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

Noor Ul Amin
Taylor's University, Subang Jaya, Malaysia
nooraminnawab@gmail.com

Abstract

The modern era of smart industries has increased heat generation and energy consumption tremendously, creating a huge demand for intelligent industrial cooling and energy optimization. But the existing coolers cannot perform adaptive prediction, intelligent monitoring and overheating prevention in dynamic industrial environment. To overcome these limitations, a Hybrid Neuro-Fuzzy Smart Cooling System (HNF-SCS) using IoT is introduced in this research. 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 now become crucial fields of research due to the swift rise of smart industries and Industry 4.0 concepts, as well as intelligent Heating

Ventilation Air Conditioning (HVAC) systems. The main limitation in the existing cooling architectures is that it use unnecessary amounts of electrical energy and do not provide stable thermal performance under varying industrial loads. To solve this problem, many studies were conducted utilizing machine learning, deep learning, Artificial Neural Networks (ANN), fuzzy logic, and intelligent control systems for temperature predictions and cooling management [1]. Energy forecasting models using deep learning were used for improving accuracy of electrical energy prediction and energy management processes [2]. Ensemble machine learning methods were introduced for building predictive models for heating and cooling loads to increase thermal regulation performance [3]. Site energy consumption prediction models using machine learning led to improved intelligent energy management systems [4]. AI-driven thermoelectric cooling and thermal storage energy predictions were conducted for optimizing HVAC processes [5]. Additionally, thermodynamic analysis of thermal processes was done for industrial cooling improvement and performance assessment [6]. ANN-based thermal energy storage systems' prediction models were created for increasing prediction accuracy and energy optimization [7]. Neural networks based on LSTM algorithms for refrigeration temperature prediction also advanced thermal prediction and cooling analysis [8]. Machine learning-based evaporative cooling prediction models also improved cooling system efficiency and effectiveness [9]. Machine learning-based HVAC energy modeling models also improved air conditioning energy prediction and efficiency [10].

Several intelligent cooling and HVAC optimization strategies have been proposed for enhancing the effectiveness of industrial thermal management systems. Intelligent HVACs based on fuzzy controller techniques facilitated intelligent environmental regulation and thermal comfort optimization [11]. Adaptive HVAC systems based on fuzzy logic controllers were designed for intelligent cooling and indoor air quality regulation [12]. Fuzzy fractional order PID controllers substantially improved industrial temperature stability and cooling regulation accuracy [13]. Adaptive fuzzy PID control mechanisms further improved industrial temperature control effectiveness [14]. Intelligent fuzzy-PID temperature control systems enhanced thermal control stability and minimized thermal oscillations in industrial applications [15]. Machine learning models based on SVM, random forest, and XGBoost for thermal comfort and energy optimization enhanced HVAC performance [16]. Adaptive fuzzy-neural control systems advanced industrial temperature prediction and thermal regulation capabilities [17]. Neuro-fuzzy inference systems optimized hotspot temperature predictions and overheating prevention performance [18]. Thermal energy storage materials with advanced properties have been developed to enhance cooling and energy storage in thermal management systems [19]. Nevertheless, existing intelligent cooling systems do not incorporate ANN-based thermal predictions, fuzzy logic decisions, PID-based adaptive cooling control, and IoT-based industrial monitoring within an integrated intelligent cooling framework. Contributions of the research include the following:

- 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.
- Employed 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: The literature survey of existing smart cooling systems, HVAC system optimization techniques, neural networks based thermal prediction and fuzzy logic along with industrial Internet-of-things (IoT) based monitoring are covered in Section 2. The Hybrid Neuro-Fuzzy Smart Cooling System (HNF-SCS) algorithmic approach and structure are explained in Section 3. Experimental findings and comparison with the various energy optimization metrics are provided in Section 4. The discussion presented in section 5. The last part of this research provides the conclusion in Section 6 describes the overall findings of the research, its significance and future work directions.

2. Background Study

Shanmugam and Sharmila (2024) [20] provide an adaptive neuro-fuzzy control approach for hybrid renewable energy power plants with intelligent converter control strategies. Although the technique enhanced energy management and system stability, it did not incorporate industry cooling optimization or HVAC thermal management.

Elboughdiri et al. (2025) [21] introduced a new optimized ANFIS-based demand side energy management scheme for hybrid renewable and grid systems. While the system optimized energy management performance, it did not have intelligent thermal prediction or adaptive industry cooling systems.

Arzate-Rivas et al. (2024) [22] designed an IoT-powered energy management system with the help of wireless sensor network technology for real-time monitoring and automation. Although the system optimized energy monitoring process, it did not include ANN-based thermal analysis and fuzzy-PID cooling control.

Quispe-Astorga et al. (2025) [23] introduced a sensor-enabled machine learning model for fault detection within cooling units. Despite increased accuracy in fault detection and maintenance activities, it did not have adaptive cooling optimization and thermal energy management capabilities.

Yang et al. (2026) [24] presented an optimization model of a thermoelectric cooler using ANN and genetic algorithms in machine learning. The approach enhanced cooling effectiveness and prediction, but did not incorporate IoT technology in industrial operations and adaptive HVAC system control using fuzzy logic.

Boutahri and Tilioua (2025) [25] presented an adaptive HVAC control algorithm using reinforcement learning for efficient cooling in residential areas. It increased the efficiency of energy optimization but lacked industrial cooling automation and thermal prediction capabilities.

Donmez et al. (2025) [26] have presented an ANN model to predict temperatures in the immersion cooling systems using dielectric fluids. This model was helpful to predict temperatures and enhance the efficiency of the cooling system. However, no adaptive fuzzy control and IIoT were used in this research.

Ekinci et al. (2025) [27] designed an optimized system for controlling temperature in electric furnace systems using quadratic interpolation optimization technique, which helped provide thermal stability as well as energy efficiency; yet, there was no application of artificial intelligence for estimation of temperature in ANNs or HVAC systems.

Shrivastava & Goswami (2025) [28], developed a Neuro-Fuzzy Hybrid Deep Learning technique that utilized IoT technology for controlling the energy consumption of buildings. The technique was successful in optimizing energy consumption, but it failed to provide an intelligent industrial cooling management and forecasting mechanism.

Al Shahrani et al. (2023) [29] introduced a framework for creating intelligent industrial automation systems through IoT systems that incorporate machine learning capabilities. The framework ensured efficient intelligent industrial automation systems; however, it was unable to address intelligent cooling methods.

Xu et al. (2024) [30] developed an adaptive learning approach for cooling water control. This model was shown to be effective regarding cooling and thermal adaptation; however, the use of ANN and fuzzy logic control for temperature forecasting was not included.

Ra et al., (2023) [31] presented a predictive control strategy for cooling applications in manufacturing industries. The model exhibited increased energy efficiency; however, there was no incorporation of hybrid neuro-fuzzy adaptive control along with IoT-based systems in monitoring industrial processes.

Elakkiya et al. (2025) [32] provide a stacked hybrid approach for predicting smart loads utilizing transformers, artificial neural network and fuzzy logic. Though the prediction model proved highly accurate and efficient, the researchers failed to incorporate adaptive cooling and an industrial thermal management system in the work.

Table 1: Existing Smart Cooling and Energy Optimization Methods

Author & Year	Concept	Methods Used	Research Gap	Limitations	Results
Boutahri and Tilioua (2024) [33]	Thermal comfort and energy optimization in smart buildings using SVM	Support Vector Machine (SVM), ML prediction	Lack of adaptive industrial cooling automation	No fuzzy-PID cooling regulation	Improved thermal comfort and HVAC energy efficiency
Wang et al. (2025) [34]	Cooling load estimation for optimized cooling systems	Random Forest algorithm	No real-time IoT monitoring integration	Limited intelligent thermal prediction	Achieved accurate cooling load estimation

Boutahri and Tilioua (2024) [35]	Smart building thermal optimization using XGBoost	XGBoost, ML-based prediction	Lack of integrated HVAC adaptive control	No industrial thermal management capability	Improved prediction accuracy and energy optimization
Tang et al. (2026) [36]	Chiller energy consumption prediction using deep learning	Physics-informed Deep Neural Network (DNN)	Absence of fuzzy logic-based cooling control	High computational complexity	Enhanced chiller prediction accuracy and extrapolation performance
Liu et al. (2026) [37]	Predictive cooling control for data centers	LSTM-driven predictive thermal analysis, GRU-based learning	Lack of integrated industrial HVAC optimization	Focused mainly on data center environments	Improved proactive cooling control and thermal prediction
Hajjaji et al. (2026) [38]	AI-driven energy optimization and load forecasting	Hybrid LSTM-RNN forecasting framework	Lack of fuzzy logic and PID-based cooling regulation	Limited industrial cooling automation	Achieved high forecasting accuracy and energy optimization efficiency

Table 1 compares current methods in machine learning and deep learning use in smart cooling and energy optimization. Some of the techniques include SVM, random forest, XGboost, DNN, GRU and LSTM models with corresponding methodologies and limitations as well as performance. Although the current smart cooling and energy optimization systems have increased accuracy in load forecast and thermal prediction, it do not incorporate an integrated system of neuro-fuzzy control mechanism and real-time monitoring in industrial environments.

