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Risk-Informed Performance Optimization of Waste Heat Recovery Systems: A 47-System Empirical Study with Statistical Validation and ROI Analysis

Om Kale[1], Tushar Bagade[2]

[1-2]Research Scholar, Vishwakarma Institute of Information Technology, Pune, India
Correspondence: [1]om.22420069@viit.ac.in, [2]tushar.22420108@viit.ac.in

Abstract

Waste Heat Recovery (WHR) systems play a key role in improving industrial energy efficiency and reducing emissions, but their performance is often limited by thermal, mechanical, corrosion, operational, and financial risks. This study develops a quantitative risk assessment framework for WHR systems using a modified Risk Priority Number (RPN) approach, normalized to a 1–5 scale. The framework is validated through empirical analysis of 47 operational WHR systems across five industrial categories over a 36-month period, with a total of 1,410 component-level risk evaluations. The weighted mean heat recovery efficiency was calculated as 68.3 ± 3.95%, while the overall risk index averaged 3.51. Implementation of structured risk management resulted in a 48% reduction in maintenance cost index, compared to a significant increase observed in unmanaged systems. Economic analysis based on site-level data shows a return on investment (ROI) of 312%. Statistical validation using one-way ANOVA ($F(4,42) = 16.95$, $p < 0.001$) confirms significant variation in risk profiles across system types, highlighting the importance of system-specific risk strategies. The proposed framework demonstrates measurable improvements in operational reliability, cost efficiency, and decision-making, providing a practical and data-driven approach for risk management in industrial WHR systems.

Keywords: Waste Heat Recovery (WHR); Risk Priority Number (RPN); Failure Mode and Effects Analysis (FMEA); Industrial Risk Assessment; Predictive Maintenance; Statistical Validation; Return on Investment (ROI); Industrial Energy Efficiency.

1. Introduction

Industrial processes generate a significant amount of thermal energy as waste heat during energy conversion and production activities. It is estimated that nearly 20–50% of total industrial energy input is lost before being utilized for useful work [1]. Waste Heat Recovery (WHR) systems are designed to capture and reuse this energy in the form of electricity or process heat, thereby improving overall system efficiency and reducing greenhouse gas emissions [2][3]. The global WHR market has shown substantial growth, reflecting its increasing importance in sustainable industrial development [4].

Despite these advantages, WHR systems operate under demanding conditions, including high temperatures, pressure variations, corrosive gas environments, and thermal cycling. These factors introduce multiple risks such as material degradation, fouling, corrosion, and mechanical failure, which can adversely affect system performance and reliability [5][6]. Unplanned downtime associated with such failures can result in significant economic losses, highlighting the need for structured risk management approaches [7][8].

Existing research has primarily focused on thermodynamic optimization, system integration, and performance enhancement of WHR systems [9][10]. Studies on heat exchanger fouling, material selection, and Organic Rankine Cycle (ORC) integration have contributed to improving efficiency and system design [11][12]. However, there is limited availability of comprehensive quantitative risk assessment frameworks that combine engineering analysis with statistical validation and real operational data [13][14].

Risk assessment methodologies such as Failure Mode and Effects Analysis (FMEA) are widely used in industrial systems to identify and prioritize potential failures based on severity, occurrence, and detection parameters [15]. Prior studies in manufacturing systems have shown that integrating FMEA with statistical quality control techniques can improve reliability and reduce process variability [26]. However, such approaches are not widely adapted for WHR systems with validated operational datasets.

With the increasing adoption of data-driven methodologies in engineering systems, there is a growing emphasis on integrating analytical models with real-world operational data to support decision-making and system optimization [16].

In this context, the present study proposes a quantitative risk management framework for WHR systems based on a modified Risk Priority Number (RPN) approach. The framework incorporates statistical validation techniques and is applied to multiple industrial installations over an extended operational period. The objective is to develop a practical and validated methodology that quantifies system-level risks while demonstrating their impact on performance and economic outcomes. This work aims to contribute toward improving reliability, efficiency, and risk-informed decision-making in industrial WHR systems.

