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Artificial Intelligence (AI) Based Predictive Maintenance of Waste Heat Recovery System

Sundar Raj Thangavelu[a], Alessio Tafone[b], Imantha Gunasekhara[c], Sivanand Somasundaram[d], Morita Shignore[e]

[a] Nanyang Technological University, Singapore, sundar.rt@ntu.edu.sg CA
[b] Nanyang Technological University, Singapore, alessio.tafone@ntu.edu.sg
[c] Nanyang Technological University, Singapore, Imantha.gunasekhara@ntu.edu.sg
[d] Nanyang Technological University, Singapore, sivanand.s@ntu.edu.sg
[e] Surbana Jurong Consultants Pte Ltd, Singapore, shigenori.morita@surbanajurong.com

Abstract:

Decarbonization and sustainability urge the deployment and utilization of distributed energy systems for high-efficiency gains. The dispatchable devices (gas turbines or diesel engines) are integrated with a waste-to-energy system to harness the energy lost or waste heat and support heat and cold loads. This paper investigates the characteristics of a waste heat recovery system and its performance degradation mechanism to assess its maintenance necessity and optimize maintenance frequency and the associated maintenance and downtime costs. The effectiveness of the waste heat recovery system (WHRS) is regularly estimated using the measured inlet and outlet parameters (flow and temperature) to identify the need for maintenance. The effectiveness changes not only with degradation but also with inlet conditions that deviate from the design conditions. Therefore, the operators are instructed to operate this system at the rated inputs and gauge its actual effectiveness. However, this approach did not provide much information on the root-cause parameters, i.e., the fouling formation and thickness in the shell and tube sides, which are quite important to decide the type of maintenance and the associated cost and duration. This paper studies the performance characteristics of the waste heat recovery system with reference to all critical and influential parameters (i.e., fouling thickness, heat transfer coefficients, and off-design inlet conditions) using a rigorous physics-based model. An AI model was developed using the derived performance characteristics to predict the fouling thickness estimation. The developed prediction model is able to accurately estimate the fouling thickness on the gas and water sides, and the error or deviation is within ±0.3 mm. By deploying this prediction model, the critical parameters can be monitored in real-time, and the performance degradation trajectory paves the way to understand degradation status and estimate the right maintenance time frame to schedule maintenance proactively, considering the maintenance cost and downtime effects.

Keywords:

Waste Heat Recovery; Performance degradation; Fouling Prediction Model; Predictive Maintenance; Sustainability.

1. Introduction

Wide deployments of renewables and distributed energy systems show promising efficiency gains toward decarbonization and sustainability goals. The local power generation reduces transmission and distribution losses, paves the way to harness the waste heat from the dispatchable turbines (gas or diesel) to support thermal loads at a competitive price, and greatly increases the overall energy efficiency ([1], [2]). Unlike turbines and chillers, the waste-heat recovery system, i.e., an apparatus of heat exchangers, is not standard equipment; it is usually passive and primarily designed based on specific process requirements. Over time, the heat exchanger faces fouling issues due to the continuous deposition of impurities or particles on the heat transfer area, which affects efficiency [3]. Most heat exchangers undergo corrective maintenance on a need-based basis or preventive maintenance at periodic intervals. The corrective approach causes equipment downtime and high maintenance costs; preventive maintenance, which proactively entails regular maintenance, does not account for the actual condition of the system and the maintenance needs accurately. This paper focuses on developing a fouling prediction model for waste heat recovery systems (specifically exhaust gas-driven WHRS) to support predictive maintenance planning and reduce maintenance costs and downtime.

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1.1 Background – Fouling & Maintenance of Heat Recovery System

Numerous studies have discussed various maintenance methods and their evolution in diverse processes [4]. Corrective or reactive maintenance is a primitive method popularly called "run-to-failure," usually conducted after the system fails, whereas preventive maintenance performs routine periodic inspections to trigger necessary replacement well in advance to avoid any failure. Unlike reactive and preventive maintenance, the predictive approach is more tied to system performance, and it requires concrete measurement to quantify the root cause and key indicators and initiate a suitable maintenance plan. In energy systems, especially in a WHR system, fouling (carbon deposit on the gas side, salt deposit on the water side) occurs gradually over time and affects the heat recovery performance and degrades the system efficiency. The underlying root cause of fouling is the impurities in the inlet streams and their affinity for the heat exchanger surface. Unfortunately, the fouling cannot be measured directly in real-time; some of the available handheld devices support offline measurement that requires perforating the equipment ([5], [6]). Notable studies investigated different heat exchangers and their fouling characteristics. Most of the studies utilized data from experiments and exploited analytical and thermodynamic models. Riverol et al. [7] used a neural network to estimate fouling in a plate heat exchanger for the pasteurization application. The simple neural network (two inputs and one output) developed reads and processes data to detect critical operation conditions and advise on the necessity of cleaning (maintenance). The fouling in heat exchangers and the effect of various factors such as velocity, temperature, concentration, and pH influencing the fouling growth [8]. This study highlighted the variation in fouling thickness over the pipe length. Other possible root causes of fouling are particulates, biological reactions, chemical reactions, corrosion, and decomposition. The NN and RSM models were developed using one-year experimental data to predict the fouling resistance of the crossflow heat exchanger system in a phosphoric acid concentration plant [9]. Elwerfalli et al. [10] estimated the probability of failure in the heat exchangers using risk-based inspection, a ranking matrix, and the associated rectification cost. This approach helps to identify high fouling and plan the shutdown maintenance activity. A few studies investigated the suitability of various machine-learning algorithms for predicting fouling resistance in plate heat exchangers [11]. Interestingly, the focus was mainly on predicting the combined resistance but not the individual resistance and its root cause parameters. Deep learning techniques [12] were adapted to predict the resistance on the gas and water sides as well as the combined resistance with reasonable accuracy. This study considered all critical measurements in the NN model, including flow at fouled conditions, but did not provide much information on translating the derived resistance into maintenance decisions.

