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Artificial Intelligence Recommendation System for Optimizing Steam Power Plant Heat Rate: A Conceptual Design

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Abstract−Steam power plants are one of the major electricity generation units in many countries around the world. The thermal efficiency of power plants is primarily dependent on decision making by the operator on real time process parameters. This decision-making process currently utilizes human expertise, in conjunction with static setpoints and operating procedures. However, variability in human operator performance and plant operating conditions often leads to non-optimal heat rate values. The purpose of this paper is to develop a conceptual framework for an artificial intelligence-based operator decision-support system for real-time heat rate optimization, integrating Model-Based Design (MBD) and Design Science Research (DSR) principles. The framework presented in this paper is informed by past high efficiency operational experience and machine learning methodology to describe the necessary steps in generating actionable, explainable recommendations for process parameter adjustments. The conceptual framework presented, which incorporates both predictive capabilities as well as domain expertise, is intended to bridge the gap between the development of predictive models and their eventual deployment as prescriptive operational support systems by providing a high-level blueprint of a system design that is expected to lead to more robust and consistent decision making. The key functional components of the framework include data capture, preprocessing, inference modeling and, ultimately, presentation of recommendations on a human-machine interface. An initial, theoretical appraisal of the proposed framework suggests promising potential for improving operational efficiency, reducing fuel consumption, and lowering emissions, and it is expected to serve as a useful reference for ongoing and future development efforts.

Keywords: Artificial Intelligence; Energy Efficiency; System Architecture; Thermal Power Plants; Recommendation Systems

1. INTRODUCTION

Various industries have started to implement intelligent systems that enhance energy consumption efficiency in response to rising demands for environmental sustainability. The rising use of fossil fuels for energy generation creates substantial environmental problems which require cross-sector solutions to address effectively [1]. Thermal power plants including steam power plants stand as essential sources within modern energy systems because they maintain the supply-demand balance throughout the power grid [2].

Heat rate serves as the standard measurement for steam power plant efficiency quantifying the energy needed to generate one unit of electricity. When heat rate decreases it indicates better efficiency while simultaneously reducing fuel usage and operational expenses and emissions. Enhancements in heat rate deliver advantages to both financial performance and environmental outcomes [3].

Despite their importance, steam power plants are often operated using conventional methods based on fixed setpoints and steady-state assumptions. These methods do not adequately reflect the dynamic nature of real-world plant operations [4]. As a result, operational decisions can vary between shifts, leading to inconsistent performance and reduced efficiency. Studies have shown that without predictive models, operators face challenges in assessing performance under fluctuating load conditions [5]. Then there is a reliance on manual procedures and operator experience which can lead to variability and limit scalability issues which are particularly problematic in dynamic and complex environments [6].

Artificial intelligence (AI) is being used more and more in various industries for performance optimization and predictive maintenance, which could revolutionize contemporary energy systems [7], [8]. The use of AI applications in thermal power plants includes emission reduction, turbine optimization, combustion control, and general operational efficiency. Heat rate optimization is one of the important cases among these as it has a direct impact on fuel consumption, operational costs, and greenhouse gas emissions.

Arferiandi et al. developed an artificial neural network (ANN) to model heat rates based on important operational parameters [9]. This approach provides a data-driven basis for efficiency improvement. By facilitating accurate predictions and enabling operational modifications, the AI-based method promises to improve heat rate performance. Similarly, Ding et al. applied AI and machine learning (ML) to hundreds of coal-fired power generation units, producing a framework that can be used to benchmark and predict station heat rates under various conditions [10].

In addition to the application of AI to heat rate optimization, several studies have explored broader plant performance objectives. Nemitallah et al. reviewed techniques for boiler optimization and NOx emission control,

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using AI ML models such as neural networks and fuzzy logic [11]. Bisset et al. presented a systematic review of ML applications in coal-fired plants, focusing on gains in energy efficiency [12]. At the system level, Malik et al. proposed an exergy energy AI framework to predict peak performance [13], while Ashraf et al. focused on improving the efficiency of high-pressure steam turbines to support net-zero goals [14]. In addition, AI has also been applied to detect thermal degradation, predict anomalies, and optimize combustion strategies, to drive consistent plant operations [15], [16].

Previous studies have shown the great potential of AI applications in process modeling, prediction, and optimization. However, most approaches remain at the diagnostic or predictive stage, without offering actionable, real-time recommendations that operators can directly apply. The lack of transparency in many AI models creates black box systems that obscure input-output relationships which reduces operator trust and slows down wider adoption of AI recommendations. Integration into existing plant control frameworks is frequently limited to overall optimization goals, with little to no accommodation of real-world, time-sensitive, and often physical constraints on various recommendations that may be made. This gap between predictive analytics and explainable, prescriptive, operator-focused guidance remains largely unresolved, restricting the practical use of AI in daily plant operations.

In this study, we attempt to narrow this gap by conceptualizing and designing an AI-based system that can provide an actionable, explainable, and prescriptive solution that goes beyond simply predicting performance and directly into recommending changes to improve it. This system is reinforced by a human-in-the-loop feedback system and enables real-time decision support to operators in the field.