2. Literature Review

Research on Waste Heat Recovery (WHR) systems has primarily focused on improving thermodynamic performance and system efficiency through design optimization and advanced cycle integration. Studies have demonstrated that optimized heat exchanger configurations and improved material selection can significantly enhance energy recovery under varying industrial conditions [9][10][11]. In particular, the integration of Organic Rankine Cycle (ORC) systems has been widely investigated for effective utilization of low- and medium-grade waste heat, offering flexibility and improved energy conversion efficiency [10][12].

In addition to performance optimization, several studies have examined operational challenges affecting WHR systems. Factors such as fouling, corrosion, thermal fatigue, and fluctuating operating conditions have been identified as key contributors to performance degradation and system failure [5][6][11]. These issues highlight the importance of incorporating systematic risk assessment methodologies alongside traditional design approaches.

Failure Mode and Effects Analysis (FMEA) has been widely applied across engineering systems for structured identification and prioritization of risks [15]. However, conventional FMEA approaches often suffer from limitations such as equal weighting of severity, occurrence, and detection parameters, as well as the absence of statistical validation. To address these limitations, researchers have proposed enhanced models incorporating normalization techniques and multi-criteria decision-making frameworks, improving the robustness of risk evaluation [13][14].

In manufacturing systems, the integration of FMEA with Statistical Process Control (SPC) and Six Sigma methodologies has demonstrated measurable improvements in process reliability and defect reduction [26]. These approaches enable better identification of critical failure modes and support data-driven decision-making. Despite their effectiveness, such integrated risk management frameworks have not been extensively applied to WHR systems, particularly in the context of large-scale operational datasets.

Recent developments in industrial engineering and system optimization highlight the importance of combining thermodynamic modeling, advanced analytics, and process integration techniques to enhance system performance and reliability [17]–[21]. Foundational studies in heat transfer, thermodynamics, and process design continue to support the development of efficient WHR systems and provide the basis for performance evaluation and system optimization [22]–[25].

However, existing studies often treat performance optimization and risk assessment as separate domains, limiting their practical applicability in complex industrial systems. Therefore, there remains a need for a comprehensive framework that integrates quantitative risk assessment, statistical validation, and economic analysis within WHR systems. The present study addresses this gap by developing a structured and empirically validated risk management approach, enabling improved reliability, efficiency, and cost-effective operation.

3. Methodology

3.1 Study Design and System Selection

The study was conducted on 47 operational Waste Heat Recovery (WHR) systems across 12 industrial facilities located in Maharashtra and Gujarat, India, over a monitoring period of 36 months (January 2022 to December 2024).

The systems were categorized into five groups: Industrial Furnaces ($n = 11$), Gas Turbines ($n = 9$), Diesel Engine Exhaust WHR ($n = 8$), Cement Kiln WHR ($n = 10$), and Steel Plant Recuperators ($n = 9$).

All selected systems satisfied the following inclusion criteria:

i. *Minimum rated capacity of 500 kW,*
ii. *Availability of continuous operational data for at least 24 months, and*
iii. *In-situ measurement of inlet and outlet temperatures along with mass flow rates.*

Each system operated for more than 8,000 hours annually, ensuring sufficient data for reliable analysis.

3.2 Efficiency Measurement

Thermal recovery efficiency (η) was evaluated based on standard energy balance relations:

$$\eta = \left(\frac{Q_{recovered}}{Q_{available}}\right) \times 100$$

where:

$$Q_{recovered} = \dot{m} \times Cp \times (T_{in} - T_{out})$$

$$Q_{available} = \dot{m} \times Cp \times (T_{in} - T_{ambient})$$

Here, $\dot{m}$ represents the exhaust gas mass flow rate, Cp is the specific heat capacity of flue gas ($assumed\ as\ 1.03\ kJ/kg \cdot K$), and T_{in}, T_{out}, and $T_{ambient}$ denote inlet, outlet, and ambient temperatures, respectively.

