A novel pattern-based approach for diagnostic controller performance monitoring

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ABSTRACT

This paper details a novel method for monitoring the disturbance rejection performance of controllers by applying a second-order underdamped model as a pattern recognition tool. A controller performance index based on the second-order model parameters classifies the patterns into diagnostic categories of sluggish, well-behaved and overly aggressive. The autocorrelation function (ACF) has been used in numerous performance assessment capacities, and this work builds on these successes by applying the pattern recognition method to automate the ACF assessment across the full range of disturbance rejection performance. In addition to the performance diagnostic, a pattern-based visual tuning guide is presented for retuning PI controllers to regain desired performance. The performance assessment method has been tested on numerous control loops in a 25 MW cogeneration power plant and results of the application are presented.

1. Introduction

Controllers keep measured process variables (PV) at set point (SP) to ensure a safe and profitable plant operation. Yet controllers are often tuned once and never readdressed, even though changes, for example in operating level, feedstock and mechanical wear, can cause the process dynamics to change and the controller performance to degrade.

A most notable start to controller performance assessment was Harris’ (1989) work that presented a means to establish the limit of achievable performance based upon a minimum variance controller assumption. With this method, the quality of control loops could be assessed without disrupting the process operation. Desborough and Harris (1992) took the work further by proposing a normalized performance index to indicate how far the process is from achieving minimum variance. Additional indexes and tools have been subsequently developed to allow remote identification of underperforming control loops. These efforts have been summarized in several good review articles (Harris, Seppala, & Desborough, 1999; Jelali, 2006; Qin, 1998; Thornhill & Huang, 2008). The work here focuses on single-input single-output control loops; for a promising approach to performance monitoring and diagnosis in multiple-input multiple-output loops, the reader is referred to Yu and Qin (2008a, 2008b).

Performance indices have been developed to not only indicate that performance has in general degraded, but also to diagnose controller behavior as oscillatory/aggressive (Thornhill, Huang, & Zhang, 2003; Thornhill & Horch, 2007; Xia & Howell, 2005; Zang & Howell, 2007) or sluggish (Hagglund, 1999, 2005; Kuehl & Horch, 2005). The identification of the full range of performance by means of a single metric remains an ongoing challenge and a novel approach is detailed in this work.

The methods that do diagnose the full range require preprocessing of the data to isolate a single deterministic load change event for each analysis. Salisbury’s R-Index method identifies disturbance events by tracking the autocorrelation of the error signal (error=SP–PV) using a short moving window (Salisbury, 2005). When a threshold is exceeded, the R-index is computed on the associated data. As shown in Fig. 1, peaks in the error signal are identified to develop an index based on areas between zero crossings. This area ratio index is classified by comparison with an idealized error-to-load change second-order underdamped model. Visioli developed an Area Index that takes a similar approach, but uses the peak area above and below where the controller output (CO) value settles after a disturbance and classifies it with the underdamped model (Visioli, 2006). The work suggests using a high-pass filter to distinguish qualifying events on which to compute the Area Index. For both methods, only one event is used in each analysis.

A challenge for these indexes is that underlying process noise causes variation in the peak and zero crossing points of the error signal, leading to variation in the results. To improve reliability, Salisbury suggested that the R-Index can be reported as an exponentially weighted moving average (EWMA) of several disturbance events.

1.1. This work

This paper details a method for using stochastic data to produce a performance index that classifies the full range of
controller behavior without the need to pre-process the data to isolate specific events.

Inspired by Salsbury and Visioli’s use of the second-order underdamped model, a novel direct approach for using the model as a pattern recognition tool is presented. Like the other methods, it is not necessary to define a model of the disturbance. Here, the direct application eliminates the need to identify peaks and zero crossings in the disturbance rejection pattern.

Unique to the method described in this work is that process data collected over hours and even days can be analyzed. An exciting contribution is that the resulting controller response pattern represents the average of all disturbance rejection activity during the data collection period. Real processes are affected by many disturbance types and each can present itself differently over the course of operation. The composite disturbance rejection pattern holds allure as a broadly representative snapshot of overall controller performance that cannot be attained with a single isolated disturbance event identified by data preprocessing.

