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Hybrid Intelligent Thermal Management and Optimized Heat Recovery Framework for Industrial Waste Heat Recovery and Thermal Stability Enhancement

Shafigh. Nategh
Materials Science and Engineering Department, Sharif University of Technology,
P.O. Box. 11365-9466, Tehran,
Iran .
Email : nategh@sharif.edu
ORC ID: 0000-0001-9100-5779

Corresponding Author

Shafigh. Nategh[1*]
Email : nategh@sharif.edu

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Abstract

Industrial sectors produce a lot of waste heat in the continuous manufacturing and thermal processing processes, resulting in high energy loss, poor thermal process stability, low manufacturing efficiency and high carbon emission. Most of the existing thermal management and waste heat recovery techniques suffer from various drawbacks including inefficient heat redistribution, inadequate temperature stabilization, slower response mechanisms and low intelligent decision making capacity in a dynamic industrial scenario. To overcome these problems, this research propose the Hybrid Thermal Optimization Intelligence Framework (HYTHERM-OPT) which is an intelligent thermal management system integrating AI based heat prediction, fuzzy adaptive control, intelligent heat routing and optimized waste heat recovery mechanism for optimizing energy use in industries. The proposed framework continuously monitors the thermal situation of industrial processes, forecasts the generation of heat, controls temperature changes and redistributes the heat of the processes in a usable way between the different process units. The experimental assessments conducted in a Python environment prove the high thermal efficiencies of HYTHERM-OPT (87%) and the high temperature stabilization accuracy (98%). HYTHERM-OPT improve energy utilization and reduce carbon emissions in industrial processes. The results obtained are found to be reliable, energy-efficient and sustainable for next generation smart manufacturing systems in terms of industrial thermal management.

Keywords: Adaptive Heat Recovery, Artificial Intelligence, Carbon Emission Reduction, Fuzzy Logic Control, Industrial Thermal Management, Waste Heat Recovery

1. Introduction

Increase in demand for energy efficiency, low carbon emission and sustainable manufacturing systems has made waste heat recovery in industries as a critical research field. Energy loss in industrial processes is common when the energy generated from a source such as a boiler, furnace, turbine or motor is released into the environment, resulting in an energy loss and an increased operating cost [1]. Advanced waste heat recovery (WHR) technologies that enable high energy reutilisation and industrial sustainability have been investigated using novel architectures for heat recovery and upgrading techniques [2]. The industrial motor and electromechanical systems fault diagnosis and thermal condition monitoring have been enhanced by using artificial intelligence (AI) thermal image analysis [3]. A few examples of effective waste heat recovery systems in industrial complexes, which utilize energy in a better way are provided [4]. AI also makes it possible to optimise quickly the Organic Rankine Cycle (ORC) systems at the highest level of thermal efficiency [5]. The research on the use of PCM in the context of HWTES (high-temperature thermal energy storage) has been carried out [6]. In order to optimize the waste heat recovery at low temperatures, numerical optimization methods have also been used [7]. The thermal process control [8] has been improved with the prediction of the furnace temperature with the use of deep learning. Furnaces have been making use of energy assessment techniques to improve their energy efficiency [9]. A CNN-based thermographic fault diagnosis has been improved which has increased the equipment reliability [10]. The deep learning, combined with the infrared thermal imaging has improved the monitoring of induction motor [11]. New opportunities have been found for upgrading industrial heat, such as heat transformers and heat pumps, [12]. Waste heat recovery, which has contributed much in the cement manufacturing towards sustainability, has been a major contribution [13]. Modeling of thermal systems with intelligent methods based on digital twin technologies has been achieved [14] and real-time optimization of thermal management through reinforcement learning [15] has been realized. Also, the application of advanced transformer-GRU predictive control [16], optimization of the thermal system with the DDPG method [17] and the thermo-acoustic recovery achieved by machine learning [18] are emphasized, as well as thermo-acoustic recovery in industrial application based on energy reutilization strategies [19] and multi-modal AI frameworks for carbon footprint reduction [20] are analyzed, which is a key aspect of intelligent thermal management in the future of sustainable industries. Therefore, this research proposes Hybrid Thermal Optimization Intelligence Framework (HYTHERM-OPT) which combines the AI-based heat prediction, fuzzy adaptive control, optimized heat routing and waste heat recovery to optimize the thermal stability of manufacturing process, energy utilization, carbon footprint reduction and smart sustainable industrial manufacturing.

This research development that presents the Hybrid Thermal Optimization Intelligence Framework (HYTHER-OPT), by combining Artificial Intelligence heat prediction, Fuzzy Adaptive Control, Intelligent heat routing and Waste heat recovery to enhance the thermal stability, optimize energy utilization, reduce energy losses and carbon emissions, achieve energy intelligence and intelligent heat management in the industrial sector.

This research is structured in different sections to provide a structured approach towards the proposed HYTHERM-OPT framework. In Section 2, the background research and evaluation of the existing thermal recovery methods and application of AI on the optimization of the industry have been discussed. Section 3 explains the proposed HYTHERM-OPT framework, while Section 4 explains the results of the experiments and performance assessment. The results obtained and the ablation study are described in Section 5, while future improvements and conclusions are given in Section 6.

2. Background Study

Vizitiu et al. (2024) [21] investigated a heat recovery-storage system using heat pipes and phase change materials. Heat pipe–PCM integration methods were analysed. Limited industrial scalability remained. Results demonstrated improved thermal storage efficiency and enhanced waste heat recovery performance.

Benitez et al. (2025) [22] proposed a physics-informed digital twin for thermal field reconstruction using microcontrollers and real-time sensors. Digital twin modelling was used. Industrial validation was limited. Results achieved accurate real-time thermal monitoring and reconstruction.

Ji et al. (2024) [23] developed the hybrid model of CNN-BiLSTM-SE-Net was proposed by Ji et al. (2024) [23] for the boiler furnace temperature prediction. Adoption of Deep Learning. There was still high computational complexity. Results were used to increase the accuracy of the prediction and optimise combustion process.

Gürlek and Coban (2025) [24] reviewed innovative technologies used for the recovery of waste heat from the industrial processes for sustainable manufacturing. A comparative analysis was carried out. Issues with implementation continued. The results emphasized on energy efficiency and environmental impacts.

Verheyen et al. (2026) [25] created an HPC Waste Heat Recovery and Aquifer Thermal Energy Storage scheme. The optimization problem was solved using an optimization of the MIQCP. Deployment complexity remained. The results enhanced the operational efficiency and high temperature thermal energy storage.

