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CORRELATION MEASURE-BASED STALL MARGIN ESTIMATION FOR A SINGLE-STAGE AXIAL COMPRESSOR

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ABSTRACT

This paper presents a method for estimating compressor stall margin and the results of applying the estimation technique to an axial compressor rig. Stall margin estimation is accomplished through the use of a compressor stability detection parameter called the "correlation measure." The correlation measure captures the periodicity of the pressure in the rotor tip region of the compressor. The downcrossing frequency of the correlation measure across some preset threshold is measured while operating the compressor rig at various steady-state points along the design speed characteristic line. These measurements are used to generate a relationship with stall margin as a function of downcrossing frequency. The estimation technique is evaluated by applying it while dynamically ramping the operating point of the compressor up the design speed line towards surge. A brief investigation on the effects of inlet distortions on the correlation measure-based estimation system is also given.

NOMENCLATURE

$C(n)$ Correlation measure
n Sample index
N Number of samples per shaft rotation
p Rotor tip pressure
RPM Revolutions per minute
SM Stall margin
v Flow velocity
w Window size in number of samples
ΔP Pressure rise
$\Delta P_s(v)$ Surge line pressure rise at flow velocity v

INTRODUCTION

The control systems for aircraft gas turbine engines typically include a cascade of protection systems for preventing violation of critical operational limits. In many cases, however, these limit parameters are uncertain and/or unmeasurable quantities. For example, compressor stall margin, which is a representation of the proximity of the operating point of the compressor component to its limit of stable operation, is a highly uncertain limit; it is sensitive to factors such as inlet distortions, thermal transients, manufacturing tolerances, and component deterioration. As a result, engine control systems compensate for this uncertainty in a somewhat passive manner by "stacking" worst-case scenarios to maintain a conservative safety margin from the compressor stability limit at all times. Although successful at avoiding compressor instabilities such as rotating stall and surge, this technique limits the performance of the engine.

Survey studies [1] have been conducted to elucidate the general benefits of more active approaches to engine control. A possible route towards active control when dealing with compressors is through the use of control modes on stall margin. Adibhatla et al. [2] carried out an assessment of intelligent control systems. They proposed a formalized methodology for evaluating various types of engine control modes based on factors such as

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weight benefits, cost benefits, retrofit capability, and risk. Based on these criteria, a stall margin/operability control mode offers the highest benefits but also constitutes a high risk.

The challenge faced when developing such a stall margin control mode is the uncertainty and unobservability of the parameter itself. Efforts to estimate stall margin generally fall into two categories of study. The first and also more extensively researched group is a model-based approach to stall margin estimation. In this instance, "model-based" may imply the usage of an onboard engine model running alongside the actual engine, or simply an estimator in the form of an observer or filter built offline using an engine model.

For instance, a linear Kalman filter may be used as an estimator for unmeasured engine parameters when augmented with a neural network to account for system nonlinearities [3]. On the other hand, Turevskiy et al. [4] utilizes a set of Kalman filters built about equilibrium points across the engine operating envelope. An example of estimation via an onboard model is given by Kobayashi et al. [5]. In this case, a Kalman filter is used to tune the health parameters of the onboard model to match a "true" engine of some level of deterioration. The outputs of the tuned model approximate the unmeasurable parameters of the true engine. Alternatively, Viassolo et al. [6] tune the health parameters of an onboard model offline, based on the assumption that deterioration occurs slowly across several usage cycles. Unmeasurable parameters such as stall margin are obtained using an extended Kalman filter. In this application, the engine model and parameter estimates are used in a model predictive control system, where the online engine model is linearized at each controller time step to solve a finite horizon Linear-Quadratic Regulator problem with constraints on stall margin.

In these typical model-based approaches, the objective is usually to estimate the health parameters as well as selected unmeasurable variables of the system. The estimated quantities typically include mass flow rate, turbine inlet temperature and engine thrust. For a given compression system, an *a priori* knowledge of the surge line can be coupled with the measured speed and pressure ratio and the estimated mass flow rate to estimate the current stall margin. It may also be possible to account for the gradual degradation of the compressor surge line via health parameters. However, transient loss of stall margin, due to inlet distortion and speed as well as thermal transients, cannot be easily formulated within the model-based framework. Moreover, the current model-based estimators have mostly been validated against "truth" models and not against experimental data.

The second category when dealing with stall margin estimation is a more direct approach and necessarily requires experimentation with a compressor or engine test rig. In this case, measurements of the flow field in the compressor are processed in some unique fashion to estimate stall margin. Although the literature on experiments involving stall inception and active expansion of the compressor operating range is extensive, experimentally estimating stall margin–or some measure of proximity to compressor stall/surge rather than inception warnings–is unfortunately not as well documented.

One such example [7] applies the stall margin calculation algorithm commonly used in engine component-level models to actual experimental data. Essentially, stall margin is interpolated from measured values of pressure ratio and spool speed via a compressor performance map lookup. The use of compressor maps imposes limitations on its applicability: any deterioration in surge line has to be externally determined for a successful implementation of this technique. Another approach by Wang et al. [8] formulated stall margin estimation as a classification problem. The aim was to correctly classify the compressor operating point into one of four classes, each corresponding to a different finite sector of the speed line (and hence, some stall margin range). Velocity and pressure measurements were condensed into different features used for classification by computing fast Fourier transforms, turbulence levels, and autocorrelations. The method was relatively successful in correctly categorizing the operating point into the appropriate class in steady-state but did not explore dynamic excursions on the compressor map.

