A New Controller Tuning Method Based on the Relative Damping Index

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***Abstract*— This paper combines the use of the Harris index and the relative damping index (RDI) to give a new method for CPM-based controller tuning. The RDI is defined based on the disturbance impulse response, which is calculated as a by-product of the Harris index. The proposed technique provides controller settings that attain the best-achievable performance by careful and systematical changing of controller parameters. The method is demonstrated on a simulation model of a steel annealing plant.**

I. Introduction

In practice, it is the norm to perform controller tuning only at the commissioning stage and never again. A control loop that worked well at one time is prone to degradation over time unless regular monitoring and re-tuning is undertaken. Typically, 30% of industrial loops have poor tuning, and 85% of loops have suboptimal tuning. There are many reasons for the degradation of control loop performance, including changes in disturbance characteristics, interaction with other loops, changes in product/process characteristics (*e.g.* product grade and component wear). Also, many loops are still "tuned by feel" without considering appropriate tuning methods – a practice often leading to very strange controller behavior. The effects of poor tuning are then [2]:

- Sluggish loops do not respond to upsets, causing disturbances to propagate and degrade the performance of other interacting loops.
- Overly-aggressive loops oscillate, creating new disturbances and increasing the risk of plant shut-down.
- Operators put the loops in manual. The loops then are unable to respond properly, leading to degraded product quality, higher material and energy consumption, and decreased productivity.

Continuous performance monitoring is therefore highly recommended to detect performance degradation and re-tune the controller and sustain top performance.

Controller tuning is a traditional topic in standard control texts, and a large number of tuning methods and rules are available. However, most of them require experimentation with the open- or closed-loop system.

A new direction for controller tuning was initiated in [1], [3], [4], which treated controller tuning in the context of control performance monitoring, *i.e.* based on only routine operating data and knowledge of the process delay. This means that control performance measures are *continuously monitored* on a regular basis, *i.e.* during normal operation, performance statistics used to schedule loop re-tuning and automatically determine the optimal controller parameters. The methods have been further developed by Jelali [7], [8], [9] under the framework of *iterative controller re-tuning*.

Techniques following this approach consist of at least two components:

(i) A control performance index or metric that should be optimized, typically the Harris index (to be maximized) or the integral of absolute error (to be minimized).
(ii) A data-based diagnosis measure, typically the idle index or the area index, to indicate in which direction the controller parameters should be changed to obtain a better value of the performance index/metric.

In this paper, the Harris index (HI) in combination with the relative damping index (RDI) is used to give a new method for control performance method (CPM) based controller tuning for regulating stochastic disturbances. Instead of using the autocorrelation function, as was done in [6], the RDI is defined based on the disturbance impulse response (IR), which is calculated as a by-product of the HI. The technique originally proposed in [8] is now presented in more detail, improved to converge to the optimal controller settings in a minimum number of iterations, and applied for the first time in a realistic process-simulation environment.

The paper is organized as follows: Section II briefly reviews the Harris index. In Section III, the relative damping index based on the disturbance impulse response is introduced. Section IV presents the new controller tuning procedure. In Section V, some strategies for the variation of controller parameters are described. Section VI presents the results of the application on a simulation model of a steel annealing plant.

II. Harris Index

MVC-based assessment first described by Harris (1989) compares the actual system-output variance σ_y^2 to the output variance σ_{MV}^2 as obtained using a minimum-variance controller applied to an estimated time-series model from measured output data. The HI is defined as

$$\eta_{\mathrm{MV}} = \frac{\sigma_{\mathrm{MV}}^2}{\sigma_y^2}. \quad (1)$$

This index will of course be always within the interval [0, 1], where values close to one indicate good control with respect to the theoretically achievable output variance. Zero means the worst performance, including unstable control. No matter what the current controller is, only the following information about the system is needed:

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- Appropriately collected closed-loop data for the controlled variable.
- Known or estimated system time delay (τ).