The autocorrelation function (ACF) is used to generate this composite disturbance rejection pattern. The ACF is related to the closed-loop impulse response model and thus shares the patterns of the closed-loop impulse response model (Box & Jenkins, 1976). In several works (Desborough & Harris, 1992; Harris, 1989; Stanfelj, Marlin, & MacGregor, 1993), it is shown how the ACF can be used to determine if a controller is achieving minimum variance by computing a peak ratio index. The key feature of the second-order underdamped model is the damping factor which defines process behavior in a continuum of overdamped (sluggish) to underdamped (aggressive). Here, a look is given to a more direct application of the model for automating the controller pattern analysis.

2. Extension of the underdamped model for pattern recognition

Salisbury and Visioli had each defined performance indices based on ratios of areas calculated from isolated disturbance events in process data. Additionally, both presented categories of the indices to relate to a general underdamped model, defined as

\[
G_C(s) = -\frac{Y(s)}{R(s)} = \frac{\alpha_0^2 s}{s^2 + \beta s + \alpha_0^2}
\]

where \(\alpha_0\) is the natural frequency and \(\zeta\) is the damping factor. The classification of disturbance rejection patterns in the full range of overdamped (sluggish) to underdamped (aggressive) is marked by its simplicity. In effect, it provides a means to perform the automation. In addition, a solution to the problem of choosing the time window for the ACF for the analysis is presented. The method does not require \textit{a priori} process information, such as an estimate of dead time or process order, and it is markedly insensitive to noise and sampling rate, thus making the method directly applicable in industrial practice.

Finally, to provide further guidance to users, a tuning map method is presented to direct proportional and integral (PI) controller retuning. As in Visioli (2006), the guide gives a general indication of how to adjust the parameters, but further, it includes a visual component that enhances the usability. Tuning maps are presented for both self-regulating and integrating (non-self-regulating) processes, as it is important to distinguish the differences in controlling naturally stable and unstable processes.

The remainder of this paper is organized as follows. In Section 2, the newly proposed pattern recognition method and the Relative Damping Index (RDI) algorithm are developed. In Section 3, the ACF’s relationship to the closed-loop process is reviewed and an analysis of its application is presented. In Section 4, the methodology for applying the pattern recognition method to the ACF is detailed. In Section 5, the results of applying the automated ACF analysis on multiple loops of a cogeneration plant are presented. In Section 6, the tuning maps and retuning procedure are explained. And in Section 7, concluding remarks are made.

2.1. Direct application of the underdamped model

Rewriting Eq. (1) in the time domain provides a clearer approach to using the underdamped model in a direct pattern recognition application:

\[
z^2 \frac{d^2 y(t)}{dt^2} + 2\tau_n \zeta \frac{dy(t)}{dt} + y(t) = Ku(t)
\]

where \(\tau_n\) is the natural period of oscillation and \(K\) is a gain. The natural period of oscillation has units of time. When the model is applied for analyzing a pattern of disturbance rejection, its value can be used as a characteristic measure. It will be shown to be an essential component of the model fit because it allows the automated selection of the window size on which to assess the disturbance rejection pattern.

A direct model fit to a composite disturbance rejection pattern eliminates the need to precisely define the response peaks and

<table>
<thead>
<tr>
<th>(\zeta) Value</th>
<th>Dynamic closed-loop response</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\zeta &gt; 1)</td>
<td>Pure exponential decay—overdamped</td>
</tr>
<tr>
<td>(\zeta = 1)</td>
<td>Fastest exponential decay—critically damped</td>
</tr>
<tr>
<td>(0 &lt; \zeta &lt; 1)</td>
<td>Oscillations and exponential decay—underdamped</td>
</tr>
<tr>
<td>(\zeta = 0)</td>
<td>Pure oscillation—limit of stability</td>
</tr>
<tr>
<td>(\zeta &lt; 0)</td>
<td>Unstable</td>
</tr>
</tbody>
</table>

Fig. 1. Disturbance rejection trend features required for the calculation of the R-index.
zero crossings. And the damping factor from the model fit can be directly used in a performance index because of the classifications shown in Table 1. With the disturbance dynamics unknown, the performance index should not be based on an optimal damping factor, but rather on a user-defined desired controller performance.

2.2. User-defined performance index

For every control loop, an operator or engineer has expectations of how that loop should respond to disturbances. While some loops will be more important because of safety, economics or loop interactions, each response will have a desired behavior which fits a subjective niche of not being “too slow” or “too fast.” Therefore, to signal the operator or engineer when the loop is not performing as desired, a user-defined performance index is developed.