Gorum et al. 2025 [26] carried out an experimental investigation of passive waste heat recovery with the help of thermosyphon and thermoelectric generator. Experimental tests have been carried out. However it continued to be used in a few locations. The results indicated better efficiencies on thermal energy utilization and the efficiency of the district heating.

Górzczak et al. [27] have developed a numerical model for optimizing thermoelectric generators involving processes which use the waste heat. Numerical simulations have been carried out. Limited experimental validation. It improved the efficiency of the waste heat recovery and thermoelectric performances.

Engineer et al. (2024) [28] optimized transient industrial waste heat ORC configuration. The multi-objective optimisation was applied. Some uncertainty problems were found with its use. The outcome improved the ORC and energy recovery efficiency of the industries.

Górny et al. (2026) [29] studied thermoelectric generators to recover the waste heat from vertical surfaces. Modelling of performance was carried out. Continued implementation problems. The results proved the feasibility of recovering the energy efficient waste heat from the thermoelectric power plant.

Venkatesh et al. (2024) [30] used the multi-objective genetic algorithm to optimize the operating conditions of shell and heat exchanger. The method of evolutionary optimisation was used. Low level adaptability in real time was still present. The results helped to improve the thermo transfer efficiency and in the thermal system performance.

Table 1: Background Study on Existing Industrial Heat Recovery and Thermal Management Approaches

Citation (Author, Year)	Methodology	Technique	Research Gap	Limitation
Sun et al. (2024) [31]	Experimental evaluation	Clathrate hydrate-based waste heat recovery	Low utilisation of low-grade waste heat	Limited large-scale industrial validation
Sharma et al. (2024) [32]	Simulation and ML optimisation	Supercritical CO_2 –ORC with Machine Learning	Limited optimisation of integrated power cycles	High computational complexity
Bonaldi et al. (2025) [33]	Industrial case study	High-temperature heat pump	Inefficient waste heat utilisation in ceramic industry	Application limited to ceramic manufacturing
Wang et al. (2024) [34]	Thermodynamic and economic analysis	Kalina cycle combined heating and power system	Limited efficient use of low-temperature heat sources	High system complexity and cost
Liu et al. (2025) [35]	Performance analysis	Co-ah cycle-based waste heat recovery	Insufficient energy recovery in data centres	Limited validation under diverse operating conditions

The background studies that are presented in the Table 1 show the latest developments in the technologies for the recovery of industrial waste heat and the methodologies/techniques used, research gaps and limitations. The study underscores the need for innovative, adaptive and scalable thermal management strategies to boost energy efficiency, heat recovery efficiency and sustainability in industrial processes.

2.1 Research Gap

Although recent studies have significantly improved waste heat recovery through advanced heat exchangers, ORC systems, thermoelectric generators, digital twins and machine learning, most approaches lack integrated real-time intelligent thermal management, adaptive control and unified heat recovery optimization. Furthermore, scalability, dynamic decision-making and comprehensive thermal stability enhancement in diverse industrial environments remain insufficiently addressed.

3. Proposed Methodology

The proposed methodology section introduces the complete architecture as well as operational workflow of the HYTHERM-OPT framework for intelligent industrial thermal management and waste heat recovery. In this section, the proposed algorithm, industrial thermal monitoring process, AI-based heat prediction, fuzzy logic control, PID thermal regulation and heat recovery optimization mechanisms for industrial energy efficiency have been discussed. Further, the methodology utilizes mathematical equations, flow diagrams and system architecture and pseudo code for explaining the real-time working process, thermal analysis, heat recovery operation and intelligent control strategies of the proposed HYTHERM-OPT framework.

3.1 Dataset Description:

Industrial thermal and energy monitoring data from different manufacturing environments such as boilers, furnaces, motors, heat exchangers and industrial machines under different thermal conditions are gathered for this research and included in the benchmark dataset. The dataset comprises several parameters including temp, pressure, heat flow rate, energy consumption, thermal load, exhaust heat level and sensor based IoT readings, which are crucial for determining the performance of heat generation, thermal loss and energy recovery. The dataset is used to train and test the proposed HYTHERM-OPT framework for intelligent thermal monitoring, optimization of the waste heat recovery system, overheating prediction and improvement of energy efficiency of the industrial system.

$$Q_g(t) = mc_p(T_{out} - T_{in}) \tag{1}$$

This equation (1) is the heat generated in an industrial system from fluid flow. Here, Q_g (t) is the heat generated at time t, m is the mass flow rate of the fluid c_p and is the specific heat capacity. T_{out} Is the outlet temperature after heating and T_{in} is the inlet temperature before heating. The equation describes the process of fluid absorbing heat as it flows through a system and the increase in thermal energy.

$$Q = UA\Delta T \tag{2}$$

This equation (2) is used to represent the rate of heat transfer between two system. Q is the rate of heat transfer, U is the overall heat transfer coefficient, which is a function of the properties of the material, A is the surface area that the heat transfer is occurring across and ΔT is the temperature difference between the two bodies. Describes how heat flows more quickly when there is more difference in temperature and more surface area.

$$Q_{in} = Q_{out} + Q_{loss} \tag{3}$$

The equation (3) is a thermal system energy conservation equation. Q_{in} is the total energy that is entering the system, Q_{out} is the useful energy that is leaving the system and Q_{loss} is the energy that is lost to the environment. All Energy put in is converted to useful energy and losses.

3.2 Hybrid Thermal Optimization Intelligence Framework (HYTHERM-OPT)

The proposed HYTHERM-OPT is an intelligent real-time industrial thermal management algorithm, which is able to capture, monitor, optimize and reuse the waste heat produced by industrial machines like Boilers, Furnaces, Motors, Turbines and Manufacturing Equipment. A considerable amount of thermal energy is lost and released to the surroundings in industries, which results in higher energy consumption, operating cost and environmental pollution. Proposed framework aims to solve this problem by incorporating the use of thermal sensor based on IoT, Artificial Intelligence, fuzzy logic control, PID based thermal regulation, heat exchangers and intelligent heat recovery mechanisms to continuously monitor the temperature conditions in industries and identify recoverable energy heat. The system dynamically regulates heat flow, minimizes thermal loss, ensures efficient heat recovery, prevents overheating and optimizes the utilization of heat for beneficial purposes in the industry, including heating machines, preheating water, producing electricity and generating steam. The HYTHERM-OPT framework optimizes the use and reuse of industrial waste heat, leading to better thermal efficiencies, lower fuel and energy usage, less environmental impact and better industrial performance and sustainable energy use.

