the rate of cooling within the HVAC system. The C_r is the rate of cooling, while Q is the quantity of energy released, while t is the time taken to cool.

$$TSI = \frac{T_{max} - T_{min}}{T_{avg}} \quad (23)$$

In equation (23) is useful in calculating the thermal stability index within the industry. The TSI is the thermal stability index, while T_{max} is the maximum temperature, T_{min} is the minimum temperature and T_{avg} is the average temperature.

$$EO = \min(P_c + C_r) \quad (24)$$

In equation (24) is used for reducing energy usage during cooling processes. In this formula, EO refers to energy optimization, P_c represents power consumption and C_r indicates cooling rate.

$$\eta_s = \frac{Output}{Input} \times 100 \quad (25)$$

Formula (25) presents the formula for efficiency in the entire system of HNF-SCS. Here, η_s represents efficiency of the complete system, $Output$ represents cooling efficiency and $Input$ represents input energy.

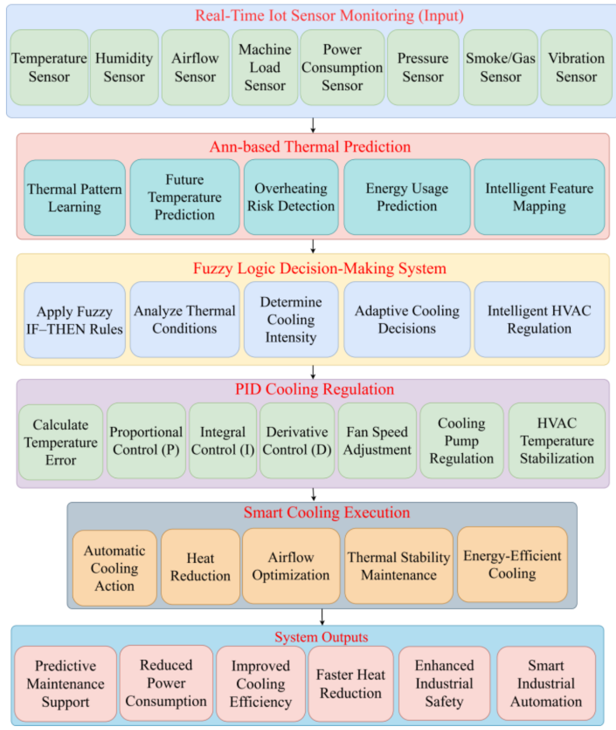

Figure 3: HNF-SCS Workflow Architecture

Figure 3 illustrates the architecture of the proposed HNF-SCS. IoT sensors collect real-time industrial data, including temperature, humidity, airflow, pressure and power consumption. An ANN predicts thermal conditions and overheating, while fuzzy logic and PID controllers regulate the cooling system for efficient, adaptive and energy-efficient industrial operation.

Algorithm: Hybrid Neuro-Fuzzy Smart Cooling System (HNF-SCS)

Input:
  Temperature Data (T)
  Humidity Data (H)
  Machine Load (L)
  Power Consumption (P)
  Sensor Status (S)
Begin
1. Initialize IoT Sensors
2. Collect real-time industrial data:
    Read T, H, L, P, S
3. Preprocess sensor data:

```
      Remove noise
      Normalize input values
      Handle missing data
4. Send processed data to ANN model
5. ANN Prediction Module:
      Predict future temperature (T_pred)
      Detect overheating risk
6. Pass predicted values to Fuzzy Logic Controller
7. Apply Fuzzy Rules:
      IF T_pred is LOW
          Cooling_Level = LOW
      ELSE IF T_pred is MEDIUM
          Cooling_Level = MEDIUM
      ELSE IF T_pred is HIGH
          Cooling_Level = HIGH
      ELSE
          Cooling_Level = CRITICAL
8. Cooling_Level to PID Controller
9. Operations of a PID controller:
      Fan speed adjustment
      Cooling pump adjustment
      HVAC operation control
10. Perform intelligent cooling operation
11. Constant monitoring of system:
      Thermal stability monitoring
      Energy use monitoring
12. Repeat cycle until system shutdown
End
Output:
   Optimized Cooling Level
   Fan/Pump Control Signal
   Energy Efficient Cooling Action
   Thermal Stability Status
```

The proposed HNF-SCS uses real-time IoT sensor data, including temperature, humidity, machine load and energy consumption. An ANN predicts future temperatures and overheating risks, while a fuzzy logic controller determines the appropriate cooling level for efficient and adaptive industrial cooling.