To compute the HI from measured (closed-loop) output data, a time-series model, typically of AR/ARMA type, is estimated:

$$y(k) = \frac{\hat{C}(q)}{\hat{A}(q)}\varepsilon(k). \tag{2}$$

A series expansion, *i.e.* the IR, of this model gives

$$\begin{aligned} y(k) &= \left(\sum_{i=0}^{\infty} e_i q^{-i}\right)\varepsilon(k) \\ &= \underbrace{\left(e_0 + e_1 q^{-1} + e_2 q^{-2} + \ldots + e_{\tau-1} q^{-(\tau-1)}\right)\varepsilon(k)}_{\text{feedback-invariant}} \\ &\quad + \underbrace{\left(e_\tau q^{-\tau} + e_{\tau+1} q^{-(\tau+1)} + \ldots\right)\varepsilon(k)}_{\text{feedback-varying}}. \end{aligned} \tag{3}$$

The *feedback-invariant terms* do not depend on the process model or the controller; they are only functions of the characteristics of the disturbance acting on the process. Since the first τ terms are invariant irrespective of the controller, the minimum-variance estimate corresponding to the feedback-invariant part is given by

$$\sigma^2_{\mathrm{MV}} = \sum_{i=0}^{\tau-1} e_i^2 \sigma_\varepsilon^2. \tag{4}$$

The first IR coefficient, e_0, is often normalized to be equal to one.

III. Relative Damping Index Based on the Disturbance Impulse Response of Closed Loop

The tuning method proposed here is based on the automatic characterization of the disturbance IR to classify the controller behavior. The IR sequence is calculated as a by-product of the HI for stochastic (normal operating) data. Thus, a model of the disturbance is not needed. Also, running experiments on the process is not required.

An approach to automate the IR analysis is to fit a second-order-plus-time-delay (SOPTD) continuous model

$$G_{\mathrm{IR}}(s) = \frac{K_{\mathrm{IR}} e^{-T_{\mathrm{d,IR}} s}}{T^2_{0,\mathrm{IR}} s^2 + 2T_{0,\mathrm{IR}} D_{\mathrm{IR}} s + 1} \tag{5}$$

to the IR coefficients. The model estimation can be easily carried out by a least-squares technique, *e.g.* using the fminsearch function of the MATLAB Optimization Toolbox. The estimated parameters, the time delay $T_{\mathrm{d,IR}}$ and the damping factor D_{IR} provide measures of the disturbance rejection performance. $T_{0,\mathrm{IR}}$ gives an indication of how fast the disturbance is rejected by the controller. D_{IR} is related to its aggressiveness: if D_{IR} is greater than one, the controller behavior is overdamped; a value smaller than one indicates

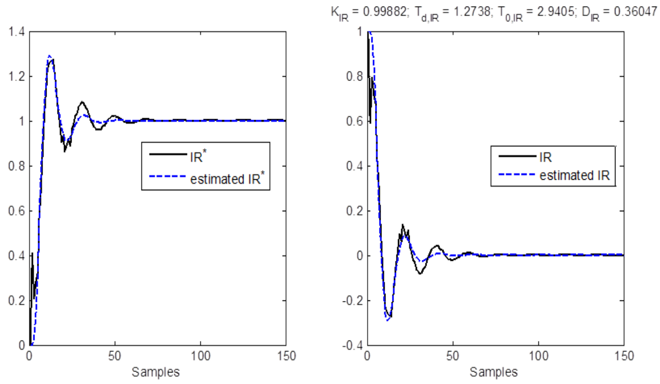

Fig. 1. Fitting of a SOPTD model to transformed IR (*left*); back-transformed IR and its approximation (*right*)

that controller behavior is underdamped with tendency to oscillate.

Prior to fitting, the IR sequence has to be transformed in such a way that it shows a behavior comparable with the step response of a SOPTD system. This can be achieved by $\mathrm{IR}^* = \max(\mathrm{IR}) - \mathrm{IR}$; see Figure 1. For this example, a SOPTD model with the parameters $K_{\mathrm{IR}} = 0.99882$, $T_{\mathrm{d,IR}} = 1.2738$, $T_{0,\mathrm{IR}} = 2.9405$ and $D_{\mathrm{IR}} = 0.36047$ has been estimated.