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[39-42].

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).

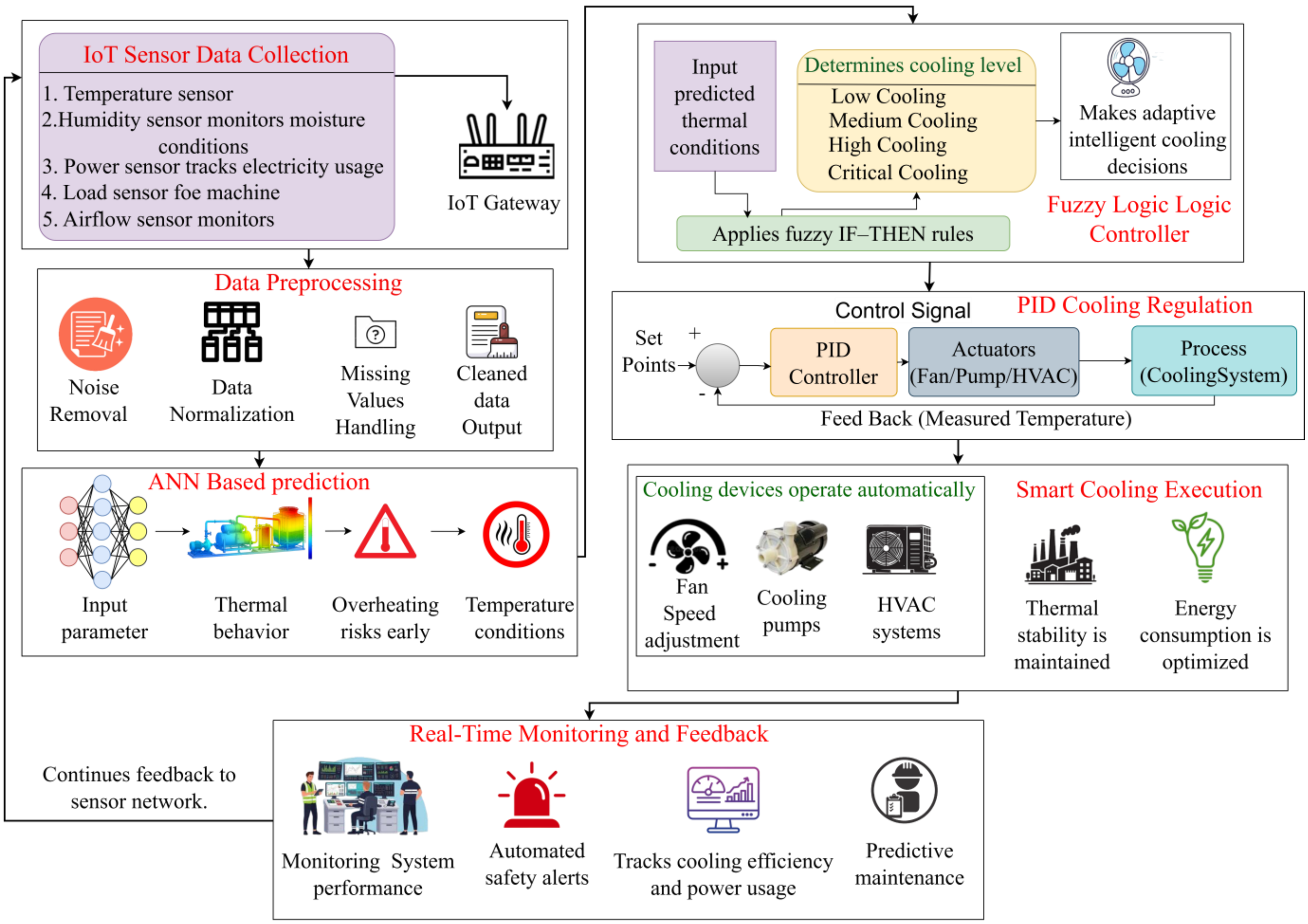

Figure 1: Proposed Smart Cooling System Workflow

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.

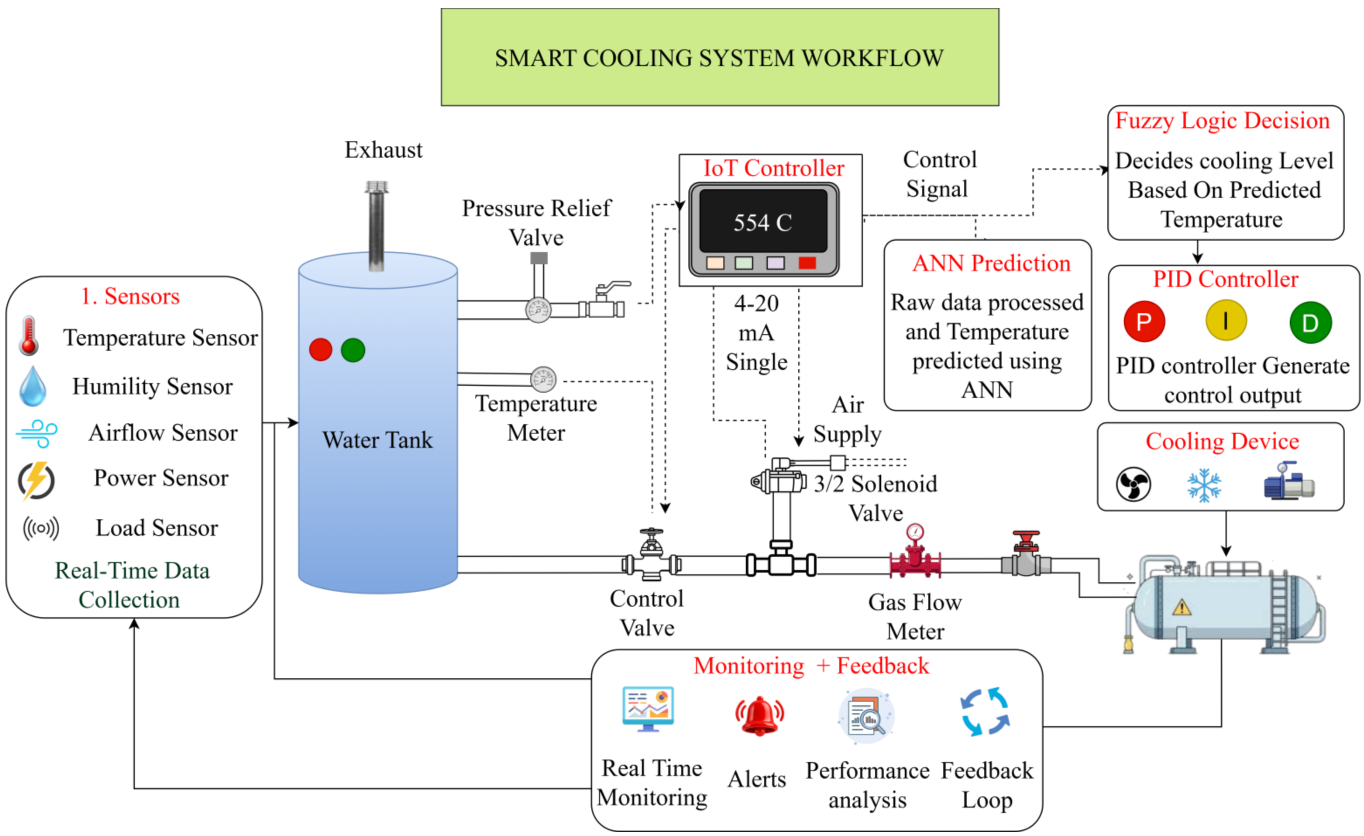

Figure 2: Smart Cooling System Workflow

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.