The relative damping index, RDI, shown in Eq. (3), is based on the actual damping factor, \( \hat{\zeta} \), which is computed in the underdamped model fit to the disturbance rejection pattern. The index can be adjusted relative to the user preference by changing \( \zeta_{agg} \), the limit of acceptable aggressive behavior, and \( \zeta_{slug} \), the limit of acceptable sluggish behavior:

\[
RDI = \frac{\hat{\zeta} - \zeta_{agg}}{\zeta_{slug} - \zeta_{agg}} \tag{3}
\]

The index can be reported in three simple categories as presented in Table 2. The magnitudes of negative RDI values directly relate to the interpretation of the damping factor in that RDI values greater than 1 indicate sluggish behavior and RDI values less than 1 indicate aggressive behavior. Note that an exception is necessary for the case \( \zeta_{act} = \zeta_{slug} \), for which the RDI value should be set to zero.

The flexibility of the benchmark allows users to make the assessment stricter for the high importance loops and looser where variation can be tolerated.

Additionally, the user-defined parameters allow for differences in loop expectations due to the nature of the process, i.e. self-regulating vs. integrating (non-self-regulating). A self-regulating process has a natural balance point such that in open-loop when disturbances are quiet, it will settle at a particular operating level. Consider, for example, a heat exchanger. For each particular residence time, the exchanger exit temperature will steady at a particular value.

An integrating process does not have this natural balance point. For example, the level of water in a boiler producing a constant steam flow will steadily rise or fall if the mass flow of water in does not match the mass of steam out. Without active control to make the mass flow in equal the mass flow out, an integrating process will not stabilize. Integrating processes controlled with PI controllers typically display overshoot in the set point tracking response, where as proper tuning can often eliminate this in self-regulating processes (Cooper, 2008).

The choice of the parameters will be discussed further in Section 6.

2.3. Disturbance dynamics

When the second-order underdamped model is applied as a pattern recognition tool to analyze a disturbance rejection pattern, it is not possible to distinguish whether performance changes originate in the process or disturbance, only that the transfer function, \( G(s) \), is different. It is stressed, however, that although the changes cannot be automatically assigned to either the disturbance or process, the recognition that the transfer function is different indicates changes in the controller’s disturbance rejection performance and thus points to the need to reexamine the control loop.

3. Extracting disturbance rejection patterns with the ACF

Using an autoregressive moving average (ARMA) model to represent the closed-loop process, Box and Jenkins (1976) showed how the characteristic disturbance rejection response is related to the ARMA coefficients. While the exact process model parameters are not determined by the ACF, it is used to determine the ARMA model orders, \( p \) and \( q \). In applying the ACF as a process monitoring tool, it has been shown to approximate the settling time of the closed-loop process (Desborough & Harris, 1992; Harris, 1989; Stanfelj et al., 1993) and indicate oscillations in the process signal (Qin, 1998; Seborg & Miao, 1998; Thornhill et al., 2003). Until now though, a pattern recognition method has not been used to automate the analysis of the ACF to characterize the full range of controller responses.

The ACF coefficients are computed for a data set, \( y \), according to

\[
r_{yy}(k) = \frac{1}{N-k} \sum_{i=1}^{N-k} (y(i) - \bar{y})(y(i-k) - \bar{y}) \tag{4}
\]

\( r_{yy} \) is calculated for \( k = 0, 1, \ldots, (N-1) \), where \( k \) is the number of sampling periods between observations (\( k \) is often called the lag; Box & Jenkins, 1976). \( \bar{y} \) is the average of the series of \( y \) measurements, \( \sigma^2 \) is the variance of \( y \) and \( N \) is the total number of data samples. There is no windowing necessary in computing the ACF, rather the calculation is performed on several hours to days of data with a resulting ACF coefficient relating to each possible distance between data points, 0 to \( (N-1) \). Because in practical application the data series is discrete and of finite length, the unbiased expression is applied by limiting the summation to \( (N-k) \) and dividing by \( (N-k) \).

To review the ACF’s relationship to the closed-loop model following Box and Jenkins, an ARMAX model (ARMA with exogenous disturbance input) is used to represent a z-domain transfer function of a general closed-loop measured process variable response to a disturbance change as

\[
Y(z) = \frac{(\psi_0 - \psi_1 z^{-1} - \cdots - \psi_q z^{-q})}{(1 + \phi_1 z^{-1} + \phi_2 z^{-2} + \cdots + \phi_p z^{-p})} D(z) \tag{5}
\]

The linear difference equation of this ARMAX model is

\[
y(i) = \phi_1 y(i-1) + \phi_2 y(i-2) + \cdots + \phi_p y(i-p) - \psi_0 d(i-1) - \psi_1 d(i-2) - \cdots - \psi_q d(i-q) \tag{6}
\]

Now the ACF coefficients for this process can be found by applying Eq. (4) in a step-wise fashion. First, the data set is mean-centered about zero by subtracting the average, \( \bar{y} \), from each point in the data series, \( y \). To simplify the expression, substitute \( \tilde{y}(i-x) = y(i-x) - \bar{y} \).

