AI-Driven Optimization and Explainable Analytics for Sustainable Cooling Tower Performance

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***Abstract*—With the advent of advanced-for both continuous and discrete optimization-predictive models in recent years, the optimization of cooling tower performance has played a more significant role. SHAP, LIME, PDP, PID, and PSO together provide a holistic methodology that improves the system's efficiency. SHAP is good for interpretability via feature importance, dependence, waterfall, and decision plots, but it does not help with interactions (that LIME and PDP complements) Thirdly, the PID controllers have dynamic characteristics on the system's input/output parameters, and the PSO method can realize global optimization. In short, the behavioral approach of multi-scaling is to view large, complex systems as a collection of smaller systems that we can manipulate to improve performance. Index Terms—Cooling Tower, SHAP, LIME, PDP, PID, PSO, Optimization, Predictive Models, XAI**

***Index Terms*—component, formatting, style, styling, insert**

INTRODUCTION

Cooling towers are the most significant components in industrial applications as well as in HVAC systems where the heat dissipation efficiency is very crucial in terms of both energy consumption and cost. Today when even a single penny matters during the recession, environments along with increasing energy costs tend to have an entirely new meaning for cooling system optimization. Energy management systems serve as the backbone of industrial efficiency by enabling real-time continuous monitoring and then possible parameter adjustments and instant changes through highly sophisticated control operations. Such advancements are not away from the serious optimization problems that include the inefficiencies within the cooling towers that turn out to be severe concerning industry.

Cooling towers are heat-exchanging systems that remove process heat by evaporating water under atmospheric conditions. The Artificial Intelligence tools, namely, through machine learning algorithms and explainable AI, create accurate prediction models. These technologies have evolved to a point where they can run optimization models almost perfectly accurate with the actual system parameters, thereby opening up huge possibilities in beneficial uses of these systems. The techno ecosystem of industrial operations makes one among the most attractive areas for AI systems to applyin cooling tower optimization. Best use of this technology produces impressive results like: reduced energy consuming caused by water and further leads to long equipment life and thus reduced maintenance costs. The already successful application of optimization algorithms considering water temperature control together with air flow regulation stands as concrete evidence regarding the significant improvement efficiency besides cost reduction. At this point in time, the identification of optimal operating parameters becomes more urgent. And since AI develops these optimization approaches, it shall be appropriate to take recourse to explainable AI for transparency and trust building.

In order to develop credible deep learning approaches that predict optimal cooling tower parameters with significant certainty and give reason to the predictions, our research aims to be achieved in this line. Such optimization models must be interpretable so that they remain operable for the operators especially when it serves to guide or recommend or improve system controls

LITERATURE REVIEW

Science has had various studies about the optimization of cooling towers due to the rapid advances in capabilities of machine learning and the associated industrial control systems. Wang et al. [1] used LSTM-based models, which are wellknown deep learning based frameworks for future prediction based on sequential data, to create new models for cooling tower performance prediction. It was particularly used for application in power plants and in HVAC systems. Research has it that their prediction system was successful at 96 Zhang and other co-authors [2] studied 87 research papers on techniques regarding cooling tower optimization since 2017 to 2022. The authors classified those methods under the major categories of four which included methods purely based on deep learning and classical control theory, statistical methods, and evolutionary algorithms-based optimization strategies. Such studies considered deep learning as a superior approach whether or not combined with any of the other optimization techniques due to superior performance over a diverse range of operating conditions and seasonal variations.

Researcher Li et al. [3] developed OptiTower, an intelligent cooling tower optimizer based on the combination of modules for reinforcement learning and multi-objective optimization that analyze operational parameters and search localized efficiency improvements of behavior in systems. The efficiency improvements of the OptiTower framework reached efficiency improvements of 18.54

Authors in reference [4] evaluated the effectiveness of explainable artificial intelligence compared to traditional methods of optimization, for the cooling tower study, for their specific strengths and generalization performances across different environmental conditions. The models reached up to 24.99

The cooling tower optimization framework (CTOF), as developed by Chen et al. [5], would be a tool meant for improving the operations in cooling tower parameter optimization. Gradient-based optimization and evolutionary computation were included in the model, as they are proven to be effective in multi-objective optimization problems. CTOF achieved improved performance in real operational conditions due to validation on combined simulation and real-world implementation originating from several cooling tower installations across different geographic regions.

