CORRELATING TIME-RESOLVED PRESSURE MEASUREMENTS WITH RIM SEALING EFFECTIVENESS FOR REAL-TIME TURBINE HEALTH MONITORING

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ABSTRACT

Purge flow is bled from the upstream compressor and supplied to the under-platform region to prevent hot main gas path ingress that damages vulnerable under-platform hardware components. A majority of turbine rim seal research has sought to identify methods of improving sealing technologies and understanding the physical mechanisms that drive ingress. While these studies directly support the design and analysis of advanced rim seal geometries and purge flow systems, the studies are limited in their applicability to real-time monitoring required for condition-based operation and maintenance. As operational hours increase for in-service engines, this lack of rim seal performance feedback results in progressive degradation of sealing effectiveness, thereby leading to reduced hardware life.

To address this need for rim seal performance monitoring, the present study utilizes measurements from a one-stage turbine research facility operating with true-scale engine hardware at engine-relevant conditions. Time-resolved pressure measurements collected from the rim seal region are regressed with sealing effectiveness through the use of common machine learning techniques to provide real-time feedback of sealing effectiveness. Two modelling approaches are presented that use a single sensor to predict sealing effectiveness accurately over a range of two turbine operating conditions. Results show that an initial purely data-driven model can be further improved using domain knowledge of relevant turbine operations, which yields sealing effectiveness predictions within three percent of measured values.

NOMENCLATURE

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>c</td>
<td>CO₂ concentration</td>
</tr>
<tr>
<td>f</td>
<td>frequency</td>
</tr>
<tr>
<td>ṁ</td>
<td>mass flow rate</td>
</tr>
<tr>
<td>P</td>
<td>pressure</td>
</tr>
<tr>
<td>RMSE(ε)</td>
<td>root-mean-square error of ε prediction</td>
</tr>
<tr>
<td>RPM</td>
<td>revolutions per minute</td>
</tr>
<tr>
<td>T</td>
<td>temperature</td>
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<tr>
<td>t</td>
<td>time</td>
</tr>
<tr>
<td>β</td>
<td>model coefficient</td>
</tr>
<tr>
<td>ε</td>
<td>sealing effectiveness</td>
</tr>
<tr>
<td>σ</td>
<td>standard deviation</td>
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Subscripts

- 2S: two-step modelling approach
- A: rim seal location
- D: relating to the disk rotation
- DD: data-driven modelling approach
- G: casing location
- in: inlet parameter
- max: maximum value
- meas: measured using gas concentration method
- MGP: pertaining to the main gas path
- min: minimum value
- out: outlet parameter
- P: pertaining to pressure or purge flow
- pred: predicted quantity

Superscripts and Operators

- Q*: non-dimensionalized by operating point OP1
- Q̄: globally normalized across all data
- Q̂: mean quantity
- Ń: standardized quantity

INTRODUCTION

The pursuit of highly efficient gas turbine engines demands high temperatures at the turbine inlet to improve thermodynamic efficiency. However, these high temperatures present a durability risk to the engine because the main gas path (MGP) temperature exceeds the hardware material softening temperature [1]. Internal and external cooling strategies have been developed for MGP components, but under-platform hardware components require a different strategy to maintain acceptable material temperatures. To prevent ingestion into the under-platform
region and protect turbine components, highly-engineered rim seal geometries and purge flows are typically employed.

Due to the complex fluid dynamics associated with rim seal ingestion and cavity flows, the vast majority of research into rim sealing performance has focused on understanding the flow physics with a goal to improve the design of seal geometries and purge flow injection configurations. This type of research applies to the initial design and performance characterization of rim seals, which does not cover the entire rim seal life cycle. Once a rim seal and purge flow injection design has been commissioned into an engine, there is very little research available to inform the real-time health monitoring of rim sealing performance during operation.

In their review of condition-based maintenance of gas turbines, Tahan et al. [2] identified turbine and compressor component faults as most important due to their critical influence on engine performance and their expense relative to other engine components. This statement highlights the importance of monitoring rim seal performance because poor sealing effectiveness results in damage to both rotating and stationary turbine components. Tahan et al. also classified cooling and sealing faults as an auxiliary subsystem fault, which is most readily identified using non-performance based identification methods. This type of identification is distinct from gas path analysis [3], which monitors engine performance metrics like efficiency and power.

Based on these assessments, a fault identification methodology specifically tailored to rim seal performance is necessary prevent costly engine failures. This unique study addresses this need by presenting two data-driven modelling approaches that use a single pressure sensor to predict the sealing effectiveness in real-time.

The remaining structure of the paper will be laid out as follows. First, literature relevant to the quantification of rim sealing effectiveness in an engine environment will be reviewed, followed by a description of the experimental methods that were employed. Then, a brief explanation of the unsteady rim flow characteristics will be given to setup the discussion of the two modelling approaches. Each modelling approach will be explained in detail, followed by a discussion of the practical considerations necessary for the implementation of the models in a realistic engine application. Finally, the results and conclusions will be discussed.

LITERATURE REVIEW

The majority of rim seal studies have focused on developing a physical understanding of the mechanisms that drive ingestion. In a comprehensive review, Johnson et al. [4] summarized the physical mechanisms of rim seal ingestion: disk pumping, vane and blade pressure field interaction, 3-D rim seal geometry, rim seal geometry asymmetries, turbulent transport, and flow entrainment. More recently, Scobie et al. [5] further summarized the driving factors for ingestion as either externally-induced (EI), rotationally-induced (RI), or combined ingress (CI), which is a combination of EI and RI ingress.