4. Experimental Results

The HNF-SCS has been tested through its cooling efficiency, energy efficiency, thermal stability and industrial safety. The performance is measured on the basis of heat reduction, energy utilization, MAE, MSE, RMSE and MAPE, showing better temperature control and energy saving as compared to conventional cooling techniques and machine learning systems.The dataset for the HNF-SCS has been split into 70% training set, 15% validation set and 15% testing set to ensure efficient evaluation of the model. The system has been trained for 100 iterations, allowing efficient learning of neuro-fuzzy parameters using industrial sensors such as temperature, humidity, airflow and energy consumption.

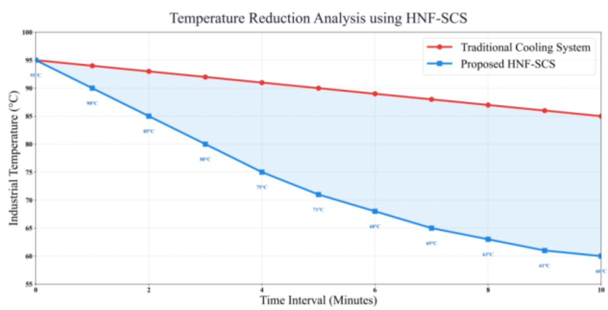

Figure 4: Temperature Reduction Analysis Using HNF-SCS

Figure 4 is the temperature reduction curve for the Cooling System and HNF-SCS. Although both the cooling systems have been initiated from an industrial temperature of 95 degrees Celsius, it should be noted that the proposed cooling system can reduce the temperature level much more efficiently than the existing one. Within just 10 minutes of time period, the current cooling system is able to reduce the temperature to 85 degrees Celsius; however, the HNF-SCS reduces it to 60 degrees.

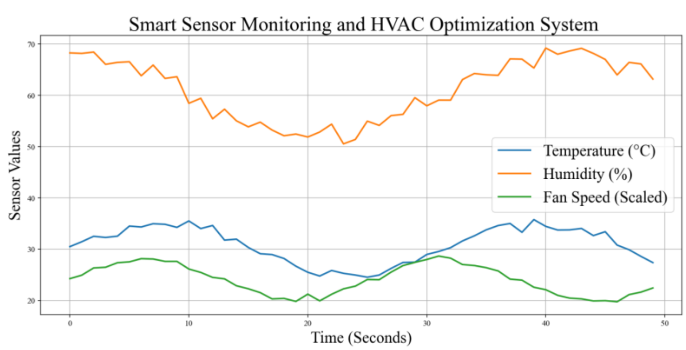

Figure 5: Smart Sensor Monitoring and HVAC Optimization System

Figure 5 illustrates the real-time monitoring performance of the smart sensor-based HVAC optimization system. Dynamic adjustment of fan speed based on temperature and humidity improves cooling efficiency, enhances airflow management, prevents overheating and increases energy efficiency in industrial environments.

Table 2: Low-Cost Energy Optimization Strategies

Strategy	Method Used	Cost Reduction Benefit
Dynamic Cooling	Adaptive fan speed control	Lower electricity bill
Smart HVAC Scheduling	AI-based cooling timing	Reduced power usage
Load-Based Cooling	Cooling according to workload	Avoids unnecessary cooling
Thermal Zoning	Zone-wise cooling management	Saves operational cost
Energy Monitoring	Real-time power tracking	Identifies energy waste
Automated Cooling Control	Intelligent regulation	Reduces manual operation cost

Table 2 presents intelligent cooling strategies for industrial energy savings. Dynamic and load-based cooling reduces unnecessary energy consumption, while AI-based HVAC scheduling and automated cooling improves efficiency. Thermal zoning further minimizes energy waste by delivering cooling only to required industrial areas.