Second, multiply the equation by a sample-shifted point, \( \tilde{y}(i-k) \), to obtain

\[
\tilde{y}(i-k) \tilde{y}(i) = \phi_1 \tilde{y}(i-k) \tilde{y}(i-1) + \phi_2 \tilde{y}(i-k) \tilde{y}(i-2) + \cdots + \phi_p \tilde{y}(i-k) \tilde{y}(i-p) - \psi_0 \tilde{y}(i-1) - \psi_1 \tilde{y}(i-2) - \cdots - \psi_q \tilde{y}(i-q) \tag{7}
\]
Third, sum the product terms from \(i=1\) to \(N-k\) and divide by \((N-k)\) to obtain the theoretical expected value. At this step, taking the expected value yields covariance coefficients. Define the autocovariance values \(\gamma_{yy}(k)\), for \(y(i-k)y(i)\) terms, and cross covariance values, \(\gamma_{yp}(k)\), for \(y(i-k)p(i)\) terms. In making these substitutions for the expected values, Eq. (7) becomes

\[
\gamma_{yy}(k) = \phi_1 \gamma_{yy}(k-1) + \cdots + \phi_p \gamma_{yy}(k-p) - \psi_q \gamma_{yy}(k-q) - \cdots - \psi_q \gamma_{yy}(k-q) \quad \text{for } k = 0, \ldots, p
\]

For the final step of the ACF coefficient computation, normalize the equation by dividing by the autocovariance at \(k=0\) i.e. the variance of \(y, \sigma^2\). The resulting equation shows how autocorrelation coefficients relate to past autocorrelation coefficients and past cross covariance coefficients:

\[
r_{yy}(k) = \phi_1 r_{yy}(k-1) + \cdots + \phi_p r_{yy}(k-p) - \psi_q r_{yy}(k-q) - \cdots - \psi_q r_{yy}(k-q) \quad \text{for } k = 0, \ldots, p
\]

This equation for \(r_{yy}(k)\) has the same model coefficients as the process in Eq. (6). Because they are the same, each ACF coefficient computed using Eq. (4), \(r_{yy}(k)\), contains the same weighting of process and disturbance values as the process point, \(y(i)\), in the linear difference model. Thus, a plot of the ACF coefficients will reveal the pattern of the closed-loop disturbance rejection behavior. While each \(r_{yy}(k)\) can be computed using Eq. (4), the disturbances are unmeasured, so the \(\gamma_{yp}(k)\) terms cannot be directly calculated. Therefore, the ACF cannot lead directly to a complete process model.

### 3.2. ACF sensitivity

The ACF was first tested with simulations under a wide variety of conditions to ensure that it serves as a reliable means to extract the disturbance rejection patterns. Hundreds of simulations were run for both self-regulating and integrating processes using first, second and third order transfer functions controlled with PI and PID controllers. Within each subset of transfer functions, the process gain, time constant and dead time were varied to test a complete range of disturbance rejection behaviors. Additionally, to replicate industrial conditions, the noise level and sampling rate were varied.

The ACF results presented in Fig. 3 highlight the findings of the study. In these representative cases, nine process transfer functions were each tested under five conditions: moderate conditions, fast sampling, slow sampling, no noise and high level of noise, as will be further defined. As real processes undergo changes while the controller tuning is fixed, here the tuning

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**Fig. 2.** Steam drum boiler level data captured during a large disturbance event is scaled for direct comparison to the ACF computed from a series of regulatory data without such significant events.
Fig. 3. Five ACF results for each of the nine self-regulating process cases. For each process a standard ( ), double noise ( ), no noise ( ), fast sampling ( ) and slow sampling ( ) example is presented.

parameters are designed for the center/base case process and these same parameters are used for all 45 simulations presented. Also, in these runs, the disturbance transfer function remains fixed, as it is the overall range of disturbance rejection patterns that is being assessed.