This work presents and evaluates a technique for stall margin estimation which uses a compressor stability detection parameter called the "correlation measure." Introduced by Dhingra et al. [9], the correlation measure is intimately tied to the unsteady flow field characteristics of the compressor rotor tip region. It has been shown through experiments performed on several laboratory compressors as well as a full aircraft engine test rig to be an effective stall warning parameter [10]. A recent study implemented a stochastic model of the correlation measure [11] in a dynamic engine simulation environment and evaluated different methods of integration with the engine control system [12]. It was shown that the use of a stall margin control mode is a possible integration approach. Additional engine simulation results demonstrated the potential of using certain stochastic characteristics of the correlation measure to estimate stall margin for the control mode [13].

The present work is an attempt to characterize stall margin estimation in an experimental environment. The correlation measure-based stall margin estimation technique described in Ref. [13] is implemented on a low speed, single stage, axial flow compressor rig. A mapping between different steady state operating points of the compressor and certain features of the correlation measure is generated to form the basis of the estimation technique. The effectiveness of the estimation is then evaluated by running transients along the design speed line of the compressor. The effect of inlet distortions on the estimation technique is also briefly assessed. The analysis of these experimental results raises issues and difficulties to be resolved and thus provide guidelines for future control system design.

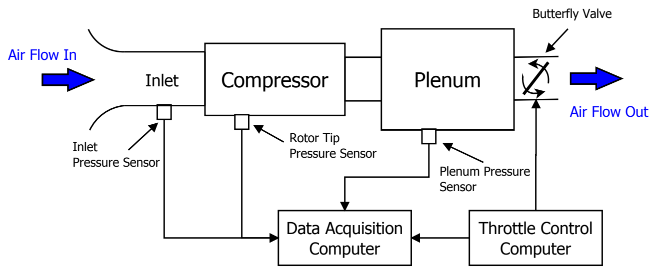

Figure 1. Diagram of experimental facility.

EXPERIMENTAL FACILITY

The experimental setup used for this work is a typical laboratory compressor rig. As depicted in Fig. 1, it consists of a bellmouth inlet, a single-stage compressor, a discharge duct, and a butterfly valve. The bellmouth inlet duct directs ambient air into the compressor. The compressor is a low speed, single stage, axial flow machine consisting of 14 rotor blades and 11 stator blades. The design speed of the compressor is approximately $11,700$ revolutions per minute, which corresponds to a tip Mach number of 0.3. The exhaust flow from the compressor is discharged through a duct into the plenum, a large metal chamber capable of withstanding pressures up to 400 pounds per square inch. A butterfly valve downstream of the plenum acts as a variable area throttle. The valve angle and hence the effective outlet duct area is fixed by a computer controlled servo-motor. Closing the exit valve decreases the exit mass flow, hence loading the compression system

The instrumentation consists of a variety of pressure sensors with the associated power and signal conditioning circuitry. Two differential pressure sensors are used to measure the static pressure at the inlet duct relative to ambient. Although not strictly a measurement of the dynamic head, given the bellmouth shape of the inlet, this differential pressure measurement is used to calculate flow velocity. A high-bandwidth pressure sensor is mounted on the compressor casing, localized roughly over the rotor midchord. This sensor is used to calculate the correlation measure, a compressor stability parameter. The last pressure sensor is connected to a pressure tap on the plenum. Since the plenum is large compared to the rest of the system, it is assumed that the pressure from this tap represents total pressure. Thus, the sensor, which measures differential pressure between plenum and ambient pressures, essentially measures pressure rise across the compressor.

STALL MARGIN ESTIMATION

Estimation of stall margin is accomplished through the use of a stability parameter known as the correlation measure. The technique is described in this section.

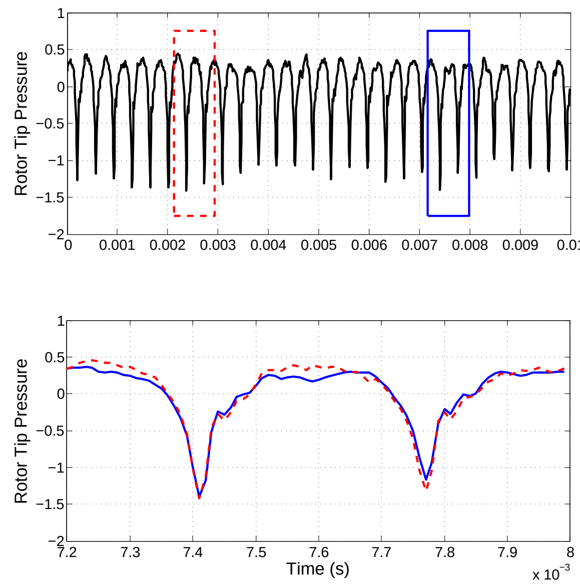

Figure 2. The correlation measure quantifies the periodicity of the rotor tip pressure signature by continuously comparing two moving windows of pressure samples separated in time by one rotor revolution.

Correlation Measure

The correlation measure is a mathematical parameter that quantifies the periodicity of a given signal. It has been experimentally observed that the repeatability of the pressure fluctuations in the compressor rotor tip region, measured in a reference frame fixed to the casing, deteriorates as the compressor is loaded towards its stability limits. Hence, applying the correlation measure to this pressure signature would provide some knowledge of the proximity of an operating point to the compressor stability limit.