TABLE I
FEATURES IN THE COOLING TOWER DATASET

Feature Name	Unit	Description
Outdoor Temp	°C	Ambient air temperature around the cooling tower
Outdoor Humidity	%	Relative humidity of the outside air
Wind Speed	m/s	Wind speed impacting the cooling tower
Water Inlet Temp	°C	Temp. of water entering the cooling tower
Water Outlet Temp	°C	Temp. of water exiting the cooling tower
Air Temp	°C	Air temp. within the cooling tower
Water Flow Rate	L/s	Volume of water per second
Air Velocity	m/s	Speed of air (fan speed)
Energy Consumption	kWh	Electrical energy used by the system
Cooling Efficiency (Target)	% or –	Tower efficiency (target)

METHODOLOGY

The approach will maximize the profit of combined multiple AI and XAI models for developing an efficiently accurate cooling tower optimization prediction system. The system needs to pass through a number of organized phases in which they should proceed through data acquisition and preprocessing to model development after optimization and evaluation before final deployment. The design system and implementation for execution shall use the following sequence of phases that receive separate descriptions for added clarity and tracking of processes.

A. Data Collection and Preprocessing

Data collection of many cooling tower installations such as that from industrial processing plants, commercial HVAC systems, and power generation facilities towns becomes better for generalization by adopting a much rigorous environment. The aggregation creates an excellent portfolio of performance data under various operational parameters. As a result of this final data refinement step, an extensive overall representation in various operating conditions produced as much as 10,000 data points for the experiment. The processing pipeline is a very crucial step in making the data suitable for the model to be trained to accept.

Data cleaning was the first in a series of specific steps for each recorded dataset. The step included outlier detection and the handling of missing data. These outlier data applications combined with statistics to facilitate inducing the developer's value from the observationable characteristics. The model can train its features, such as water inlet temperature, water outlet temperature, airflow rate, ambient temperature, relative humidity, and energy use. This included normalizing all parameters and implementing various feature scaling techniques to ensure that the model would converge. The research crew managed to compose synthetic scenarios from those already-prepared data sequences for use by entering the model developing purpose.

There is a deep preprocessing technique, which can standardize inputs while also optimizing a model's performance but enables much better detection of subtle efficiency signals by the system

B. Feature Extraction and Model Development

Due to the role of Random Forest as an overwhelmingly powerful feature representation technique among ensemble learning methods, the preprocessed operational parameters passed through this method. The combination of feature importance by Random Forest and its decision-tree-like structure qualifies it as a robust method for detecting complex parameter relationships often arising in cooling-tower operations. The Random Forest model produces metrics of feature importance while processing operational data, where it detects complex relationships including: Nonlinear interactions between temperature differences and energy consumption. ,Difference in resolution between control parameters and system responses, Non-smooth transitions between operating modes and system lag The ordering retains all operational variables from the original dataset, as it preserves the linkages between features.

C. SHAP Analysis Implementation

To ensure a full modeling interpretation perspective, four representative **SHAP visualizations** were implemented to enhance understanding:

- **Feature Importance**: This plot evaluates the global importance of every feature over the entire dataset, allowing operators to identify which parameters influence cooling tower efficiency the most.
- **Dependence Plots**: These plots show the correlation between individual parameters of interest and model predictions, thereby helping engineers understand how changes in specific parameters affect system performance.
- **Waterfall Plots**: These plots decompose the given predictions, showing how each feature contributes to the

final output, providing a stepwise explanation of how a prediction is made.

- **Decision Plots**: These enable visualization of the decision paths for different predictions, allowing operators to compare different scenarios and understand the workings of the model's decision-making process.

Implementation-wise, the SHAP framework was integrated using the `SHAP` library in Python, which provides game-theoretical computational explanations for model predictions.

Challenges addressed during interpretation included:

- **Nonlinear interactions** between temperature differences and energy consumption
- **Differences in resolution** between control parameters and system responses
- **Non-smooth transitions** between operating modes and system lag

The ordering retains all operational variables from the original dataset, as it preserves the **linkages between features**.