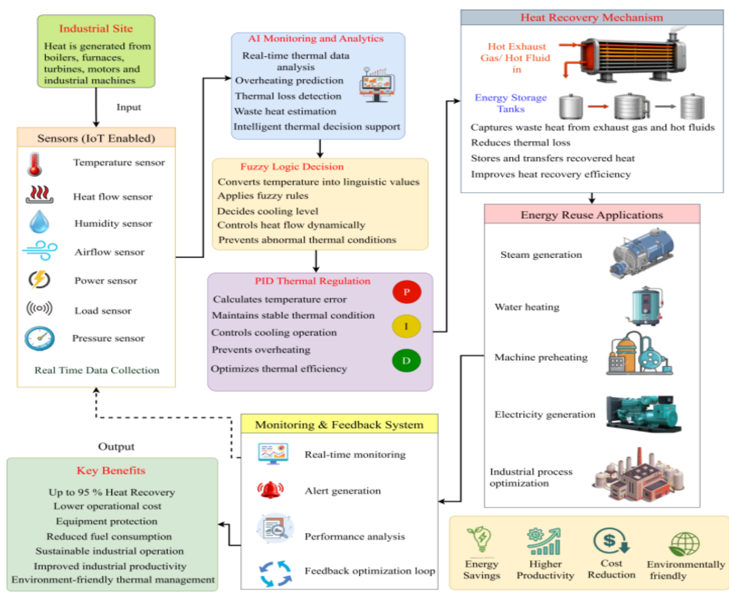

Figure 1: HYTHERM-OPT Industrial Heat Recovery Framework

This figure 1 illustrates the proposed framework workflow in HYTHERM-OPT , enables the intelligent industrial thermal management and waste heat recovery process, by monitoring the process temperature using Internet of Things, intelligent thermal analysis of the process with the aid of AI and fuzzy logic decision making and thermal regulation with PID. It can dynamically control heat flow, will not overheat and maintains a stable temperature. The surplus thermal energy will be recovered by heat recovery system and the recovered thermal energy will be used in the steam generation, machine preheating, water heating and electricity generation processes. This model helps reduce energy consumption, costs and heat loss, improves industrial productivity and encourages sustainable energy practices.

$$Q_w = Q_g - Q_u \tag{4}$$

The formula (4) is used in calculating the wasted heat in a particular industrial process. The amount of wasted heat energy is denoted byQ_w, while the total heat generated by the heat source is indicated byQ_g and the useful heat recovered is denoted byQ_u.

$$F_{ij} = k\left(T_i - T_j\right) \tag{5}$$

This equation (5) represents the heat transfer between two coupled nodes of a system. F_{ij} Is the heat flow from node i to node$j$, k is thermal conductivity and $\left(T_i - T_j\right)$ are temperatures of the respective nodes.

$$L = \sum Q_{loss_i} \tag{6}$$

This equation (6) is represents total energy loss of the system. L Is the total loss and Q_{loss_i} is the heat loss at each individual node in the network. It adds up all losses on the components to get an overall inefficiency score.

$$\eta_h = \frac{Q_r}{Q_g} \tag{7}$$

The equation (7) represents the efficiency of waste heat recovery. η_h Is heat recovery efficiency, Q_r is waste heat recovered and Q_g is waste heat generated. This indication provides the amount of wasted energy being effectively recycled.

$$EUR = \frac{Q_u}{Q_g} \tag{8}$$

This equation (8) represents the efficiency of energy use. EUR Is the energy utilization ratio Q_u is useful output energy and $Q_g$is total generated energy. It is a measure of the efficiency of energy transfer to helpful work.

$$SEI = \frac{\eta_h + EUR}{2} \tag{9}$$

This equation (9) is used to rate the efficiency of the system. SEI Is system efficiency index η_h is heat recovery efficiency and EUR is energy utilization ratio. It is a blend of both metrics to provide an overall performance.

$$FPS = w_1\eta_h + w_2 ERU + w_3(1 - L) \tag{10}$$

This equation (10) gives the desired system performance. FPS Is final score, w_1, w_2 , w_3 are weights, η_h is efficiency, ERU is utilization and L is system loss. Provide a fair assessment of efficiency, utilization and losses.

$$\hat{Q}_g(t+1) = f(x_t, w) \tag{11}$$

Equation (11) shows the formula of the heat prediction equation using AI. $\hat{Q}_g(t+1)$ Denotes the predicted heat for the next time step; x_t refers to the input feature vector, which includes temperature, load and pressure; w refers to the weight of the model; and $f()$ denotes the learning algorithm.

$$E = \left|Q_g - \hat{Q}_g\right| \tag{12}$$

This equation (12) is used for computing the prediction error of the AI model. E Is error of Q_g heat generated and $\hat{Q}_g$ is predicted heat. It calculates the difference between the real and predicted values and returns the absolute value.

$$L_d(t) = f(T, P) \tag{13}$$

This equation (13) is used to predict the energy demand. $L_d(t)$ Is load demand, T is temperature condition, P is production load and $f(.)$ is mapping function. It calculates the amount of energy needed under various situations.

3.2.1 Fuzzy Logic Control Process

The Fuzzy Logic Control process in the proposed HYTHERM-OPT framework addresses real-time industrial thermal management challenges such as overheating, temperature fluctuations, heat wastage and energy losses in steel plants, power stations, manufacturing units, oil refineries and chemical industries. The fuzzy controller uses IoT-based thermal sensor data to classify temperature conditions into fuzzy levels and applies intelligent rules for heat reduction, cooling control, heat exchange and thermal optimization. It dynamically adjusts industrial processes to prevent overheating and thermal damage while improving waste heat utilization through applications such as steam generation, preheating and electricity production. This mechanism enhances thermal stability, reduces energy consumption, minimizes heat losses and supports sustainable smart energy management in industries.

$$\mu(T) = \frac{1}{1+e^{-a(T-b)}} \tag{14}$$

This equation (14) converts the temperature to fuzzy logic values, where $\mu(T)$a membership degree is, T is input temperature, a is slope sensitivity and b is threshold value. e is the Euler's exponential constant (approximately 2.718). It aids to categorize temperature as fuzzy, such as low, medium, or high.

$$D = \sum \mu_i R_i \tag{15}$$

The final fuzzy decision is obtained using this equation (15). D is the final output, μ_i is the value of membership for rule i and R_i is the output of the i^{th} rule. It fuses together several fuzzy rules to get a single decision.