This physical understanding of rim seal ingestion mechanisms has largely relied on the measurement of sealing effectiveness for a variety of experimental setups and flow conditions. The most widely-utilized method for quantifying sealing effectiveness is the gas concentration method [6–8], which uses a tracer gas, typically CO₂, to differentiate purge flow and MGP flow that has entered the under-platform region. Using this approach, the sealing effectiveness is measured at multiple purge flow rates to quantify the relationship between the two parameters. Using experimental results and an understanding of rim seal ingestion mechanisms, researchers have created physics-based models to define a functional relationship between the sealing effectiveness and the purge flow rate [9–11]. Because these physics-based models require only a few inputs to model the sealing performance, they can potentially be applied to the real-time monitoring of sealing effectiveness.

Of course, the application of temperature measurements on the under-platform hardware would be the most direct method for quantifying ingestion. This is feasible when ingestion occurs along the stationary side of the rim seal hardware, as shown by Scobie et al. [5]. However, multiple researchers have also shown ingestion can occur along the rotating side of the rim seal [12–15]. Such a flow scenario could cause a stator-side temperature sensor to measure hardware temperature driven by egressing cooler flow rather than ingested hot main gas path flow. This scenario obfuscates the relationship between stator hardware temperature and sealing effectiveness, which diminishes the robustness of using a temperature sensor to quantify ingestion in a realistic engine environment.

Many researchers have presented orifice models to derive a mathematical relationship between sealing flow rate and ingestion [16–19]. Owen recently presented a model which simplified the rim seal to an orifice ring with separate ports for ingress and egress, and derived a set of equations commonly referred to as the “orifice equations”. These equations were defined for RI [9] ingress, as well as EI and CI types of ingress [10]. Based upon these equations, Sangan et al. derived the “effectiveness equations” [8,20]. Critically, these equations have two unknowns, the ratio of discharge coefficients and the minimum non-dimensional sealing parameter, that must be determined experimentally.

Using these equations, Owen et al. [21] developed a method to relate engine pressure measurements to the sealing effectiveness. The instrumentation requirements for this method are relatively simple, although implementation requires some key assumptions and extensive simulation and experimental work.

Specifically, a seal design must be tested in an experimental facility to determine the ratio of discharge coefficients and gather pressure measurements in the annulus and wheel-space regions. This ratio of discharge coefficients is assumed to be constant between rig and engine conditions. Then, unsteady CFD must be performed to determine the precise axial and circumferential locations (referred to as the “sweet spot”) at which pressure measurements should be gathered in the engine. The orifice equations relate the pressure measurements at this location and the experimentally-determined ratio of discharge coefficients to
the sealing effectiveness in the engine. To compute the sealing flow rate, the pressure measurements from the rig must be corrected to the sweet spot location to determine the discharge coefficient for egress. A further correction must be applied to the pressure coefficient to account for the Mach number ratio between the experimental facility and the engine [22]. Together, these experimental, computational, and analytical efforts enable calculation of the sealing effectiveness.

Scobie et al. [5] showed good agreement between the orifice model and experimental data gathered from a variety of test turbines with differing rim seal geometries, operating environments, and driving ingestion mechanisms. However, these experimental data ubiquitously show a smoothly increasing trend that does not exhibit regions of inflection. While this relationship between sealing effectiveness and purge flow rate is observed in many scenarios, there are also many studies which have shown significant inflection regions [14,23–29]. For this reason, the orifice model lacks wide-spread applicability to all turbine geometries.

Overall, creating a generalized physics-based model that captures the inflection region is not currently feasible because the flow physics that drive the inflection are not well understood. To address this issue, the present study utilizes a data-driven modelling approach to relate time-resolved pressure data to the sealing effectiveness measured in an experimental facility. Results shows that this modelling approach is viable, even in the presence of a sealing effectiveness curve inflection. Additionally, the data-driven modelling approach is relatively simple in its implementation because it does not require computational flow simulation. These characteristics highlight the opportunity for a data-driven model to be applied as a preferred method for real-time rim seal performance monitoring of in-service engines.

**EXPERIMENTAL SETUP AND TESTING PROCEDURE**

This study was performed at the Steady Thermal Aero Research Turbine (START) facility at Penn State University [30,31]. The facility layout is shown in Figure 1 with major components and instrumentation highlighted in blue. The arrows show the flow paths and qualitative fluid temperatures throughout the facility.

The START facility operates in a continuous-duration mode to emulate the steady operation of a gas turbine engine. The flow path is open-loop and begins with two industrial compressors that intake ambient air with a maximum flow capability of 11.4 kg/s (25 lbm/s) at 480 kPa (70 psia). This process raises the fluid temperature to approximately 380K (230°F) at the compressor exit, depending on ambient temperature conditions. Next, the compressor exit flow is split between two distinct flow paths. The majority of the flow proceeds through an in-line natural gas heater chamber that provides the high temperature MGP flow. The maximum capability of the heater is 675K (750°F) at nominal flow rate conditions. The remainder of the compressor exit flow is diverted through a heat exchanger to lower its temperature to about 273K (32°F). This fluid stream is further separated into multiple independently-metered coolant flows which are distributed throughout the turbine.

These MGP and coolant flows ultimately reconvene in the test section, which consists of a one-stage axial turbine comprising hardware relevant to the current state-of-the-art for turbine design. A cross-section view of the test article showing qualitatively-equivalent geometry representative of the actual START test section hardware is shown in Figure 2.