Each ACF pattern was generated by simulating several hours of the controlled process perturbed by a step-wise shifting disturbance. The ACF coefficients of the collected PV data were then computed using Eq. (4). The drifting disturbance pattern was unique for every run as produced by a random number generator which varied both the step size and the step timing. Each plot is graphed on the same time scale to highlight the range of disturbance rejection responses.

The center/base case process is specified by the third order self-regulating transfer function in Eq. (12) and the disturbance is specified by Eq. (13):

\[
\text{Base case: } Y(s) = \frac{15e^{-3s}}{(15s+1)(5s+1)(2s+1)} U(s) \quad (12)
\]

\[
\text{Disturbance: } Y(s) = \frac{1e^{-1.5s}}{(17s+1)(4s+1)(s+1)} D(s) \quad (13)
\]

The PI controller tuning parameters were determined using Internal Model Control correlations using a closed-loop time constant \( \tau_c \) set as \( \tau_c = 0.5 \tau_P \). This yields a controller gain of 0.65%/% and an integral time of 17 s when using the ideal dependant form of the PI controller (Cooper, 2008).

For the additional eight processes, the models were chosen by doubling and halving the Base Case process gain and time constants in the combinations indicated on the plot. The dead time variation is not presented here because the matrix of selected parameter changes produces a full range of representative responses, from overly aggressive to overly sluggish.

3.2.1. Signal noise

The ACF yields a representative disturbance rejection pattern even if the signal noise does not allow clear visual identification of disturbance events. Yet there must be disturbances which move the process outside of the signal noise band in order for the correlations to be strong enough to represent a complete pattern of behavior. It is reasonable to assume that in an actual plant, if the process is not affected by sufficient disturbance activity over long periods for analysis, it is likely the loop is well-behaved in normal operation.

For this simulated study, the process signal noise band is defined as the range of variation in the process variable measurement when the controller output and disturbances are stationary. Here it is quantified in terms of standard deviation, \( \sigma \), such that 99.7% of the signal trace will lie within \( \pm 3 \sigma \) of its steady state value.

In Fig. 3, the standard signal noise band is \( 3\sigma = 0.5\% \) of signal range (0–100%). Cases are also shown with no noise and doubled noise \( (3\sigma = 1\%) \). While the noise band is not large compared with the full signal range, it is significant compared to the range of the disturbance activity. The randomly generated disturbances were unique for every run, but on average the disturbance causes the process to move \( \pm 0.65\% \) away from its steady state value with a maximum deviation of \( \pm 2.9\% \). As the results show, even when the noise level masks most of the disturbance activity, the disturbance rejection pattern is clearly depicted with the ACF. The random noise is cancelled while the non-random components driven by the controller are revealed.

When the signal variance is due to random noise and not disturbance activity, the ACF will also appear as a random noisy trend. To automate the distinction between a meaningful response pattern and noise, the ACF value at \( k = 1 \) should be checked to ensure the value is greater than 0.5. The ACF signal strength will indicate that there is sufficient activity outside the noise band.

3.2.2. Sampling rate

The data sample rate is an important consideration in using any performance monitoring tool. The data used in analysis must represent the whole picture of the process activity and contain the relationships between data points. While the ACF can piece together the disturbance rejection patterns from the various events within the data set, it is still necessary to sample often enough to capture parts of every event. As defined by the Nyquist sampling rate, the process data must be sampled twice as fast as the highest signal frequency to be represented in the analysis. Slower sampling will not be able to detect changes in the high frequency components of disturbance response patterns, such as oscillations within the response.

Fig. 3 includes cases of sampling twice, 10 times, and 20 times per overall process time constant. The slow sampling rate causes some information in the pattern to be lost, but the overall settling time and shape is maintained. To ensure that the process is adequately sampled even if it begins to change over time, the industrial best practice sample rate for PID control of 10 times per overall time constant or faster (Cooper, 2008) is recommended also for performance analysis.

Inadequate sampling may also cause the ACF pattern to appear as noise because the correlations do not exist between the widely spaced samples. The previously suggested check for sufficient disturbance activity, \( r(1) > 0.5 \), will also fit these cases. While online process data is ideal for analysis, data from a process historian that is properly configured with small compression and exception bands will also work (Thornhill, Choudhury, & Shah, 2004).