Table 2: Smart Cooling System Process

Concept Component	Description	Real-Time Industrial Purpose
IoT Sensors	Collect temperature and humidity data	Continuous industrial monitoring
ANN Prediction Model	Predicts future temperature conditions	Early overheating detection
Fuzzy Logic Controller	Determines intelligent cooling levels	Adaptive cooling decisions
PID Controller	Regulates cooling devices	Stable cooling operation
Smart HVAC System	Automatically adjusts cooling	Energy-efficient temperature control
Real-Time Monitoring	Tracks system performance continuously	Improves industrial reliability
Energy Optimization	Minimizes unnecessary cooling	Reduces electricity usage
Automated Alerts	Sends overheating warnings	Enhances industrial safety

Some of the components associated with the Hybrid Neuro-Fuzzy Smart Cooling System (HNF-SCS) model are listed in Table 2 below. The Internet of Things (IoT) sensors, artificial neural network (ANN) prediction, fuzzy logic control and proportional-integral-derivative (PID) control of cooling management each play it own roles when it comes to managing the industrial cooling process. The system constantly monitors the environmental status of the industrial environment, predicts an overheating condition and controls the cooling process.

$$T_s = \frac{1}{n}\sum_{i=1}^{n} T_i \tag{1}$$

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.

$$H_s = \frac{1}{n}\sum_{i=1}^{n} H_i \tag{2}$$

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.

$$L_m = \frac{W_{active}}{W_{max}} \times 100 \tag{3}$$

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.

$$P_c = V \times I \tag{4}$$

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.

$$E = P \times t \tag{5}$$

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.

$$Q = mc\Delta T \tag{6}$$

The Equation (6) is employed 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 andΔT, denoting the temperature difference. This equation can be used for calculating the rise in temperature in industrial machinery.

$$\eta_c = \frac{Q_{removed}}{P_{input}} \tag{7}$$

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.

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

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.

$$S_f = k(T_p - T_{set}) \tag{21}$$

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 rate S_f, fan constant k, predicted temperature T_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 offered by the real-time monitoring system include energy savings, risk reduction, fault detection improvement and intelligent industry 4.0-based industrial automation systems.

$$C_r = \frac{Q}{t} \tag{22}$$

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.

$$TSI = \frac{T_{max} - T_{min}}{T_{avg}} \tag{23}$$

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.

$$EO = \min(P_c + C_r) \tag{24}$$

In equation (24) is employed 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.

$$\eta_s = \frac{Output}{Input} \times 100 \tag{25}$$

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.

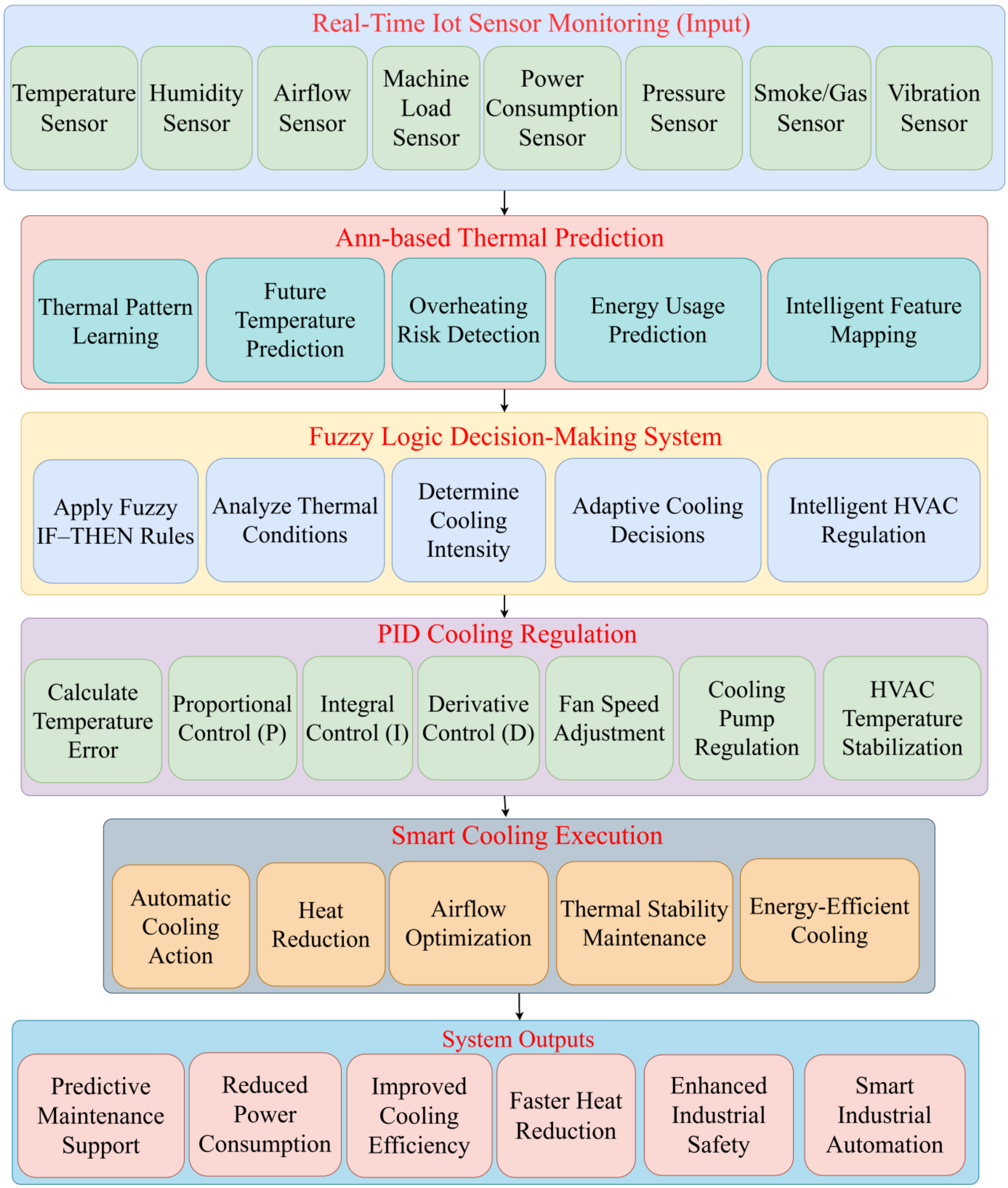

Figure 3: HNF-SCS Workflow Architecture

The figure 3 shows how the architecture of HNF-SCS. To start with IoT sensors play a vital part in collecting information related to real-world conditions like temperature, humidity, air flow rate, pressure and power consumption inside the industrial unit. The next step would be for the system to perform data preprocessing and thermal forecasting through artificial neural networks that would even enable the prediction of overheating conditions and thermal properties of the system. Finally, the data gathered during thermal forecasting would be utilized by fuzzy and PID controllers to operate the cooling system.

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

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        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
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The proposed HNF-SCS algorithm utilizes live data that involves various aspects of industrial activities, including temperature, humidity, load of machines and consumption of energy by means of IoT sensors. The collected data is then subjected to analysis via the use of ANN. ANNs have proven to be quite efficient in forecasting future temperature values and determining whether overheating could take place in the future. This is accomplished by employing an intelligent Fuzzy Logic controller, whose main function is to determine the necessary strength of the cooling process based on future temperature predictions in varying environments.

4. Experimental Resut

4. Experimental Results

This research evaluates the efficiency of the proposed HNF-SCS based on its cooling efficiency, energy efficiency, thermal stability and industrial safety. The performance of the proposed algorithm will be evaluated against existing methods for cooling and machine learning based on metrics such as heat transfer rate, energy consumption, MAE, MSE, RMSE and MAPE. The results indicate that the HNF-SCS outperforms conventional methods when it comes to temperature reduction and energy consumption.

The dataset used in developing the Hybrid Neuro-Fuzzy Smart Cooling System (HNF-SCS) was divided into 70% training data, 15% validation data and 15% testing data to ensure efficient learning and evaluation of the model. Furthermore, during the training process, 100 iterations were conducted using adaptive learning to improve the prediction and cooling control efficiency of the HNF-SCS. As such, during the course of these iterations, the system adapted its neuro-fuzzy parameters using the input gathered from the sensors of the industries, which include temperature, humidity, air flow and power consumption.

Table 3: Industrial Parameters and Effects

Parameter	Condition	Effect on Cooling System
Temperature	High	Increased cooling demand
Humidity	High	Reduced cooling efficiency
Machine Load	Heavy	Excess heat generation
Airflow Rate	Low	Poor heat dissipation
Power Consumption	High	Increased operational cost
Cooling Speed	Low	Thermal instability
Sensor Accuracy	Poor	Incorrect control decisions
HVAC Efficiency	Low	Higher energy usage

The impact of the smart cooling system’s performance depends on a number of factors including environment and operational variables that are shown in Table 3. Temperature is directly proportional to cooling requirement as a result of higher heat production due to elevated temperature and machine load. Higher humidity and lower airflow cause ineffective heat removal and inefficient air flow distribution which adversely affects cooling capacity. Likewise, low cooling speed and inaccurate sensors readings lead to thermal fluctuations and improper control decisions. In addition, reduced HVAC efficiency and high energy consumption contribute to increased costs of operations.