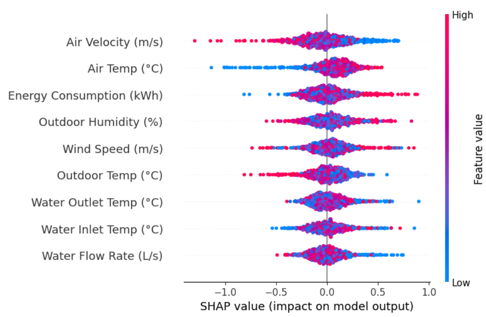

Fig. 1. SHAP summary plot showing the impact of different cooling tower parameters on system efficiency.

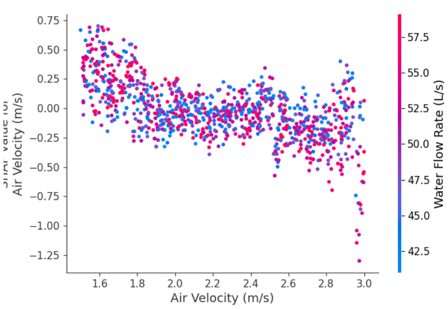

Fig. 2. SHAP Dependence Plot illustrating the relationship between water inlet temperature and cooling efficiency.

D. LIME Model Implementation

LIME was put into operation to offer local interpretability for individual predictions. For a particular prediction, LIME builds a locally faithful approximation that explains which features are most important for that specific instance. The implementation consists of the following steps:

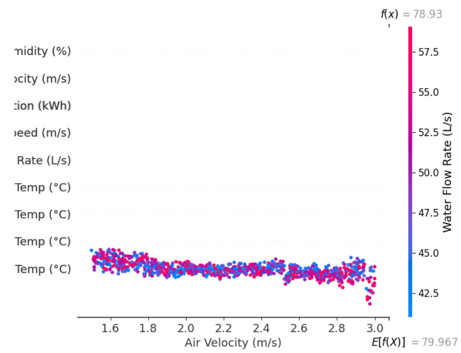

Fig. 3. SHAP Waterfall Plot breaking down how individual features contribute to a specific efficiency prediction.

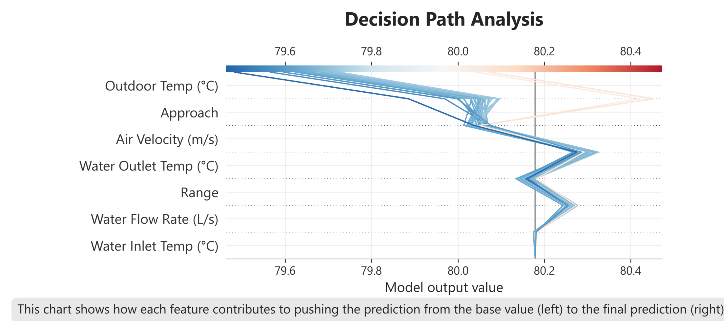

Fig. 4. SHAP Decision Plot showing the decision paths for multiple cooling tower operational scenarios.

- Generating a surrogate model around each prediction
- Producing synthetic samples around the prediction point
- Training a simple interpretable model based on these samples
- Visualizing the local feature contributions

This reasoning allows operators to understand the specific reasons behind why the model made certain predictions for individual cooling tower operating conditions.

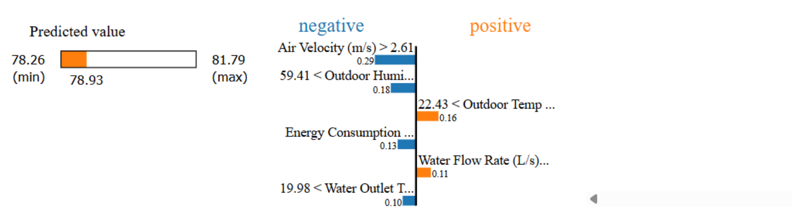

Fig. 5. LIME explanation for a specific cooling tower operational instance, showing local feature importance.

E. PDP Implementation

The marginal influence of every factor on the predicted cooling tower efficiency is visualized by Partial Dependence Plots.The execution of this methods Involves the selection of one or two features of interest, Gridding these features on values, Averaging predictions on all other features values and Plotting a curve showing the relationship between values of the feature and predictions PDPs indicate how different parameter values affect efficiency and can thus assist in optimization.