The correlation measure, as applied to a given pressure sample, is given as [9]:

$$C(n) = \frac{\sum_{i=n-w}^{n} p_i p_{i-N}}{\sqrt{\sum_{i=n-w}^{n} p_i^2 \sum_{i=n-w}^{n} p_{i-N}^2}} \tag{1}$$

where $C(n)$ is the correlation measure, n is the sample index, N is the number of samples per rotor revolution, w is the window size in number of samples, and i is a dummy variable. Figure 2 is a visualization of how this correlation measure equation is applied. Two moving windows of pressure samples (each of length w) separated in time by one shaft cycle are compared using an

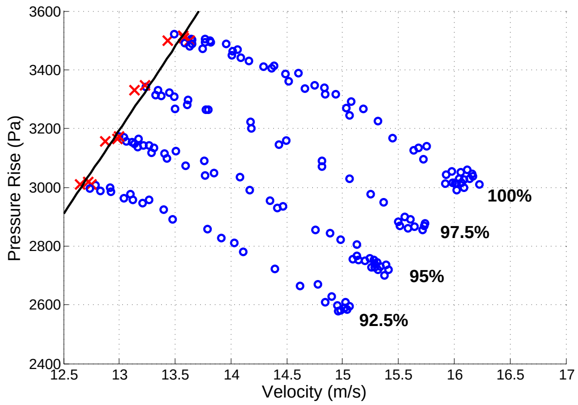

Figure 3. Compressor rig performance map: pressure rise versus flow velocity for 92.5% to 100% of design speed.

inner product operation. The result is then normalized with the Euclidean norms of the two windows, thus bounding $C(n)$ between -1 and 1. Higher values of $C(n)$ indicate higher levels of repeatability, with 1 representing a perfectly periodic signal. It has been observed that $C(n)$ usually falls between 0 and 1 for typical compressor operation.

Compressor Map & Stall Margin

Figure 3 shows the performance map of the compressor used in this study. The map represents data taken at four different speeds (from 92.5% to 100% of design speed) and across four different days. Each symbol represents measurements taken while operating the machine in steady-state in terms of rotor speed and butterfly valve setting. Each blue circular symbol represents an average over 10 seconds of pressure rise and velocity measurements. Each red X symbol represents a throttle setting where surge occurred. The location of each red X symbol is determined by averaging the pressure rise and velocity measurements just before the first surge cycle in that particular run. The surge line is then obtained by applying a least squares fit through the surge data points.

The surge line is used to calculate stall margin for any point on the compressor map. The commonly-used definition of stall margin is:

$$SM = \left[1 - \frac{\Delta P}{\Delta P_s(v)}\right] 100\% \qquad (2)$$

where ΔP and v are the pressure rise and flow velocity, respectively, of the operating point of interest, and $\Delta P_s(v)$ is the surge line pressure rise corresponding to the flow velocity. Physically, this definition of stall margin is essentially a measure of the vertical distance on the compressor map between the operating point and the surge line. This equation for stall margin is used for two purposes in this work. First, it assigns stall margin values to the steady state operating points and, as it will be shown in the next section, thus assists in defining a mapping between the correlation measure and surge line proximity. Second, it serves as a reference stall margin and baseline for comparison with the stall margin estimation procedure during the speed line transients.

It is worthwhile to note that as a result of this definition of stall margin and how the surge line is obtained, it is possible for surge to occur at a stall margin value which is not equal to 0% (in either the positive or negative direction). This fact is clear by noting the scatter of the surge points around the surge line on the compressor map in Fig. 3, which is likely due to a combination of numerous factors such as pressure and velocity measurement uncertainties, operating conditions, and variation in the surge point itself. The stall margin of these surge points range from -1.9% to 1.6%. These observations foreshadow what will be seen when attempting to estimate compressor stall margin. Namely, a good estimate is not necessarily one which faithfully tracks the stall margin values defined in Eqn. 2. Instead, it is important that the time histories of the stall margin estimates display the trend expected based on the type of operating point excursion the compressor is commanded to perform.

Estimation Procedure

As previously mentioned, it has been observed that the rotor tip pressure time history becomes less repeatable as a compressor is loaded towards the surge line. Since the correlation measure captures this periodicity, it may be possible to use this parameter for stall margin estimation. To do so, the correlation measure is continuously monitored for drops across some constant preset value. These threshold crossings are henceforth referred to as "events." As one might expect, event frequency generally increases as the operating point approaches the surge line. The study described in Ref. [13] exploited this observation by using a functional relationship between stall margin and event frequency to estimate stall margin in an engine simulation. For this work, the technique is applied to the axial compressor rig.

The mapping between event frequency and stall margin for this compressor is shown in Fig. 4. The plot comprises of data taken across four days. Each point on the plot represents a different point along the compressor design speed line. The butterfly valve aft of the plenum was used to transition from one point to another. At each point, plenum pressure, flow velocity, and rotor tip pressure were measured and sampled at 100 kHz for 10 seconds while the position of the valve was held constant. Stall margin for each point is calculated by averaging the plenum pressure and flow velocity and applying Eqn. 2. Event frequency was obtained by calculating the correlation measure for the rotor tip pressure signal with a threshold of 0.85. To estimate stall mar-

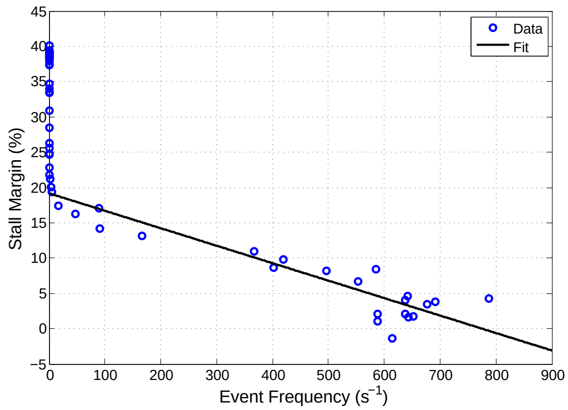

Figure 4. Relationship between stall margin and correlation measure event frequency.

gin while operating in steady-state, the relationship depicted in Fig. 4 is indicative of the what one would obtain. The correlation measure is unable to discern stall margin above approximately 20%. Stall margin values in the range of 5% to 20% are readily estimated with relatively low uncertainty using event frequency. The uncertainty increases, however, when stall margin is low.