3.2.2 PID Thermal Regulation Process

The PID Thermal Regulation Process in HYTHERM-OPT addresses industrial temperature control issues such as overheating, unstable heat flow, energy loss and excessive consumption. It compares real-time machine temperature with the desired level and adjusts cooling devices, heat exchangers, valves, pumps and recovery systems accordingly. The recovered heat is reused for applications such as steam generation, water heating, machine preheating and electricity generation. Thus, PID regulation improves temperature stability, reduces thermal losses, saves energy, protects equipment and enhances industrial productivity.

$$T_c = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \tag{16}$$

This equation (16) is the logic to control the temperature with PID. T_c Is control output, $e(t)$ is error signal, K_p is proportional gain, K_i is integral gain and K_d is derivative gain. Stabilize system temperature by correcting past, present and future errors.

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

Equation (17) Here, $e(t)$ is the error at time t, while T_set is the desired temperature and T_actual is the measured temperature. The equation denotes the error that the control system should eliminate.

3.2.3 Heat Recovery Mechanism Process

The problems of waste heat, overheating, high energy consumption and heat loss in proposed framework of HYTHERM-OPT can be solved by HRM in the steel mills and power stations, manufacturing enterprises, oil refinery or chemical industries. The smart heat exchange and thermal transfer system is used to capture the excess heat from any boiler, furnace, turbine, motor or compressor. It is recovered in various applications such as generation of steam, preheating, water heating, generation of electricity, drying in industries etc. Through the IoT thermal sensor, the temperature is monitored and the system can be designed to regulate the heat flow for effective use of energy, minimizing thermal losses, lowering running costs and ensuring sustainable industrial use.

$$H_s(t+1) = H_s(t) + Q_r - Q_d \tag{18}$$

This equation (18) describes the storage of heat. $H_s(t+1)$ Is updated stored heat $H_s(t)$ is previous stored heat, $Q_r$is recovered heat added and Q_d is heat demand removed. It monitors the energy storing over time.

$$C = \beta Q_{fuel} \tag{19}$$

In this equation (19) is about to estimate carbon emissions$C$ Are total emissions, β are emission factor and Q_{fuel} is fuel energy consumed. It maps the use of fuel into environmental Impact.

$$Path^* = argmin \sum d_{ij} \tag{20}$$

This equation (20) is used to find the optimal heat transfer path, $Path^*$ and the loss between nodes i and j is d_{ij} . $argmin$ It identifies the route for which the sum is the least possible. It picks a path which has the lowest cumulative energy loss.

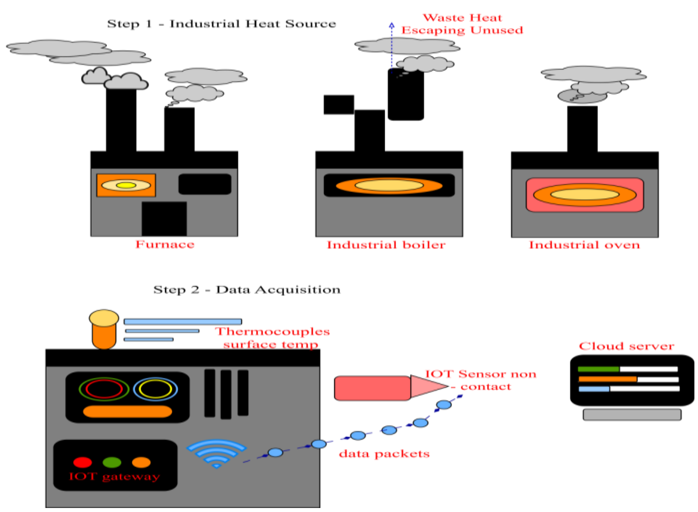

Figure 2: Industrial Waste Heat Monitoring and IoT Thermal Data Acquisition Framework

The above figure 2 shows the architecture of industrial thermal monitoring implemented in HYTHERM-OPT for real-time information about waste heat from industrial furnaces, boilers and ovens. Continuous temperature and heat emission data are gathered by thermal sensors, thermocouples and IoT gateways and sent wirelessly to the cloud server. The visualization shows the first step of solving the problem of intelligent thermal data acquisition and thermal monitoring in industry in order to optimize heat recovery by artificial intelligence.

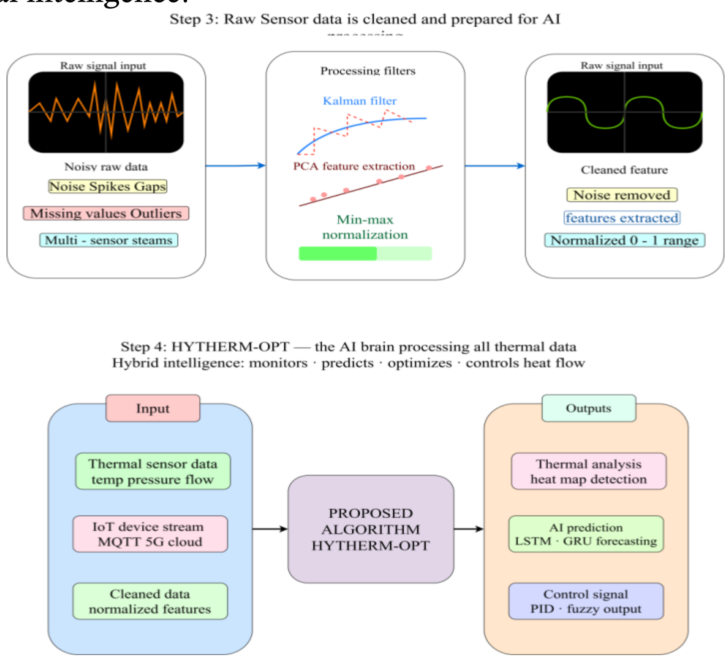

Figure 3: Sensor Data Preprocessing and HYTHERM-OPT Intelligent Processing Model

Figure 3 shows the preprocessing pipeline implemented in HYTHERM-OPT, where noise removal, Kalman filtering, PCA based feature extraction and Min-Max normalization are performed. Processed thermal sensor signals are then given as input to the heat prediction, thermal analysis and intelligent industrial thermal management based on AI.