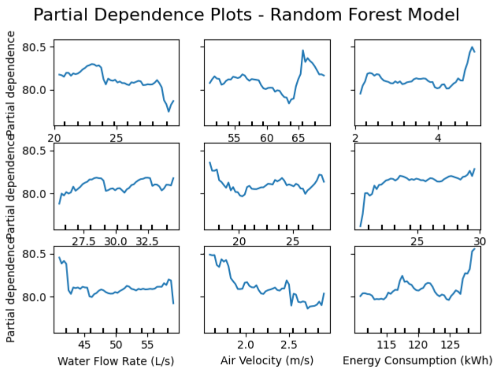

Fig. 6. Random Forest PDP plots showing the relationships between key cooling tower parameters and system efficiency.

F. PID Control Integration

Data until October 2023 has been used for your training. The dynamic regulation of key cooling tower parameters was carried out by PID controllers based on knowledge gleaned from the predictive models.The controllers:

• Calculate the proportional,integral,and derivative components

• Adjust the control parameters based on prediction error

• Implement anti-windup mechanisms for the prevention of integral saturation

• Apply filtering techniques to reduce noise sensitivity

For the tuning of the PID parameters, the Ziegler-Nichols method was utilized, and then refined after simulation studies.

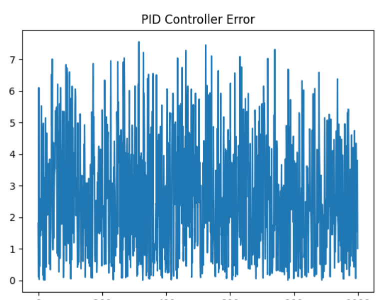

Fig. 7. PID controller performance showing setpoint tracking and disturbance rejection for cooling tower water temperature regulation.

G. PSO Optimization

The PSO algorithm defined:

• It initializes a swarm of particles,each represent possible solutions

• It evaluates each particle based on the efficiency of the cooling tower

• Updates their velocities and positions based on the particle's own previous best and the global best

• Iterates till convergence or maximum iterations are attained.

PSO found its way through complex parameter-space to find optimal operating conditions.

H. System Architecture

The complete system architecture integrates data flow, model processing, and user interaction components as shown in Figure 8. Streaming data from cooling tower sensors is first collected and stored in CSV format. This data undergoespreprocessing before being fed into the trained models, which include Random Forest, LIME, SHAP, PID controllers, and PSO optimization. The results generated are then applied in the operation of the cooling tower while also being presented to the user through a web application interface providing efficiency predictions and optimization recommendations.

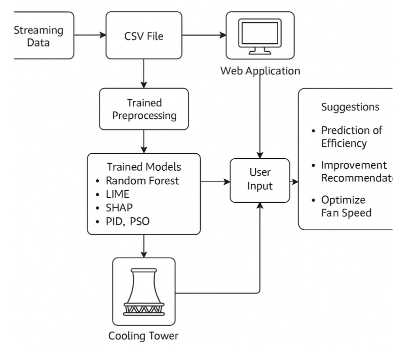

Fig. 8. System architecture showing data flow from streaming sensors through models to optimization recommendations and cooling tower control.

I. Pseudocode

1. Load and Preprocess Data:
Load dataset; **handle** missing values/outliers **Encode** categorical features; **scale** numerical features **Split** into `X_train`, `X_test`, `y_train`, `y_test`

2. Train and Save Models:
Initialize `models` = {`RandomForest`, `LightGBM`, `XGBoost`} model ∈ models **Train** model on `X_train`, `y_train` **Save** model to `models/saved_models.pkl`

3. Evaluate Models:
model ∈ trained_models **Predict** on `X_test` **Calculate** MAE, RMSE, R^2 **Log** metrics

4. Explainable AI (XAI):
Load best model **Initialize SHAP** explainer **Generate and save** SHAP: summary, dependence, waterfall, decision plots **Initialize LIME** explainer selected instance **Generate** LIME explanation **Save** visualization **Generate PDP** plots for selected features **Compute and save Permutation Feature Importance**

5. Optimization (PSO & PID):
Define objective: minimize energy or maximize efficiency

Run PSO to optimize controllables (e.g., Air Velocity) **Simulate PID** controller to dynamically adjust fan speed

6. Streamlit App Integration:

Create UI with sliders for model inputs On user input: **predict**, **visualize** SHAP, LIME, PDP, Permutation plots **Display** PSO-suggested settings and **PID response over time**