Specifically, this research proposes a design for a conceptual AI-based system capable of predicting a target operating parameter and prescribing a set of operating parameters that optimize Net Plant Heat Rate (NPHR) in a thermal power plant. The system takes in real-time sensor data and historical operating records and combines it with a simulation model to estimate current NPHR values and map out a set of recommended operating parameters across a range of possible scenarios. The analytical model provides operators with data-driven suggestions to help them make more informed, consistent decisions, supporting better NPHR performance without directly intervening in control of operations.

2. RESEARCH METHODOLOGY

2.1 Overview of Key Concepts

2.1.1 Artificial Intelligence (AI)

Artificial Intelligence refers to computational systems that are created to imitate human intelligence like reasoning, learning, or self-correction. In this research, we are implementing the model to predict the plant performance and to provide the prescriptive recommendation to the plant operator using live data stream [7], [8]. The ability of AI to process vast operational datasets in real time allows it to identify subtle performance patterns that may not be visible to human operators, thereby supporting improved decision-making and long-term efficiency gains.

2.1.2 Recommendation System

A recommendation system leverages the past and live data to build predictive model and recommend the best operating decision that needs to be taken at any given time to the process operators. The recommendation system is the core mechanism of this research work. It will help in guiding the plant operator to take decisions on control set points for the betterment of heat rate [17]

2.1.3 Net Plant Heat Rate (NPHR)

NPHR is the overall measure of thermal efficiency in steam power plants. It is defined as the amount of heat energy (kCal) required to produce 1kWh electricity. Lower NPHR values signify better conversion efficiency, reduced fuel consumption, and lower environmental impact. Monitoring and optimizing NPHR is therefore central to power plant performance improvement strategies [3].

2.1.4 Explainable AI (XAI)

Explainable AI (XAI) aims to make machine learning outputs interpretable by human operators, ensuring that model-driven predictions and recommendations are both transparent and trustworthy. In this study, SHAP (SHapley Additive exPlanations) is employed to provide interpretable justifications for the system's recommendations . This capability is vital in industrial settings where operators must not only act on AI outputs but also understand the rationale behind them to build confidence, validate decisions, and adhere to safety protocols [18].

2.1.5 Thermal Power Plant Operations

Thermal power plants work on the principle of converting fuel based thermal energy to electrical energy through a series of complex interrelated sub-systems such as boilers, turbines, generator, condenser, etc. Their operation

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involves complex dynamic conditions, making real-time optimization essential for maintaining efficiency under varying loads [4], [19].

2.2 Research Stages

The research utilizes a Model-Based Design (MBD) approach to create a conceptual framework for an AI-based recommendation system that enhances heat rate performance in steam power plants. The research adopts the Design Science Research (DSR) paradigm to focus on the creation and validation of design artifacts such as conceptual framework and architectures that address real-world challenges [20], which stands apart from empirical studies that concentrate on machine learning model training and deployment.

MBD offers a systematic simulation-based methodology to develop complex systems through iterative cycles of modeling and analysis and validation of system behavior. The approach has demonstrated success in energy-related applications such as hybrid power plant control design [21], steam systems with AI-enhanced exergy modeling [13], and conceptual applications of AI [13], [22]. The findings demonstrate that MBD is an effective tool during the conceptual design phase for high-complexity safety-critical systems such as thermal power generation.

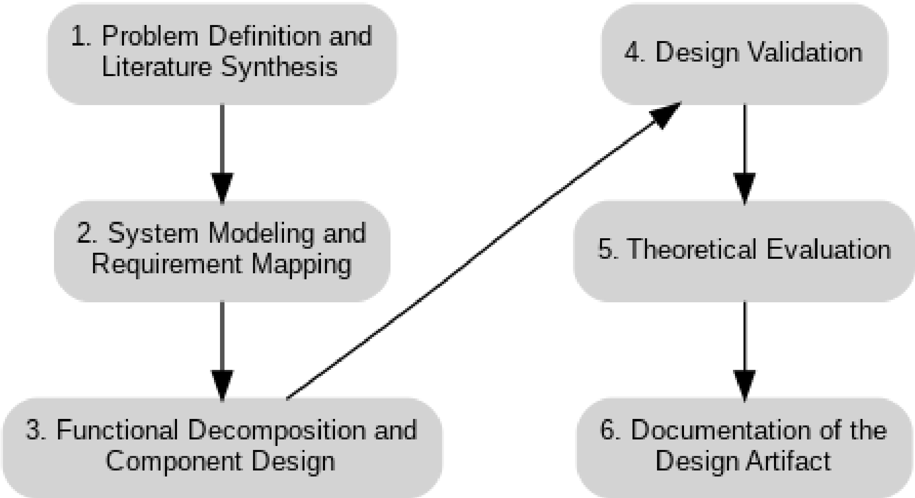

Figure 1. Research Workflow Using Integration of MBD stages

The research workflow is structured into six phases, as shown in Figure 1, which follow the principles of MBD. The overall conceptual framework aligns with the iterative processes of the DSR paradigm, incorporating the relevance, design, and rigor cycles. These stages establish a continuous feedback loop that evaluates and refines the conceptual framework of the AI-based recommendation system [23], as illustrated in Figure 2. Table 1 details each stage and its corresponding output, ensuring traceability from problem identification to the finalized conceptual design artifact.