However, the primary aim of this work is to demonstrate estimation of stall margin in a dynamic sense–that is, while the compressor operating point moves on the performance map. The procedure, then, to determine stall margin from the correlation measure is summarized as follows. As the compressor runs, pressure from the rotor tip is sampled and used to calculate the correlation measure. A fixed number of the most recent values of the correlation measure are stored and used to calculate event frequency. For this work, only the latest 0.7 seconds of the correlation measure signal were considered. A simple linear fit of the data in Fig. 4 is then used to estimate stall margin from the event frequency. This stall margin value is updated with each new iteration of the correlation measure.

DESCRIPTION OF EXPERIMENTS

Throttle transient runs were used to evaluate the stall margin estimation technique. Twenty-seven transient runs were performed across seven different days. Each transient involved progressively closing the butterfly valve aft of the plenum while holding the compressor at its design speed of 11,700 RPM. Figure 5 shows the commanded valve setting versus time. Closure of the butterfly valve is measured in degrees from the fully open position. The valve position was ramped over a period of 20 seconds from zero to 27 degrees. A valve position of 27 degrees was known to be more than enough to consistently induce surge in the compressor. During each transient, the sensors measuring

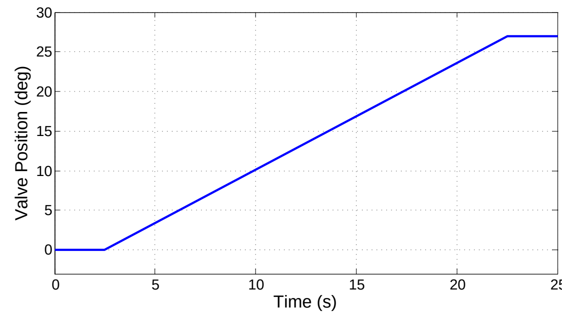

Figure 5. Butterfly valve position during a throttle transient, measured in degrees away from fully open position (zero degrees).

flow velocity and pressure rise were used to determine the reference stall margin. The signal from the rotor tip sensor was used to calculate correlation measure, which in turns gives the stall margin estimate.

ESTIMATION RESULTS

A total of 27 throttle transient runs were performed to evaluate the correlation measure-based stall margin estimation technique. The results are mixed. In this section, we will present and evaluate 5 example runs which represent the entire spectrum of the quality of stall margin estimation encountered in this study. Explanations will be given for why each particular example is considered a good (or bad) instance of stall margin estimation as well as for the possible underlying reasons. We will also discuss observations, issues, and difficulties that deal with the overall estimation process.

Example 1

The first example is an instance of the correlation measure providing a good quality estimation of stall margin. Figure 6 presents the results as a time history of the transient run. The first subplot shows the evolution of the pressure rise across the compressor as well as the surge pressure rise; together, the two signals are used to calculate the reference stall margin. As previously described, the surge pressure rise is a linear function of flow velocity (i.e. the surge line). As it will be in most cases, the surge line pressure rise may drop below the compressor pressure rise just before surge occurs, resulting in a negative value for stall margin for a brief moment.

The second and third subplots show the correlation measure and its event frequency for the threshold of 0.85. As the compressor is loaded, the correlation measure experiences more sharp dips and thus event frequency increases.

The reference and estimated stall margins are shown in the last subplot. The saturation of the estimate at high stall margin

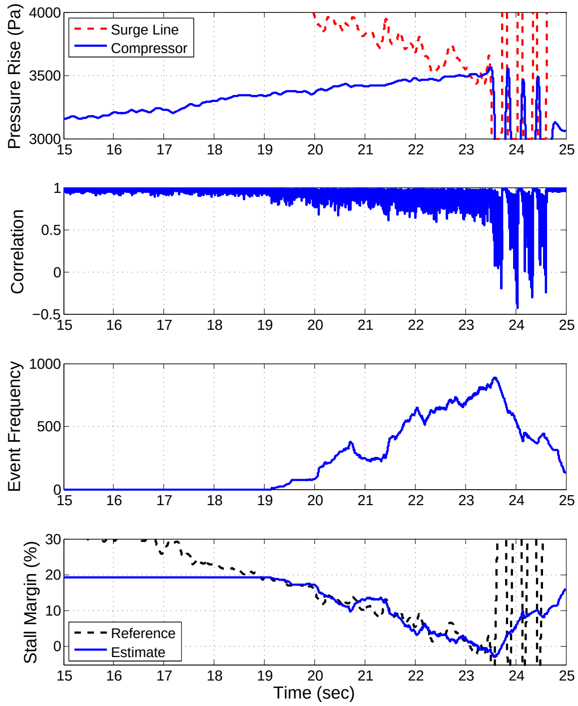

Figure 6. Example 1: Good quality estimation of stall margin.

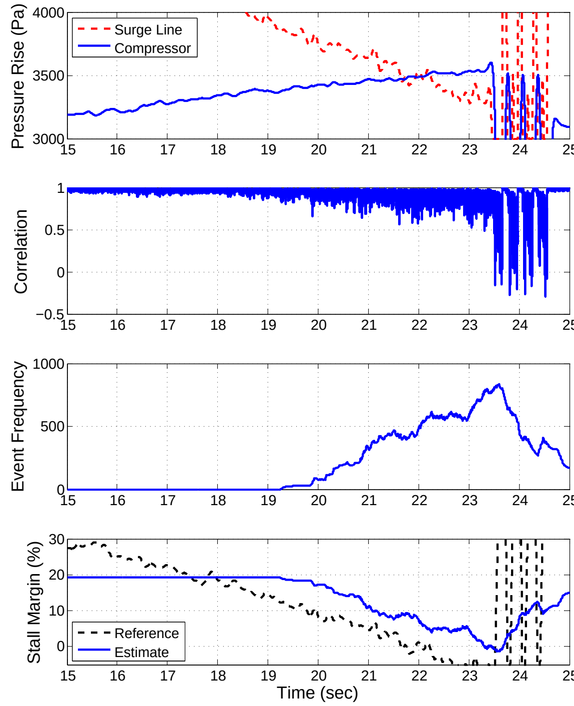

Figure 7. Example 2: Estimated stall margin outperforms reference stall margin.

is due to the fact that event frequency reduces to zero when the operating point is higher than a certain stall margin value (Fig. 4). The quality of the estimate exhibited in this example is high since estimated stall margin decreases essentially monotonically until surge occurs. This is what would be expected given the time evolution of the pressure rise. In this case, the reference stall margin decreases monotonically to zero as well. As it will be seen, this is actually not true in general.