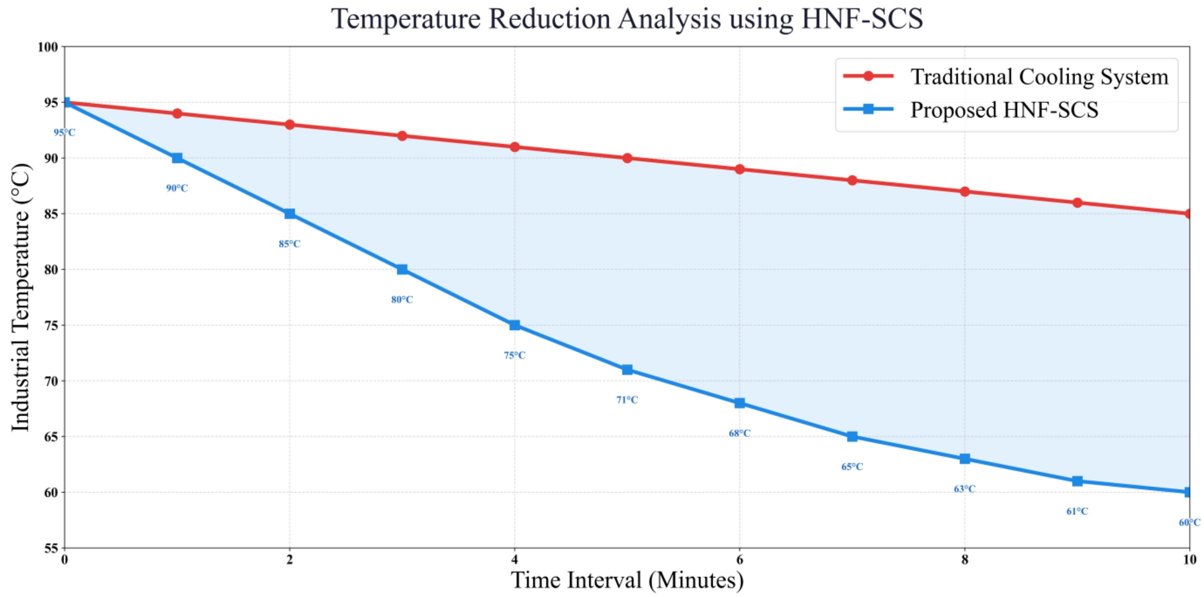

Figure 4: Temperature Reduction Analysis Using HNF-SCS

The following graph depicted by figure 4 is the temperature reduction graph comparing the existing Cooling System and the HNF-SCS. Both the systems have started from an industrial temperature of 95°C, but the proposed system HNF-SCS is able to reduce the temperature much faster as compared to the other system. In just 10 minutes, the existing cooling system reduces the temperature to 85°C, but on the other hand, the HNF-SCS reduces the temperature to 60°C, which clearly shows its superiority as far as cooling efficiency is concerned.

Table 4: Sensors Used in Real-Time Industrial Smart Cooling System

Sensor Type	Function	Real-Time Industrial Use
Temperature Sensor	Measures heat level	Detects machine overheating
Humidity Sensor	Measures moisture level	Maintains stable cooling environment
Airflow Sensor	Monitors air circulation	Controls ventilation efficiency
Power Sensor	Tracks electricity usage	Reduces excessive energy consumption
Load Sensor	Detects machine workload	Adjusts cooling based on load
Pressure Sensor	Monitors cooling pressure	Prevents HVAC system failure
Smoke/Gas Sensor	Detects hazardous gases	Improves industrial safety
Vibration Sensor	Detects machine vibration	Predicts equipment faults

Table 4 indicates the real-time industrial smart cooling system that uses several sensors to keep track of the environment and operation status for effective cooling. The temperature, humidity and airflow sensors play a role in maintaining optimum heat levels by measuring overheating, humidity and air flow respectively. On the other hand, power and load sensors measure electricity use and machinery loads to allow for adaptive cooling and minimize energy consumption. Moreover, pressure, smoke/gas and vibration sensors increase safety in the industries by measuring any HVAC problems, gas leakages and mechanical problems.

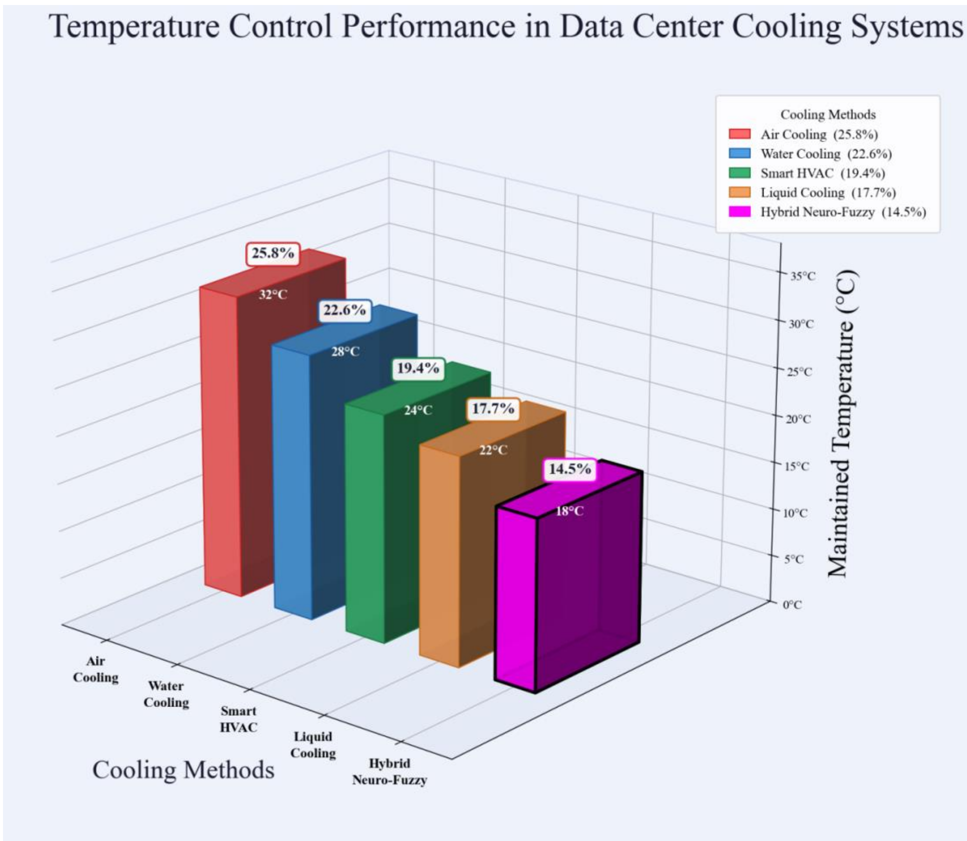

Figure 5: Temperature Control Performance in Data Center Cooling Systems

Figure 5 depicts the effectiveness of various cooling strategies applied in data center settings. Air cooling system retains a higher temperature value of 32°C. On the other hand, more sophisticated cooling approaches such as water cooling, smart HVAC cooling system and liquid cooling show improvement in cooling efficiencies. The new hybrid neuro-fuzzy smart cooling system attains the minimum temperature value of 18°C indicating its effectiveness and high level of smart cooling performance. Through combining neural networks with fuzzy logic, the proposed method manages cooling processes more effectively leading to less overheating and better energy usage.

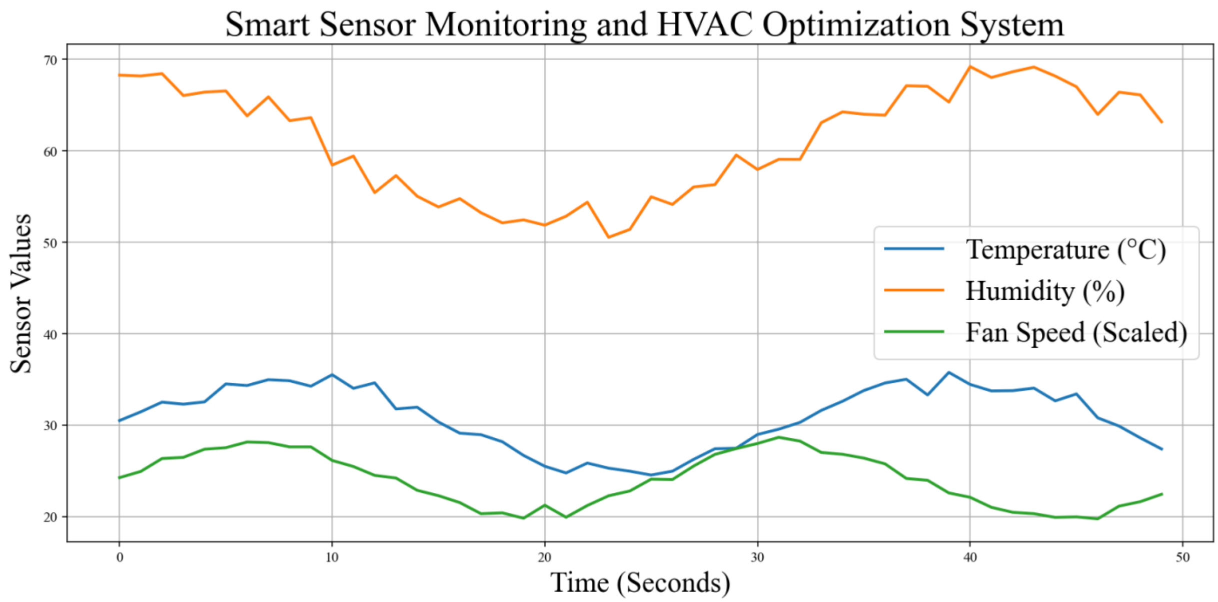

Figure 6: Smart Sensor Monitoring and HVAC Optimization System

Figure 6 shows the real-time monitoring efficiency of the Smart Sensor Monitoring and HVAC Optimization System through the temperature, humidity and fan speed data. The data of the temperature and humidity vary consistently depending on the environmental factors and operating parameters. Fan speed, on the other hand, varies dynamically to ensure consistent cooling performance. With rising temperatures and humidity levels, the HVAC system will increase fan speeds in order to enhance heat dissipation and ensure consistency in temperature control. The use of sensor-based control systems in the HVAC optimization process helps mitigate overheating, improve airflow management and increase energy efficiency within an industrial setting.