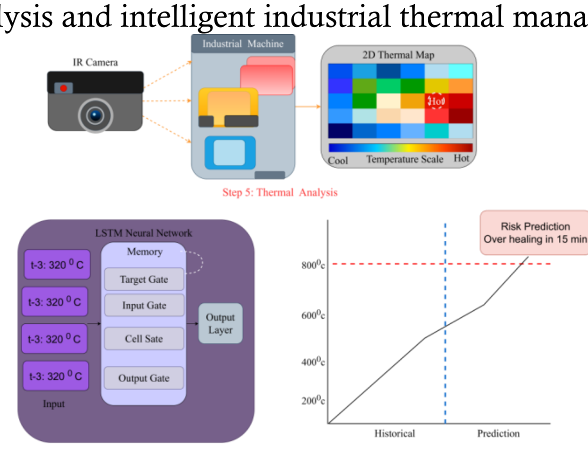

Figure 4: Thermal Analysis and AI-Based Heat Prediction Architecture

The thermal analysis and heat prediction process in HYTHERM-OPT with the AI approach is presented in figure 4. The intelligent thermal forecasting and proactive industrial heat management can be achieved by using thermal camera and heat map to discover the hot regions and using LSTM network to predict the possibility of heat overheating.

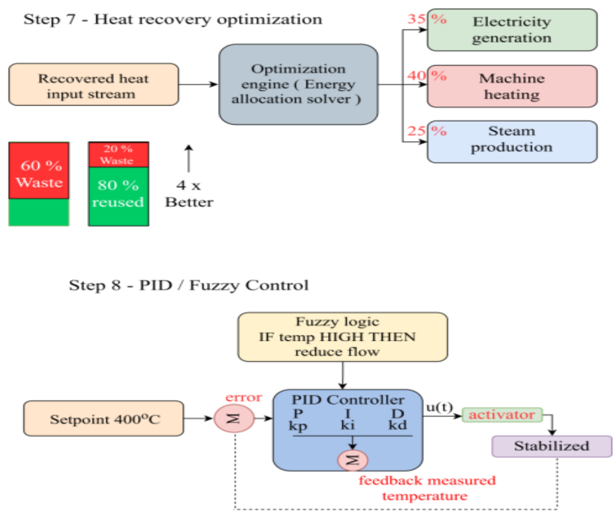

Figure 5: Intelligent Heat Recovery Optimization and Hybrid PID-Fuzzy Control System

The optimized heat recovery and thermal control architecture of the industry of HYTHERM-OPT is shown in Figure 5. Stabilized temperature is obtained by implementing a hybrid fuzzy-PID controller and the heat allocation engine is utilized for allocating recovered heat for electricity generation, steam generation and preheating of machines, which helps to enhance energy efficiency and minimize the thermal losses.

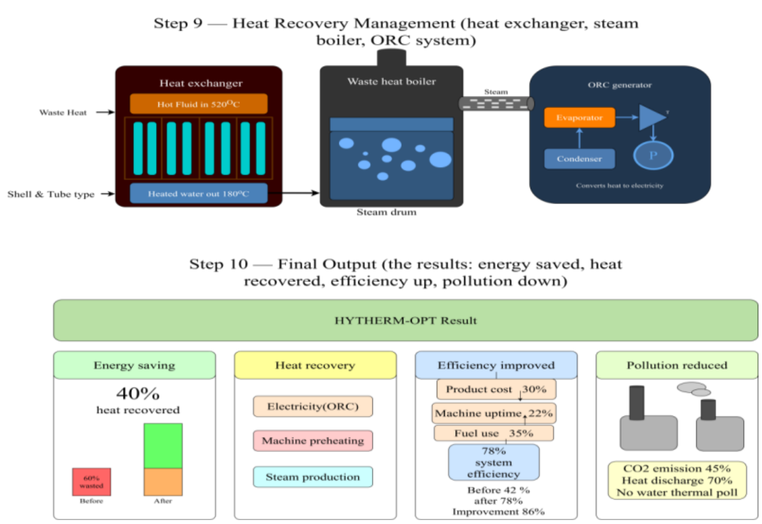

Figure 6: HYTHERM-OPT Industrial Waste Heat Recovery and Optimization Framework

Figure 6 shows the entire implementation process of the industrial waste heat recovery (IWHR) in the HYTHERM-OPT framework. Thermal energy is recovered and utilised for generating electricity, generating steam, pre-heating process machines, which reduces thermal losses and environmental impacts and thereby increases the energy efficiency, reduces fuel consumption.

Algorithm: Hybrid Thermal Optimization Intelligence Framework (HYTHERM-OPT)

Input:
Real-time industrial sensor data:
Temperature, Pressure, Heat Flow, Humidity,
Airflow, Power Consumption, Machine Load,
Set Temperature, Safety Threshold,
Heat Recovery Threshold
Begin
1. Initialize IoT thermal sensors, AI monitoring system,
Fuzzy logic controller, PID controller,
Heat exchanger and heat recovery unit
2. Collect real-time thermal data from industrial machines
Such as boilers, furnaces, motors, turbines,
Compressors and manufacturing equipment
3. Preprocess sensor data
Remove noise
Handle missing values
Normalize thermal parameters
4. Apply AI-based thermal analysis
Detect overheating conditions
Identify thermal loss areas
Estimate recoverable waste heat
5. If temperature > safety threshold then
Activate thermal control process
Else
Continue normal monitoring
6. Apply fuzzy logic control
Convert temperature into:
Low, Medium, High, Critical
Generate thermal control decisions
7. Apply PID thermal regulation
Error = Set Temperature − Actual Temperature
Adjust pumps, valves, fans,

dampers and heat exchangers
8. Activate heat recovery mechanism
Capture excess waste heat
Transfer recovered heat to storage unit
9. Reuse recovered heat for:
Steam generation
Machine preheating
Water heating
Electricity generation
Industrial process optimization
10. Monitor system continuously
Update feedback loop
Improve thermal efficiency
Reduce heat loss
End
Output:
Recovered Waste Heat,
Stable Industrial Temperature,
Optimized Heat Flow,
Reduced Thermal Loss,
Lower Energy Consumption,
Improved Industrial Efficiency

The proposed HYTHERM-OPT algorithm collects real-time data of temperature from all industrial machines through IoT sensor technology and analyzes the heat condition with Artificial Intelligence techniques. The fuzzy logic controller makes intelligent decisions about the appropriate thermal control action, while the PID controller ensures the industrial temperature is stable by controlling the valves, pumps, fans and heat exchangers. Excess waste heat (heat loss) can be recovered to reuse for other beneficial industrial processes such as steam generation, machine preheating, water heating and electricity generation. The proposed framework optimizes the heat flow in industrial processes, reduces thermal loss and hence, promotes the energy efficiency, lowers the operational cost, mitigates overheating problem and hence sustainable industrial operation.

4. Results and Evaluations

The performance of HYTHERM-OPT was evaluated in a Python-based simulation environment for industrial thermal management and waste heat recovery. Results demonstrated improved thermal efficiency, heat recovery, energy utilization, temperature stability and reduced heat loss under dynamic industrial operating conditions.