Table 1. Description of Research Activities Per Stage

No	Stage	Description
1	Problem Definition and Literature Synthesis	This phase pinpoints inefficiencies in steam power plant heat rate management systems while examining traditional approaches and modern AI solutions.
2	System Modeling and Requirement Mapping	The high-level system architecture should comprise the data input layer utilizing real-time sensors and include an AI inference engine based on an ML model block to generate recommendation outputs.
3	Functional Decomposition and Component Design	Decompose the system into functional blocks: preprocessing, inference, interpretability, and feedback.
4	Design Validation	The proposed system undergoes validation through a complementary conceptual approach when a working prototype is unavailable.
5	Theoretical Evaluation	The evaluation examines how well the system matches established best practices for AI-based energy optimization against criteria including modularity and explainability along with scalability and integration capability.
6	Documentation of the Design Artifact	The design artifact documentation combines insights from earlier stages to improve the system for upcoming deployment.

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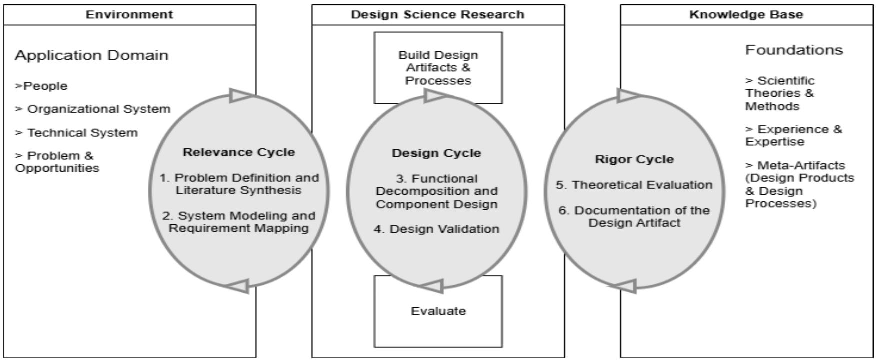

Figure 2. Integration of Model-Based Design (MBD) stages with the Design Science Research (DSR) framework, illustrating the Relevance Cycle, Design Cycle, and Rigor Cycle for developing the conceptual AI-based recommendation system.

2.3 Problem Definition and Literature Synthesis

Steam power plants face continuous heat rate optimization difficulties due to the complex and dynamic operational settings they operate in. The Introduction explains how differences in operator performance outcomes along with fluctuating load conditions and strict procedural guidelines contribute to poor thermal efficiency [3], [4]. The growing demand for improved operational decision-making has sparked interest in data-driven methods that utilize artificial intelligence capabilities [6], [13].

The current AI applications in energy mainly address predictive functions including load forecasting and fault detection as well as maintenance scheduling. For example, *Arferiandi et al*. applied Artificial Neural Networks (ANNs) to simulate heat rate from operational parameters which helped in early performance degradation detection [9]. Similarly, Ashraf et al. implemented gradient-boosted machine learning models to improve steam turbine efficiency in different thermal environments [14]. Ding et al. created extensive datasets for heat rate benchmarking utilizing supervised learning models [10]. Zhan et al. utilized offline reinforcement learning techniques to enhance combustion processes [16]. While these methods yield important information they function mainly as diagnostic or predictive tools without real-time guidance for operators.

Research publications are divided into three main categories. AI applications in anomaly detection involve models which detect performance deviations from expected standards [11], [15]. The second AI application category focuses on forecasting and optimization through load prediction and emission modeling alongside parameter tuning employing methods like XGBoost, fuzzy logic or reinforcement learning [8], [24]Click or tap here to enter text.. Modern research explores new hybrid architectures that unite AI inference capabilities with digital twins to create integrative control systems that synchronize virtual models with actual plant operations [19].

Prescriptive AI systems that produce actionable recommendations for plant operators represent a relatively rare area of research and development. As noted by Heymann et al, there is a significant design gap in creating AI decision-support platforms that require technical strength alongside practical usability within operator work environments and limitations [18].

The review indicates a current lack of AI systems designed for operators which integrate data-driven predictive capabilities with immediate operational guidance. Current models often fail to connect insights with action because although they predict performance decline, they lack direct intervention suggestions. Many system functions as opaque black boxes which reduces their interpretability and diminishes user trust [17].

From this synthesis, several design imperatives emerge. There exists an obvious requirement for instantaneous inference capabilities and actionable advice to support operator decision-making during rapidly changing situations. The system needs to implement explainable AI (XAI) techniques to maintain transparency and build trust in its recommendations [17], [18]. The solution needs to be modular and interoperable to handle plant environment complexity and ensure compatibility with control systems like DCS, SCADA, and data historians [21], [25].

This research introduces a conceptual framework for an AI-based recommendation system designed to connect predictive analytics with practical and understandable operational guidance. The system design combines machine learning techniques, optimization processes and human-in-the-loop feedback mechanisms to enable ongoing performance enhancements for steam power plants.

2.4 System Modeling and Requirement Mapping

This research presents a conceptual framework architecture to overcome literature-design challenges through an AI-based decision-support system that enhances heat rate performance in steam power plants. The development of the system follows MBD approach while being directed by DSR paradigm so that both technical feasibility and real-world applicability can be met. The fundamental goal of our system design is to support operators by providing real-time recommendations that understand the context and offer clear explanations for operational decisions.