Table 5: Automation Technologies Used Industry

Automation Technology	Function	Industrial Application
IoT Monitoring	Real-time sensor communication	Smart industrial monitoring
Smart HVAC System	Automatic cooling regulation	Energy-efficient cooling
Automated Fan Control	Dynamic airflow adjustment	Prevents overheating
Cloud Monitoring	Remote system analysis	Industrial data

		management
Edge Computing	Fast local processing	Real-time cooling response
Smart Alert System	Sends emergency alerts	Improves industrial safety
Automated Energy Optimization	Controls power usage	Reduces electricity cost

Table 5 illustrates some automation technologies that are employed by current industry smart cooling and monitoring systems to increase the efficiency, ensure safety and manage energy consumption. IoT monitoring and cloud systems allow for seamless data transmission from sensors as well as remote analysis of operations within an industrial environment. Smart HVAC systems and fan automation can help ensure that the cooling system is working efficiently and will not lead to any overheating in the facility. Finally, edge computing makes it possible to perform calculations at a local level and initiate the cooling process quickly.

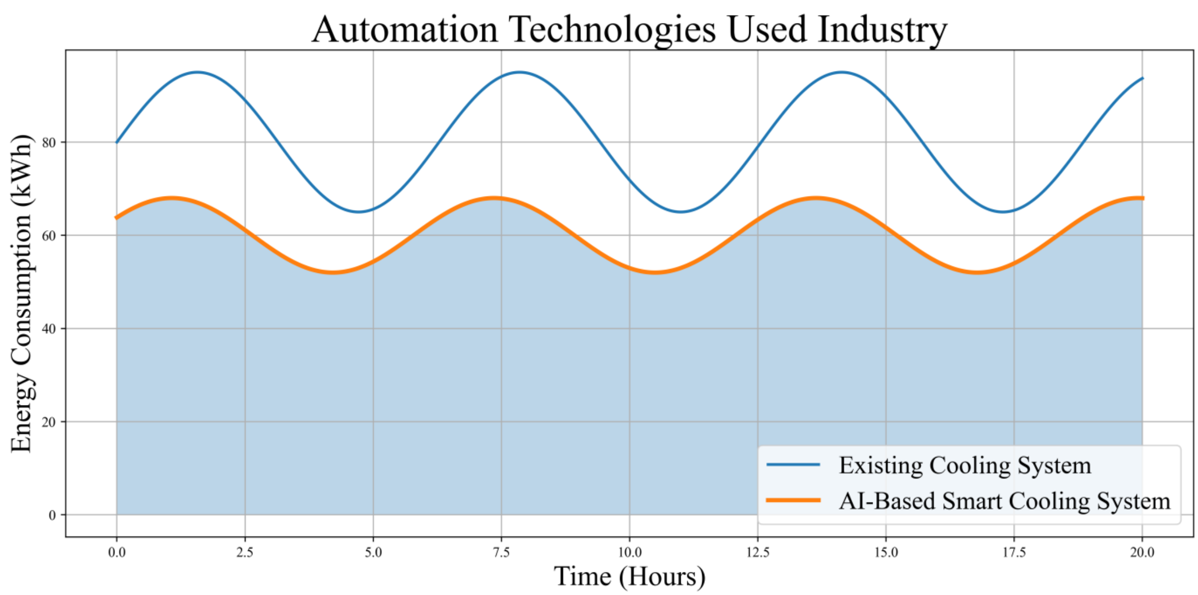

Figure 7: Automation Technologies Used Industry

Figure 7 below is a graph illustrating the energy consumption of two different cooling mechanisms in use in the automation sector over a period of 20 hours. The blue line indicates the current cooling system that uses more energy, with an average range of 65–95 kWh. The orange line shows the AI-based smart cooling mechanism that consumes lesser energy, with an average range of 52–68 kWh. From the graph, it is clear that both types of cooling systems have a similar energy consumption trend, with a wavy pattern providing variations in cooling demands throughout the hours.

Table 6: 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

The table 6 describes various intelligent cooling technologies that can be adopted for energy savings in industrial settings. The cooling techniques like dynamic cooling and load-dependent cooling are dependent on the demand of cooling at that particular instance and thus prevent any wastage of energy. The intelligent scheduling of HVAC systems and automatic control of cooling through artificial intelligence ensures enhanced performance of the cooling systems with minimum manual efforts. The thermal zoning technique enables distribution of cooling only in required areas, thereby preventing any energy wastage.

Table 7: Industrial Safety Enhancement Using HNF-SCS

Safety Issue	Smart Cooling Solution	Safety Improvement
Equipment Overheating	ANN thermal prediction	Prevents fire hazards
Hazardous Gas Emission	Gas sensor monitoring	Worker protection
HVAC Failure	PID stabilization	Maintains safe temperature
Electrical Overload	Power monitoring system	Prevents system damage
Sudden Machine Failure	Real-time fault detection	Improves operational safety
Excess Industrial Heat	Automated cooling control	Safe working environment

The table 7 depicts intelligent cooling solutions enhance safety in industry by avoiding overheating, system failures and dangerous situations. Some of these intelligent techniques include the use of ANN to predict thermal behavior and fault detection in real time. The gas sensor will help detect any dangerous gases and make the work environment safer for the workers. PID will ensure that operations run stably without any chance of the HVAC system failing. This will help avoid damages in the power system.

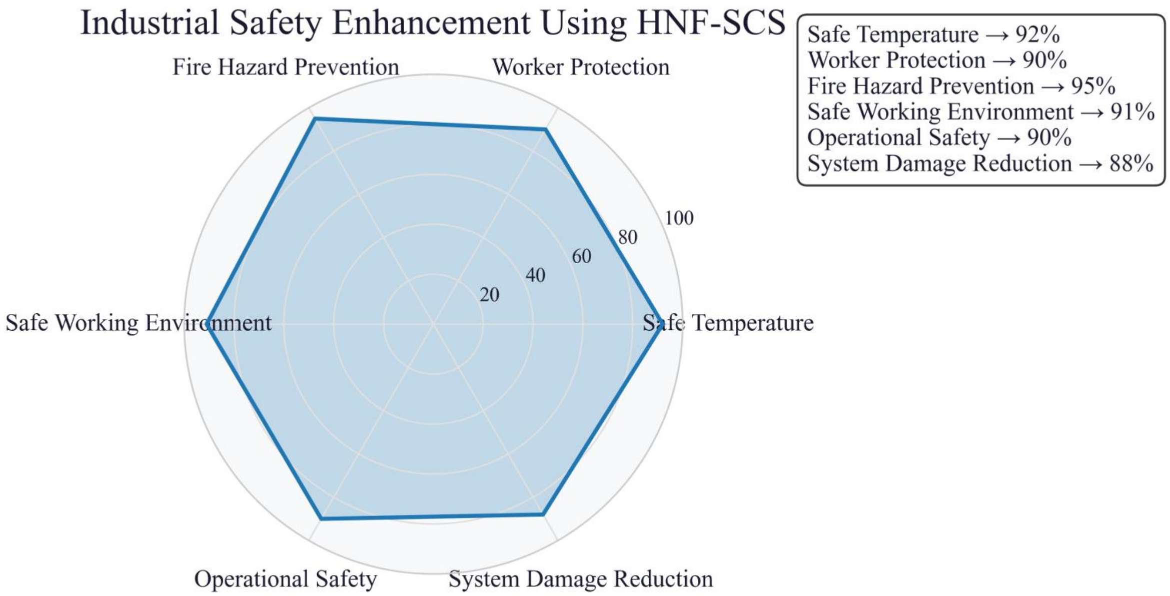

Figure 8: Industrial Safety Enhancement Using HNF-SCS

This figure 8 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.