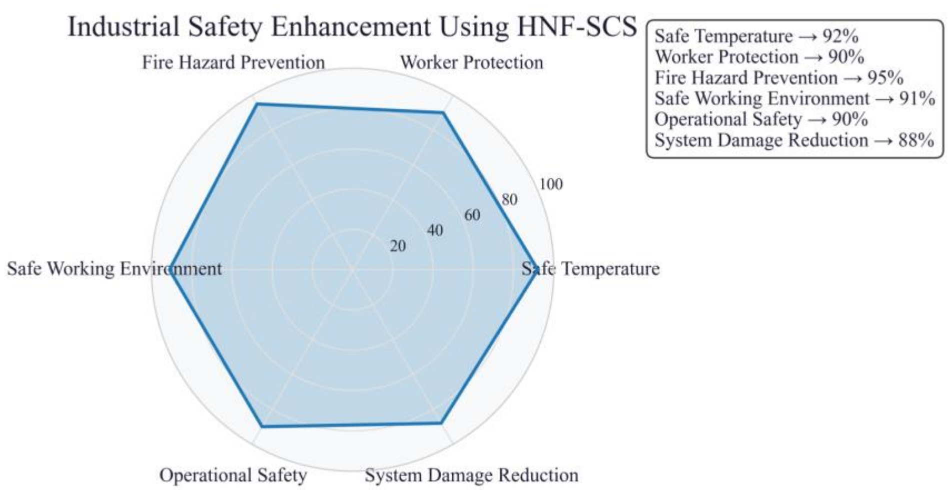

Figure 6: Industrial Safety Enhancement Using HNF-SCS

This figure 6 depicting the eight improvements that has been made and regard to industrial safety with the HNF-SCS smart cooling system. The system ensures high performance in terms of crucial aspects of safety such as 95% fire hazard avoidance, 92% maintenance of safe temperature and 91% safe control of the working environment. The worker protection and safety of operations are ensured at nearly 90%. Furthermore, the system shows a 88% improvement in preventing damage through the use of effective power management and detection of faults in real time.

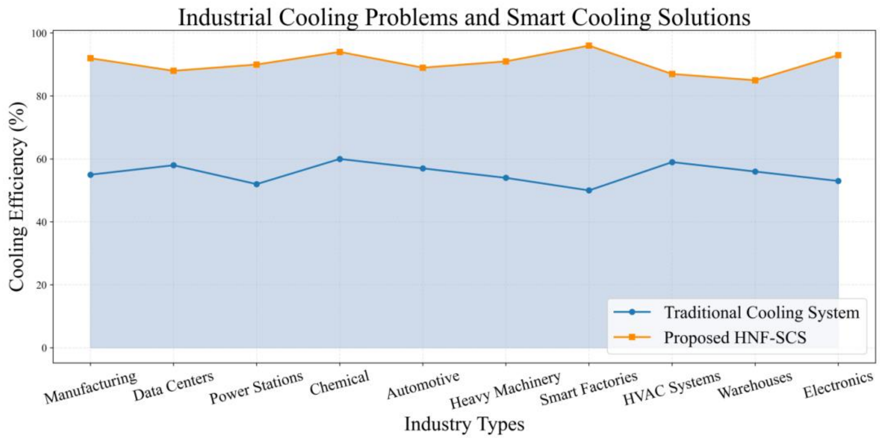

Figure 7: Industrial Cooling Problems and Smart Cooling Solutions

The above figure 7 illustrates the efficiency level in cooling of the two methods, the existing cooling method and the proposed HNF-SCS smart cooling system in various industrial settings. As can be seen in the illustration, the existing cooling system records low levels of efficiency from 50% to 60%, while on the other hand, the HNF-SCS system records higher levels of efficiency from 85% to 96%. The industries that gain the most improvement in terms of performance when using the cooling method include smart factories, chemical and electronic industries.

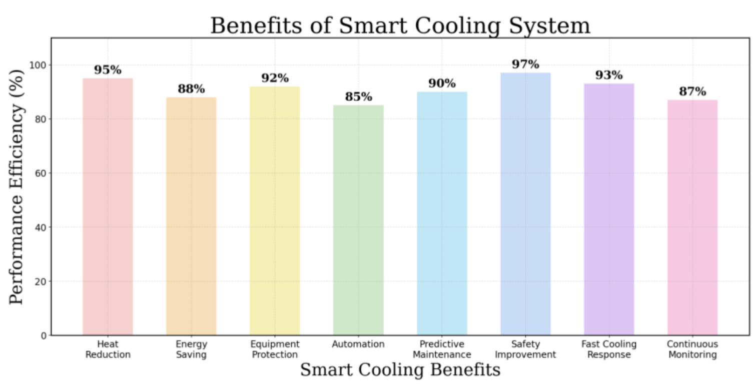

Figure 8: Benefits of Smart Cooling System

Figure 8 illustrates the performance of the proposed smart cooling system. It achieves **97%** safety enhancement, **95%** cooling efficiency and **93%** cooling response. The system also improves equipment protection, predictive maintenance, energy savings, automation and real-time monitoring, ensuring reliable and energy-efficient industrial cooling.