Most of the above studies focused on improving the accuracy of the prediction model by using rigorous and sophisticated machine learning and artificial intelligence algorithms using limited real-time data or adequate data from analytical and thermodynamic models. In the majority of processes, upstream processes supply the inlet gas and water; in such cases, fouling mainly imposes an additional pressure drop when the inlet and outlet flow remain the same. This paper aims to study the influence of each measurement (feature) on the prediction results and discover the crucial measurements that can provide acceptable accuracy. Identifying the key inputs prevents needless sensor and instrumentation costs and mainly reduces the complexity of the prediction model to apply in real-world applications. By deploying the prediction model in the process monitoring system, it helps the operator identify the fouling thickness and growth phenomenon regularly. The continuous prediction and monitoring of fouling thickness helps identify the fouling growth rate and type (linear, falling, asymptotic, or saw tooth) [13] that depends on the inlet streams, such as velocity, impurities, and affinities towards the heat exchange surface [14]. By projecting the fouling trend at every time period (monthly or quarterly), the operator can estimate the fouling status for the next time period and decide the need for maintenance activity by comparing it with the tolerance level. Identifying the right time well in advance allows the operator to plan the maintenance activity efficiently, i.e., devise the right maintenance schedule or frequency (washing, purging, antifouling agents, etc.), conduct a cost analysis covering maintenance cost, performance gain cost, and downtime cost, and accordingly trigger the necessary redundancy and alternative operation choices to reduce the production loss.

2. Methodology

2.1 Predictive maintenance concept

The concept of the proposed preventive maintenance methodology for the waste heat recovery system (WHRS) is illustrated in Figure 1. The actual operational data for the duration of a year is the prerequisite for this methodology to model the system's performance and study the effect of scaling parameters. The expected outcome is a maintenance schedule recommendation considering all critical factors such as maintenance cost, downtime effects, and energy efficiency gains. Generally, the actual operation data can be extracted from the process energy management system (EMS). Data pre-processing is required to remove measurement noise and outliers and mainly extract the required steady-state values from the time-series operation data [15]. In WHRS, the flow, pressure, and temperature of the exhaust gas and water are the critical variables that can be easily measured using appropriate sensors at the inlet and outlet streams. The challenge is measuring the fouling thickness on the interior and exterior of the tubes. Real-time measurement is not possible to measure fouling readily; some of the available hand-held devices require dismantling the system, which is expensive, and regular measurement is not possible [6]. In such cases, leveraging thermodynamic models is very relevant for the user to generate system performance at various inlet, surrounding, and fouling conditions. The minimal computational resources, fast computation, and freedom from measurement noise are additional benefits. Alternatively, in cases of limited operational data, it is good to supplement additional data from thermodynamic models, mainly to account for atypical operation conditions.