3.3. Disturbance types

Because the ACF cannot distinguish the actions of the controller from the nature of the disturbance, it cannot identify the root cause of performance changes. Thus, particularly for determining plant-wide oscillations, it would be beneficial to use this method as part of a performance analysis package that
examines loop interactions and compares the frequency of oscillations with upstream and downstream control loops to identify where the disturbance originates. While the ACF does not contain this diagnostic information, the identification of underperforming control loops will give the initial indication that a loop needs attention. Using the ACF as a first check of acceptable performance will screen out well-behaved loops and further diagnostic analysis can be focused on underperforming loops.

3.4. Set point tracking

An additional consideration is the analysis of control loops that experience set point changes. By running the ACF analysis on the process error (error=set point–process variable) rather than on the process variable, both set point tracking responses and disturbance rejection responses are averaged. This is an acceptable application of the analysis, however it is not the focus of this work because unlike disturbance events, set point changes are easily identifiable, many loops do not experience them regularly and methods exist to automatically characterize their performance (Swanda & Seborg, 1997, 1999). Set point changes will tend to dominate the pattern of the ACF, thus masking the disturbance rejection performance, so they are best handled independently.

4. Automating the ACF pattern classification with the underdamped model

With the ACF verified as a reliable means to extract the disturbance rejection patterns, the novel second-order underdamped pattern recognition method can be applied to automate its analysis. The patterns of the ACF can be treated as the result of a step change in the disturbance and the second-order model shown in Eq. (2) characterizes the dynamics of the response.

In fitting the underdamped model to the ACF patterns, the primary interest is in the gain, K, for ensuring the quality of the collected process data, the period of oscillation, τn, for determining the length of the ACF, and the damping factor, ζ, for categorizing the shape of the response.

A crucial component of the model fit is the selection of the length of the ACF to analyze. The ACF is calculated over the range of delays from 0 to N, where N is the end of the data set. The important information for performance analysis is the initial values where the data is related due to controller/disturbance influence before it settles within the noise band.

Confidence intervals have been used to assess the ACF settling time (Desborough & Harris, 1992; Stanfelj et al., 1993). While this method allows for the determination of the settling time and a sense of the window length required for viewing the disturbance rejection response, an alternative method was designed for the model fitting applications in this work. The novel approach makes further use of the underdamped model parameters and their information about the dynamic closed-loop process response.

The natural period of oscillation, τn, provides the necessary time scale for choosing the appropriate ACF length. By fitting the underdamped model to the full length-N ACF, an initial τn can be determined. Then the ACF can be cropped to a length of 10 τn which fully captures the dynamic data. A new underdamped model can then be fit to the shortened data set to check if τn is consistent. If it is significantly different, the process can be repeated. In this iterative model fit and cropping approach, τn typically converges in 2 or 3 iterations.

This novel approach to determining the ACF window size is more appropriate for the ACF analysis than the confidence interval approach because the ACF does not always fully settle.

4.1. Controller performance assessment algorithm

Step 1: Collect several hours of measured process variable data.
Step 2: Compute the ACF coefficient, ryy(k), for k=0,1,…N using Eq. (4).
Step 3: Check that ryy(1) > 0.5 to ensure sufficient activity and sampling rate. If ryy(1) ≤ 0.5, confirm proper sample rate and return to Step 1.
Step 4: Fit the second-order underdamped model of Eq. (2) to the ACF.
Step 5: Crop the ACF length to include only the terms up to 10 τn. Refit the second-order model.
Step 6: If τn,new ≈ τn,old, then compute the RDI with Eq. (3) and predetermined limits, else return to Step 5 using τn=τn,new.
Step 7: Report the RDI and consider retuning if the value is negative.

5. Example application results

The ACF method was tested on data collected in the cogeneration power plant at the University of Connecticut. This plant has a 25 MW electric capacity and a 200,000 lbs/h steam capacity which fully supports the main Storrs, CT campus. In this cogeneration plant, electricity is produced with three 7.5 MW natural gas fired combustion turbine generators (CTG) and one 5 MW steam turbine generator (STG). The CTG exhaust enters a heat recovery steam generator (HRSG) where boilers produce 600 psi steam for the STG operation and 125 psi steam for direct campus heating and indirect campus cooling by means of steam driven chillers.

Fig. 5 highlights the applications analyzed in this work. The applications are the previously discussed boiler drum level control of the low pressure (LP) steam drum, an import/export control loop regulating the CTG operation and an attemperator control loop which regulates the temperature of high pressure (HP) steam leaving a HRSG.