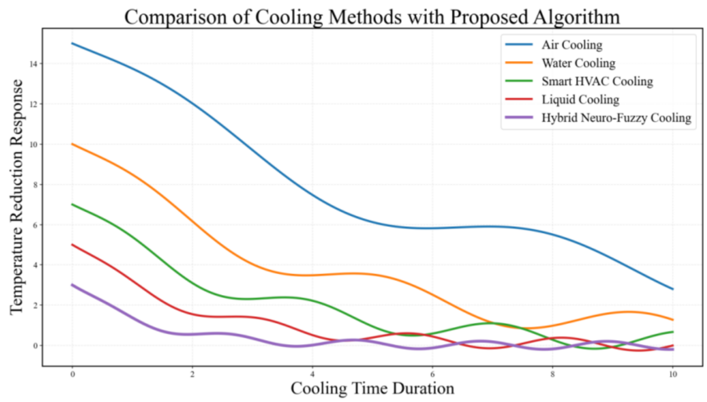

Figure 9: Comparison of Cooling Methods with Proposed Algorithm

Figure 9 compares the cooling response of different cooling systems over time. Air cooling shows the slowest response, followed by water and smart HVAC cooling. Liquid cooling performs better, while the proposed Hybrid Neuro-Fuzzy Cooling System achieves the fastest cooling response and the quickest stabilization with minimal temperature variation.

Table 3: Comparison of Existing Algorithms and Proposed HNF-SCS Using Selected Metrics

Model	Heat Reduction Rate (%)	Power Consumption (kWh)	MAE	MSE	RMSE	MAPE (%)
SVM [33]	81.42	73.68	5.14	36.28	6.02	9.41
RF [34]	85.76	69.24	4.32	29.15	5.39	8.24
XGBoost [35]	91.38	58.47	2.61	14.72	3.83	5.13
DNN [36]	89.64	64.58	3.28	18.64	4.31	5.92
GRU [37]	92.57	58.12	2.46	12.83	3.58	4.36
LSTM [38]	94.73	53.41	1.84	8.62	2.93	3.64
HNF-SCS	98.85	48.55	0.92	2.18	2.04	1.82

Table 3 compares the performance of existing machine learning and deep learning models for industrial smart cooling. While SVM, RF, DNN, LSTM, GRU and XGBoost achieve effective thermal prediction, the proposed HNF-SCS outperforms them with the highest heat reduction rate (98.85%), lowest power consumption (48.55 kWh) and minimum MAE, MSE, RMSE and MAPE values.