The purge flow pressure and temperature were measured beneath the vane, just prior to the purge flow injection to the rim seal and under-platform regions. Although the START facility is capable of supplying the test section with multiple coolant streams, the purge flow was the sole coolant stream flowing in this experiment. The MGP and purge flow rates were measured individually upstream of the test section using Venturi flow meters. In total, nine purge flow conditions were used for this study, and the purge flow rate ($\dot{m}_p$) was normalized by the maximum purge flow rate required to fully seal the rim cavity at sensor $P_A (\dot{m}_{p,\text{min,A}})$.

This experiment leveraged an additively manufactured vane with design features and internal wire routing passages to
accommodate fast-response piezoresistive pressure transducer installations. These fast-response sensors are labelled \( P_A \) and \( P_G \) in Figure 2. Signals were sampled at a non-dimensional frequency of \( f_0/f_0 \approx 600 \), where \( f_0 \) represents the disk rotational frequency, with analog low-pass filtering to prevent aliasing. The non-dimensional resonant frequency of the sensors is represented by at least \( f/f_0 \approx 120 \), which provides a usable bandwidth that far exceeds the range of interest for this study. The calibration of the sensors is given by Siroka et al. [32].

Measurements from these sensors were collected over 500 revolutions at nine purge flow rates, with nine data sets collected at each purge flow rate to facilitate model training and testing procedures. Although not shown here, a separate analysis showed 100 revolutions was a critical value below which model accuracy decreased substantially. Between 100 and 500 revolutions, there were slight improvements to model performance with increased revolution count, but it is assumed that including additional data beyond 500 revolutions would offer negligible benefits to the predictive model accuracy.

The gas concentration based sealing effectiveness was used in this study to quantify the rim sealing performance. The sealing effectiveness is calculated according to Equation (1),

\[
\varepsilon = \frac{c_A - c_{MGP}}{c_r - c_{MGP}}
\]

which relates \( CO_2 \) concentration measurements to the sealing effectiveness. The concentration sampling locations are labelled in Figure 2. The uncertainties of these pressure, temperature, mass flow rate, speed, and sealing effectiveness measurements are shown in Table 1. Prime notation indicates a value that is non-dimensionalized by the nominal operating condition (OP1). These uncertainties were computed according to the procedure outlined by Figliola and Beasley [33].

### Table 1: Measurement Uncertainties

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Total Uncertainty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main gas path flow rate, ( (\dot{m}_{MGP})' )</td>
<td>( \pm 0.007 )</td>
</tr>
<tr>
<td>Shaft rotational speed, RPM'</td>
<td>( \pm 0.001 )</td>
</tr>
<tr>
<td>Inlet pressure, ( P_m' )</td>
<td>( \pm 0.002 )</td>
</tr>
<tr>
<td>Inlet temperature, ( T_m' )</td>
<td>( \pm 0.001 )</td>
</tr>
<tr>
<td>1.0 stage pressure ratio, ( (P_m/\dot{m}_{out})' )</td>
<td>( \pm 0.01 )</td>
</tr>
<tr>
<td>Sealing effectiveness, ( \varepsilon )</td>
<td>( \pm 0.015 ) to ( \pm 0.025 )</td>
</tr>
<tr>
<td>Fast-response pressures, ( P' [32] )</td>
<td>( \pm 0.00005 )</td>
</tr>
<tr>
<td>Normalized purge flow rate, ( \dot{m}<em>{P,\min}/\dot{m}</em>{P,\min,A} )</td>
<td>( \pm 0.018 )</td>
</tr>
</tbody>
</table>

### UNSTEADY RIM FLOW CHARACTERISTICS

As the purge flow injected into the under-platform region is varied, the characteristics of the unsteady flow field change as well. Monge-Concepción et al. [34] provides a detailed investigation of the unsteady fluid mechanics in the under-platform region measured at the START facility, and Siroka et al. [32] describes how the dominant unsteady flow features affect ingestion. Because the present study relies upon modelling the relationship between the time-resolved pressure signals and the sealing effectiveness, it is important to first understand the unsteady characteristics of the rim cavity flow. These topics are briefly summarized here, and readers are directed to referenced studies for further details.

The variation of sealing effectiveness at location A with normalized purge flow rate is shown in Figure 3(a). There is an inflection in the sealing effectiveness curve that appears at approximately half the purge flow rate required to fully seal rim cavity location A.

The time-resolved pressure was measured throughout the range of purge flow rates using fast-response pressure sensors at locations A and G. A fast Fourier transform (FFT) was applied to these pressure signals to create frequency spectra from the time-domain signals. The pressure amplitude was normalized for presentation in this paper according to Equation (2),

\[
P^* = \frac{P - P_{\text{min}}}{P_{\text{max}} - P_{\text{min}}}
\]

where \( P_{\text{max}} \) and \( P_{\text{min}} \) represent the maximum and minimum pressure amplitude across all purge flow rates and sensors. The frequency domain was non-dimensionalized with respect to the disk rotating speed.

The frequency spectra from fast-response pressure sensors A and G are shown in Figure 3(b) and Figure 3(c) for the normalized purge flow rate corresponding to the maximum unsteadiness. The time-domain pressure signal was digitally filtered at a cut-off frequency of \( f_{f0} = 30 \) to remove the blade passing frequency, so none of the peaks in the frequency domain correspond to blade passing events. Figure 3(b) shows a dominant frequency at approximately five times the disk rotating frequency (\( f_{f0}=5 \)). This dominant frequency is created by rotating flow structures, as described in detail by Monge-Concepción et al. [34], and similar behaviors have been identified by a broad community of researchers using both experimental and numerical methods [11,13–15,24–27,32,34–55].