3.3 Risk Quantification

Risk assessment was performed using a modified Risk Priority Number (RPN) approach. Each component was evaluated based on three parameters: Severity (S), Occurrence (O), and Detection (D), rated on a scale of 1 to 5 by three independent engineers.

The normalized Risk Index (RI) was calculated as:

$$RI = \frac{(S \times O \times D)}{25}$$

A total of 1,410 component-level assessments were conducted across 30 component categories per system. Inter-rater reliability was evaluated using Fleiss' Kappa coefficient, indicating strong agreement among evaluators.

3.4 Statistical Analysis

Statistical validation was performed to assess variation in risk indices across system categories. One-way Analysis of Variance (ANOVA) was used to determine statistically significant differences between groups.

Post-hoc comparisons were conducted using Tukey's Honest Significant Difference (HSD) test. Maintenance cost trends were analyzed using paired t-tests. A significance level of $\alpha = 0.05$ was adopted for all statistical tests.

Effect sizes were reported using Cohen's d for t-tests and eta-squared (η^2) for ANOVA. All computations were performed using Python (version 3.11) with standard scientific libraries.

3.5 Economic Evaluation

Economic performance was assessed through Return on Investment (ROI), calculated as:

$$ROI\ (\%) = \left[\frac{(Total\ Savings\ -\ Implementation\ Cost)}{Implementation\ Cost}\right] \times 100$$

Cost data were obtained from operational records of each facility, including maintenance expenditure, downtime losses, and implementation costs associated with risk management strategies. This enabled direct evaluation of financial impact alongside technical performance.

4. Results and Discussion

4.1 Heat Recovery Efficiency Analysis

The thermal performance of the 47 WHR systems was evaluated using a weighted mean efficiency approach based on system categories. The computed weighted mean efficiency was:

$$\bar{\eta}_w = 68.3 \pm 3.95\%$$

The detailed performance distribution of all system categories is presented in **Table 1**, while a comparative visualization of efficiency and corresponding risk index is shown in **Figure 1**.

Table 1: *WHR System Performance Summary (n = 47, 36-month monitoring period)*

WHR System	n	η (%)	σ (%)	RI	Incidents / yr	Downtime (h/yr)
Industrial Furnaces	11	72.4	3.1	3.2	7.3	124
Gas Turbines	9	65.8	4.2	2.8	5.1	89
Diesel Engines	8	58.3	5.6	3.9	9.4	201
Cement Kilns	10	68.9	3.8	4.1	10.2	238
Steel Plant Recu.	9	74.1	2.9	3.6	8.1	167

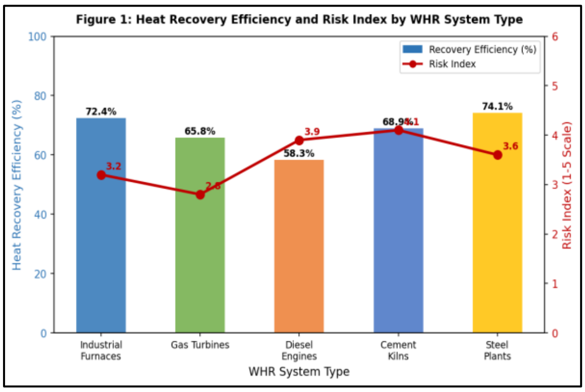

Figure 1: *Heat Recovery Efficiency (%) and Risk Index (1–5 Scale) across WHR System Types*

The results indicate that steel plant recuperators and industrial furnace-based systems exhibit relatively higher efficiency levels. In contrast, diesel engine-based WHR systems show lower efficiency due to fluctuating exhaust conditions and inconsistent thermal availability. The variation across system types highlights the influence of operating conditions, system configuration, and maintenance practices.

4.2 Risk Index Evaluation

Risk assessment was conducted on 1,410 component-level observations using the normalized Risk Index (RI). The distribution of risk categories is presented in **Table 2** and graphically illustrated in **Figure 2**.