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System requirements must first be mapped to operational objectives during the design process's initial phase. These requirements are grouped into two categories: Functional requirements specify the required functions of the system while non-functional requirements describe the system's performance criteria. The structured mapping serves as the foundational element for making architectural decisions and setting validation criteria.

2.4.1 Functional Requirements

Functional requirements identify essential system capabilities including data acquisition and prediction as well as optimization, interpretability, and feedback learning. These are summarized in Table 2.

Table 2. Functional Requirement Mapping

No	Category	Description
FR-01	Functional	Acquire real-time operational data on an hourly basis from plant sensors.
FR-02	Functional	Predict NPHR using machine learning models trained on historical and live data.
FR-03	Functional	Evaluate and optimize NPHR by simulating parameter adjustments.
FR-04	Functional	Generate prescriptive recommendations for operators to implement actionable efficiency improvements.
FR-05	Functional	Provide interpretability and transparency of AI model outputs to improve operator trust and acceptance.
FR-06	Functional	Support feedback integration from operator responses and outcomes to enable continuous model refinement.

The functional requirements serve as the central framework that enables the system to operate effectively. The system collects critical data inputs including steam flow and fuel input along with temperature and pressure measurements from plant sensors before preprocessing them to maintain compatibility with machine learning models (FR-01).

The inference engine both predicts real-time NPHR values and evaluates parameter modifications to establish optimal control methods (FR-02, FR-03). The system implements SHAP (SHapley Additive exPlanations)-based feature explanations to build operator trust and enhance model transparency (FR-05). The recommendation interface provides operators with actionable control recommendations based on prediction insights (FR-04) and a feedback module records operator choices and plant reactions which support ongoing system learning (FR-06).

2.4.2 Non-Functional Requirements

The proposed system needs to meet its primary functional duties while also achieving non-functional requirements (NFRs) that guarantee dependable, secure and user-friendly performance in industrial applications. Steam power plants require real-time responsiveness and data integrity together with operator trust which makes these quality attributes essential for practical deployment. Table 3 summarizes how NFRs establish essential benchmarks for evaluating system architecture completeness and feasibility.

2.4.3 Optimization Strategy Design Justification

The inference engine uses machine learning models for regression, since the mappings between operating parameters and heat rate may be nonlinear. Prior work suggests that suitable regression models include artificial neural networks (ANN), particularly Multilayer Perceptrons (MLP), and gradient-boosted decision trees such as XGBoost. These have demonstrated capabilities on high-dimensional, noisy, multivariate datasets and prior work has validated them for power plant efficiency prediction tasks[9], [14].

The system is designed to be agnostic to the optimization method and easily extensible to new approaches. Grid search is relatively computationally expensive, but it is easy to interpret and does not assume a problem space, making it useful as a baseline for black-box models like ANN-based HRSG steam production predictors [26]. For complex or continuous search spaces, metaheuristic approaches like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have demonstrated efficacy and scalability.

GA-based optimization has demonstrated capital cost and heat transfer surface area reduction in HRSG systems [27], as well as better exergy efficiency and annual costs in cogeneration case studies [28]. For more general thermodynamic cycle optimization, GA has also been used on geothermal systems [29]. Empirical comparisons of GA and PSO performance on economic-emission dispatch have shown faster convergence and lower computational burden for PSO [30], which may be more relevant for real-time plant optimization scenarios.

The system should support these or other configurable optimization strategies, letting operators or plant engineers decide if they prioritize interpretability, speed, or other considerations.

2.5 Validation and Evaluation Strategy

The research uses the DSR approach to validate the conceptual framework architecture of the AI-based recommendation system proposed in this study. The evaluation assesses how well the system maintains theoretical

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integrity while achieving functional completeness and demonstrating architectural suitability for deployment in steam power plant operations. Two complementary validation methods are employed:

a. **Requirement Validation Matrix**: This method establishes a systematic relationship between functional and non-functional requirements with their respective architectural modules and measurable evaluation metrics. The system components fully support the predetermined objectives for performance, usability, reliability, and maintainability as detailed in requirement mapping.
b. **Design Heuristic Evaluation**: The assessment evaluates the conceptual framework design by comparing it to established patterns found in industrial systems incorporating AI. The evaluation criteria consist of modularity, real-time responsiveness, explainability, robustness, and human-in-the-loop support. Through these heuristics we can check if the proposed system embodies the best practices and if it can be practically implemented in working plant environments.

The combined validation strategies deliver an exhaustive design evaluation that verifies the proposed system's conceptual integrity while ensuring operational compatibility and scalability for industrial deployment.

Table 3. Non-Functional Requirement Mapping

No	Category	Description
NFR-01	Performance	The system must generate real-time recommendations within 5 minutes of receiving new data.
NFR-02	Compatibility	The system should establish seamless connections to DCS, SCADA, and historian systems through standard communication protocols.
NFR-03	Usability	AI recommendation interpretation should require limited training for system operators.
NFR-04	Reliability	The system should operate without failure while processing sensor noise and missing values to achieve greater than 99% system availability.
NFR -05	Security	Access to logs and model parameters is restricted to authorized personnel through Role-Based Access Control (RBAC) permissions.
NFR-06	Maintainability	The system must support independent upgrades of each module like preprocessing and inference while avoiding operational disruptions.