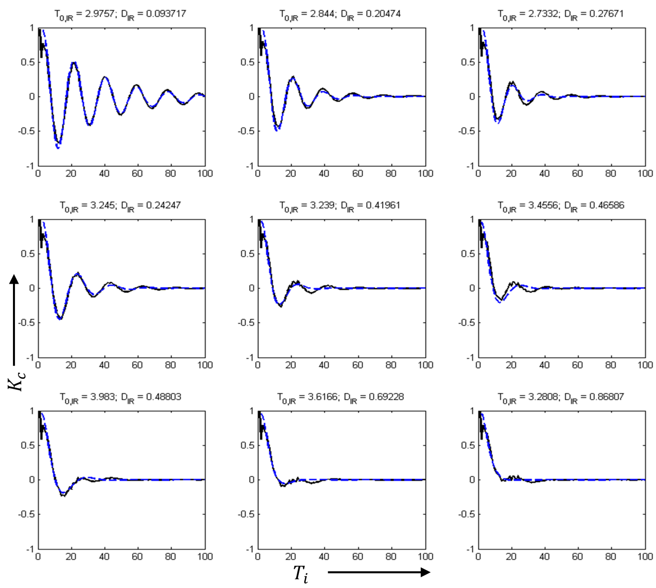

Fig. 2. A tuning map based on the IR damping factor

To get a relative measure of performance, the (IR-based) *relative damping index* (RDI) is defined, in a similar way to autocorrelation-based RDI [5], [6], as

$$RDI = \frac{D_{\mathrm{IR}} - D_{\mathrm{IR,agg}}}{D_{\mathrm{IR,slug}} - D_{\mathrm{IR}}}, \tag{6}$$

where D_{IR} is the damping factor of the fitted model, $D_{\mathrm{IR,agg}}$ the limit of aggressive controller behavior, and $D_{\mathrm{IR,slug}}$ the limit of sluggish controller behavior. These performance limits should be selected according to the desired performance specification, typically

- $D_{\mathrm{IR,agg}} = 0.6$ and $D_{\mathrm{IR,slug}} = 0.8$ for self-regulating processes,
- $D_{\mathrm{IR,agg}} = 0.3$ and $D_{\mathrm{IR,slug}} = 0.5$ for integrating processes.

The RDI can be interpreted as follows:

- If $RDI \geq 0$, *i.e.* $D_{\mathrm{IR,agg}} \leq D_{\mathrm{IR}} \leq D_{\mathrm{IR,slug}}$, the control performance is good, and there is no need for controller re-tuning.
- If $-1 \leq RDI < 0$, *i.e.* $D_{\mathrm{IR}} < D_{\mathrm{IR,agg}}$, the control behavior is aggressive, thus the controller should be detuned.
- If $RDI < -1$, *i.e.* $D_{\mathrm{IR}} > D_{\mathrm{IR,slug}}$ the control behavior is sluggish, thus the controller should be made more aggressive.

IV. Iterative Tuning Procedure

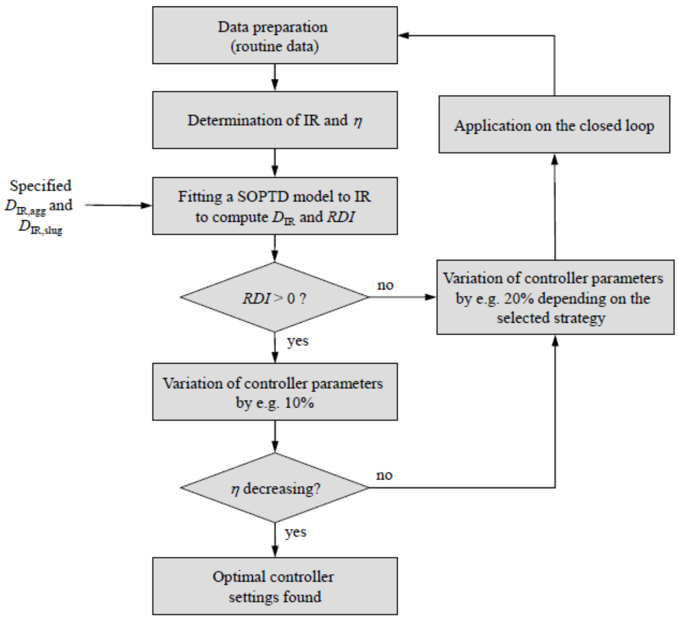

Fig. 3. Flow chart of iterative controller assessment and tuning based on the relative damping index [9]

Based on the RDI, a straightforward strategy for optimal controller re-tuning is proposed, as shown in Figure 3. The procedure starts with using a routine operating data set to determine the IR and the HI (η). The IR pattern is fitted to a SOPTD model to compute the damping factor D_{IR} and the RDI. As long as $RDI < -1$ or the HI is not decreasing, the controller parameters are changed according to the selected variation strategy, the current controller settings (ensuring a stable closed-loop system) are applied on the process, and a new operating data set is recorded.