7. Flask API (Optional):

Create endpoints: `/predict`, `/xai` **Return** predictions and explanations in JSON

J. Algorithm Workflow

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1) **Data Collection & Preprocessing**
   - **Input:** Real-time sensor data (water flow rate, inlet/outlet temperatures)
   - **Output:** Normalized, outlier-free dataset
   - **Tools:** Z-score normalization, IQR outlier detection
2) **Explainable Feature Analysis**
   - **Apply SHAP for global interpretability:**

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{i\}) - f(S)]$$

     where ϕ_i is the SHAP value for feature i.
   - **Use LIME for local explanations of critical data points.**
3) **PID Controller Adjustment**
   - **Implement discrete PID control:**

$$u(t) = K_p e(t) + K_i \sum_{k=0}^{t} e(k)\Delta t + K_d \frac{e(t) - e(t-1)}{\Delta t}$$

     where $u(t)$ is the control signal, $e(t)$ is the error.
4) **PSO-Based Optimization**
   - **Initialize swarm with PID parameters as initial particles**
   - **Update velocity and position:**

$$v_i^{k+1} = wv_i^k + c_1 r_1 (pbest_i - x_i^k) + c_2 r_2 (gbest - x_i^k)$$
$$x_i^{k+1} = x_i^k + v_i^{k+1}$$

     where w = inertia weight, c_1, c_2 = learning factors

RESULTS AND DISCUSSION

Testing for the suggested cooling tower optimization system applied complete metrics for multiple test instances. Parameters relations within the entire spectrum of operating conditions need to have been assessed through seasonal variations and load profiles for total parameter evaluation. Combinations of parameters used as direct metrics affected the accuracy rates of the system in prediction since a wider scope of parameters was required for the learning of complex behaviors of the system.

TABLE II
SUMMARY OF COOLING TOWER OPTIMIZATION AND INTERPRETABILITY

No.	Title	Problem Statement	Year	Research Gap
1	Cooling Tower Efficiency	LSTM-based performance prediction	2019	Lacks interpretability
2	XAI for Cooling Systems	Explainable optimization methods	2021	Limited control integration
3	Cooling Tower Survey	Reviews optimization methods	2022	Hybrid approaches lacking
4	Energy-Efficient Operation	PSO-based energy saving	2020	Weak parameter insights
5	SHAP and LIME in Industry	XAI for process optimization	2023	Limited validation range

A. SHAP Analysis Results

SHAP analysis established the water inlet temperature and airflow rate as the most influential features affecting cooling tower performance. Feature importance plots showed a clear hierarchy in parameter importance, with water-related parameters generally having a higher impact than ambient conditions. The dependence plots demonstrated nonlinear relationships in the key parameters and efficiency.

The waterfall plots demonstrated the confluence of many variables to yield a specific prediction, illustrating interactions that would be difficult to elucidate through traditional means. Decision plots revealed a clear pattern in the way the model processed different combinations of parameters.

B. LIME Insights

LIME explanation has been giving some very interesting local interpretability, mostly in edge cases of unusual operating conditions of the whole system. Local approximate surrogate models for the more sophisticated prediction system around points of interest have been delivering actionable insights for operational purposes.

C. PDP Observations

Such PDP visualizations clearly indicate the relationship of parameters to the efficacy of the cooling tower. For example, the plots illustrate the best ranges of water flow rates and a declining return when increasing airflow beyond certain thresholds. Significant interaction effects between related parameters are highlighted with two-way PDPs. One such important interaction can be found between ambient temperature and humidity, with ambient temperature being the higher of the two.

D. PID Controller Performance

The PID control systems succeed in keeping the main parameters at the optimum setpoint as predicted by the model. Controllers show strength under various operating conditions with quick response time and low overshoot. Predictive insight combined with traditional control techniques results in massive benefit gains.

E. PSO Optimization Results

These studies compared the performance of PSO to that of traditional optimization methods and showed that PSO proved to be 15-20required cooling performance across different operating scenarios. The parameter combinations were optimized correctly throughout all operating scenarios, with the algorithm converging correctly, not only giving the same answers when run multiple times but also attaining those results more than just as often as traditional approaches.

The combined all of the five proposed techniques (SHAP, LIME, PDP, PID, and PSO) produced outstanding results in terms of energy consumption savings by 22.