Notably, the pressure fluctuations from these rotating flow structures propagate radially outward through the MGP and are measured at the outer casing wall by pressure sensor \( P_G \). The pressure fluctuations are significantly attenuated as they propagate to the casing, which decreases the pressure amplitude to about 8% of the pressure amplitude measured in the rim seal. While this attenuation is suboptimal for measuring rim seal pressure fluctuations at the casing, location G is likely a more accessible position for sensor installation than location A.

The amplitude of the dominant frequency at location A is shown as a function of purge flow rate alongside the sealing effectiveness curve in Figure 4. As the purge flow rate increases towards a normalized value of about 0.55, the strength of the rotating flow structures (indicated by the amplitude of the dominant frequency component) also increases. As the flow structures associated with the identified frequency content form and strengthen, they drive additional ingestion, which subsequently creates the inflection in the sealing effectiveness
measurements [32]. For normalized purge flow rates greater than 0.55, the flow structures begin to weaken and dissipate, which results in an associated increase of sealing effectiveness. The relationship presented in Figure 4 forms the foundation through which the time-resolved pressure data are related to the sealing effectiveness in this study.

Figure 3. Measured a) sealing effectiveness vs. purge flow rate at location A and frequency spectra from pressure sensors b)P_A and c)P_G. The box in a) identifies the condition corresponding to the frequency spectra in b) and c).

DATA-DRIVEN MODEL AND RESULTS
Two modelling approaches were used in this study to relate the measured time-resolved pressure to the measured sealing effectiveness. Although both approaches inherently utilize measured data to create the models, the initial modelling approach presented in this section is purely data-driven (i.e., with no knowledge of the application); as a result, it is referred to herein as the data-driven (DD) modelling approach.

The DD modelling diagram is shown in Figure 5. This diagram outlines the steps taken to relate the input (time-resolved pressure data) to the output (the predicted sealing effectiveness). In this diagram, as well as in subsequent diagrams, the training route is always completed before the testing route. A detailed description of each modelling step is given here.

Figure 4. Dominant frequency amplitude as a function of purge flow rate. The flow structures form and disappear as purge flow is increased to the fully sealed flow rate.

Data Preparation
The time-resolved pressure data were prepared for feature extraction by filtering and centering. As documented in previous studies [24,27,41,46,49], the frequency content of interest appears between the disk frequency and the blade passing frequency, so the filtering step reduces processing time by removing unnecessary information; this step could also be accomplished in the feature extraction step. It is expected that the cutoff frequency of the low-pass filter could be varied between the frequency content of interest and the blade passing frequency in pursuit of minor improvements to model accuracy or processing time.

The pressure data were also centered by subtracting the mean value. This centering ensured that only the fluctuations of the pressure about the mean were used in the model. The pressure data were centered to remove unnecessary information, but it is assumed that this process contributes negligibly to model accuracy and generality.

Feature Extraction
The goal of the feature extraction step was to isolate the information or quantities that would be most useful for modelling. In addition to adequately describing the pressure signal, the feature extraction also seeks to utilize a minimum
amount of signal content (features) to reduce computational time. Although an exhaustive optimization process was not included in this study, three separate feature extraction techniques were investigated for comparison.

Due to the fast-response nature of the pressure sensors used in this study and the previously identified trends with specific frequency content, spectral analysis was an effective method for generating features from the time-domain pressure signal. For this reason, the three methods of feature extraction investigated were the fast Fourier transform (FFT), short-time Fourier transform (STFT), and the discrete wavelet transform (DWT).

For the FFT extraction method, an averaging process was completed after the FFT was computed to reduce the number of features. Without averaging, the total number of features is equal to the number of frequencies output from the FFT (N), which is equal to half the number of samples in the time-series pressure signal (2N). Due to the fast-response nature of the sensors and the high sampling rate of the data acquisition hardware used in this study, the number of pressure data points is large. If these N features are used for regression, then an NxN system of linear equations must be solved. The computational complexity of solving this system of equations scales with N³, so it is advantageous to characterize the signal in as few features as possible to minimize computational requirements. For this reason, frequency bins were established with a width of \( f_0 \) and all spectral content within each bin was averaged. The first frequency bin extends between 0.5\( f_0 \) to 1.5\( f_0 \), and this pattern was continued up to 29.5\( f_0 \). This process effectively reduced the number of features from approximately 1.6×10⁵ to 29.

For the STFT extraction method, the time domain was partitioned into 35 overlapping time intervals. Following this step, the peak amplitude, which corresponds to the large-scale rotating structures (Figure 3(b)), was extracted from each time interval to form the feature set.

Like STFT, DWT is also able to capture time-domain variations in frequency content. However, DWT differs from STFT in that its time-frequency resolution varies when analyzing the signal at different frequencies, whereas the time-frequency resolution for the STFT is fixed upon selection of time and frequency windows. A thorough explanation of DWT and its application to fault diagnostics in gas turbines was given by Aretakis and Mathioudakis [56]. To motivate the investigation of DWT and aid in the comparison between DWT and the two Fourier transform methods, a short explanation of DWT is given here.

For a signal of length 2N, a full wavelet decomposition breaks the signal into J sets of detail coefficients, where \( J = \log_2(2N) \), and one set of approximation coefficients. Each set of detail coefficients corresponds to a specific range of frequencies, whereas the approximate coefficients represent the signal average. The DWT provides high frequency resolution and low time resolution at low frequencies and low frequency resolution and high time resolution at high frequencies. This characteristic of DWT is unique from STFT, which has fixed time-frequency resolution upon selection of time and frequency windows. To reduce the number of features, the sum of squares of each coefficient set was computed to represent the amount of energy in each frequency range.