This method is intuitive and can be completely automated. Simultaneously, the user has the possibility to specify the target performance region by selecting the corresponding limits $D_{\mathrm{IR,agg}}$ and $D_{\mathrm{IR,slug}}$. For stricter performance requirements, $D_{\mathrm{IR,agg}}$ has to be increased, and $D_{\mathrm{IR,slug}}$ decreased.

As the iterative technique presented above mimics the work of an optimization routine, there is a risk of trapping in local minima. This can happen when the objective function has such minima and bad starting parameters are selected. Therefore, it may be sometimes necessary to repeat the re-tuning task for different starting points, which means that the optimization work takes longer.

V. Strategies for Variation of Controller Parameters

Iterative controller tuning requires the specification of a proper step size for each controller parameter, usually given as percentage. Cautious adjustments to the controller parameters are necessary to guarantee closed-loop stability and performance improvement. There are many strategies for varying the controller settings in each iteration; see [4], [7], [9]. Some of them are described below, including their strengths and weaknesses.

Basically, a large step size helps to reduce the number of iterations required but may increase the risk that convergence is towards nonoptimal controller parameters. The number of iterations needed for re-tuning the controller depends on the specified IR damping interval [$D_{\mathrm{IR,agg}}$, $D_{\mathrm{IR,slug}}$]. The stricter the performance requirement is, *i.e.*, the narrower the interval limits are, the more iterations will be required. Moreover, it is recommended to start with a large step size if the initial controller behavior is too sluggish. As soon as $RDI \geq 0$ is reached, the step size should be reduced.

A. Variation of proportional gain alone and fine tuning of integral time

The simplest approach is to vary only the proportional gain (K_{c}) unless the existing controller is either too sluggish or too aggressive. In such cases, the integral time (T_{i}) can also be changed (but only one parameter at a time). Otherwise, the variation of K_{c} only should lead one to a value near the optimum, and then a "fine tuning" could be done by slight variation of T_{i}. Results from many simulations showed that an initial change of 20% in K_{c} or T_{i} in each iteration is reasonable to improve the controller without destabilizing the loop. If the resulting change in the performance index η is not significant, then the controller gain or integral time can be gradually increased up to 50% in the subsequent iterations [4]. However, this assumes that the current T_{i} value is not far from the optimum. It should be clear that the number of iterations required for finding the optimum depends directly from the step size.

Practically, some integral action is always desired in industrial environment for offset free set-point tracking and rejection of step-type disturbances. Hence, there should be at least moderate integral action in the final controller suggested, though this could come with a marginal drop in η.

Moreover, Goradia et al. [4] pointed out that the performance index takes a unimodal locus. Once the proper direction to improve the controller performance is determined, *i.e.* to make the controller aggressive or detuned, one can proceed iteratively in that direction as long as η is continually increasing. After reaching the peak, η starts to decrease even though we are moving in the same direction. The peak value of η is the PI-achievable performance. The change in control performance index (CPI) in any iteration should be accepted only if it is greater than or less than the inherent variation in the CPI.

B. Simultaneous variation

The simultaneous adjustment of the controller settings, *i.e.* decreasing K_c and increasing T_i (and possibly decreasing T_d) when the controller is aggressive and vice versa in the case of a sluggish controller, is the fastest method to find the optimal tuning. However, this approach is not transparent in practice and should be only considered by qualified users.

C. Successive variation

In this approach, the proportional term is tuned first until the highest performance index value is reached. This is followed by tuning the integral time and possibly derivative time, which may lead to further improvement in η. The three cases of controller tuning in this strategy are as follows:

1) If the estimated IR is similar to the sluggish IR profile, increase the proportional gain, K_c, until the highest η has been reached. Then, check the IR against the signature IR plots. If the controller is still sluggish (aggressive), decrease (increase) T_i until the highest η is obtained.
2) If the estimated IR is similar to the optimal IR profile, the controller is approaching optimal performance and does not need to be tuned too much. Slight tuning of the parameters by about 10% is sufficient to obtain the maximum performance index, i.e. to make sure that the maximum η has been crossed.
3) If the estimated IR is similar to the aggressive IR profile, decrease K_c until the highest η has been reached. Then, check the IR used to determine the optimal controller settings against the signature IR plots. If the IR plot is sluggish (aggressive), decrease (increase) T_i until the highest performance index is obtained.