3. RESULT AND DISCUSSION

A modular multi-layered framework forms the conceptual framework design of the AI-based recommendation system that processes real-time data to offer actionable insights for steam power plant operators. The design integrates MBD and DSR principles to develop a prescriptive decision-support tool that surpasses standard monitoring and prediction capabilities.

The system architecture comprises four key modules, each with specific functionalities tailored to the unique operational context of steam power plants: The system incorporates four main modules which are Data acquisition and Pre-processing followed by the AI-Based Inference Engine then the Interpretable Recommendation Module and finally the Feedback and Learning Module.

3.1 Data Acquisition and Pre-processing Module

This module gathers operational data from Distributed Control Systems (DCS), Supervisory Control and Data Acquisition (SCADA) systems and plant historians and transforms it for further use. The main operational variables include steam pressure levels, turbine load capacity, fuel input quantities, excess oxygen (O_2), Gross Calorific Value (GCV), flue gas temperature data points and turbine vacuum measurements.

The module employs a standardized preprocessing pipeline to ensure data reliability and consistency for both offline model training and real-time inference tasks (Figure 2 illustrates this process). This process includes:

a. Time-alignment across multivariate data streams to maintain synchronized observations among all parameters.
b. Noise filtering uses statistical smoothing and moving averages to minimize sensor variability.
c. Missing value imputation substitutes missing data points through forward fill, interpolation methods, or the application of rules specific to the domain.
d. Variable transformation and normalization through techniques like min-max scaling and log transformations

3.2 Inference engine based on AI models

The proposed AI-based recommendation system uses its inference engine as the principal computational element to produce real-time NPHR predictions while optimizing control setpoints. The system performs as a critical intermediary between data analysis and operational decisions while providing advanced heat rate management capabilities in steam power plants. The engine leverages ML models trained on historical plant data to discover intricate nonlinear dependencies among operational parameters and thermal efficiency. The chosen models include ANN, MLP, and Gradient Boosted Trees (e.g., XGBoost), which have shown promise in handling high-dimensional and noisy multivariate data.

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After training, these models are exported and imported into the inference environment for real-time deployment. They will be applied to the preprocessed operational data on an hourly basis to produce predictions to allow for early detection of efficiency anomalies by operators and to support corrective decision-making. In addition to monitoring, the system also includes an optimizer that evaluates a set of promising operating scenarios. The controllable parameters (e.g., feedwater temperature, excess oxygen) in the system are set to sample from ranges of candidate values. Each sampled point is evaluated by the trained model and assigned a score corresponding to its expected NPHR. The result is a set of alternative actions with their associated lower expected NPHR values that an operator can execute. This process simulates the reasoning process of an expert operator who mentally simulates a few scenarios to identify the most favorable before implementation.

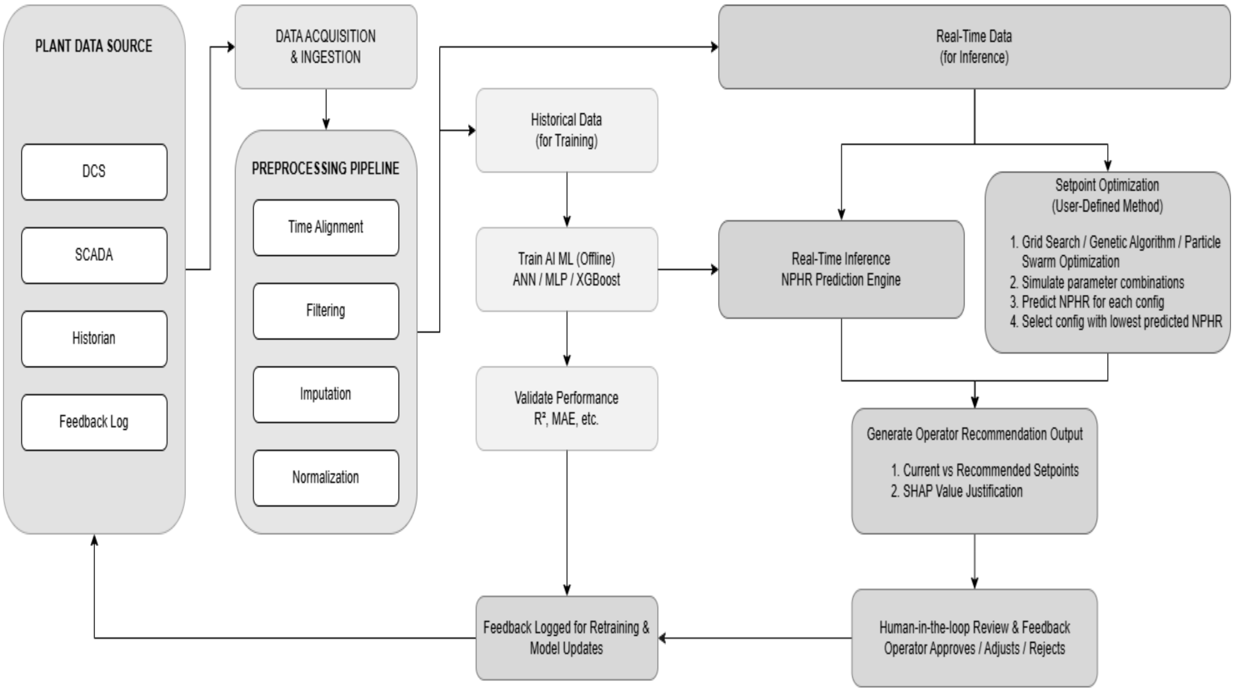

Figure 3 The conceptual framework structure of an AI-driven recommendation system which optimizes heat rates for steam power plants.