Example 2

The second representative transient run, shown in Fig. 7, is another favorable example of using the correlation measure to estimate stall margin. The difference between this case and the first is that the reference stall margin in this example is not a good measure of proximity to surge. This is a result of using a definitive surge line when the point at which compressor surge occurs is uncertain. As the first plot in Fig. 7 shows, the compressor surges at a pressure rise that is similar to that for Example 1. However, the flow velocity at surge, manifested here as the surge line pressure rise, is noticeably lower than before. As a result, the reference stall margin drop to zero nearly two seconds before surge actually occurs.

On the other hand, the correlation measure reacts seemingly independently of this discrepancy in surge flow velocity. The time history of the estimated stall margin is similar to that in Example 1: monotonically decreasing as the compressor approaches surge. Consequently, in this case, the estimated stall margin actually gives a better idea of how close the compressor is to surge than using a predetermined surge line. This example illustrates that the reference stall margin, though based on the standard definition, is quite noticeably susceptible to the uncertainty of the actual point of surge. Therefore, in this study, we treat the reference stall margin not as an authoritative baseline but rather a parameter which provides some measure of comparison with stall margin estimated from the correlation measure.

Example 3

Whereas the first two examples represent more or less ideal cases, the results of the transient run for this third example (shown in Fig. 8) are of lower estimation quality. Although the correlation measure-based stall margin exhibits the appropriate downwards trend, it reaches zero well before surge occurs. As a result, the estimation does not give as accurate of a measure of

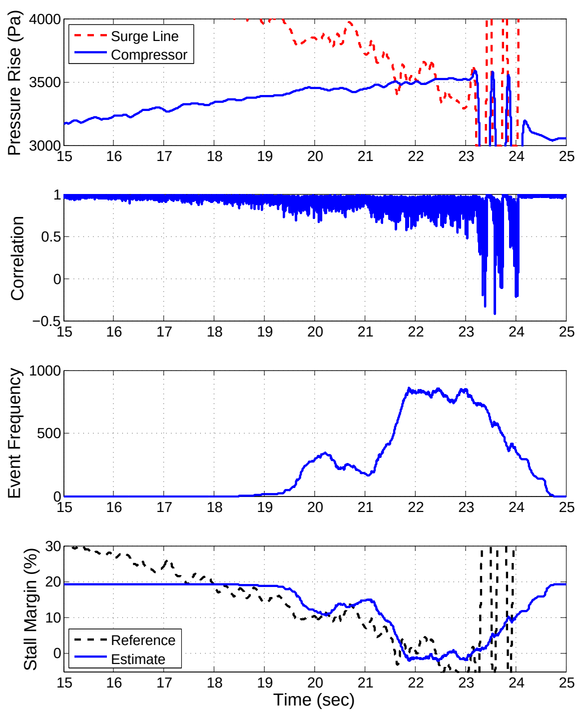

Figure 8. Example 3: Overly conservative stall margin estimation.

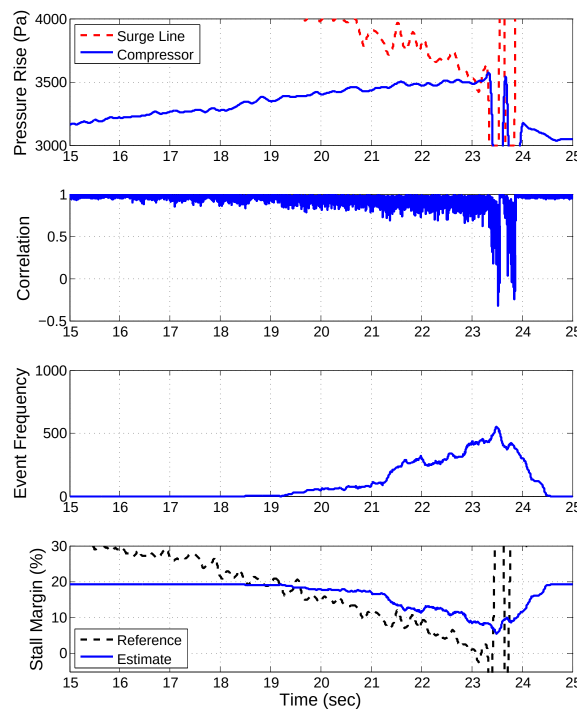

Figure 9. Example 4: Estimated stall margin underperforms reference stall margin.

surge proximity as the previous two examples did. A redeeming feature of this run, however, is that the correlation measure does indeed provide continuous warnings of impending surge by remaining near zero stall margin for the short time period just preceding surge. In this case, the reference stall margin does not perform any better. The downwards time evolution of the reference stall margin is more monotonic than the estimate, but it reaches zero at essentially the same time.

Example 4

Examples 1 through 3, though of varying estimation quality, are runs where estimated stall margin performs as well if not better than the reference stall margin. These next two examples are representative of the type of transient runs where the estimate is of lower quality and outperformed by the reference stall margin.

The results of the run for this fourth example are shown in Fig. 9. In this run, the reference stall margin performs relatively well since surge occurs near the surge line: the compressor pressure rise and surge line pressure rise in the first subplot coincide just before surge. The correlation measure, however, does not do a good job of estimating proximity to surge. Although the trend of the event frequency time history–and hence estimated stall margin–is correct, the estimated stall margin reaches a minimum value of approximately 6% before surge occurs. From the previous three examples, we can see that event frequency tops 800 per second before surge. As Fig. 4 shows, this corresponds to an estimated stall margin of approximately 0%. In this instance, however, event frequency does not even reach 600 per second. As a result, the correlation measure under-predicts how close the compressor operating point is to surge.