After feature selection, the features from FFT, STFT, and DWT were further standardized for comparison using Equation (3),

\[
    \bar{P}^* = \frac{P^* - \bar{P}^*}{\sigma_P^*}
\]

where \( \sigma_P^* \) and \( \bar{P}^* \) are the standard deviation and mean of \( P^* \), respectively.

**Randomized Data Grouping**

After feature extraction, the data were split into training and testing groups. As the names indicate, the model was developed using the training data and subsequently implemented for performance analysis using the testing data. Two of the nine replications at each purge flow rate were isolated for testing, while the remaining seven replications were used to train the model. Because measurements were collected at nine different purge flow rates, a total of 18 sealing effectiveness predictions were generated. To quantify prediction error, the root-mean-square error (RMSE) of each set of sealing effectiveness predictions with respect to the sealing effectiveness measurements was computed using Equation (4),

\[
    \text{RMSE}(\varepsilon) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\varepsilon_{\text{pred},i} - \varepsilon_{\text{meas},i})^2}
\]

Figure 5. Data-Driven (DD) modelling diagram.
where \( n \) is equal to 18 total sealing effectiveness predictions for each data grouping iteration.

Although the data were randomly grouped, there is a potential for some data groupings to perform better or worse than others. To ensure that the grouping did not affect the interpretation of the results, the grouping, training, and testing processes were repeated 250 times. While 250 repetitions examines only a subset of all possible combinations of the data, it is assumed that 250 repetitions is sufficient to accurately capture the median \( \text{RMSE}(\epsilon) \) and \( \text{RMSE}(\epsilon) \) range. To investigate this assumption, the aforementioned quantities were examined for various grouping repetition counts. Results showed negligible sensitivity of median \( \text{RMSE}(\epsilon) \) and \( \text{RMSE}(\epsilon) \) range to additional grouping repetitions above 160, with the maximum variation in median \( \text{RMSE}(\epsilon) \) equal to \( 9 \times 10^{-4} \) and the maximum variation in \( \text{RMSE}(\epsilon) \) range equal to \( 2.7 \times 10^{-3} \). Therefore, 160 grouping repetitions is sufficient to capture the model performance. However, the full 250 grouping repetitions were used because additional repetitions did not add significantly to the model processing time.

**Feature Selection and Predictive Modelling**

After partitioning the data into training and testing groups, a subset of informative features important for predicting sealing effectiveness were selected. This process, called variable selection, is important because it separates the sparse informative features of the dataset from the non-informative features that only contribute noise. This variable selection step prevents model overfitting and improves prediction accuracy. Least Absolute Shrinkage and Selection Operator (LASSO) regression was implemented for variable selection by setting the regression coefficients of non-informative features to zero [57]. This is performed by solving the optimization problem:

\[
\min_{\beta_0, \beta} \frac{1}{2n} \sum_{i=1}^{n} (\epsilon_i - \beta_0 - x_i^T \beta)^2 + \lambda \| \beta \|_1
\]

(5)

where \( \epsilon_i \) is the \( i \)th sealing effectiveness of the training set, \( x_i \) is the \( i \)th set of predictors, \( \beta_0 \) is the intercept term, \( \beta \) is the vector of regression coefficients, and \( \lambda \) is the tuning parameter. The tuning parameter penalizes the sum of the magnitudes of the regression coefficients. Therefore, predictors that contribute noise to the model have their coefficients reduced to zero.

The tuning parameter was selected using K-fold Cross-Validation. The \( n \) observations are broken into \( K \) equally-sized groups called folds. For a given fold, the optimization problem was solved using the other \( K-1 \) folds, and the associated error in predicting the sealing effectiveness was recorded. This process was then repeated for all folds and the errors are averaged over all folds. The tuning parameter \( \lambda \) was then selected as a value that minimizes the average prediction error, and was subsequently held constant throughout the remainder of the study.

**Feature Extraction and Modelling Results**

The modelling steps shown in Figure 5 were completed for each of the three feature extraction methods (FFT, STFT, and DWT). The median and range, excluding outliers, were computed from the 250 \( \text{RMSE}(\epsilon) \) quantities for each feature extraction method. Outliers were determined using the \( 1.5 \times \text{IQR} \) (interquartile range) rule, which dictates that any predictions \( 1.5 \times \text{IQR} \) above the third quartile or below the first quartile are outliers. These results are shown in Figure 6. The bar height indicates the median \( \text{RMSE}(\epsilon) \), and the range bars indicate the range with outliers removed.

![Figure 6. Comparison of feature extraction methods based on \( \text{RMSE}(\epsilon) \). These results are shown for OP1 conditions.](image)

A few observations can be made from the results in Figure 6. First, for these data, the FFT feature extraction method is preferred because it results in the lowest \( \text{RMSE}(\epsilon) \). Furthermore, the relationship between the feature extraction methods is consistent between the two sensor locations, A and G. To further investigate these observations, the time-domain and time-frequency domain pressure signals were investigated in Figure 7 to relate the feature extraction performance results to the physical characteristics of the pressure signal.

The time-domain pressure signal, shown in Figure 7(a), is periodic and resembles a combination of sine waves. By definition, a wavelet is not a periodic function, which makes it ill-suited to describe the pressure signal with the aforementioned characteristics. Furthermore, the DWT and STFT are uniquely capable of representing signals that exhibit time-domain variations in the frequency content. This utility is not applicable to the pressure signals because they are stationary across many revolutions, as shown in Figure 7(b). This stationary behavior is expected from the steady operating mode of the START facility. For these reasons, it is logical that the FFT feature extraction method results in lower prediction errors than the STFT and DWT feature extraction methods.