Table 8: Industrial Cooling Problems and Smart Cooling Solutions

Industry Type	**Real-Time Industrial Issue**	**Existing Cooling Limitation**	**Proposed Smart Cooling Solution**	**Benefit**
Manufacturing Plants	Machine overheating during continuous	Continuous cooling consumes high electricity	AI-based adaptive cooling control	Reduced energy consumption

	operation			
Data Centers	Excess server heat generation	Fixed-speed cooling systems	Dynamic HVAC temperature regulation	Improved cooling efficiency
Power Stations	High thermal load in equipment	Manual cooling monitoring	IoT-enabled smart monitoring	Improved thermal stability
Chemical Industries	Heat-sensitive industrial processes	Delayed cooling response	ANN-based temperature prediction	Prevents overheating risks
Automotive Industries	Battery and motor heat generation	Inefficient conventional cooling	Smart PID-based cooling regulation	Enhanced equipment lifespan
Heavy Machinery Industries	Excessive machine load temperature	No predictive maintenance	Fuzzy logic intelligent cooling	Reduced maintenance cost
Smart Factories	Continuous industrial heat fluctuation	Limited automation	Fully automated smart cooling system	Real-time industrial automation
HVAC Industrial Systems	High power consumption	Constant HVAC operation	Energy-optimized cooling control	Lower operational cost
Industrial Warehouses	Uneven airflow and heat distribution	Existing ventilation methods	Smart airflow management	Better cooling distribution
Electronics Manufacturing	Sensitive component overheating	Poor thermal monitoring	Real-time sensor-based cooling	Improved industrial safety

The Table 8 indicates that there have been notable improvements in fire hazard prevention, safe temperature control and creation of safe environment among other aspects related to safety performance of HNF-SCS Smart Cooling System. The smart system operates at almost 90% efficiency in terms of safety for workers and system operations. It ensures real-time faults and power monitoring thus contributing greatly towards minimization of equipment damages. Overall, it is evident that there are remarkable advancements made by HNF-SCS systems in terms of industrial safety.

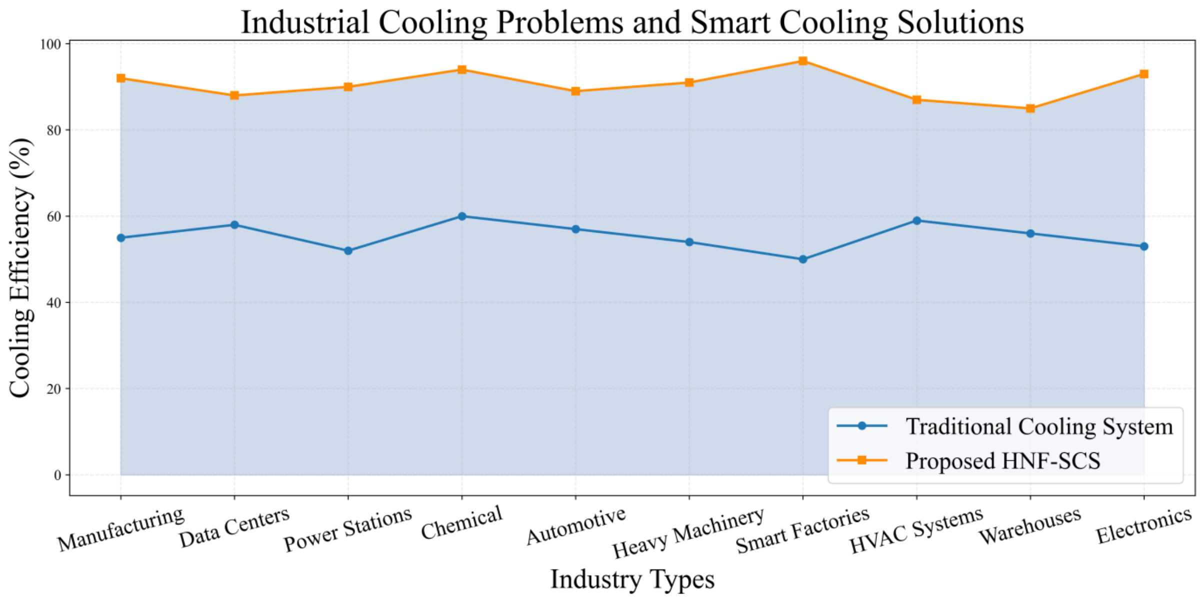

Figure 9: Industrial Cooling Problems and Smart Cooling Solutions

The above figure 9 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.

Table 9: Real-Time Benefits of Smart Cooling System

Industrial Requirement	Smart Cooling Feature	Industrial Benefit
Heat Reduction	Intelligent cooling adjustment	Prevents overheating
Energy Saving	Dynamic cooling optimization	Reduced electricity cost
Equipment Protection	Thermal stability monitoring	Increased machine lifespan
Automatic Operation	AI-based automation	Reduced human intervention
Predictive Maintenance	ANN prediction analysis	Reduced maintenance frequency

Safety Improvement	Real-time fault detection	Prevents industrial accidents
Fast Cooling Response	PID adaptive control	Improved cooling performance
Continuous Monitoring	IoT-enabled sensing	Better operational efficiency

The table 9 highlights how the smart cooling technologies satisfy key industrial needs by virtue of the intelligence and automation capabilities. The benefits that come from dynamic cooling optimization and intelligent cooling adjustment include reduced heat production and energy savings. Prediction analysis using ANN and thermal stability management can be used to protect equipment and allow for predictive maintenance, which increases the longevity. With AI-based automation and IoT-based sensing, monitoring is improved without relying on human intervention during industrial processes. Real-time fault detection and PID adaptive control also contribute to safety and efficient performance in industry.

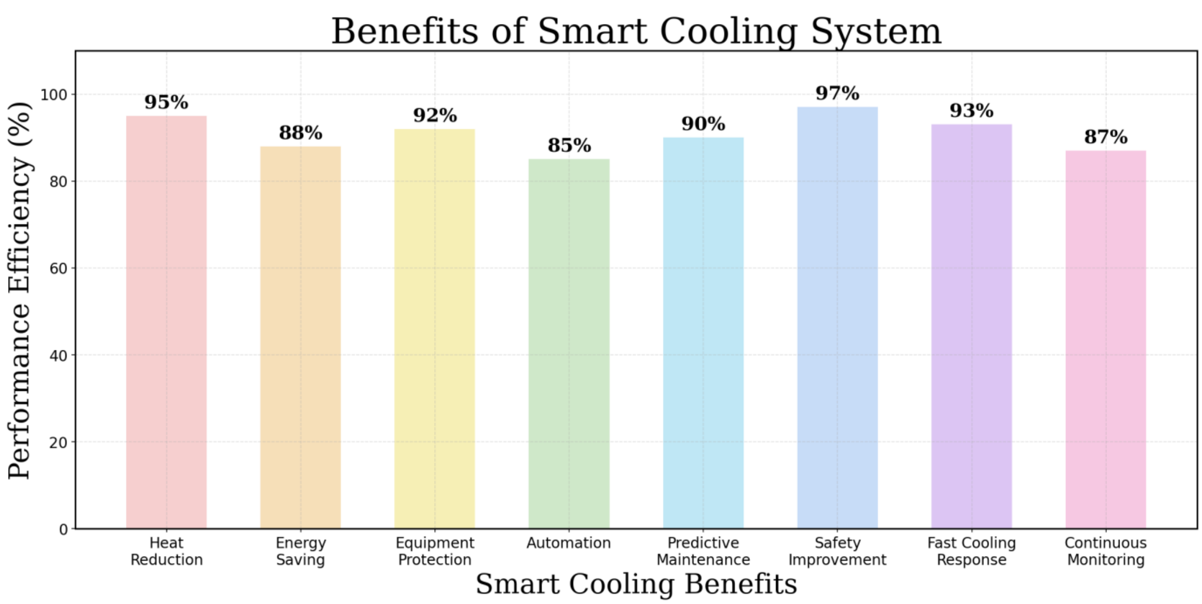

Figure 10: Benefits of Smart Cooling System

The Figure 10 shows the main strengths and efficiency of performance of the smart cooling system in the industries. The system is highly efficient with respect to safety enhancement with 97%, cooling with 95% and quick cooling response with 93%. These figures indicate how well the smart cooling system works with regard to ensuring stable performance in industries. Protection of equipment and predictive maintenance are also effective since it help decrease machine breakdowns. Other strengths include energy-saving, automated and monitoring operations which are efficient but do not consume much energy.