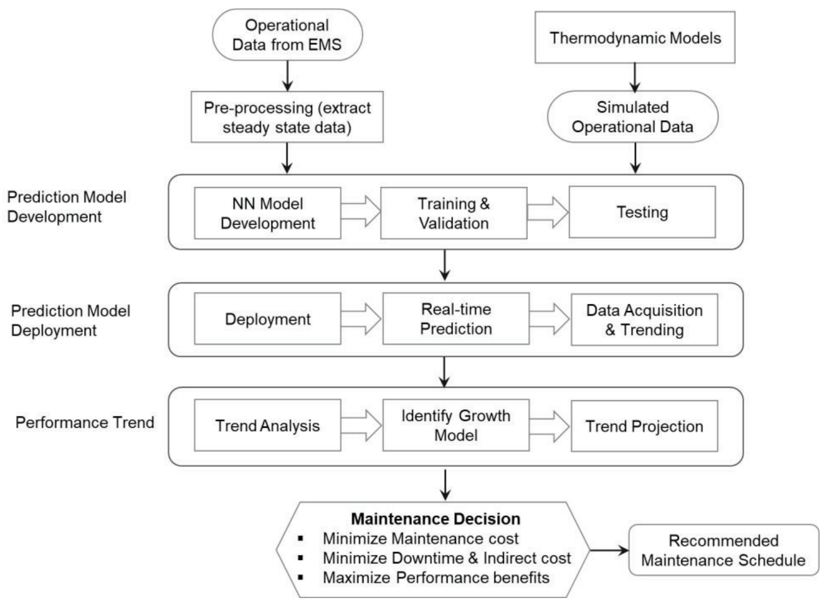

Figure. 1. Schematic of proposed preventive maintenance methodology

Numerous AI-based data-analytic algorithms are emerging to understand and capture system behavior from the data. Interestingly, in certain situations, AI-based data-analytic model development outperforms conventional physics-based models in terms of development time, resources, and prediction accuracy, especially for complex multi-variate systems. However, a data-analytic model requires substantial data for model training, validation, and testing, and the representative data should cover wide ranges to capture the system behavior comprehensively [16].

Deploy the developed data-analytic model in the process EMS and estimate the essential variables using the measurements available in real-time. Of course, the estimated variable may show some variations due to measurement noises, system dynamic behavior, and different inlet conditions. The key takeaway is the trend of the estimated variable on a long run (i.e., on a weekly, monthly, or even quarterly basis) to understand the scaling growth or build-up and performance deterioration trends. Incorporating or configuring a few processing techniques in EMS helps to remove the noise and outliers in the trend so that the system operator can identify the trend and extrapolate for future timeframes of interest. This projection will give an indication of the time when the system performance could fall below the acceptable tolerance and enable the operator to decide the maintenance schedule accordingly. Mainly, this insight or alert comes well in advance so that the operator has adequate time and operation flexibility to plan the maintenance schedule optimally by considering key factors such as system performance, expected downtime, downtime implications, maintenance cost, and benefits.

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2.2 WHRS Performance

Figure 2 illustrates a cross-section and elevation view of a tube surface and pinpoints the type of fouling formation on the inner and outer surfaces of the tubes. The exhaust gas flows inside the tube, and water flows outside the tube (i.e., in the shell). Various thermodynamic models, such as the e-NTU method and physics-based ODE and PDE approaches, can estimate heat exchanger performance in diverse inlet scenarios. The e-NTU method [17] is widely employed to estimate the outlet conditions (T_{go} and T_{wo}) of the WHRS for the given inlet conditions (M_g, T_{gi}, M_w, T_{wi}), system (U_{ref}, A), and fouling parameters (t_{shell}, t_{tubes}). The e-NTU model, the pressure drops, and the performance of WHRS are described in Eq. 1 – 11, these equations can be either solved simultaneously using the EES or sequentially and iteratively using MATLAB or Python. The Cp_g and Cp_w represent the heat capacities of exhaust gas and water at their arithmetic mean temperatures. The U_{ref} and U_{calc} refer to the overall heat transfer coefficient of clean and fouled WHSR. The U_{ref} and A are taken from the specification sheet of the pilot plant facility. To simplify and balance the complexity of the thermodynamic model, a few key assumptions were incorporated, such as (i) uniform scaling along the tube length, (ii) fouling causes additional heat resistance and the effect on the heat transfer area is insignificant, and (iii) negligible heat losses to the surrounding area due to perfect insulation on the shell side.

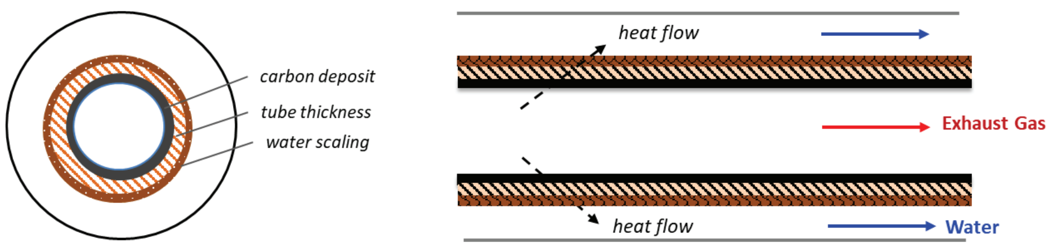

Figure. 2. Cross-section and elevation view of heat exchanger section

$$Q_g = Q_w = Q_{LMTD} \tag{1}$$

$$Q_g = M_g Cp_g\left(T_{gi} - T_{go}\right) \tag{2}$$

$$Q_w = M_w Cp_w(T_{wi} - T_{wo}) \tag{3}$$

$$Q_{LMTD} = U_{calc} A \Delta T_{LMTD} \tag{4}$$

$$Cp_g = \frac{1}{2}\left(Cp_{g,@T_{gi}} + Cp_{g,@T_{go}}\right) \tag{5}$$

$$Cp_w = \frac{1}{2}\left(Cp_{w,@T_{wi}} + Cp_{w,@T_{wo}}\right) \tag{6}$$

$$\Delta T_{LMTD} = \frac{(\Delta T_1 - \Delta T_2)}{ln\left(\frac{\Delta T_1}{\Delta T_2}\right)}, \quad \Delta T_1 = T_{gi} - T_{wi},\ \Delta T_2 = T_{go} - T_{wo} \tag{7}$$