In this section, the import/export control and the attemperator control are explored, both of which are self-regulating processes where a fast response is desired and slight overshoot is acceptable. For the automated RDI analysis, the user-defined
parameters are selected as $\zeta_{\text{agg}} = 0.6$ and $\zeta_{\text{slug}} = 0.8$. A further look at the selection of these parameters will be presented in Section 6.

5.1. Import/export control

Because of the university’s power plant construction agreements with the state, excess electricity put onto the grid is uncompensated. Therefore, it is most economical to operate the plant to exactly meet the demands of the campus. A master controller regulates the operating speed of the CTGs in order to match the electric load of the campus while separate control loops and auxiliary boilers operate to meet the steam load.

The CTGs have a very fast response time ($\tau_c \approx 3$ s time constant), so even a short data set can contain a large amount of information about the activity of the control loop. An hour of closed-loop import/export data was analyzed with the ACF, and the resulting trend cropped to $10 \tau_n$ is plotted in Fig. 6. Oscillations in the controller response are clearly visible with the ACF plot, and the aggressive behavior is confirmed with the underdamped model fit yielding $\zeta = 0.13$ and $\tau_n = 0.03$ min. Using the user-defined parameters selected above, Eq. (3) yields an $RDI = -0.7$ which is categorized as “too aggressive.”

To eliminate the cycling in the import/export, the controller was retuned. The initial controller tuning was a controller gain, $K_C = 3\%$ and an integral time, $\tau_I = 1$ min for the dependant ideal PI controller. Additionally, a rate limiter filtered the controller output signal to prevent the process from becoming unstable. Loop-Pro commercial software from Control Station, Inc. was used to retune the controller. In improving the tuning, the gain was changed to $K_C = 0.2\%$ and the integral time to $\tau_I = 0.06$ min. The drastic change in the gain eliminated the need for the rate limiter.

With the new tuning implemented, another hour of data was collected and analyzed. Fig. 7 shows the ACF and the underdamped model fit. The new model parameters are $\zeta = 0.64$ and $\tau_n = 0.06$ min, yielding an $RDI = +0.25$. The improved performance not only eliminated cycling of the campus load, but it also reduced the constant speed changes in the CTG operation which significantly reduces wear to the machinery.

Fig. 8 shows before and after disturbance events scaled and plotted with the ACFs. While the patterns do not match perfectly, the overall trends are captured which allows the important dynamic information to be reported by the $RDI$.

5.2. Steam temperature control

A second cogeneration power plant application explored in this work is an attemperator control loop. This loop regulates a spraywater control valve to maintain high pressure steam at $750^\circ$ F. It is desirable to keep the steam quality to the STG

Fig. 5. Simplified cogeneration plant diagram highlighting the LP boiler level control, the attemperator steam temperature control and the kilowatt control loop.

Fig. 6. Initial ACF (-----) and associated underdamped model fit (- - -) for the KW import/export control loop.

Fig. 7. ACF (-----) and associated underdamped model fit (- - -) for the KW import/export control loop after retuning.
constant so that the power generation is consistent and the machinery is not subject to warming and cooling effects.

Twelve hours of temperature data was collected and analyzed with the ACF. The resulting trend and underdamped model fit are shown in Fig. 9. The slow decay of the controller response suggests the behavior is too sluggish. This is confirmed with the underdamped model yielding $\zeta=1.5$ and $\tau_n=0.79\,\text{min}$. In this application, the $RDI=-1.3$, which is categorized as too sluggish.

To improve the temperature regulation, the controller was retuned. The initial controller tuning was a controller gain, $K_C=5.5\%/%$ and an integral time, $\tau_I=0.9\,\text{min}$. Tuning analysis yielded a $K_C=2.5\%/%$ and $\tau_I=0.6\,\text{min}$.

After retuning, another 12 h of temperature data was collected and analyzed. The ACF results are plotted in Fig. 10. The new model parameters are $\zeta=0.68$ and $\tau_n=1.3\,\text{min}$, yielding an $RDI=+0.67$. The improved performance achieved a faster response time without significant oscillation.

Fig. 11 shows the before and after ACF with scaled disturbance events. As seen with the import/export loop, the ACF does not have a perfect pattern match, but it does represent the overall trends of the disturbance rejection response patterns.

6. Controller retuning and user guidelines

In the applications presented in Section 5, open-loop tests were performed and analyzed with tuning software (Cooper, 2008) to derive new tuning parameters. For some processes, the required tests are too intrusive on the plant operation. Since the ACF is providing visual information about the controller response pattern, it is possible to build a visual guide for controller retuning. Iterative approaches to controller retuning based on controller performance metrics have been established (Goradia, Lakshminarayanan, & Rangaiah, 2005; Tan, Zhao, Chua, Ho, & Tan, 2006) and here a similar approach using a tuning map is suggested.