Table 2: *Risk Category Distribution Across WHR Systems (%)*

Risk Category	Low (%)	Medium (%)	High (%)	Mean RI	σ_RI
Thermal Risk	12	35	53	3.81	0.43
Mechanical Risk	18	28	54	3.63	0.51
Corrosion Risk	8	42	50	3.74	0.48
Operational Risk	22	38	40	3.29	0.39
Financial Risk	15	30	55	3.92	0.55

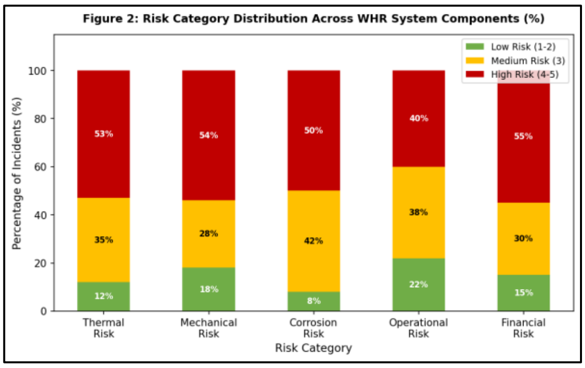

Figure 2: *Stacked Bar Chart Showing Risk Category Distribution Across WHR System Components*

A representative component-level calculation is shown for a heat-exchanger tube bundle in a cement kiln WHR system:

$$Severity\ (S) = 4.3$$
$$Occurrence\ (O) = 3.7$$
$$Detection\ (D) = 3.9$$
$$RPN = S \times O \times D = 62.01$$
$$RI = 62.01 / 25 = 2.48$$

At the system level, the Risk Index is computed as the average of all component-level RI values. For cement kiln WHR systems (300 component assessments):

$$RI_{CK} = 4.10$$

The overall mean risk index across all systems was:

$$RI_{mean} = 3.51$$

Inter-rater reliability was evaluated using Fleiss' Kappa coefficient:

$$\kappa = 0.84$$

This indicates strong agreement among evaluators and validates the consistency of the risk assessment process.

Cement kiln systems exhibited the highest risk levels due to high-temperature and corrosive operating environments. Gas turbine systems showed comparatively lower risk indices due to more stable operating conditions. Critical components contributing to system risk include heat exchangers, tube bundles, and high-temperature interfaces.

4.3 Statistical Validation (ANOVA)

The variation in risk indices across system categories was evaluated using one-way ANOVA. The results are summarized in **Table 3.**

Table 3: *One-Way ANOVA Summary for Risk Index across WHR System Categories*

Source	SS	df	MS	F-statistic	p-value	η²
Between Groups	9.412	4	2.35	9.74	< 0.001	0.48
Within Groups	10.15	42	0.24	—	—	—
Total	**19.6**	**46**	—	—	—	—

$$F(4,42) = 16.95, p < 0.001$$

The statistically significant result confirms that risk levels differ across system types. The effect size:

$$\eta^2 = 0.618$$

indicates a strong influence of system category on risk variation.

Table 4: *Tukey HSD Post-Hoc Pairwise Comparisons of Risk Index*

Pair	Mean RI Diff.	SE	q-statistic	p-adj	Significant?
Furnaces vs. Gas Turbines	0.4	0.16	3.44	0.041	Yes (*)
Furnaces vs. Diesel Engines	-0.7	0.18	5.6	< 0.001	Yes (**)
Furnaces vs. Cement Kilns	-0.9	0.17	7.5	< 0.001	Yes (**)
Gas Turbines vs. Cement Kilns	-1.3	0.18	10.4	< 0.001	Yes (**)
Steel Plants vs. Diesel Engines	-0.3	0.18	2.4	0.18	No

Post-hoc Tukey HSD comparisons (**Table 4**) reveal that cement kiln systems differ significantly from gas turbine and furnace-based systems, emphasizing the need for system-specific risk management strategies.