Based on these results, it is difficult to say why the correlation measure overestimates stall margin in this example but not in the previous ones. The correlation measure is an *inherently* stochastic parameter because it is directly calculated from pressure over the rotor tip. Therefore, even in the previous examples, estimated stall margin is not the same before surge. In this case, however, the event frequency is significantly lower than in the previous runs. We can only infer that in certain cases such as this, the “regularity” of the pressure signal need not deteriorate to such a high level before surge onset.

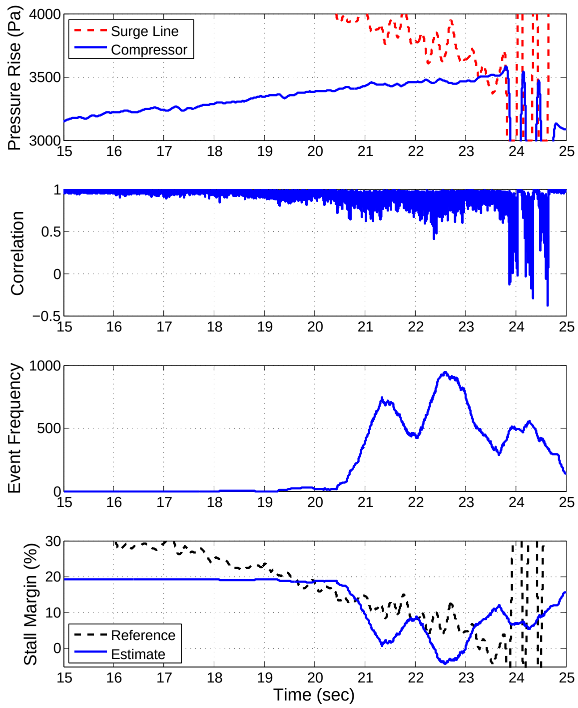

Figure 10. Example 5: Estimated stall margin lacking expected trend.

Example 5

The last example given here is representative of the lowest estimation quality encountered in this study. Figure 10 presents the results of the Example 5 transient run. The estimated stall margin profile displays a vaguely downwards trend, but is unfortunately dominated by the large fluctuations. The source of the fluctuations are evident in the time history of the correlation measure, where a large concentration of dips occur around the 23-second point. This large grouping of downcrossings are both preceded and followed by relatively high correlation measure values, creating the oscillations in the estimation. Even though the estimate reaches zero unlike in the case of Example 4, the lack of a distinctive downwards trend betrays confidence of that fact as an indication of impending surge. Again, it is difficult to determine why the correlation measure would react in such a manner. In this case, the periodicity of the rotor pressure signal did not degrade *progressively* until surge as in all the previous examples. This estimation result suggests that a more complex method beyond the current single threshold crossing scheme for processing the correlation measure may be required. For example, the magnitude of a downcrossing event may be an important parameter and will be an issue examined for future work.

Table 1. Summary of estimation quality for 27 transient runs.

Rating	Occurrences	Percentage
1	10	37%
2	11	41%
3	3	11%
4	3	11%

Summary of Results

The five examples presented in this paper were chosen because they represented the entire range of estimation quality encountered. In fact, all 27 runs can be qualitatively categorized as similar to one of these examples. Thus, these five examples are used to create four classes that can be used to rate estimation quality:

Class 1 is representative of Examples 1 and 2. The defining feature is the clear downwards trend and estimated stall margin nearly zero just preceding surge.
Class 2 is representative of Example 3, where there was a downwards trend, but estimated stall margin nears zero more than a second before surge.
Class 3 is representative of Example 4, where again a downwards trend is observed, but estimated stall margin stays well above zero.
Class 4 is representative of Example 5, where there is lack of a downwards trend. The lack of a trend supersedes whether or not estimated stall margin reaches zero.

Although this rating system is rather ad-hoc and requires some level of subjectivity, it gives some idea of how well the correlation measure is able to estimate stall margin in the present, relatively simple implementation. Table 1 shows how the 27 runs are broken down in terms of these ratings. More than three-quarters of the runs fall in Classes 1 and 2; thus, for the majority of the time, the correlation measure is able to provide a measure of proximity to the surge line. Unfortunately, for the remaining cases, the expected trend is either not present or not sufficient to accurately estimate stall margin. The results here show that while the current implementation of a simple moving average of events may be satisfactory as a proof of concept most of the time, more sophistication and refinement in the technique is needed to increase consistency and robustness.

FURTHER INVESTIGATION & DISCUSSION

Surge Proximity Warnings

Although the main purpose of this study is to investigate experimentally the possibility of using the correlation measure to

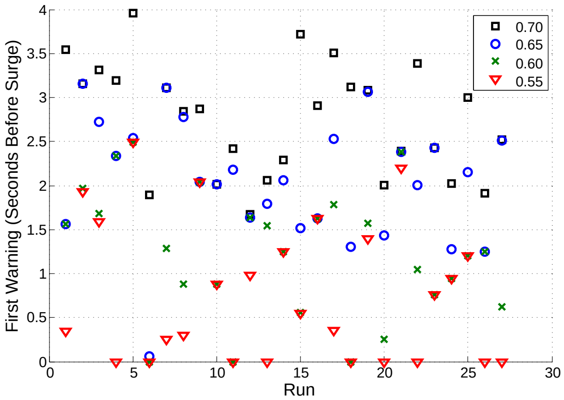

Figure 11. Time of first warning signal encountered in terms of seconds before surge for four different threshold levels.