Table 10: Comparison of Cooling Methods with Proposed Algorithm

Cooling Method	**Control Type**	**Cooling Time**	**Energy Efficiency**	**Automation Level**	**Performance**
Air Cooling	Manual	15 min	Medium	Low	Basic
Water Cooling	Semi-Automatic	8 min	High	Medium	Better
Smart HVAC Cooling	Intelligent Control	5 min	Very High	High	Advanced
Liquid Cooling	Automated	3 min	Excellent	High	Fast Cooling
HNF-SCS (Proposed)	AI + Fuzzy Logic	2 min	Excellent	Fully Intelligent	Best Performance

Table 10 illustrates the comparative analysis of various cooling techniques used in industries depending on the type of control employed, cooling time, energy efficiency, automation level and performance achieved. Conventional air cooling is characterized by ordinary performance, low automation level and high cooling time, whereas water cooling is more efficient and fast in performance. Other modern cooling techniques include smart HVAC cooling technology and liquid cooling technique which use automated or intelligent controls in improving energy efficiency and minimizing cooling time greatly. The proposed HNF-SCS demonstrates the highest performance level due to utilization of artificial intelligence and fuzzy control techniques to achieve minimum cooling time of 2 minutes.

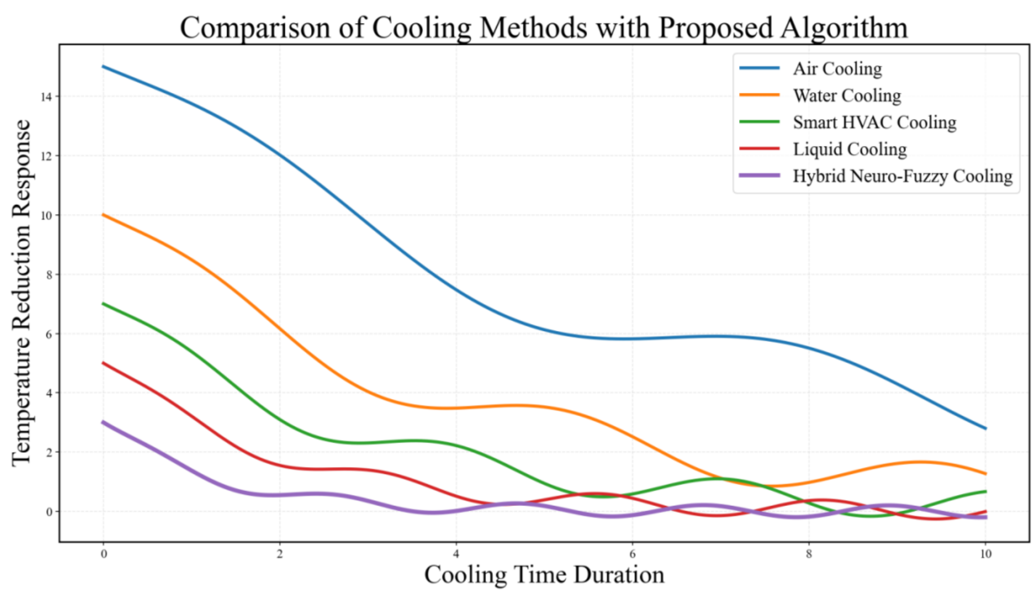

Figure 11: Comparison of Cooling Methods with Proposed Algorithm

The figure 11 represents the relationship between time and the cooling response of various cooling systems is illustrated. Existing air cooling takes the longest time to cool down, followed by water cooling and smart HVAC cooling. This means that the latter two are somewhat effective in reducing temperature, but the cooling response rate is still relatively slow. Liquid cooling cools faster than existing cooling techniques and temperatures stabilize more efficiently. The hybrid neuro-fuzzy cooling technique, on the other hand, cools at an impressive rate and reaches close to zero temperature variability in a shorter period of time.

Table 11: 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 11 shows a comparison of the performance of several machine learning and deep learning algorithms that have been applied for smart cooling and energy efficiency in an industrial setting. From the models considered Support Vector Machine (SVM), Random Forest (RF), Deep Neural Network (DNN), Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) show high performance when predicting thermal temperatures and cooling processes due to the ability to process time-series temperatures. The optimization process in XGBoost is effective with less power consumption and prediction errors compared to existing machine learning algorithms. Nevertheless, the HNF-SCS provides the highest performance with maximum heat reduction at 98.85% and low power consumption at 48.55 kWh. Moreover, the proposed model gives the least error values in MAE, MSE, RMSE and MAPE.

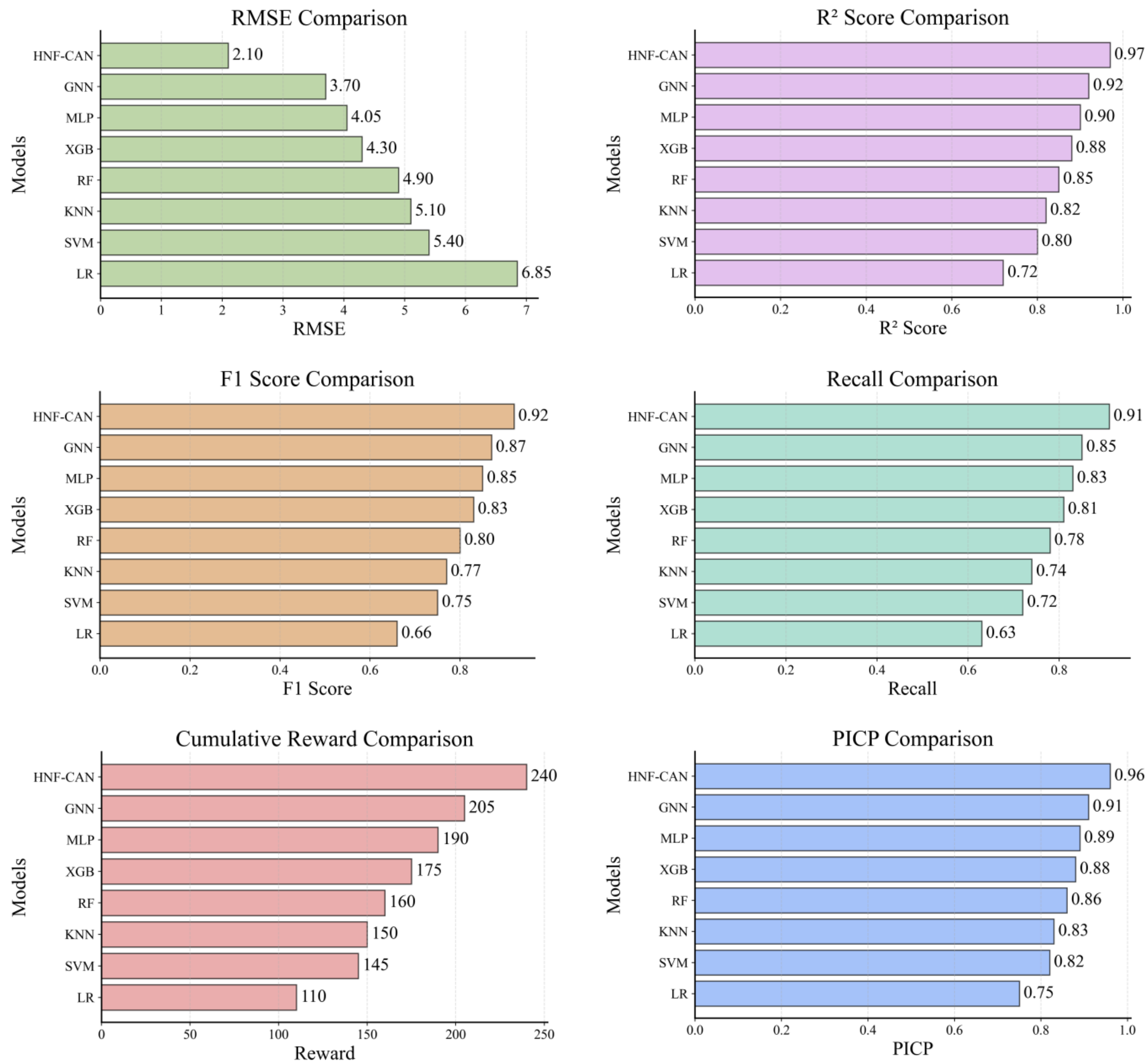

Figure 12: Model Performance Comparison across Multiple Evaluation Metrics

Figure 12 shows the comparative analysis of the performances of various machine learning and deep learning algorithms for smart cooling and energy optimization purposes in an industrial environment. The HNF-SCS attains the highest performance level in terms of having the maximum heat reduction rate of 98.85% while keeping its energy consumption at a minimal 48.55 kWh. For the purpose of predicting the thermal behavior, the framework shows very small error rates of 0.92 in MAE, 2.18 in MSE, 2.04 in RMSE and 1.82% in MAPE, indicating highly accurate thermal behavior prediction and adaptive cooling. However, conventional machine learning algorithms such as SVM and Random Forest show comparatively higher error rates in predictions as well as increased power consumption, whereas deep learning techniques such as LSTM and GRU show improved learning behavior for sequences. From the graph shown below, it is evident that the use of neuro-fuzzy intelligence in adaptive cooling has helped to improve thermal stability and industrial cooling reliability.