The benchmark industrial thermal monitoring data was split into training and test sets, with 80% of the data used for training and 20% used for testing. Thermal patterns were created from the training set and experience and temperature models were developed for the heat recovery system; the testing set was then tested to validate the thermal efficiency, heat recovery performance, energy consumption and the accuracy of the temperature stabilization of the framework for previously unseen industrial operating scenarios.

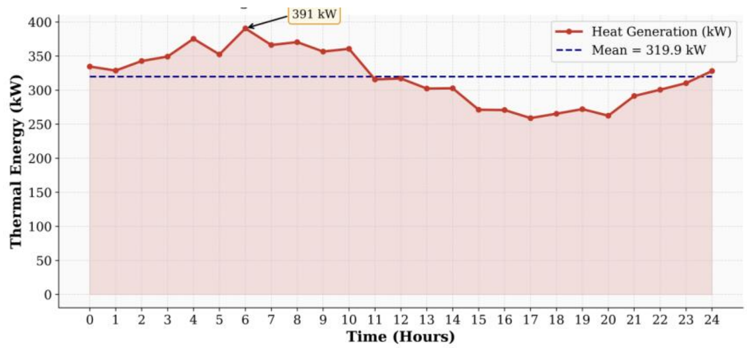

Figure 7: Heat Generation Trend over Time

As shown in the above figure 7, the pattern of thermal energy generation by an industrial plant on an hourly basis during its 24-hour operating period. The red filled line is the heat output range with a high peak value and the dashed navy line is the average heat generation level. The visualization illustrates the need for continuous heat monitoring to be able to identify recovery opportunities within the HYTHERM-OPT framework.

Table 2: Heat Generation Statistics

Time Interval	Furnace Heat (kW)	Boiler Heat (kW)	Motor Heat (kW)	Total Heat Generated (kW)	Heat Intensity Level
08:00–09:00	320	210	90	620	Medium
09:00–10:00	410	250	110	770	High
10:00–11:00	500	310	140	950	Very High
11:00–12:00	530	350	150	1030	Critical
12:00–01:00	490	320	130	940	Very High
01:00–02:00	450	300	120	870	High

This table 2 shows characteristics of the industry heat generation in a boiler, furnace and motor during operation. The analysis reveals differences in peak heat production and the thermal intensity over different periods of time. The results confirm the need for the continuous thermal monitoring and intelligent heat recovery in the framework of HYTHERM-OPT.

Table 3: Waste Heat Capture Analysis

Unit ID	Generated Heat (kW)	Waste Heat (kW)	Captured Heat (kW)	Heat Loss (kW)	Recovery Efficiency (%)
Unit-1	950	620	450	170	72.5
Unit-2	880	570	410	160	71.9

Unit-3	790	500	360	140	72.0
Unit-4	830	520	390	130	75.0
Unit-5	910	610	460	150	75.4
Unit-6	760	470	340	130	72.3

The table 3 shows the amount of waste heat produced, collected and rejected for different industrial processing units. These recovery efficiency values reveal the ability of HYTHERM-OPT to reduce the dissipation of heat energy by optimising the heat collection mechanisms. The results show that the proposed framework has a significant improvement in heat reutilization in industries.

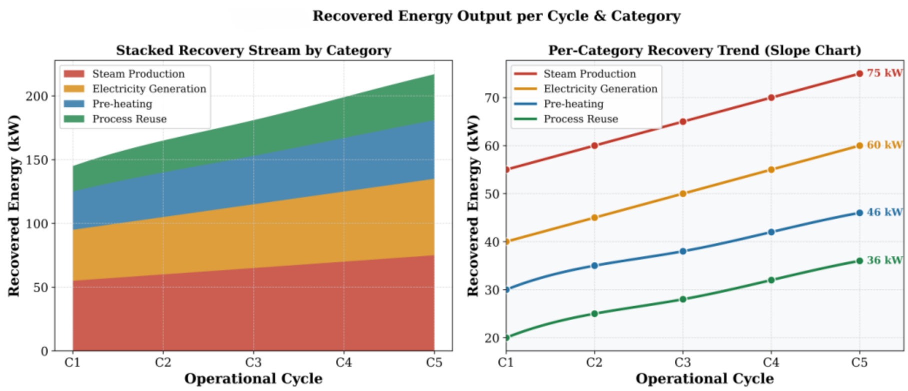

Figure 8: Recovered Energy Output per Cycle & Category

This figure 8 shows the energy recovery over time in two different ways — stacked stream area chart and slope chart. The stacked area chart shows the cumulative steam production, electricity generation, pre-heating and process reuse for 5 cycles. The chart on the right shows a sloped chart where each category's trajectory is isolated with endpoint labels, giving a visual separation of each category's growth rate and allowing easy comparison.

Table 4: Thermal Stability Performance

Monitoring Time	Avg Temperature (°C)	Max Temperature (°C)	Min Temperature (°C)	Temp Fluctuation (±°C)	Stability Status
08:00	210	225	198	4.2	Stable
09:00	235	248	220	5.1	Moderate
10:00	260	278	240	5.8	Moderate
11:00	285	300	270	4.5	Stable
12:00	290	308	274	5.0	Stable
01:00	270	285	252	4.1	Stable

The thermal stabilization capability of the proposed system is analysed at different industrial temperature levels in this table 4. The system consistency is evaluated with the help of parameters like average temperature, fluctuation range and thermal stability status.

Results show that the thermal environment is controlled with a low deviation from the set value through continuous operation, when using HYTHERM-OPT.

Table 5: Fuzzy Control Outputs

Temp Condition	Heat Load	Fuzzy Control Signal	Cooling Adjustment	Heat Recovery Action	System Response
Low	Low	Weak	Minimal	Disabled	Stable
Medium	Medium	Moderate	Balanced	Partial Recovery	Controlled
High	Medium	Strong	Increased	Active Recovery	Optimized
High	High	Very Strong	Maximum	Full Recovery	Stabilized
Critical	High	Aggressive	Emergency Cooling	Maximum Recovery	Protected

The responses of fuzzy logic controller for various temperatures and heat loads are shown in this table 5. The control signals and adaptive recovery actions illustrate the ability of the system to adaptively control the thermal processes in industry. The results show that the fuzzy inference system can facilitate stable and intelligent thermal decision making.