$$\frac{1}{U_{calc}} = \frac{1}{U_{ref}} + \frac{R_{f,g}}{A_i} + \frac{ln\left({}^{D_o}/{}_{D_i}\right)}{2\pi kL} + \frac{R_{f,w}}{A_o} \tag{8}$$

$$P_{go} = P_{gi} - \Delta P_{tubes,foul} \rightarrow \frac{\Delta P_{tubes,foul}}{\Delta P_{tubes,clean}} = \frac{f_f}{f_c}\left(\frac{d_{tubes,clean}}{d_{tubes,foul}}\right)^2 \tag{9}$$

$$P_{wo} = P_{wi} - \Delta P_{shell,foul} \rightarrow \frac{\Delta P_{shell,foul}}{\Delta P_{shell,clean}} = \frac{f_f}{f_c}\left(\frac{d_{eff\_shell,clean}}{d_{eff\_shell,foul}}\right)^2 \tag{10}$$

$$\eta = \frac{Q_{act}}{Q_{opt}} \times 100\% = \frac{Q_{act}}{UA(\overline{T_g} - \overline{T_w})} \times 100\% \qquad \overline{T_g} = \frac{1}{2}\left(T_{gi} + T_{go}\right),\ \overline{T_w} = \frac{1}{2}\left(T_{wi} + T_{wo}\right) \tag{11}$$

Equation 9 and 10 estimate the pressure drop of the gas and water streams (adapted from Kakac et al. [3]). The efficiency of the heat exchanger is the ratio of the actual and optimal heat transfer rates expected in the heat exchanger. The optimal (maximum) heat transfer rate is the product of the UA of the heat exchanger and the arithmetic mean temperature difference (AMTD) of the inlet and outlet streams [18]. Deploying the e-NTU model in the process EMS to estimate the fouling thickness in real-time is challenging because the e-NTU model requires accurate measurement of all critical measurements and computation resources. On the other hand, the AI model can be easily deployed in EMS and is capable of estimating the fouling thickness in real time with minimal computation effort without facing any convergence issues.

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2.3 Fouling Prediction Model

The AI-NN architecture (as shown in Figure 3) comprises seven inputs and two outputs used for fouling prediction on the inner (gas fouling) and outer (water fouling) surfaces of the tubes. The inputs (features) are gas flow, gas inlet and outlet temperature, water inlet and outlet temperature, and the pressure drop on the gas and water streams. The water flow remained at its designed condition. The operational data is the requirement for the prediction model development, and the data should cover the board operation range, i.e., all possible operation scenarios such as design and off-design conditions.

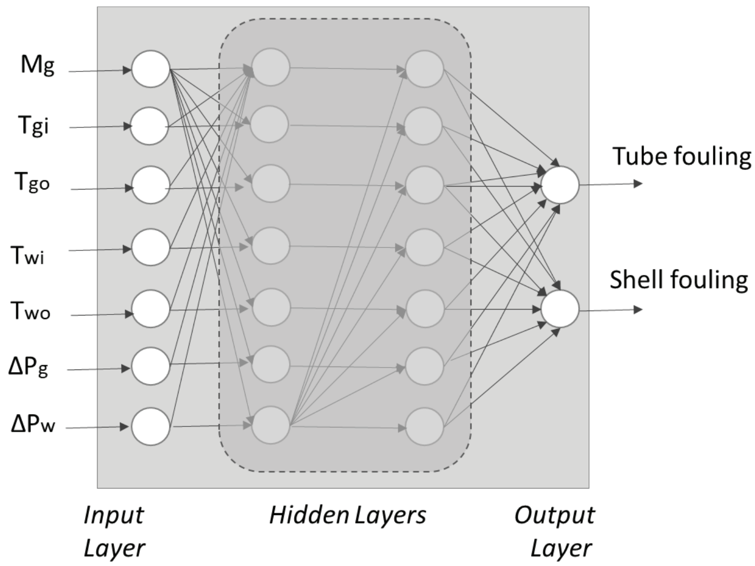

Figure. 3. Schematic of Neural Network architecture used for the fouling prediction.

The number of hidden layers and epochs are the tuneable parameters to balance the model complexity and achieve the desired prediction accuracy. In addition to the fouling prediction, this study aims to understand the importance of inputs (features) and their effects on prediction accuracy. By comprehending the importance of the inputs, they can be categorized as primary and secondary; eventually, the secondary inputs can be either eliminated or wisely chosen to simplify the prediction model and the associated data and instrument requirements without losing the accuracy of fouling prediction. The workability of the proposed methodology will be discussed in the following section using a case study problem.