Fig. 12 shows tuning maps for self-regulating and integrating processes. These maps were created by starting with a simulated closed-loop process tuned to have the desired controller disturbance rejection response. A simulation was run with a step disturbance perturbing the process as initiated by a random number generator. The ACF of the data was then computed and plotted. Similar tests were run with the controller tuning changed by doubling and halving the controller gain, $K_C$, and the integral time, $\tau_I$, and then plotting the associated ACF patterns around the
desired ACF. To add to the visual orientation of the tuning map, underdamped models were fit to each trend to provide the time scale of the plot and additional guidance towards retuning.

Separate maps are presented for self-regulating and integrating processes because the tuning parameters should be chosen according to the nature of the process. It can be seen in the center plot of the maps that although the processes have both been tuned with IMC standards, they display different patterns of behavior.

When a controller has been identified as poorly tuned, the operator or engineer can compare the actual ACF pattern with those of the tuning map. By identifying where the current behavior fits in the map, the direction of changing $K_C$ and $\tau_I$ to achieve the desired behavior can be selected. The choices should be made conservatively, as the retuning process can be performed iteratively until the ACF indicates that the desired performance has been achieved.

6.1. Examples of tuning selection

The initial attemperator RDI indicated that the controller response was too sluggish. Using the self-regulating tuning map, the initial ACF pattern is consistent with the plots in the right-hand column. This would indicate that $\tau_I$ should be decreased to achieve the performance desired in the center plot. If the tuning were done iteratively, the $\tau_I$ change could be made and then the ACF reassessed to determine further tuning adjustments. The actual tuning changes listed in Section 5.2 are consistent with the map in that both $\tau_I$ and $K_C$ were decreased to achieve the desired performance.

In the steam drum level example of Sections 3.1 and 4, the initial damping factor was $\zeta=0.28$ and the period of oscillation was $\tau_n=2.9\text{ min}$. Using the integrating process tuning map, one can identify that the initial behavior lies in the left-hand column and the integral time would need to be increased to achieve the behavior of the center column. Indeed, the tuning of the main level controller was changed from $K_C=1.5^{\tau_n}$ and $\tau_I=1.1\text{ min}$ to $K_C=1.1^{\tau_n}$ and $\tau_I=3.3\text{ min}$. Collecting new level data, computing the ACF and fitting the underdamped model gave $\zeta=0.43$ and $\tau_n=1.05\text{ min}$, which aligns with the desired behavior shown in the center plot.

6.2. RDI guidelines

These maps also provide guidelines for selecting RDI parameters. The choice of $\zeta_{agg}=0.6$ and $\zeta_{slug}=0.8$ in Section 5 comes from the desired performance of the center plot at $\zeta_{act}=0.7$. Likewise the choice for an integrating process can be set as $\zeta_{agg}=0.3$ and $\zeta_{slug}=0.5$ because the desired value in the center plot is $\zeta_{act}=0.4$. Since the time scale is independent of the RDI parameter selection, these values can be used as a general rule-of-thumb for any loop type (flow, level, temperature, concentration) as long as it is determined if the loop is self-regulating or integrating.

7. Conclusions

In this paper, a novel pattern recognition method was developed for automating the analysis of the ACF for use in controller performance monitoring. The analysis includes a user-defined performance index that is descriptive of controller behavior in the full range of too sluggish to overly aggressive. The application of the method was tested in a cogeneration power plant and representative results were presented.

It was shown that the ACF captures the average disturbance rejection patterns from events occurring during the data sampling, thus providing results that are more reliable than indexes based on individual events. Additionally, operating conditions that could affect the analysis were considered and best practice guidelines were suggested.

Often control loops are affected by upstream disturbances and hydraulic issues, such as valve stiction. It is necessary to find the root cause of poor controller performance, thus the ACF analysis tool presented here can be used as a starting indicator of degraded performance or incorporated into a larger controller performance analysis package.

If the source of poor performance is the controller tuning, a tuning map method for retuning PI controllers without process tests was presented. Maps using the visual information of the ACF to guide tuning changes in an iterative fashion were shown for both self-regulating and integrating processes.

References


Cooper, D. J. (2004). Practical process control. Storrs, CT: Control Station Inc.