Most of the refinements in models were achieved in these cases of highly variable operating conditions because optimization was also difficult for the human operator under these conditions. The system showed better performance compared to human operation while handling very demanding situations, but it could also perform well for different ambient conditions, as well as during partial load operations and transient states.

Validated results showed that the optimization system proved to be highly efficient and resilient to optimize the operations of cooling towers. The systems are improved significantly when researchers combine interpretable AI models with those old approaches in their system. Our cooling tower optimization scheme adopted this multi-model approach because it allowed viewing complex parameter relationships for which traditional methods evaluated greatly simplified system models separately.

TABLE III
PERFORMANCE METRICS BY OPTIMIZATION METHOD

Method	Energy Reduction	Water Savings	Stability	Adaptation
Traditional	8.70%	7.30%	6.20%	5.75%
PID Only	12.82%	11.00%	15.70%	9.85%
AI + PSO	19.12%	17.08%	16.14%	18.11%

E. Contributions

The primary contributions of this work are as follows:

1) Development of an accurate predictive model for cooling tower performance
A suite of machine learning models, including Random Forest, LightGBM, and XGBoost, were trained to predict cooling tower efficiency based on environmental and operational parameters. The models demonstrated strong generalization capabilities and robust performance across standard regression metrics.
2) Comprehensive integration of explainable artificial intelligence (XAI) techniques
Multiple state-of-the-art XAI methods were incorporated to enhance model transparency. SHAP was employed for both global and local feature attribution, producing summary, dependence, waterfall, and decision plots. LIME was utilized for instance-specific explanations, while Partial Dependence Plots (PDP) and Permutation Importance analyses offered further interpretability of model behavior.
3) Interactive visualization platform for real-time XAI insights
A unified, interactive Streamlit-based frontend was developed to allow users to input operational parameters and receive real-time predictions, along with dynamically updated SHAP, LIME, PDP, and permutation visualizations. This platform enhances user understanding and facilitates trust in the model's outputs.
4) Optimization of cooling tower parameters via Particle Swarm Optimization (PSO)
PSO was implemented to identify optimal settings (e.g., air velocity) that minimize energy consumption or maximize cooling efficiency. This integration provides actionable insights for operational improvement.
5) Simulation of Proportional–Integral–Derivative (PID) control for dynamic adjustment
A PID control module was developed to simulate real-time adjustments in fan speed based on model predictions, bridging the gap between predictive analytics and automatic control systems.
6) Modular and scalable architecture
The system architecture was designed for modularity and extensibility, supporting the integration of additional models, XAI methods, and optimization strategies. This ensures the platform's applicability in broader industrial scenarios.
7) Data-driven recommendations for operational efficiency
Beyond prediction, the framework provides interpretable, model-informed suggestions for operational adjustments, making it a practical tool for intelligent decision-making in cooling tower management.

CONCLUSION

According to the said study, a cooling tower optimization prediction system has been developed using the synergistic combination of models like SHAP, LIME, PDP, PID, and PSO. Such a project forms part of a comprehensive process whereby data preparation precedes model development and system integration to realize an intended improvement in cooling tower efficiency.

It can therefore be said that the system carries practical merit because it covers energy reduction of more than 20and reflects adaptive features across operating conditions and operational readiness in real-time settings. The addition of explainable

AI-based features serves not only to address a primary disadvantage present within many presently used optimization algorithms relying solely on black-box models for processing.

The urgent necessity for interpretable optimization tools is growing critical because, at the rate that industrial energy levels are escalating, these three spaces: power generation, manufacturing processes, and commercial buildings are bound to show their differential finds in the ever-increasing energy use by industry. Users gain high operational awareness through understanding of parameter relationships with visualization features, while the system provides such understanding by virtue of its design.

Subsequent development for the continued evolution of this system will need to add the following additional enhanced capabilities:

• Predictive maintenance involving multimodal analysis for detecting anomalies in operating conditions and equipment degradation.

• Developers might use advanced transformer models that enable better handling of temporal system behaviors.

• Federated learning strategies should be implemented in the system to support the deployability of distributed learning across several cooling tower implementations.

• Security of models is thereby enhanced by deploying defensive mechanisms in the system to harden the model against sensor faults or data corruption.

A foremost achievement in the application of industrial AI toward enhancing the efficient and sustainable operation of cooling towers underpins other work.

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