4.1 Statistical Analysis

Through the statistical analysis, the accuracy, reliability and efficacy of the proposed HNF-SCS are tested using different factors such as the rate of heat reduction, energy consumption, MAE, MSE, RMSE and MAPE. From the findings obtained through the descriptive statistical analysis, it can be concluded that the proposed HNF-SCS is very reliable and effective for use in the industrial cooling process since there will hardly be any prediction errors due to the consistency of the system. From the ANOVA and hypothesis testing statistical analyses, it is evident that the improvements brought about by the HNF-SCS have a high degree of significance as compared to the use of machine learning models.

4.1.1 Descriptive Statistics

Table 12 gives the result of descriptive statistics analysis of the proposed HNF-SCS. Measurement of statistical parameters like mean, standard deviation, variance and confidence level demonstrate the efficiency, reliability and stability of the system. These minimal errors and confidence levels indicate that the hybrid system is capable of providing precise thermal prediction and optimize energy usage under various industrial settings.

Table 12: 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

From Table 12, the descriptive statistics analysis shows that the proposed HNF-SCS is highly stable and reliable in terms of performance. This is based on the fact that the existing model has a high average heat removal efficiency of 98.85%, coupled with minimum energy consumption by 48.55 kWh. Therefore, the proposed model can be considered highly efficient in terms of thermal management purposes. Additionally, the proposed model has low values of standard deviation and variance in relation to the mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE) and mean absolute percentage error (MAPE). These values imply that the performance of the proposed model is both consistent and reliable.

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 13: Hypothesis Testing Analysis of Proposed HNF-SCS

Evaluation Metric	**Null Hypothesis (H_0)**	**Alternative Hypothesis (H_1)**	**p-value**	**Significance Level (α)**	**Decision**	**Result**
Heat Reduction Rate	No significant improvement in cooling efficiency	Proposed HNF-SCS improves cooling efficiency	0.002	0.05	Reject H_0	Significant Improvement
Power Consumption	No reduction in energy usage	Proposed HNF-SCS reduces power consumption	0.004	0.05	Reject H_0	Significant Reduction

MAE	No improvement in prediction accuracy	Proposed HNF-SCS reduces prediction error	0.001	0.05	Reject H_0	Significant Improvement
MSE	No significant difference in prediction stability	Proposed HNF-SCS improves thermal prediction stability	0.003	0.05	Reject H_0	Significant Improvement
RMSE	No improvement in model reliability	Proposed HNF-SCS improves cooling reliability	0.002	0.05	Reject H_0	Significant Improvement
MAPE	No reduction in percentage prediction error	Proposed HNF-SCS minimizes percentage error	0.001	0.05	Reject H_0	Significant Improvement

Table 13 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 14: 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 14, 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

The evaluation of the performance, efficiency and industrial applications of the innovative HNF-SCS model is done comprehensively within the discussion section. In the Hybrid Neuro-Fuzzy Smart Cooling System, the utilization of ANN thermal prediction, fuzzy logic control, IoT sensors and HVAC optimization guarantees efficiency of industrial cooling operation. According to experimental results, the novel HNF-SCS model is more efficient compared to existing cooling models and existing machine learning and deep learning models in avoiding overheating, conserving energy and ensuring thermal stability. With the HNF-SCS, one is capable of conducting real-time monitoring and executing intelligent processes for faster cooling actions, prediction of faults and prevention of faults. The innovation exhibits minimal error prediction levels when it comes to mean absolute error, mean square error, root mean square error and mean average percentage error.

5.1 Ablation study:

In the ablation study test, the assessment of the contribution of the various modules in developing the HNF-SCS takes place. From the experiment performed, it is clear that the inclusion of artificial neural networks in thermal estimation, the implementation of fuzzy logic in temperature control, IoT sensors and HVAC improvement progressively improves the efficiency of the cooling process while minimizing errors. In general, the HNF-SCS system outperforms all other systems individually.

Table 15: 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

The Table 15 depicts ablation analysis represents the results obtained during the testing of the proposed HNF-SCS on the significance of each component included in the system. As it can be seen from the results presented, a existing cooling system that does not incorporate intelligent optimization techniques shows poor performance in terms of efficiency of cooling and prediction errors. When using ANN to predict temperature changes, the heat reduction capability of the proposed system increases as well as the learning capability of the network. In the case where fuzzy logic is used, the effectiveness of the cooling procedure increases with a minimum number of prediction errors. Incorporation of IoT sensors helps in monitoring the environment and implementing intelligent feedback control to improve the performance of cooling systems.

5.2 Scalability Analysis

The scalability analysis shows the scalability capability of the proposed HNF-SCS by ensuring its ability to deliver efficient cooling and energy efficiency amid growing industrial load levels. Moreover, the recommended intelligent cooling system can deal with more numbers of industrial sensors as well as varied thermal dynamics of the HVAC without impacting the precision and cooling speed of the cooling process. From experiments conducted, it was observed that the HNF-SCS is highly effective in delivering thermal reductions and minimizing energy consumption despite the high number of industrial devices, cooling areas and monitoring points in the system. With the employment of Internet of Things technologies for monitoring, artificial neural networks and fuzzy logic for HVAC optimization and controlling cooling process, the system becomes scalable for diverse smart industrial applications such as smart factories, data centers and manufacturing facilities.

5.3 Real-Time Sensor Monitoring

The proposed HNF-SCS uses live sensors to monitor relevant variables that facilitate intelligent cooling in an industrial setting. Live sensors can detect several industrial variables such as temperature, humidity, air flow rate and load consumption power of industrial machines for adaptive HVAC controls. The use of IoT sensors to enable live detection plays an important role in making appropriate decision on how to carry out heating, ventilation and cooling operations in industrial facilities. Also, the integration of ANN and fuzzy logic into the system will make the system able to predict when overheating and thermal stability occur effectively. Live monitoring is also instrumental in detecting abnormal industrial thermal behaviors, gas emissions and industrial machine instability.

5.4 Limitations of the Proposed HNF-SCS Algorithm Performance

Even though HNF-SCS yields exceptional results related to energy optimization and cooling efficiency, there are still a few disadvantages related to practical use of HNF-SCS in industry. First of all, integration of ANN, fuzzy logic, monitoring based on the usage of IoT technology and optimizing HVAC systems will increase computational process level. Second of all, sensors' performance reliability can affect the work of HNF-SCS when there are problems with sensors' performance because of malfunctioning or incorrect communication. In addition to that, continuous updating and training are required in order to keep the system working efficiently. Costs of implementation will be higher than in case of existing cooling systems because of smart monitoring, communication and HVAC systems optimization. Moreover, sudden changes in temperatures because of equipment behavior can affect the work of system.

5.5 Overall Industrial Performance Discussion

The presented HNF-SCS smart cooling system possesses a great extent of improved performance in the industrial field due to the application of the ANN method to predict temperatures, use of fuzzy logic for managing the cooling process and the IoT in monitoring and energy-efficient process control. Experimental results show that the proposed HNF-SCS possesses an increased rate of heat dissipation efficiency, decreased power consumption and thermal stability compared to conventional methods and the most up-to-date machine learning and deep learning approaches. This is because the integration of sensor monitoring and cooling process management enables users to achieve faster process responses and conduct predictive maintenance and fault detection. The HNF-SCS possesses a high accuracy of temperature dynamics predictions by decreasing the MAE, MSE, RMSE and MAPE rates.

6. Conclusion

The proposed IoT-Enabled HNF-SCS was developed to provide intelligent industrial cooling, thermal stability and energy optimization to modern smart industries. The use of ANN, FLC cooling control and IoT sensor monitoring brought a huge efficiency gain to industrial thermal management and overheating prevention. The proposed framework was able to successfully measure the real-time values of industrial conditions like temperature, humidity, airflow, machine load and power consumption and act accordingly with adaptive cooling and automatic HVAC control. The experimental results showed that the proposed HNF-SCS gave the best results with the maximum heat reduction rate of 98.85% and the power consumption of 48.55 kWh, respectively, against the existing machine learning and deep learning based approaches. Moreover, it was found that the system can minimize its prediction error having minimum MAE of 0.92, MSE of 2.18, RMSE of 2.04 and MAPE of 1.82%, which shows the accuracy and reliability of the thermal prediction process. The proposed intelligent cooling framework, besides improving the energy efficient automation in industrial environment, also improved the industrial fault detection capability, continuous monitoring and industrial safety. Additionally, hypothesis testing, confidence interval analysis and ANOVA were used to confirm the stability and effectiveness of the proposed model. Therefore, the developed HNF-SCS can be considered an efficient and reliable smart cooling solution for industrial applications. For future research, the use of reinforcement learning, digital twin technology and advanced edge AI methods can be enhanced to further enhance intelligent cooling prediction, adaptive automation and large-scale industrial energy management performance.

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