We developed the optimizer through a method-agnostic approach that supports extensibility to meet diverse application requirements and computational demands. As detailed in Section 2.4.3, grid-based methods are available for their transparency, and metaheuristic approaches (e.g., Genetic Algorithms and Particle Swarm Optimization) can be used to navigate more complex optimization landscapes. This design allows the system to meet different plant requirements and preferences in terms of interpretability, speed, and resilience.

Figure 3 demonstrates how the inference engine combines real-time data ingestion with predictive modeling while enabling optimization and operator interaction. The system presents setpoint recommendations together with SHAP-based explanations to maintain transparency and enhance operator understanding. The system records feedback by logging whether recommendations received operator approval or rejection to enhance continuous learning and improve model performance.

3.3 Interpretable Recommendation Module

The module ensures that the AI-based recommendation system provides precise predictions and optimization results while maintaining transparency about their underlying reasoning. Steam power plant operations require safety and regulatory compliance which makes interpretable AI indispensable for gaining operator trust and promoting system usage.

The inference engine works to mitigate the opaque characteristics of complex machine learning systems including neural networks and gradient-boosted trees. These models provide accurate NPHR predictions but lack inherent transparency about which inputs impact each prediction. The system adopts SHAP, which uses game theory to distribute input feature contributions to each output result fairly. SHAP values demonstrate the impact of individual inputs on predicted NPHR values relative to a baseline by evaluating every potential feature combination.

The system outputs each recommendation not merely as plain results but as organized insights that include interpretability information. The system delivers four pieces of information for each control parameter: the current operating value, the optimized value, the SHAP value indicating the parameter's influence on predicted NPHR and a straightforward explanation about the direction of its impact. The enriched format helps operators both comprehend necessary adjustments and understand their impact on plant performance.

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Table 3. Example of SHAP-Based Recommendations with Interpretability Context

Parameter	Current Value	Recommended Value	SHAP Value (kCal/kWh)	Explanation
Feedwater Temperature (°C)	219	222	15	Higher feedwater temp improves turbine efficiency and reduces boiler heat load
Reheat Steam Temp (°C)	538.02.00	542.01.00	-12	Higher reheat temp increases cycle efficiency by maximizing enthalpy drop
Main Steam Spray Flow (t/h)	54	49	10	High spray flow lowers steam temperature and cycle efficiency

Table 3 shows a sample of SHAP-augmented recommendation output. The table delivers a clear quantitative analysis for operators to understand how each control parameter affects the predicted heat rate. The system reveals how each feature affects performance both positively and negatively as well as quantifies impacts in kCal/kWh to transparently validate its recommendations rather than just presenting them. Operators gain the ability to rank interventions and evaluate AI results with their knowledge while maintaining the power to dismiss AI suggestions when required.

The interpretability process becomes an essential component within the AI recommendation workflow as demonstrated by the system workflow in Figure 2. The system displays SHAP explanations with each setpoint suggestion so operators can understand the reasoning behind recommendations instead of receiving opaque outputs. The system develops beyond a simple decision engine into a cooperative interface through this integration which builds user trust and allows informed decisions while ensuring machine recommendations align with human judgment.

3.4 Feedback and Learning Module

The feedback and learning module serve as the AI-based recommendation system's adaptive core by enabling continuous improvements through human operator input and system performance evaluation. Human operators retain ultimate control over system operations to either follow guidance from the inference engine and recommendation module or modify actions based on current operational conditions.

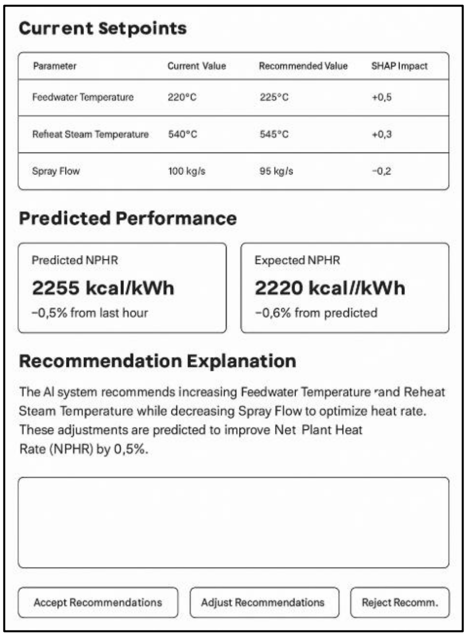

Figure 4 Operator interface showing AI-generated setpoint recommendations with SHAP explanations, predicted performance, and action buttons for feedback used in model retraining.

The system establishes its connection to real-world plant conditions using the human-in-the-loop mechanism depicted in Figure 3. The structured interface depicted in Figure 4 both tracks operator decision-making and presents recommended setpoints alongside SHAP-based interpretability measures and anticipated performance outcomes.

The system documents all operator responses including recommendation acceptance or modification and rejection while capturing details about environmental conditions and unit load together with fuel quality metrics.