3. Case Study – Combined Heat & Power (CHP) System

The proposed preventive maintenance methodology is applied in a pilot plant facility at NTU's Experimental Power Grid Centre (EPCG), Singapore. EPGC has a unique test facility, rated above 1 MW of distributed energy resources that allows test-bedding and research, development, and demonstration (RD & D) of a variety of energy technologies. Figure 4 shows the schematic of the integrated electrical and thermal grid facility at EPGC [19]. The generators serve the electrical load, and the exhaust gas from the generators powers the thermal grid to harness waste heat and convert it into useful energy. The thermal grid comprises critical systems such as a WHRS, an adsorption chiller, and thermal storage responsible for recovering waste energy and generating useful forms of thermal energy. The WHRS recovers heat in the form of steam or hot water, depending on the heat potential of the exhaust gas and the type of thermal load. Figure 5 shows a shell and tube heat exchanger as WHRS based on the generator size and the thermal and chemical properties of exhaust gas. The designed WHRS recovers 55%–80% of heat from the exhaust gas, whereas the rest is rejected to the atmosphere, considering the thermodynamic and design limits. The real benefits occur when the heating loads are located near the WHRS; otherwise, the pumping cost needs to be considered. When the generated steam or hot water is higher than the heating loads, either thermal storage is a preferable option to store excess energy for later use or convert it to other forms of useful energy, such as chilled water for air conditioning purposes. This integrated system improves overall energy efficiency by recovering the waste heat from the exhaust gas and converting it into various useful forms of thermal energy [20].

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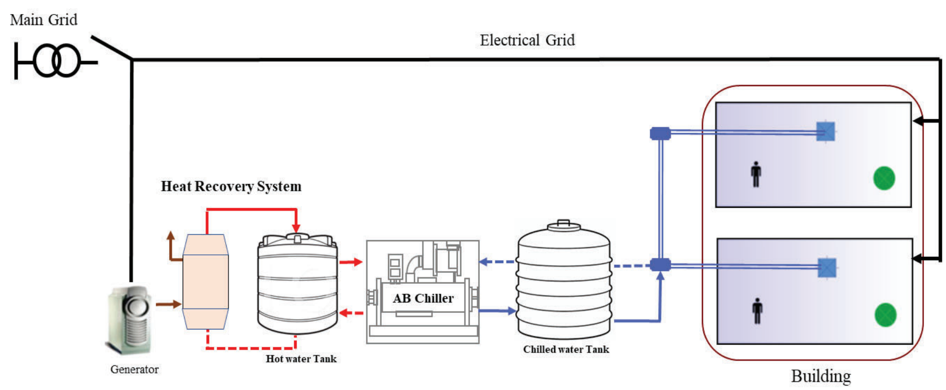
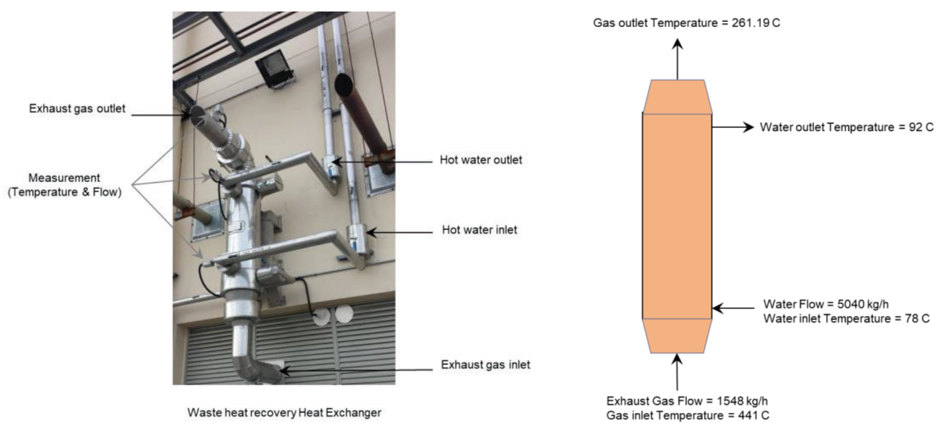


Figure. 4. Schematic of integrated electrical and thermal grids at EPGC



Actual Testbed Design Condition

Figure. 5. Waste heat recovery system: a) Actual system; b) Design conditions

Figure 5 shows the actual WHRS supporting various experiments and testing smart technologies and its design conditions (Table 1). The performance of the WHRS deteriorates over time due to fouling at the inner and outer tubes due to exhaust gas and water, respectively. The carbon and salt deposit builds up gradually, increases the thermal resistance significantly, and reduces the heat transfer between gas and water. The fouling on the interior of the tubes reduces the gas flow area, increases the pressure drop, and influences the back pressure of the generator and its performance. The fouling on the exterior of the tubes reduces the flow area of water and increases the pressure drop and pumping power. Therefore, real-time estimating of fouling is important to understand the system condition and plan maintenance optimally.

Table 1. WHRS designed inlet and outlet properties.

Parameters	Design Condition
Flue gas inlet Flow & Temperature	1548 kg/h and 441 C
Water inlet Flow & Temperature	5040 kg/h and 78 C
Flue gas inlet & outlet pressure	105 and 104.2 kPa
Water inlet & outlet pressure	1000 and 998.5 kPa
Flue-gas fouling factor	0.6 W/mK
Water scaling factor	2.941 W/mK

The actual operational data is the prerequisite for predictive maintenance methodologies. Representative operational data should capture wide operation conditions (i.e., all possible inlet and scaling cases). Unfortunately, in the actual system, the possibility of collecting broad operational data is difficult because (i) fouling occurs in the long run, (ii) all variables cannot be measured online, especially fouling thickness [6], and (iii) the actual operating range is limited, not wide-ranging. Hence, this study exploits a thermodynamic model to generate complete data under diverse operational conditions.