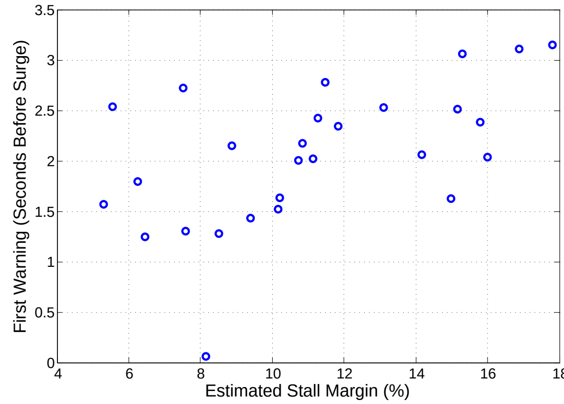

Figure 12. Time of first warning signal encountered and corresponding estimated stall margin values for threshold level of 0.65.

estimate stall margin, in lieu of the type of estimation qualities represented by Classes 3 and 4, it may be necessary to incorporate a warning system able to give Boolean-type signals representing proximity to surge (i.e. "close" or "not close"). Therefore, we briefly investigate the possibility of supplementing the estimation procedure with a "second line of defense" in the form of correlation measure-based surge proximity warning signals. For estimation purposes, a relatively high threshold (0.85) was used to relate the deterioration level of the correlation measure with the compressor stall margin. To generate warning signals, a low threshold is used. Instead of a running calculation of event frequency, a single downcrossing event across this low threshold is assumed to be an indicator of proximity to surge. Such a warning system would not, and indeed need not, estimate compressor stall margin but must have high reliability in terms of generating a warning before the surge event.

Figure 11 summarizes the results of applying this procedure to the 27 throttle transient runs used to evaluate the stall margin estimation technique in the previous sections. The plot shows, for each run and for four different threshold levels, the point in time during the transient when the first warning signal was encountered in terms of seconds before the surge event. A value of "0 seconds" for a particular run means that no event occurred before surge. Since the correlation measure is a stochastic parameter, there is some variation for each threshold. Nevertheless, as we might intuitively expect, the general trend is that the first warning signal occurs closer to the surge event as the threshold is lowered, though as the plot shows, the frequency of no event occurring before surge also increases.

Since high reliability is a priority for this warning system, based on these results, we would choose a threshold of 0.65 or 0.7. Figure 12 shows the first warning occurrences for a threshold of 0.65 plotted against the corresponding estimated stall margin value for that occurrence. The results provide some initial insight into how the warning signals may be coupled with the estimation system. For instance, a simple control logic may be to ignore warning signals if the estimated stall margin is above 9% or 10%; however, if estimated stall margin drops below that, the warning signals trigger corrective control action. Even this simplistic logic would protect against all runs categorized as Class 3 and 4. In fact, the point in Fig. 12 with a first warning signal occurring about 0.2 seconds before surge is from Example 4 in the Results section, where the correlation measure overestimated stall margin.

Window Size & Thresholds

Some aspects of the present stall margin estimation technique requiring refinement are the window size over which events are averaged and the correlation measure threshold values. For the implementation of this estimation system in simulation in previous studies [13], it was assumed that event frequencies at various stall margins were relatively high. Thus, instead of using a moving window, events were simply averaged at each controller time step (approximately 15 milliseconds). The magnitude of the event frequencies for this compressor does not allow such a small window: 800 events per second, which corresponds to zero stall margin, translates into only 12 events per 15-ms window. Implementing such a small window causes the estimation to be very noisy and devoid of any discernable trend since the randomness of the correlation measure itself would create large uncertainties in the event frequency. Unfortunately, utilizing a large window restricts us to relatively slow transients. Indeed, the current system with its 0.7-second window would have trouble with a 5-second transient as opposed to the current 25-second one.

Some efforts have also been made to investigate the use of

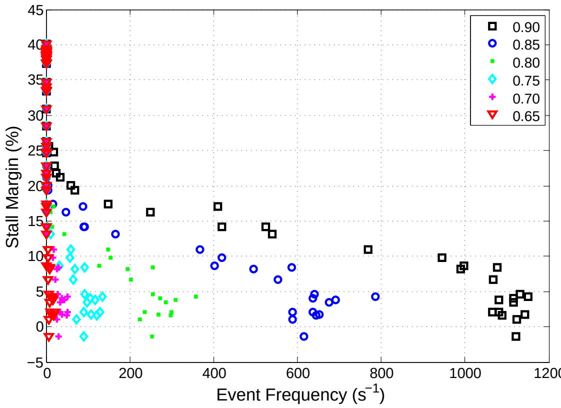

Figure 13. Relationship between stall margin and event frequency for different threshold levels.

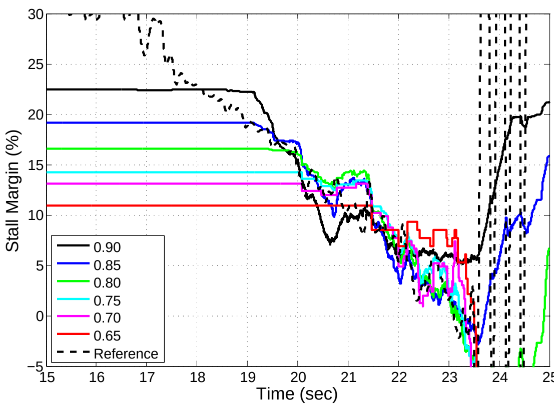

Figure 14. Example 1 transient run with multiple threshold levels.