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The system uses enriched feedback records as training data which it updates on a monthly or quarterly basis to adapt to plant behavior changes and new operator preferences.

The module ensures long-term operational relevance by maintaining model accuracy and building operator trust through continuous feedback between human input and AI output.

3.5 System Architecture

Figure 5 illustrates an extensible modular architecture for an AI-powered recommendation platform that enhances heat rate performance in steam power plants. The architecture is organized into six core layers: The Orchestration Layer manages time-based control and automation across Sensor Data, Data Processing, Machine Learning, Middleware, Front-End, and Database.

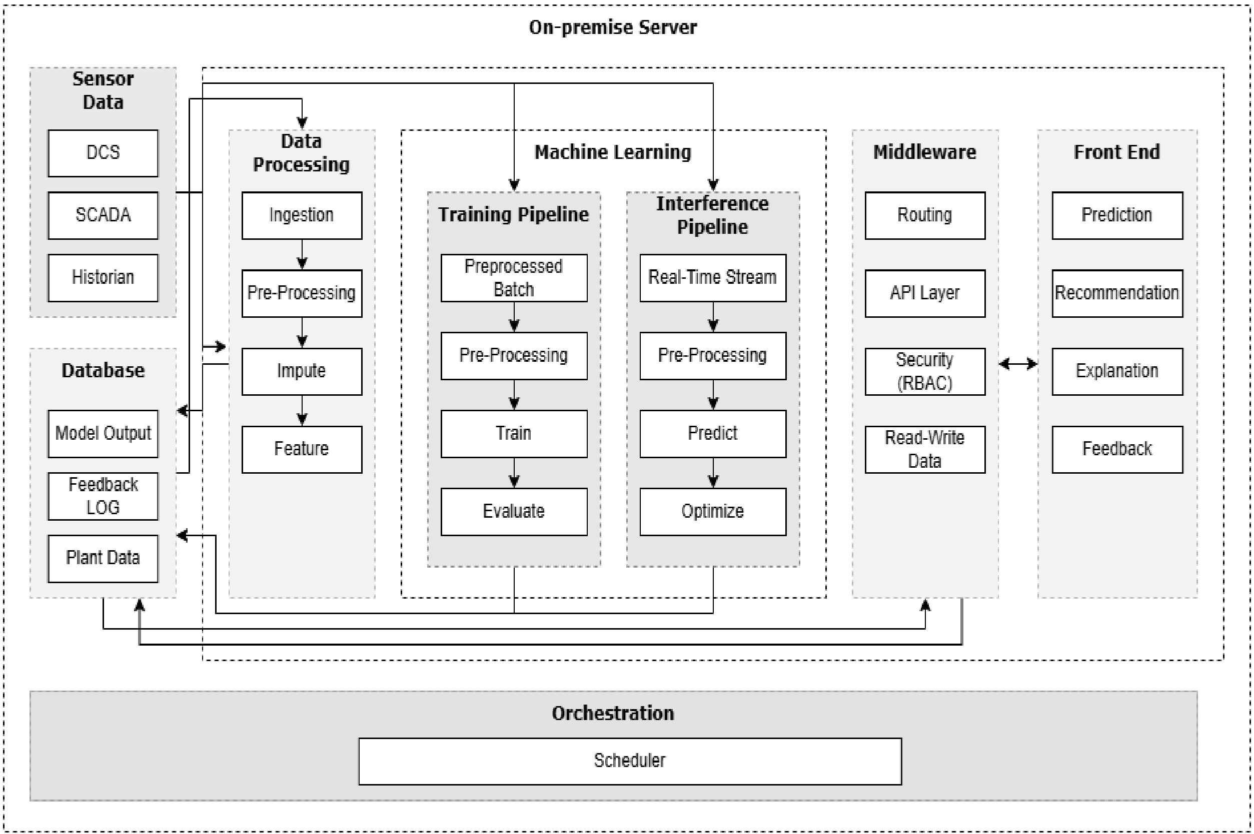

Figure 5 System architecture of the proposed AI-based recommendation system for steam power plant optimization.

In the Data Processing module sensor information from DCS, SCADA, and historian systems goes through ingestion, cleaning, imputation, and feature engineering processes. The process produces high-quality input data for subsequent machine learning operations. The system design incorporates real-time streaming capabilities as well as batch-processing options to address varying needs for latency and accuracy.

The Machine Learning block uses historical data for model training and evaluation through its pipeline while a separate inference pipeline manages real-time data processing. The inference process combines prediction and optimization elements to produce outputs that help determine operational decisions. The separation of operations allows model retraining and inference to proceed independently which facilitates model updates without interrupting real-time services.

The Middleware Layer performs critical module integration functions. The system manages routing operations and authentication while exposing APIs to facilitate connections between machine learning services and operator interfaces. The system incorporates a security layer which uses role-based access control (RBAC) to restrict access to sensitive model parameters and recommendation overrides to authorized personnel only.

The Front-End provides operators with capabilities for prediction visualization and recommended setpoints alongside SHAP-based interpretability features and feedback collection tools. The interface operates independently from the backend system which allows for deployment in user-defined formats or integration with existing HMI infrastructures.

The Orchestration Layer coordinates the architecture by scheduling tasks including periodic retraining runs, hourly inference operations, and management of logs. The system enables automated processes while keeping centralized oversight over time-based functions.