3.1 WHRS Performance Characteristics and Effects of Fouling

Figure 6 shows the derived outlet condition of WHRS under diverse fouling conditions derived using the e-NTU model. Both carbon deposits and water fouling reduce the heat exchange between exhaust gas and water; therefore, the outlet temperature of exhaust gas increases and the outlet temperature of water decreases compared to the rated outlet condition. The carbon deposit greatly influences the outlet temperature more than water scaling because the heat flows from the gas to the water, and the carbon deposit has low thermal conductivity and imposes high resistance. For example, flue gas resistance is roughly five times higher than that of water. Figure 7 shows the expected performance of the heat exchanger under diverse fouling conditions.

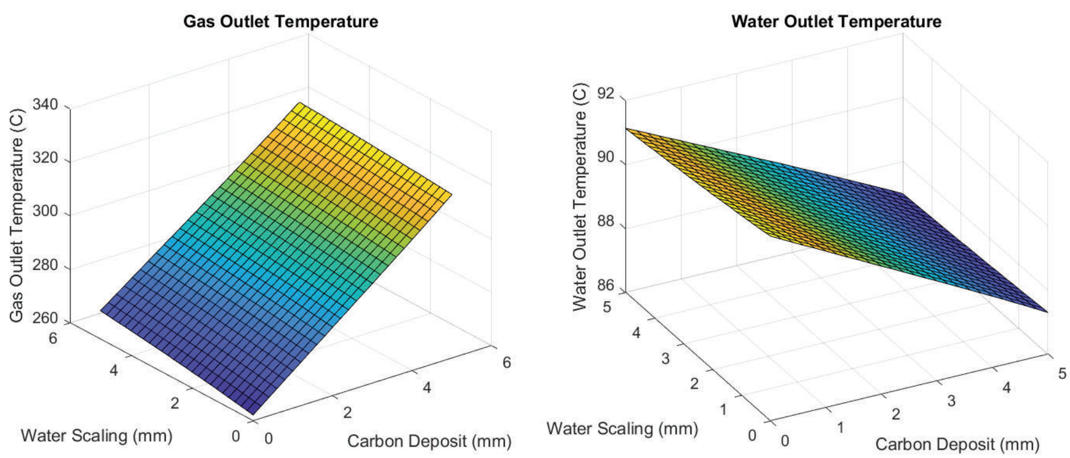


Figure. 6. WHRS performance at diverse fouling (at rated inlet conditions)

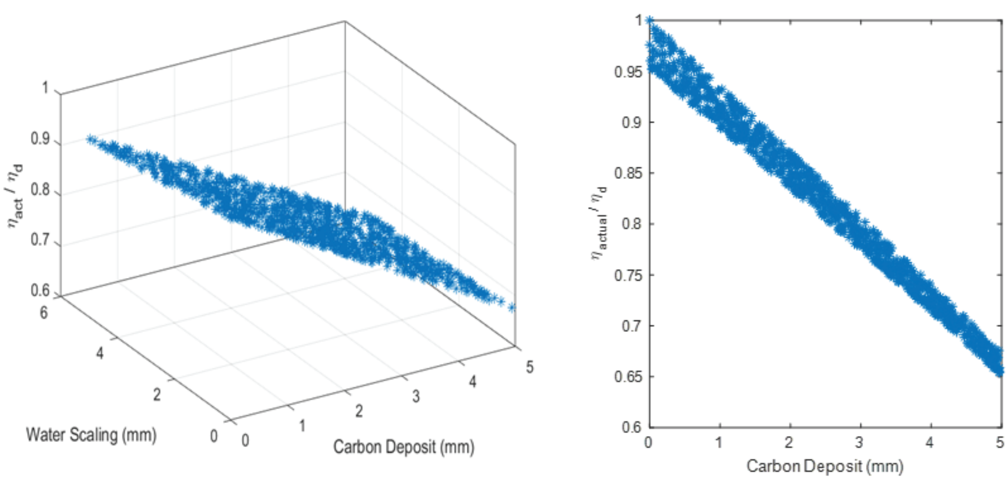


Figure. 7. Normalized performance of WHRS at different fouling (at rated inlet conditions)

In real-world operation, the inlet exhaust gas flow and temperature to the WHRS change with upstream processes such as generator loading and return water conditions. Table 2 shows the operating range