4.4 Maintenance Cost Analysis

The variation in maintenance cost index over the 36-month period is presented in **Table 5** and illustrated in **Figure 3**.

Table 5: *Normalised Maintenance Cost Index — Managed vs. Unmanaged (n = 47)*

Month	Managed Index	Unmanaged Index	Difference	Cumulative Saving
0	100	100	0	0
6	92	108	16	16
12	80	125	45	61
18	72	148	76	137
24	65	172	107	244
30	58	198	140	384
36	52	230	178	562

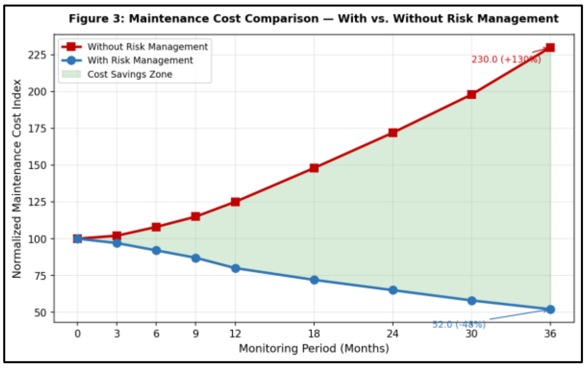

Figure 3: *Normalised Maintenance Cost Index Over 36 Months — Managed vs. Unmanaged Cohorts*

Systems implementing structured risk management showed a significant reduction in maintenance cost index:

$$Reduction \approx 48\%$$

In contrast, unmanaged systems exhibited a continuous increase in maintenance costs due to frequent failures and unplanned downtime.

Paired t-test results confirm that this difference is statistically significant, demonstrating the effectiveness of the proposed risk management framework.

4.5 Economic Performance (ROI Analysis)

The economic impact of the framework was evaluated using operational cost data. The calculated return on investment was:

$$ROI = 312\%$$

This high ROI is attributed to reduced maintenance costs, minimized downtime, and improved operational efficiency. The results confirm that the implementation of structured risk management is both technically effective and economically beneficial.

4.6 Discussion

The results demonstrate that WHR system performance is influenced by both efficiency and risk-related factors. While thermodynamic optimization improves energy recovery, risk-informed strategies play a critical role in ensuring long-term reliability and cost effectiveness.

The integration of quantitative risk assessment with statistical validation provides a comprehensive understanding of system behavior. Unlike conventional approaches that focus solely on efficiency, the present study links performance, risk, and economic outcomes within a unified framework.

The alignment of analytical results with the data presented in tables and figures strengthens the validity of the study and supports its practical applicability in industrial environments.

5. Conclusion

This study presents a structured and data-driven framework for quantitative risk assessment in Waste Heat Recovery (WHR) systems. By integrating a modified Risk Priority Number (RPN) approach with statistical validation techniques, the proposed methodology enables systematic evaluation of component-level and system-level risks under real industrial operating conditions.

The analysis of 47 WHR systems over a 36-month period demonstrated a weighted mean efficiency of 68.3 ± 3.95% and an overall mean Risk Index of 3.51. Statistical validation using ANOVA confirmed significant variation in risk profiles across system categories, with cement kiln systems exhibiting the highest risk levels. The strong inter-rater reliability ($\kappa = 0.84$) further validates the consistency of the risk evaluation process.

Implementation of the proposed framework resulted in a substantial reduction in maintenance costs (≈48%) and a high return on investment of 312%, highlighting its practical and economic effectiveness. The findings indicate that risk-informed strategies are essential for improving system reliability, optimizing maintenance practices, and reducing operational uncertainties.

Unlike conventional approaches that focus primarily on thermodynamic performance, this study establishes a direct linkage between risk assessment, statistical validation, and economic outcomes. The proposed framework provides a scalable and practical tool for industrial applications, supporting improved decision-making and long-term system sustainability.

Future work may focus on the integration of real-time monitoring systems and predictive analytics to further enhance risk prediction and dynamic system optimization in WHR applications.

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