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The system design which organizes discrete services and layers allows containerized deployment along with API-based communication and scalable infrastructure. Individual components support independent deployment and updates without system interruption and isolated maintenance which helps maintain the system's robustness and reliability in industrial settings.

3.6 Design Validation

The design validation phase confirms that the AI-based recommendation system achieves its goals and adheres to standard industrial AI system design principles. This validation is performed through two complementary approaches: The design validation process utilizes two fundamental tools which are the Requirement Validation Matrix and Design Pattern Mapping.

3.6.1 Requirement Validation Matrix

The Requirement Validation Matrix connects Functional Requirements from Section 2.3.1 and Non-Functional Requirements from Section 2.3.2 with the corresponding architectural modules that implement them. This mapping creates full traceability between design objectives of the system and the actual implemented solution.

Table 4 demonstrates that every system module from data acquisition to the feedback loop fulfills one or more functional requirements which allows the architecture to directly support the operational needs of the AI-based recommendation system.

Table 4. Mapping of System Modules to Functional Requirements

System Module	Mapped Requirements	Description
Data Acquisition and Pre-processing	FR-01	Enables hourly data collection and prepares it for model inference
AI Inference Engine	FR-02, FR-03	Predicts NPHR and simulates setpoint scenarios using ML models
Interpretable Recommendation	FR-04, FR-05	Converts optimization output into prescriptive operator actions and provides SHAP-based explanations for operator understanding
Feedback and Learning Module	FR-06	Captures operator responses and retrains models periodically

Table 5 delivers an extensive mapping between non-functional requirements and architectural components that support essential quality attributes including performance, usability, security, and maintainability. The system design satisfies both operational needs and quality-related criteria according to the information presented in these tables.

Table 5. Non-Functional Requirement Mapping to Architecture

NFR Category	Supported by	Description
Performance	Inference Engine, Preprocessing Pipeline	Real-time prediction and optimization within a defined response window.
Compatibility	Data Ingestion Layer	Seamless integration with DCS, SCADA, and historians via standard protocols.
Usability	Recommendation Interface	Operator-friendly UI with interpretable outputs and minimal training needs.
Reliability	Preprocessing, Modular Architecture	Captures operator responses and supports periodic model retraining.
Security	Access Control Mechanisms (RBAC)	Restricts access to sensitive components and logs.
Maintainability	Modular Architecture	Each component can be upgraded or retrained independently.

3.6.2 Design Pattern Mapping

Beyond requirement fulfillment, the conceptual framework system is evaluated against established design heuristics and patterns found in high-performing industrial AI systems. These include modularity, real-time responsiveness, human-in-the-loop interaction, interpretability, and feedback integration. Table 6 summarizes how the system adheres to these principles.

The proposed system architecture has been verified to meet both functional and non-functional requirements and coincides with established AI design patterns used in industrial settings. The Requirement Validation Matrix demonstrates that each system module connects directly to its operational objective which maintains both traceability and alignment with stakeholder needs. The architecture aligns with essential design heuristics including modularity and real-time responsiveness along with interpretability and human-in-the-loop control and continuous learning which are necessary for maintaining system scalability in addition to usability and trustworthiness within actual power plant settings.

Table 6. Design Pattern Mapping to Architectural Features

Design Heuristic	Evidence in Proposed System
Modularity	System is composed of loosely coupled modules—data preprocessing, inference engine, interpretability, recommendation interface, and feedback loop—allowing independent scaling and maintenance.
Real-time Operation	Data is processed and predictions generated on an hourly basis to support operational responsiveness.
Interpretability	SHAP explanations clarify the contribution of each input variable to predictions, supporting operator trust and safety.
Human-in-the-loop	Operators can accept, modify, or reject recommendations through an interactive interface, maintaining oversight and operational control.
Continuous Learning	Operator feedback is logged and used in periodic model retraining cycles to adapt to changing conditions.

Through its dual-layered validation approach the system proves complete from a technical standpoint and demonstrates engineering for sustainable maintainability and real deployment. The framework establishes a durable base for future implementation procedures and field testing operations.

4. CONCLUSION

This study addresses the identified gap in steam power plant operations, where traditional heat rate management practices lack prediction and recommendation systems. The methodology follows Model-Based Design (MBD) and Design Science Research (DSR) principles to establish an AI-based for heat rate optimization conceptual design. The approach establishes a six-stage workflow encompassing problem definition, system model specification, functional decomposition and abstraction, conceptual solution validation, theoretical evaluation, and final documentation. Operating within ongoing cycles of relevance, design, and rigor, this process enables the development of a scalable design solution that supports future iterative enhancements. The proposed conceptual design architecture incorporates data acquisition and preprocessing alongside an inference engine with an interpretable recommendation interface which integrates a human-in-the-loop feedback control. Evaluation of the conceptual design against its intended criteria for modularity, explainability, scalability, and integration readiness demonstrated successful result. This approach has the potential to improve operational efficiency by providing data-driven guidance while ensuring interpretability for human operators, offering valuable reference for future development and deployment in real-world power plant environments. While the work is currently at the conceptual stage, future work will be aimed at the development of a working prototype with real time plant data and evaluation of the feasibility and effectiveness under all types of operating conditions.

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