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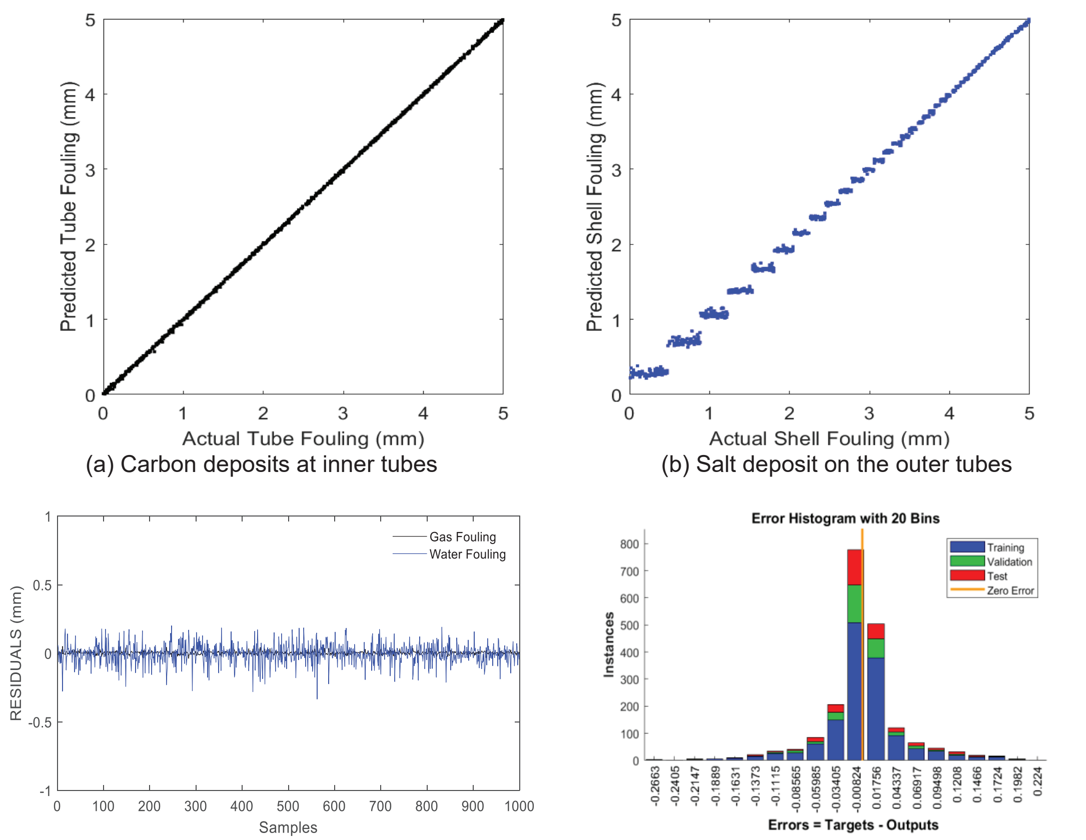
extracted from the historical data of the WHRS. Regrettably, the fouling information is not readily available; therefore, the e-NTU method was exploited to estimate the fouling thickness. The next section will discuss the development of a prediction model to support the predictive maintenance of the WHRS.

Table 2. WHRS Operation Range.

Inlet and outlet streams	Operating range
Flue gas inlet flow	60-100% of designed gas flow
Flue gas inlet temperature	441 – 492.1 C
Water inlet flow	60-100% of designed water flow
Water inlet temperature	78 – 84 C

3.2. AI-NN Fouling Prediction Model

The required performance data was generated for 1000 operational scenarios (uniformly distributed) covering design and off-design conditions, accounting for the actual operation range (as stated in Table 2), and the corresponding fouling estimated by solving the e-NTU model using the EES solver [21]. The AI-NN model with five hidden layers offers acceptable prediction accuracy (R^2 = 99.87% and MSE = 0.005). Figure 8 shows the actual and predicted fouling thickness on the inner and outer tubes (shell sides). The fouling on the inner tube is dominant due to high resistance (as mentioned in Table 1) compared to the fouling on the outer tube. Figure 8c and Figure 8d confirm the error is within an acceptable range and well below ±0.3 mm. To keep in mind, the performance data utilized is smooth; however, in the real application, the actual data may contain instrumentation errors and measurement noises that need to be pre-processed cautiously before applying to the prediction model.



(a) Carbon deposits at inner tubes (b) Salt deposit on the outer tubes

(c) Residuals (d) Error distribution - training, validation & testing

Figure. 8. (a) and (b) show the actual and predicted fouling thickness on the tube and shell side. (c) and (d) shows the residuals and prediction error of training, validation, and testing set.

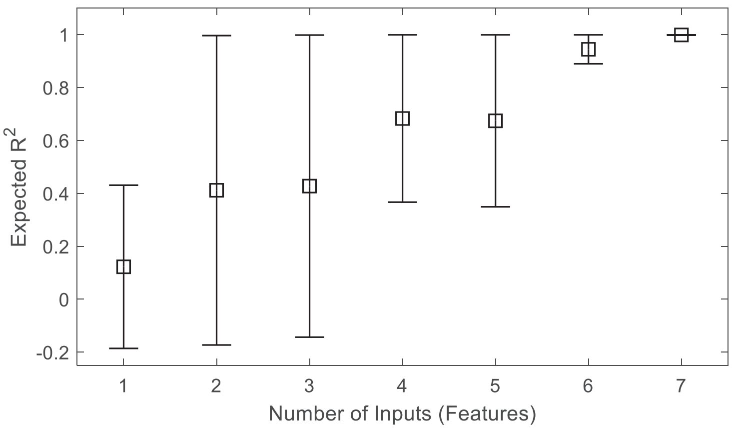


Figure. 9. Number of features and the expected prediction accuracy in regression coefficient.