different and/or multiple thresholds on the correlation measure for the purpose of stall margin estimation (as opposed to generating surge warning signals as described previously). Theoretically, higher thresholds may be used for higher stall margins and lower ones for low stall margin values. However, the situation is more difficult in practice. Figure 13 shows the relationship between event frequency and stall margin for six different thresholds. For threshold values higher than 0.9, the inherent stochastic nature of the correlation measure dominates and events become more random and less so a result of compressor loading. Hence, no trend between event frequency and stall margin would be seen. For low thresholds, events become scarce, making them more useful for the surge warning signals previously described than stall margin estimates. For the values in between, it was found that estimation quality does not improve by using different thresholds. This can be seen in Figures 14 and 15, which show

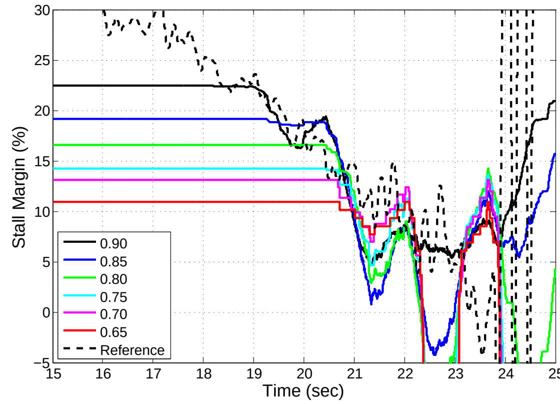

Figure 15. Example 5 transient run with multiple threshold levels.

stall margin estimated with various threshold levels for the runs in Examples 1 and 5, respectively. Although it may be difficult to discern specific details from those two plots, the overarching message that the plots convey is that estimation quality remains–as before–generally high with Example 1 and relatively low with Example 5 regardless of threshold level.

Inlet Distortion

A relatively limited investigation has also been initiated to determine the effect of inlet distortion on stall margin estimation. The previously described transient run was performed with a partial flow blockage placed in front of the inlet. Results from this run are shown in Fig. 16. For this case, reference stall margin is not calculated because flow velocity is unknown. Since the blockage likely causes significant total pressure loss and the inlet sensor measures inlet static pressure, there is not enough information to calculate flow velocity. However, even if flow velocity were known, the reference stall margin would nonetheless be inaccurate since the inlet distortion has moved the surge line (pressure rise at surge in this case (3300 Pa) is significantly different than before with a nominal inlet (3500-3600 Pa)).

The plots do show that the correlation measure-based stall margin estimate exhibits the expected trend. However, the estimate is not quantitatively accurate and noticeably under-predicts stall margin. Repeated runs with the inlet distortion show that the high event frequency is a consistent phenomenon. Hence, it is likely the inlet distortion has altered the stall margin/event frequency relationship.

SUMMARY & CONCLUSIONS

A correlation measure-based stall margin estimation technique has been demonstrated and evaluated on a laboratory axial compressor rig. The correlation measure is a quantitative repre-

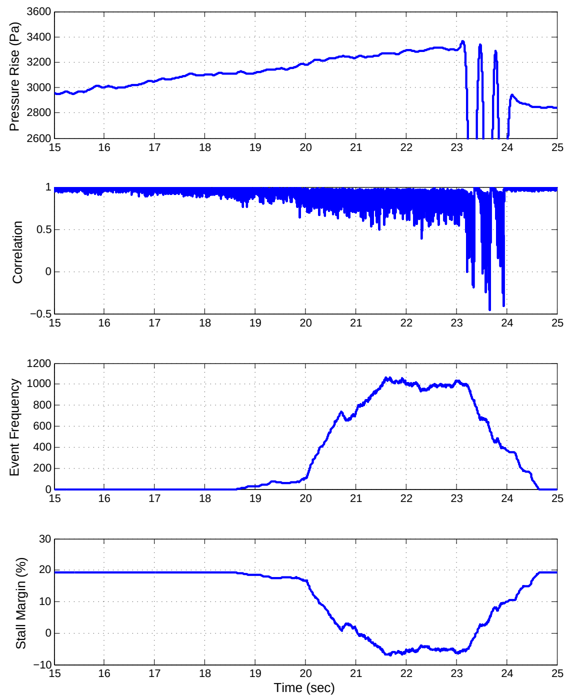

Figure 16. Stall margin estimation for transient run with inlet distortion.

sentation of the periodicity of the pressure in the flow field over the compressor rotor. Downcrossing frequency of the correlation measure across a preset threshold were monitored and mapped to compressor stall margin. This mapping was then used to estimate stall margin during ramp-to-surge transient runs.

The results of applying the estimation procedure are satisfactory. Out of 27 runs, more than three-quarters were considered to be relatively good quality estimates. The others, however, were either not useful as quantitative estimates of distance to surge, or worse, did not exhibit the expected trend. Since the correlation measure is directly calculated from the rotor tip pressure signature, these unfavorable instances are believed to be a result of the inherently stochastic and uncertain nature of that signal. However, it was shown that supplementing the stall margin estimation system with a surge proximity warning system derived from low-threshold crossings of the correlation measure may increase the robustness of the overall procedure to the variations seen in the experimental results.

The effects of inlet distortion were also briefly assessed. The inlet distortion was shown to have altered the location of the compressor surge line. The correlation measure-based stall margin estimation displayed the expected trend but were not quantitatively accurate. This was attributed to the inlet distortions affecting the relationship between event frequency and stall margin.

For future work, methods of increasing the robustness of the stall margin estimation procedure will be investigated. For instance, as mentioned previously, a possible area of examination may be the magnitude of the correlation measure downcrossings. Additionally, the issue of how to complement the estimation technique with the surge warning system will be researched in the context of application to engine control.

This work documents and evaluates the implementation of a stall margin estimation system in an experimental environment. For a robust control design, it is necessary to address the variability present in a measured signal. It is unlikely that a control law designed with an assumption of perfect measurement would yield expected results in practice. It is also unlikely that a very noisy measurement can provide useful, actionable information. The results presented here are an attempt to characterize stall margin estimation in an experimental setting and hence provide guidelines for future control system design.

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