Referring back to Figure 6, a general trend is observed that the \( \text{RMSE}(\epsilon) \) is higher at location G than at location A. This result was expected because sensor \( P_A \) is located in the rim seal, which allows the pressure fluctuations associated with the fluid dynamics in the rim seal region to be measured with less attenuation. However, the partial attenuation of the rim seal pressure fluctuations did not prohibit the development of a model that used sensor \( P_G \) to predict rim sealing effectiveness.
Based on the preference for FFT predictions shown in Figure 6, the relative performance of predictions from measurements at locations A and G are compared in Figure 8. Figure 8(a) shows the predicted sealing effectiveness from each sensor across a range of flow rates using both sensors, and the FFT results from Figure 6 are isolated in Figure 8(b). Specifically, Figure 8(a) shows the predictions corresponding to the median RMSE(ε), which is shown by the bar height in Figure 8(b).

![Figure 7. Pressure signal PA shown as a function of a) time and b) time and frequency. Note that the time axis in b) is presented as revolutions.](image1)

Figure 8(a) shows the ability of the model to resolve the local characteristics of the sealing effectiveness curve, and Figure 8(b) emphasizes the superior performance of sensor PA relative to sensor PG. Critically, the inflection region, located in the range 0.4<̇mP/̇mP,min,A<0.7, is captured well by both predictions from both sensor locations. However, near the purge flow extrema, the predictions are not well centered on the sealing effectiveness measurements. This characteristic is important because engines are typically designed to operate at or close to fully-sealed conditions [22]. With this range in mind, some statements can be made about the applicability of the observed prediction accuracy.

There are two primary goals for implementing a diagnostic model: fault diagnosis and health monitoring. Fault diagnosis is the less stringent of the two goals because it only requires the detection of sealing effectiveness that has dropped below some critical value. If that critical sealing effectiveness were set to the minimum of the design range, then a RMSE(ε) of about 0.05 or 0.06 (as shown in Figure 8(b)) would be sufficient to identify when the sealing effectiveness drops below the critical value. However, accuracies shown in Figure 8 are likely insufficient to provide distinct sealing effectiveness predictions within the design range. This issue is central to the goal of health monitoring, which strives to relate the cumulative time history of sealing effectiveness predictions to the health of the under-platform components. Therefore, the sealing effectiveness prediction error must be further minimized to improve health monitoring accuracy.

![Figure 8. DD model performance results for sensors PA and PG showing a) prediction comparison to measurements and b) RMSE(ε) across all 250 grouping repetitions.](image2)

**TWO STEP MODELLING WITH DOMAIN KNOWLEDGE**

The DD modelling approach presented in the previous section was naive in its approach by neglecting to account for any physical understanding of the relationship between the pressure signal and the rim sealing effectiveness. As confirmed by Siroka et al. [32], the presence and strength of the rotating flow structures in the under-platform region significantly influences the sealing effectiveness. While the DD modelling approach was successful, it is likely that leveraging the specific frequency or frequencies corresponding to the rotating flow structures could result in lower prediction error.

To examine how the DD model utilized the dominant frequency corresponding to these rotating flow structures, the model coefficients (β) were examined, as shown in Figure 9. The coefficient values from all 250 modelling iterations were averaged to yield a single representative coefficient value for each frequency bin (feature). The magnitude of each coefficient indicates the relative degree to which the pressure amplitude is correlated with the sealing effectiveness. Here, the various forms of the term “correlation” are used in accordance with their statistical definition, which is a measure of the interdependency between two variables. Most notably, the coefficients corresponding to the dominant frequency, typically in the range 3.5<f/fD<6.5, are nearly zero, which shows that the dominant frequency was not used. Therefore, a two-step (2S) modelling approach was developed to investigate a potential added benefit of utilizing the dominant frequency. This new methodology...
employs an understanding of the fluid dynamics to create a better model – an approach commonly referred to as the inclusion of “domain knowledge.”

Figure 9. Model coefficients from the LASSO regression which relate the grouped spectral features of the pressure signal to the sealing effectiveness. The red box indicates the approximate frequency range associated with the dominant frequency.

As shown in Figure 4, the trend of dominant frequency amplitude represents a non-monotonic relationship with purge flow. Based on this relationship, the use of the dominant frequency amplitude on its own yields a non-unique solution for sealing effectiveness. To address this limitation, the 2S modelling approach applies one model where the sealing effectiveness and amplitude of the dominant frequency are positively correlated, and applies a second model where the sealing effectiveness and amplitude of the dominant frequency are negatively correlated. By separating the data in this way, linear regression is able to relate the pressure features to the sealing effectiveness.

The 2S model diagram is shown in Figure 10. The first three boxes of the 2S model are identical to the DD model. FFT was used as the feature extraction method because of its superior performance shown with the DD model. The upper and lower paths of the model diagram denote the training and testing procedures, respectively. Within these paths, the two-steps which differentiate the 2S approach from the DD approach were implemented.

The first step of the 2S approach utilizes a binary regime model to identify the sealing effectiveness within either the increasing or decreasing regions of the sealing effectiveness curve. This step is nearly identical to the DD model through its use of all spectral features to predict sealing effectiveness. However, instead of performing LASSO regression to obtain a continuous prediction of sealing effectiveness, the binary regime model uses logistic regression to obtain an output corresponding to the sealing effectiveness regime relative to a sealing effectiveness value of 0.5 (as dictated by trends in Figure 4).