Even though the above model can predict the fouling thickness accurately, it is essential to understand the importance of each feature to reduce the complexity of the prediction model and operational data requirements. Various recursive feature elimination methods such as random forest, SVM, k-nearest, and neural networks can be useful to study the importance of the features. These methods conduct model training repeatedly and eliminate the weakest feature in each iteration until the specified number of features is reached. The feature selection is purely based on the coefficients; in the case of decision tree-based models (i.e., random forest), the feature selection is based on the importance attribute. This study employed Random Forest for feature selection, which identifies the best feature to split at the next node from a subset of features based on a criterion such as mean squared error, which explains variance reduction to minimize the loss [22]. Figure 9 shows the expected prediction performance when using a different number of features. For example, using three features, the expected prediction performance ranges from 0 to 99.79%.

Table 3. Best features and the expected prediction accuracy

Features	Best Features	R^2 %	MSE $\times 10^{-3}$	$\pm\sigma$ mm
1	Tgo	43.08	-	-
2	Tgo and ΔPw	99.59	19.1	6.6
3	Tgo, ΔPw and ΔPg (or Mg)	99.79	9.3	4.1
4	Tgo, ΔPw, ΔPg and Mg	99.87	5.5	2.9
5	Tgo, ΔPw, ΔPg, Mg and Tgi	99.87	5.4	2.9
6	Tgo, ΔPw, ΔPg, Mg, Tgi and Two	99.87	5.4	2.9
7	Tgo, ΔPw, ΔPg, Mg, Tgi, Two and Twi	99.87	5.2	2.8

The best combination of input features offering high prediction accuracy is studied using a feature search algorithm using recursive learning. Table 3 shows the best features and the expected prediction performance; it shows the accuracy improves with the number of features. Especially for this application, a minimum of three features are required to get reasonable accuracy. Using the right number of features would also reduce the data requirements and model complexity. The deployment of the developed prediction model estimates the fouling thickness (on the inner and exterior of the tubes) continuously and aids monitoring and analysis. In the CHP system, fouling occurs slowly over a long period of time; therefore, a minimum of six to twelve months of data is required for complete analysis. Generally, the efficiency of WHRS is a key factor in deciding maintenance. For example, maintenance is activated when the efficiency drops below 20% compared to the design condition. By knowing the actual root cause factors, such as fouling thickness, one can decide on appropriate maintenance methods. The proposed prediction model accurately estimates the root cause factors and their severity, which allows the operator to decide on the right maintenance options and cut down on unnecessary downtime and maintenance costs. Even by knowing the root cause, one can

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cautiously redefine the tolerance level (i.e., efficiency losses) considering the dependent process system and costs.

Conclusion

This study proposed a predictive maintenance methodology for waste heat recovery systems to identify an optimal time frame accounting for efficiency loss, maintenance cost, and downtime. An AI-based fouling prediction model is a critical requirement for maintenance methodology and was developed using actual data and supplemented data obtained from the thermodynamic model. The developed model helps identify the root cause and predict the fouling thickness with acceptable accuracy. To simplify the prediction model and data requirements, the importance of each feature and its effects on prediction accuracy were examined. The exhaust gas outlet temperature, the pressure drop of the water and gas streams, and the mass flow of exhaust gas are critical inputs or features required for the AI-based prediction model. Interestingly, the pressure drop data greatly helps the fouling prediction as it inherently accounts for the flow and the effective diameter influenced by the gas and water side fouling. The rest of the features help to improve the prediction accuracy and show a marginal effect. Deploying the developed fouling prediction model in the energy management system provides a fouling trend that greatly supports a project in the future time frame to identify the key time or sweet spot for maintenance accounting, proper redundancy, and mitigation plans.

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Nomenclature

Acronyms

AI	artificial intelligence
EMS	energy management system
eNTU	effectiveness number of transfer unit method
WHRS	waste heat recovery system
A	heat transfer area, m2
Cp	specific heat, J/(kg K)
d	diameter, m
M	mass flow, kg/s
P	pressure, kPa
ΔP	pressure drop, kPa
Q	heat transfer, W
T	temperature, °C
$\overline{T}$	average temperature, °C
ΔT	temperature difference
U	overall heat transfer coefficient, W/(m^2 K)

Greek symbols

η	heat exchanger efficiency

Subscripts

act	actual heat exchange
calc	fouling condition
g	flue gas
i	inlet
LMTD	log mean temperature difference.
o	outlet
opt	optimal or maximum heat transfer
ref	reference condition
shell	within shell (exterior of tube)
tube	interior of tube
w	water

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