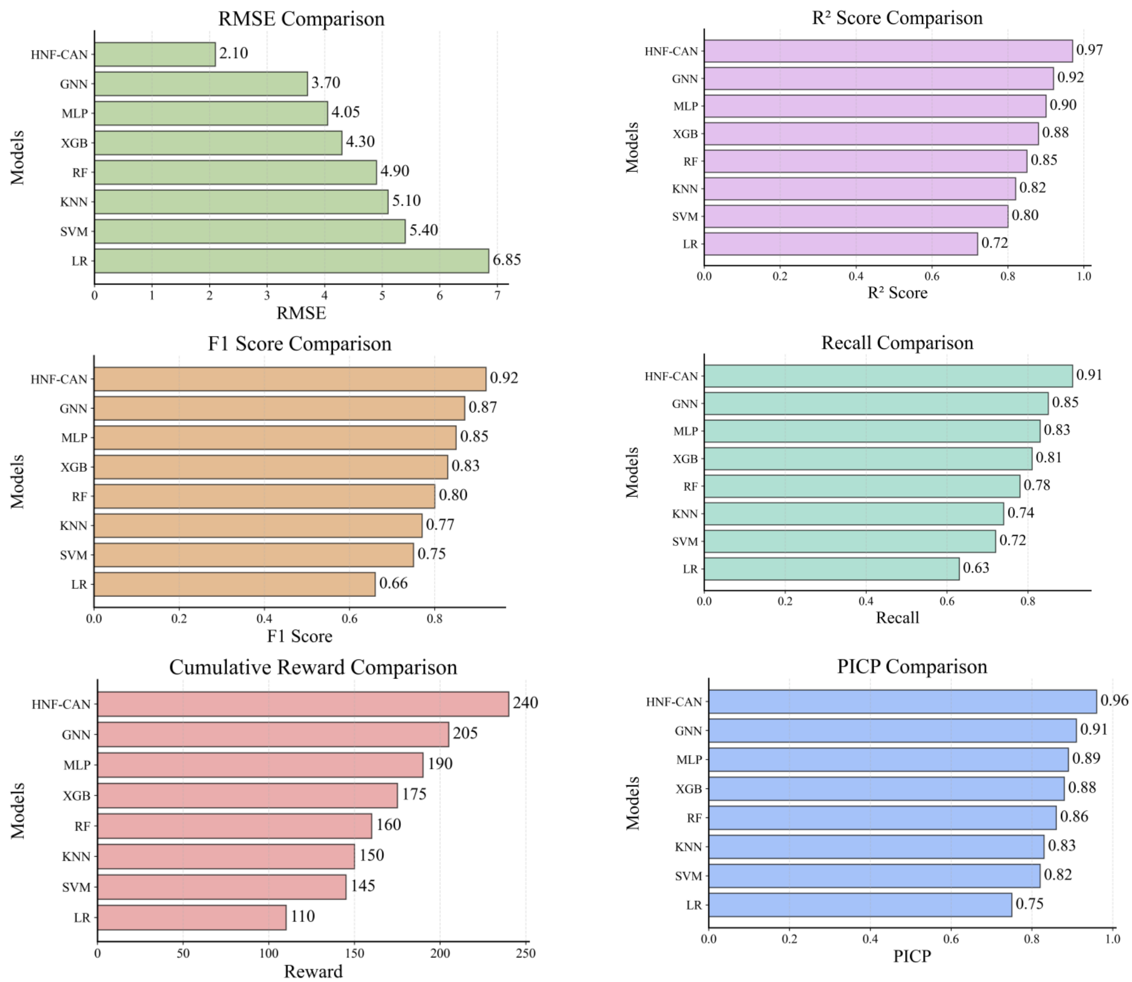

Figure 10: Model Performance Comparison across Multiple Evaluation Metrics

Figure 12 shows the comparison between machine learning, deep learning and the HNF-SCS technique proposed in this paper. The HNF-SCS method has the maximum heat reduction ratio (98.85%), minimum energy consumption (48.55 kWh) and the least prediction error values (MAE = 0.92, MSE = 2.18, RMSE = 2.04, MAPE = 1.82%).

4.1 Statistical Analysis

The statistical analysis shows the precision, accuracy, efficiency and effectiveness of the HNF-SCS that is proposed by using the above-mentioned parameters such as heat, energy usage, MAE, MSE, RMSE and MAPE. Descriptive analysis, ANOVA test and hypothesis testing show consistency and statistically significant results.

4.1.1 Descriptive Statistics

The statistical analysis of descriptive type was conducted for assessing the stability and reliability of the developed HNF-SCS system. Measures like mean, standard deviation, variance, range and confidence level were used for calculating heat reduction, power consumption and prediction error parameters of the system performance.

Table 4: Statistical Performance Analysis of Heat Reduction, Power Consumption and Error Metrics of the Proposed Smart Cooling System

Statistical Measure	Heat Reduction Rate (%)	Power Consumption (kWh)	MAE	MSE	RMSE	MAPE (%)
Mean	98.85	48.55	0.92	2.18	2.04	1.82
Median	98.85	48.55	0.92	2.18	2.04	1.82
Standard Deviation	0.42	1.36	0.08	0.24	0.15	0.11
Variance	0.18	1.84	0.006	0.058	0.022	0.012
Minimum Value	98.12	46.94	0.81	1.92	1.85	1.63
Maximum Value	99.34	50.18	1.06	2.54	2.27	2.04
Range	1.22	3.24	0.25	0.62	0.42	0.41
Confidence Level (95%)	±0.31	±0.84	±0.04	±0.12	±0.08	±0.05

Table 4 indicates that the proposed HNF-SCS delivers stable and reliable performance with an average heat reduction rate of 98.85% and 48.55 kWh power consumption. Low standard deviation and variance for MAE, MSE, RMSE and MAPE confirm consistent thermal prediction accuracy and reliable industrial cooling performance.