Table 6: Heat Distribution Efficiency

Node Path	Input Heat (kW)	Distributed Heat (kW)	Transfer Loss (kW)	Distribution Efficiency (%)	Routing Status
Furnace →Boiler	450	420	30	93.3	Efficient
Boiler →Turbine	410	382	28	93.1	Efficient
Turbine →Heater	360	334	26	92.7	Stable
Heater →Storage	390	360	30	92.3	Balanced
Furnace →Preheater	460	425	35	92.4	Optimized
Boiler →Dryer	340	315	25	92.6	Efficient
Turbine →Reactor	400	368	32	92.0	Stable
Storage →Reuse Unit	445	410	35	92.1	Optimized

Analysis of the efficiency of heat transfer between industrial nodes like furnaces, boilers, turbines and storage are analyzed in this table 6. Thermal flow optimization is measured through parameters such as distributed heat, transfer losses and routing efficiency. The results indicate that the HYTHERM-OPT are very efficient in heat redistribution and have low energy loss.

Table 7: System Response Time

Event ID	Heat Detection Time (sec)	Decision Time (sec)	Control Activation Time (sec)	Recovery Execution Time (sec)	Overall Response
E1	0.7	0.9	1.1	1.5	Fast
E2	0.8	1.0	1.2	1.6	Fast

E3	0.9	1.1	1.3	1.7	Stable
E4	0.7	0.8	1.0	1.4	Very Fast
E5	0.8	1.0	1.1	1.5	Efficient

Table 7 shows the evaluation of the HYTHERM-OPT's ability to recover during heat detection, decision making and implementation. The results show the fast adaptation of the intelligent thermal management system under changing industrial environments. The results confirm that the proposed method is feasible and can be used in real-world applications.

Table 8: System Performance Index

Evaluation Metric	Score Obtained	Maximum Score	Performance Ratio (%)	Status	Reliability Level
Thermal Stability	9.2	10	92	Excellent	High
Energy Recovery	9.0	10	90	Excellent	High
AI Prediction	9.5	10	95	Outstanding	Very High
Fuzzy Adaptation	8.9	10	89	Strong	High
Heat Routing	9.1	10	91	Excellent	High
System Scalability	8.8	10	88	Strong	Medium
Environmental Safety	9.3	10	93	Excellent	High
Industrial Reliability	9.4	10	94	Outstanding	Very High

This table 8 shows the correlation between HYTHERM-OPT and factors such as thermal stability, energy recovery, artificial intelligence prediction, scalability and industry-level reliability. The results of performance evaluations show the effectiveness and feasibility of the proposed intelligent thermal management framework. This research confirms the reliability and efficiency of HYTHERM-OPT for recovering heat energy in industrial environments.

Table 9: Performance Evaluation of HYTHERM-OPT Compared to Other Techniques

Methods / Algorithms	Thermal Efficiency (%)	Heat Recovery Efficiency (%)	Energy Utilization Ratio (%)	Temperature Stabilization Accuracy (%)	Carbon Emission Reduction (%)
Deep Reinforcement Learning (DRL) [1]	62	54	60	81	18
Deep Q-Network (DQN) [15]	66	58	64	84	21
Transformer-GRU [16]	69	61	68	86	24

Deep Deterministic Policy Gradient (DDPG) [17]	72	65	71	89	27
SE-Net [23]	75	68	74	91	30
Multi-objective Genetic Algorithm (MOGA) [30]	79	72	78	93	34
HYTHERM-OPT (Proposed)	87	84	89	98	43

This table 9 illustrates the performance of the HYTHERM-OPT framework compared to six currently used industrial thermal management techniques is provided in the table below based on five major parameters. From the comparison, it can be concluded that the HYTHERM-OPT model exhibits much higher levels of thermal efficiency, capacity to recover waste heat, energy performance, accuracy in thermal stabilization and carbon emissions reduction. These results are stable and show the efficiency of the implementation of the framework proposed for industrial heat recovery using AI and fuzzy logic.