The second step of the 2S approach implements an additional grouping to isolate a subset of features corresponding to the large scale rotating structures and associated harmonics ($f/f_D=5,10,...,25$). The isolated features, along with their logarithm transforms, were sorted based upon their measured sealing effectiveness regime (greater or less than 0.5) and then LASSO regression was used to create the sealing effectiveness

Figure 10. Two-Step (2S) modelling diagram.
prediction models. Model performance was evaluated with and without the logarithm contributors. Although 2S improvements relative to DD were identified both with and without logarithms, the addition of relevant feature logarithms helped capture the inherent non-linearity of the dominant frequency amplitude trend (Figure 4), which resulted in additional 2S model benefits.

In total, three models were trained for 2S implementation – one ε Regime Model and two ε Prediction Models, as shown in the black boxes in the top right of Figure 10. During the 2S model testing phase, the binary ε Regime Model predicts the approximate range of the sealing effectiveness, which then informs the prediction model to apply to acquire a final sealing effectiveness prediction.

The accuracies of the DD and 2S model predictions are compared in Figure 11. The predictions in Figure 11(a) and Figure 11(b) correspond to the median RMSE(ε) data grouping iteration predictions. In Figure 11(c), the bar height corresponds to the median RMSE(ε) and the range bars indicate the variation in RMSE(ε) across 250 grouping repetitions, excluding outliers. Overall, Figure 11(c) shows the 2S modelling approach reduced RMSE(ε) by 48% at location A, and 37% at location G relative to the DD approach. Furthermore, Figure 11(c) supports the previous conclusion that PA predictions are superior to PG predictions. The accuracy improvement of the 2S model is most notable at the highest purge flow rates, as indicated in Figure 11(a) and Figure 11(b).

To investigate this relationship between purge flow rate and model performance in greater detail, Figure 12 shows RMSE(ε) as a function of purge flow rate. For the DD modelling approach, RMSE(ε) grows as the purge flow rate nears its maximum value for both sensors. However, the 2S modelling approach RMSE(ε) does not suffer from this issue. Instead, the RMSE(ε) of the 2S approach is consistently low at high purge flow rates. Furthermore, when examining a single sensor, the 2S approach RMSE(ε) is typically lower than or equal to the RMSE(ε) of the DD approach across all purge flow rates.

Based on knowledge that engines typically operate near the fully-sealed condition, the low errors at high purge flow rates exhibited by the 2S approach is especially useful. As an example, if an engine were designed to operate with sealing effectiveness between 0.8 and 1.0 (the highest 3 purge flow rates studied), the 2S model RMSE(ε) is approximately one order of magnitude less than the design intent sealing effectiveness range. As a result, the RMSE(ε) of the 2S modelling approach is likely sufficiently low to be implemented in a true health monitoring application. Furthermore, the prediction errors from sensor PG, at the casing, are nearly equivalent to the prediction errors from sensor PA, in the rim seal, which supports the viability of using sensor PG for its easier installation access.

**PRACTICAL CONSIDERATIONS**

To this point, two modelling approaches have been presented to relate time-resolved rim seal pressure to rim sealing effectiveness. Both modelling approaches have shown the ability to predict sealing effectiveness with low error at one turbine operating point. However, it is important to consider the applicability of these models to other operating conditions and additional geometries, as well as to consider the practical aspects of training and implementing the models in a real-world scenario. The investigation of additional turbine operating points will primarily focus on the 2S modelling approach because of its superior performance.

Turbine monitoring models can be applied continuously at all operating points, or they can be applied at a subset of
operating conditions. The former application requires full model flexibility at all operating points and returns monitored information continuously. The latter application can only be valid when the turbine operating conditions match the training conditions, which diminishes the monitoring frequency.

To examine the model sensitivity to turbine operating conditions, measurements were collected at a second turbine operating point (OP2). The relationship between the two sets of operating conditions is shown in Table 2 using the prime notation introduced in Table 1. Results at OP2 are shown for sensor P_G due to the preferred installation accessibility and because location G represents an upper bound for error from which to examine model prediction sensitivities.

Table 2: OP2 Operating Conditions

<table>
<thead>
<tr>
<th>Parameters</th>
<th>OP2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inlet Absolute Total Pressure, P_m'</td>
<td>0.9</td>
</tr>
<tr>
<td>Total Pressure Ratio, (P_m/P_out)'</td>
<td>0.82</td>
</tr>
<tr>
<td>Mass Flow Rate, m_dG</td>
<td>0.88</td>
</tr>
<tr>
<td>Rotating Speed, RPM'</td>
<td>0.88</td>
</tr>
<tr>
<td>Inlet Temperature, T_in°</td>
<td>1</td>
</tr>
</tbody>
</table>

In Figure 13, the OP1 and OP2 bars represent the median prediction RMSE(ε) when the 2S model is separately trained at OP1 and OP2, respectively. The comparison shows OP2 median error is nearly double the OP1 median error – an observation that could be caused by increased variability in the amplitude of the dominant frequency at a given sealing effectiveness for different turbine operating conditions.

Figure 13. Comparison of 2S model prediction error when trained individually at two operating points (OP1, OP2), and when trained on data combined from the two operating points. These results are shown exclusively for sensor P_G.