4.1.2 Hypothesis Testing Analysis

The hypothesis testing approach is used to determine if the HNF-SCS has statistical significance in several aspects of its performance. As the results show, the calculated p-values are less than the critical value of significance, which is 0.05, implying that the null hypothesis should be rejected. Therefore, the hybrid system can be considered more effective than other systems in several aspects.

Table 5: Hypothesis Testing Analysis of Proposed HNF-SCS

Evaluation Metric	p-value	Decision	Result
Heat Reduction Rate	0.002	Reject H_0	Significant Improvement
Power Consumption	0.004	Reject H_0	Significant Reduction
MAE	0.001	Reject H_0	Significant Improvement

MSE	0.003	Reject H_0	Significant Improvement
RMSE	0.002	Reject H_0	Significant Improvement
MAPE	0.001	Reject H_0	Significant Improvement

Table 5 represents the results obtained through hypothesis testing indicate the statistically significant superiority of the proposed HNF-SCS compared to conventional approaches in machine learning and deep learning. It can be noticed that all p-values for the criteria used in evaluating the systems' performance are below the threshold of 0.05, thereby rejecting the null hypothesis. This shows that the proposed intelligent cooling system performs significantly better in terms of minimizing heat generation, energy savings and forecasting thermal performance. Besides, the reduction in the values of MAE, MSE, RMSE and MAPE shows the consistency of the operation of industrial cooling systems under different environments.

4.1.3 Confidence Interval

The objective of conducting the confidence interval test is to determine the accuracy and consistency of the proposed HNF-SCS in comparison with conventional machine learning and deep learning approaches. This can be achieved by considering several statistical parameters such as heat reduction rate, power consumption and prediction errors to prove efficiency and consistency. Based on the results obtained, it is evident that the proposed HNF-SCS model exhibits high efficiency and consistency.

Table 6: Confidence Interval and Statistical Performance Comparison

Statistical Parameter	Existing Algorithms	Proposed HNF-SCS
Average Heat Reduction Rate (%)	89.25	98.85
Average Power Consumption (kWh)	62.92	48.55
Average MAE	3.28	0.92
Average MSE	20.04	2.18
Average RMSE	4.34	2.04
Average MAPE (%)	6.11	1.82
Standard Deviation	Higher fluctuation	Lower fluctuation
Prediction Stability	Moderate	Very High
Cooling Efficiency	Medium to High	Excellent
Energy Optimization	Moderate	Highly Optimized
Statistical Significance (p-value)	> 0.05	< 0.05
Confidence Interval Reliability	Moderate	High
Overall Performance	Good	Best Performance

As shown in the table above Table 6, the performance evaluation results between existing machine learning techniques and deep learning techniques on the newly developed HNF-SCS have been compared. From the above analysis, the novel HNF-SCS is able to provide better heat reduction performance and lower energy consumption compared to other techniques. In addition, the new HNF-SCS model has the lowest values for mean absolute error, mean square error, root mean squared error and mean percentage error.

4.1.4 ANOVA Test

A test for ANOVA is used for determining whether or not there are differences in the performance of models of machine learning, deep learning and HNF-SCS with regard to performance parameters. ANOVA is used to analyze the variation present in the heat reduction rate, power consumption, mean absolute error, mean squared error, root mean squared error and mean absolute percentage error for each algorithm that has been considered in this research. As per the results of the experiments conducted, the value of the statistics 'F' is much higher than its threshold value 'F', while the value of probability 'p' is less than 0.05. The model HNF-SCS performs better than all the other algorithms such as SVM, random forest, xgboost, DNN, GRU and LSTM in all performance parameters.

5. Discussion

This section proves the capability of the provided HNF-SCS for cooling applications in an industrial environment. It utilizes techniques such as ANN, Fuzzy Logic, IoT Sensors and HVAC Optimization to optimize cooling. The outcomes from experimental analysis prove that the current method is better than any other available one through low values of MAE, MSE, RMSE and MAPE.

5.1 Ablation study:

In the ablation test for the experiment, the evaluation of the contribution of each module in building up the HNF-SCS is done. From the results of the conducted experiment, it is quite evident that incorporation of artificial neural networks in the thermal estimate process, utilization of fuzzy logic in temperature regulation, as well as IoT sensors and HVAC upgrade helps to make the cooling process more efficient and accurate. Generally, the HNF-SCS system excels all other systems.