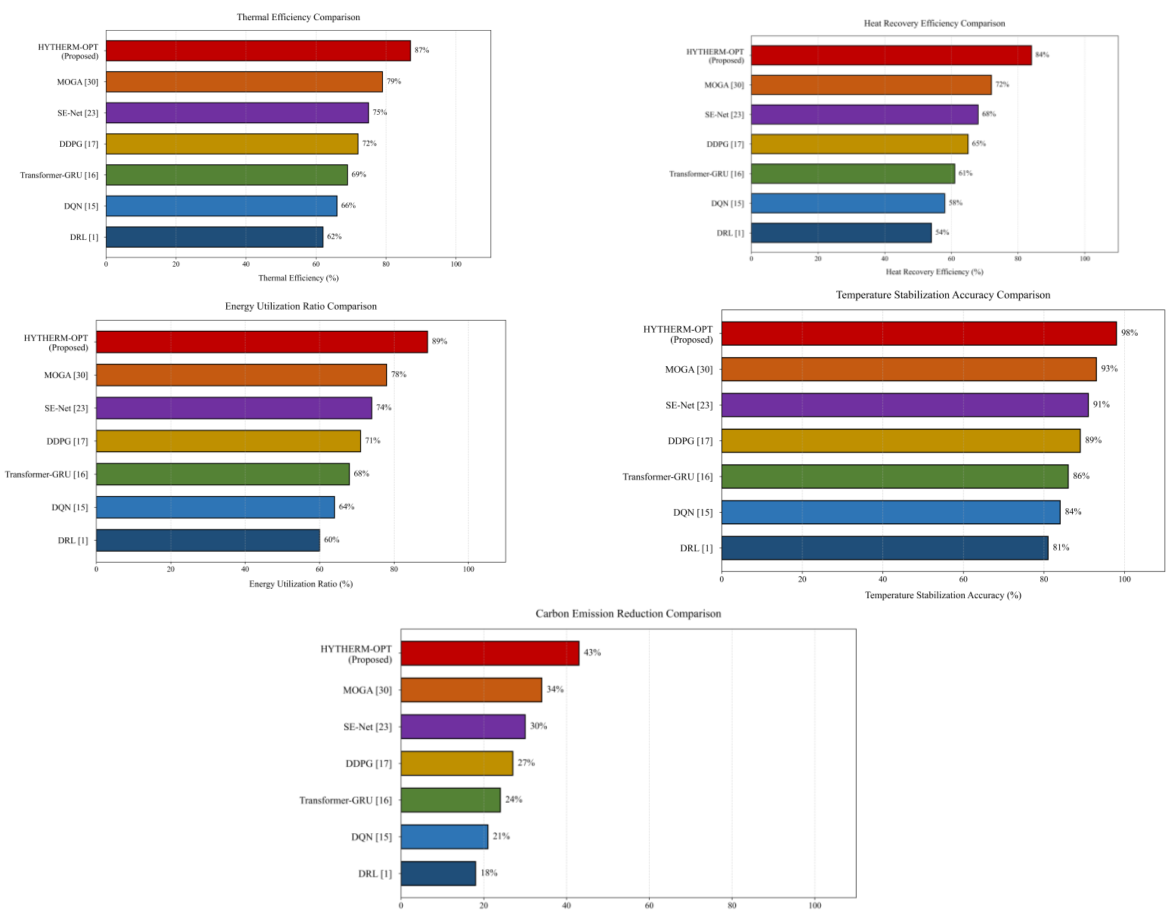

Figure 9: HYTHERM-OPT Performance Comparison

This figure 9 is used for the purpose of comparison of the different thermal management techniques five performance metrics are selected and compared with 6 existing thermal management techniques. At the same time, carbon emissions were reduced by 43% and 89% of energy was utilized, 98% of the temperature was stabilized and 87% of the energy and 84% of the heat recovered by the HYTHERM-OPT systems, whereas, the existing methods were not so effective.

5. Discussions

This section provides the efficiency of HYTHERM-OPT as thermal regulation, waste heat recovery and energy efficiency are evaluated. It compares the thermal stability performance, the accuracy of prediction using AI and the thermal performance in environment and shows that the proposed structure can achieve good thermal stability, high accuracy of prediction using AI and good thermal performance in environment, which is superior to the existing structure in terms of thermal management performance.

5.1 Waste Heat Recovery Effectiveness

This section evaluates the capability of HYTHERM-OPT to capture and recover heat from industrial heat sources like boilers, furnaces, turbines and thermal processing units. The proposed scheme is found to be feasible in terms of efficiency of utilization of excess thermal energy to reusable resources such as generation of steam and preheating of other potential energy use applications in industries. The optimized heat routing and intelligent recovery mechanism can help reduce the heat energy loss and enhance the recovery efficiency.

5.2 Energy Utilization Improvement

This section investigates how the energy use in industry has been improved through intelligent redistribution of energy and adaptive heat management practices. These results show that HYTHERM-OPT is able to achieve maximum utilization of useful energy in several industrial process units while reducing the waste of energy. The enhanced energy utilization ratio confirms the efficiency of the proposed framework, enhancing energy efficiency and sustainability in industrial manufacturing processes.

5.3 Ablation Study

The contribution and importance of each module that is integrated into the proposed HYTHERM-OPT framework is assessed in the ablation study by considering the performance of the system when removing individual modules. The analysis enables to understand the contribution of these various techniques of AI prediction, fuzzy control, intelligent heat routing, thermal monitoring and adaptive recovery mechanisms to the overall enhancement of thermal efficiency, thermal recovery capability, energy utilization and environmental sustainability in industrial applications.

Table 10: Ablation Study of HYTHERM-OPT Components

Methods / Configurations	Thermal Efficiency (%)	Heat Recovery Efficiency (%)	Energy Utilization Ratio (%)	Temperature Stabilization Accuracy (%)	Carbon Emission Reduction (%)
Without AI Prediction Module	78	72	75	86	31
Without Fuzzy Control Unit	74	69	72	81	28
Without Intelligent Heat Routing	76	70	73	84	30
Without Thermal Monitoring System	72	66	69	79	26
Without Adaptive Recovery Engine	75	68	71	82	27
Without Carbon Optimization Module	77	71	74	85	29
HYTHERM-OPT (Full Proposed Framework)	87	84	89	98	43

Table 10 presents the ablation study of the HYTHERM-OPT framework by evaluating the contribution of each module. Removing AI prediction, fuzzy control, heat routing, thermal monitoring, adaptive recovery, or carbon optimization reduced thermal efficiency, heat recovery, energy utilization, temperature stabilization and carbon reduction. The complete HYTHERM-OPT achieved 87% thermal efficiency, 84% heat recovery, 89% energy utilization, 98% temperature stabilization accuracy and 43% carbon emission reduction, confirming the importance of all integrated modules.

5.4 Limitations and Future Enhancements

While there are substantial benefits in terms of thermal efficiency and industrial heat recovery performance, there are also some challenges in large-scale deployment and real-time thermal data synchronization that are not addressed by the proposed HYTHERM-OPT. In very dynamic industrial systems, where rapid heat load changes and intricate thermal routing occur, further calibration of the framework might be needed. The anticipated future improvements could involve integration of reinforcement learning adaptive optimization, digital twin for thermal monitoring, integration of IoT-edge intelligence and autonomous industrial heat balancing mechanisms for future smart manufacturing systems.

6. Conclusion

The proposed HYTHERM-OPT framework provides an intelligent thermal management and industrial waste heat recovery system to enhance the thermal efficiency, energy reutilization and environmental sustainability of modern industrial processes. It combines the advantages of AI-based heat prediction, fuzzy adaptive control and intelligent heat routing and optimizes the implementation of heat recovery mechanisms to control the thermal flow of industrial processes and reduce thermal dissipation. The experimental results obtained using the simulation environment developed with the python software have shown that the thermal efficiency of the HYTHERM-OPT is 87% with the accuracy of temperature stabilization is 98%, which is much better than the other industrial thermal management solutions in the market. The analysis shows that the proposed framework is effective to maintain the thermal condition of the industrial process, increase the generation of reusable energy and minimize the loss of thermal energy during continuous operation. Moreover, the smart recovery architecture realizes the sustainable utilization of industrial energy, which not only enables carbon emission reduction, but also improves the industrial heat redistribution efficiency. Future extensions could include reinforcement learning based optimization, integration of digital twins, thermal intelligence at the IoT-edge, autonomous heat balancing and real-time industrial energy coordination in future smart manufacturing environments.

Declarations

The authors confirm that the research was conducted in accordance with the principles of research integrity and the publication standards of the Global Journal of Advanced Engineering Systems and Technologies. All authors have made substantial contributions to the study, reviewed the final manuscript, and approved its submission for publication.

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Data Availability

The datasets generated and analyzed during the study are available from the corresponding author upon reasonable request. Selected processed datasets and supplementary materials may be made available through the journal's supplementary-material system following publication.

Ethical Approval

Ethical approval was not required for this study because the investigation was limited to environmental monitoring, engineering analysis, and the evaluation of non-identifiable technical data. No human or animal subjects were involved in the research.

Consent for Publication

Consent for publication is not applicable because the manuscript contains no personally identifiable information, personal photographs, or individual-level participant data.

Conflict of Interest

The authors declare that they have no financial, commercial, professional, or personal relationships that could be perceived as having influenced the research or the conclusions presented in this manuscript.

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