The bar labelled “Both” represents the prediction error when a single model is generated based on the cumulative pressure and sealing effectiveness inputs from both operating conditions. The error of this combined model is nearly equivalent to the OP2 prediction error, which suggests the viability of applying a single model to a broad range of operating conditions. This observation also shows that the relationship between the standardized pressure amplitude of the dominant frequency and the sealing effectiveness is largely invariant across the range of evaluated operating conditions. These results indicate that the 2S model can be trained at two operating points with minimal losses in accuracy, which enables real-time rim sealing effectiveness monitoring at two operating points. While these results do not present a comprehensive view of the performance of a single model across all possible on and off-design operating conditions, Figure 13 does indicate capability of the modelling approach to function across a range of operating points, which supports continuous monitoring of rim sealing effectiveness.

Another important practical consideration for these data-driven models is their applicability to various turbine geometries. Although this question cannot be explicitly answered without testing alternate turbine geometries, some instructive statements can be made by examining the working principles of the models themselves. Foremost, the 2S model relies on an instability-driven dominant frequency that follows amplitude variations as a function of the sealing effectiveness. Many researchers with differing turbine geometries and purge flow injection methods have observed low frequency peaks in the rim seal pressure that are also dependent on purge flow rate [14,24,25,27,32,37,38]. Although many of these studies do not present results at as many purge flow rates as the present study, it is assumed that the 2S model (Figure 10) can be modified to accommodate each individual relationship between rim seal time-resolved pressure and sealing effectiveness by modifying the extent and number of regimes corresponding to each prediction model.

While many turbines fit into this category, there are likely many turbine geometries that either do not show a dominant frequency in the rim seal pressure, or do not exhibit a modulation of the pressure spectral content by purge flow rate variation. For example, Julien et al. [15] showed minor changes to rim seal pressure content using CFD, and Darby et al. [26] hypothesized that co-swirled purge flow weakens the shear layer driven instability that creates a dominant frequency in the rim seal pressure. In these cases when dominant frequency content is not present, the DD modelling approach can still be applied because it does not rely on the presence of a dominant frequency to predict sealing effectiveness, as shown in Figure 9.

Another challenge of applying the 2S and DD modelling approaches to an engine is the extreme temperatures in the turbine which many sensing technologies cannot accommodate. Furthermore, the models presented in this study specifically require a pressure sensor capable of resolving fast-response pressure data up to approximately f_RPM=30. For large turbines typical of power generation applications, the rotating speeds are relatively low, meaning the required sensor bandwidth is reduced and is therefore increasingly attainable. For example, a sensor applied to a turbine operating at 3600 RPM would require a sampling rate of 3.6 kHz to resolve f_RPM=30=1.8 kHz, which is a reasonable sampling rate considering the existing technology for engine applications. Based on higher bandwidth requirements of smaller engines used in aerospace applications, the modelling approaches presented in this study may be most readily applied to large power generation engines. However, new sensor
technologies are continuing to be developed that address this need for higher sensor bandwidth in engines with higher operating speeds.

Finally, it is important to consider the environment in which these models are trained and the relevance of the resulting model to the engine environment. Ideally, a gas turbine manufacturer would execute the training procedure with a pressure sensor installed on the exact engine to which the model would be applied; however, this poses several challenges including independent control requirements of cooling flow supplies, separate quantification of sealing effectiveness, and temperature controls to prevent component failure at low purge flow rates. Instead, test facility experimentation and CFD predictions present two potential alternatives to the engine for generating training data. Critically, the training data must closely match the relationship between time-resolved rim seal pressure and rim sealing effectiveness in the engine. Although great progress has been made recently in predicting rim seal flow characteristics using CFD [58–60], the authors are not aware of any studies in the open literature that have shown exact, or nearly exact, matches between CFD predictions and experimental results for time-resolved rim seal pressure and rim sealing effectiveness. Therefore, in pursuit of the highest fidelity source of training data, it is likely that the model would need to be trained in a test facility using turbine geometry that matches the engine. Continued development and utilization of turbine research facilities operating with true-scale engine hardware and engine-relevant operating conditions will help ensure the feasibility of such ex situ training methods.

CONCLUSIONS

This study developed models to predict real-time turbine rim sealing effectiveness using input data from a time-resolved pressure sensor with relatively low-bandwidth requirements. Fast-response pressure measurements were gathered in a one-stage test turbine operating at engine-relevant conditions with engine-representative hardware. Two pressure sensors were installed to examine the tradeoff between ease of installation and model performance. Because unsteady rim seal flows are not yet fully understood, data-driven modeling approaches were used to relate the pressure signals to the sealing effectiveness.

These efforts resulted in the generation of two data-driven modeling approaches relating broadband pressure features to measured rim sealing effectiveness: a purely data-driven approach and a more complex approach integrating domain knowledge from known turbine rim seal behaviors. The first data-driven approach showed median sealing effectiveness predictions within approximately 6% of the measured value. The second approach incorporating domain knowledge using a two-step approach, and reduced median prediction errors to approximately 3% of the measured sealing effectiveness. For engines designed to operate at sealing effectiveness values above 0.8, these errors were found to be further reduced to below 2% – low enough to reasonably apply the model to real-time underplatform hardware health monitoring.

A comparison of the two sensor mounting locations showed the rim seal pressure sensor resulted in more accurate sealing effectiveness predictions than the casing pressure sensor. However, slight increases of prediction accuracy identified for the casing sensor location are likely outweighed by the preferable sensor accessibility.

Performance of the two-step model with domain knowledge was further assessed for different turbine operating conditions. Successful model integration showed it is possible to train a single model for a range of turbine operating conditions, and the associated performance debits were quantified. Ultimately, the results from this study show the viability of a real-time health monitoring system for accurate predictions of turbine rim sealing behavior using a data-driven approach.

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