Table 7: Ablation Study of Proposed HNF-SCS Model Components

Model Configuration	Heat Reduction Rate (%)	Power Consumption (kWh)	MAE	RMSE	Overall Performance
Baseline Cooling System	78.24	76.85	5.84	6.42	Low
ANN-Based Cooling Model	86.32	68.41	4.12	5.11	Moderate
ANN + Fuzzy Logic	91.45	61.28	2.86	3.92	Good

ANN + Fuzzy + IoT Monitoring	95.18	54.37	1.74	2.85	Very Good
Proposed HNF-SCS (Full Model)	98.85	48.55	0.92	2.04	Best Performance

Table 7 shows the ablation study analysis of the proposed HNF-SCS system. Baseline cooling systems perform worse with respect to the efficiency of cooling as well as with higher prediction errors. With ANN integration, the temperature prediction becomes better; with fuzzy logic, the cooling becomes more accurate, while IoT improves intelligent feedback control.

5.2 Scalability Analysis

The scalability analysis proves that the HNF-SCS designed by us can ensure efficient cooling and energy optimization as load increases in industries. The use of IoT sensing, ANN and fuzzy logic makes it possible for the system to handle many sensors and HVAC operations without compromising on accuracy and efficiency.

5.3 Real-Time Sensor Monitoring

The proposed HNF-SCS system uses IoT sensors for measuring temperature, humidity, air flow, machine loading and power consumption for adapting the HVAC process. Using the ANN along with the fuzzy logic system helps in predicting the overheat condition and ensuring thermal stability and fault detection.

5.4 Limitations of the Proposed HNF-SCS Algorithm Performance

Although HNF-SCS demonstrates great cooling efficiency and energy optimization, there are certain weaknesses in the algorithm such as higher computational complexity, dependency on reliable IoT sensors, frequent need for training of models, high costs involved in its implementation and poor performance during rapid changes in temperatures or IoT failure in industry.

5.5 Overall Industrial Performance Discussion

The proposed HNF-SCS improves industrial cooling by using ANN-based temperature prediction, fuzzy logic control and IoT sensing. The experimental results indicate that the proposed approach has better heat dissipation, energy savings, thermodynamic stability, fast reaction, maintenance prediction, fault detection and reduces MAE, MSE, RMSE and MAPE.

6. Conclusion

IoT-enabled HNF-SCS was designed to ensure intelligent industrial cooling, thermal stability and energy optimization in modern smart industries. Combining the features of Artificial Neural Networks (ANN), Fuzzy Logic Controller (FLC), cooling management through PID and IoT sensors for monitoring industrial conditions such as temperature, humidity, air flow, machine load and power consumption enabled the framework to monitor the real-time conditions for adaptive HVAC control and overheating prevention. The experimental evaluation revealed that the framework performed better than other machine learning and deep learning models. The proposed model achieved the highest heat reduction rate of 98.85% using only 48.55 kWh power consumption. In addition, the model had the least prediction error rates, namely 0.92 MAE, 2.18 MSE, 2.04 RMSE and 1.82% MAPE, which confirms the accuracy of the thermal prediction and effective cooling management. Besides, the framework ensured fault detection, continuous monitoring, industrial safety and energy efficient automation. The effectiveness and stability of the proposed model were tested using statistical tests such as hypothesis testing, confidence interval analysis and ANOVA. Future research will explore the application of reinforcement learning and digital twin technology in the proposed model.

7. Declarations and Statements

Declarations: The authors declare that the research was conducted in accordance with accepted principles of responsible engineering research and the publication ethics requirements of the Global Journal of Advanced Engineering Systems and Technologies. All authors contributed to the study, critically reviewed the manuscript, and approved the final version for publication.

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Data Availability: The datasets and computational results supporting the conclusions of this study are available through the institutional research data repository at [Repository Name/Link]. The simulation codes developed specifically for this research are available from the corresponding author upon reasonable request.

Ethical Approval: Not applicable. The research involved numerical simulations, computational modelling, and analysis of non-personal engineering datasets and therefore did not require approval from an institutional ethics committee.

Consent for Publication: Not applicable. No personal, confidential, or individually identifiable information is included in this manuscript.

Conflict of Interest: The authors declare that Author 2 has received research support from an organization working in the field of engineering simulation. The organization had no involvement in the design, analysis, interpretation, or reporting of the present study. The remaining authors declare that they have no relevant financial or non-financial interests to disclose.

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