This approach is highly recommended in practice owing to its transparency, although it usually takes more iterations than the simultaneous strategy.

VI. Application Example

A. Process description of the strip annealing furnace

Continuous annealing furnaces are widely used for heat treatment after cold rolling in flat steel production, with the aim to produce steel strips of high tensile strength and high formability. For the simulation study, a validated furnace model based on thermodynamic fundamentals [10] is used.

The simplified furnace design is shown in Figure 4. It is direct-fired with natural gas and has three connected chambers and the strip is running from the first to the third chamber. The furnace is divided into several zones, numbered in the direction of strip movement, each having different lengths. The goal of furnace is to heat up flat stainless steel as fast as possible to a reference temperature.

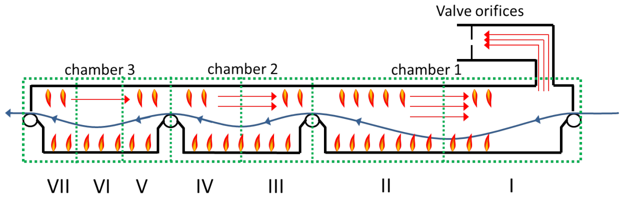

Fig. 4. A horizontal annealing furnace

B. Control structure

Each zone of the furnace has a gas temperature-control loop and is the inner loop of the cascaded control structure. The gas temperature references are set by an outer strip-temperature controller that compares the desired strip temperature with the outgoing strip temperature at the end of furnace.

The auto-tuning routine is applied to the inner gas control loop. Therefore, some assumptions are done to simplify the considered annealing process:

- The mathematical model of the continuous annealing line is reduced in length, so that only the first chamber is realized and the estimated strip temperature at the end of chamber one is treated as the outgoing strip temperature. The down-stream process, chamber two and three, is neglected.
- The gas reference temperature for both Zone 1 and 2 are set to a constant value.
- Measurement noise is realized by a user-defined pseudo-randomized signal that is applied to the simulation data.
- The incoming strip parameters, thickness and width, are randomized by a user-defined signal.

The control structure for the simplified model is shown in Figure 5. For this study, conventional discrete PI-controllers are used for the gas temperature control loops GC_1 and GC_2.

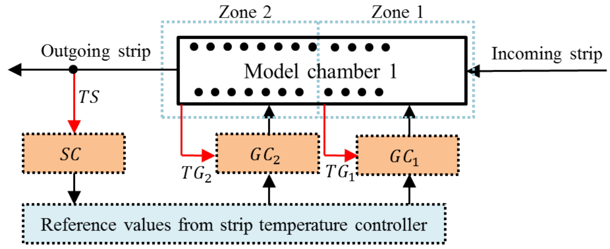

Fig. 5. Control structure under consideration

C. Simulation study

The focus of this simulation study is on the application of the auto-tuning routine to the continuous annealing process. In practice, the gas reference temperature and input parameters would vary over a wide range and control parameters have to be adapted to furnace power state and input parameters. To show the controller performance improvement, it is necessary to define constant input variables and gas reference values. In practice, the parameter optimization would be done for different furnace operating states. The incoming strip parameters are set to constant values, where to the width of $w_{\mathrm{in}} = 1296\,\mathrm{mm}$ and to the thickness of $t_{\mathrm{in}} = 0.7\,\mathrm{mm}$, an additive white noise with a standard deviation of 5% is applied. The strip velocity is set to $v_{\mathrm{in}} = 80\,\frac{\mathrm{m}}{\mathrm{min}}$ without measurement noise.

The main advantage of this tuning routine is the usage of normal operating data. The error vector $e(k)$ of the inner gas temperature control loop of Zone 2 is used to optimize the control parameters, as described in Figure 3. Preprocessing of the error vector is necessary because of furnace model realization. The initial conditions of the furnace are not completely at steady state, so that the transient time until the temperature inside the furnace reaches steady state is cut out to satisfy the calculation of the HI and IR coefficients.

In this case study, two mainly appearing different tuning tasks are investigated. The first is an aggressively-tuned controller, with the initial conditions $K_c > K_{c_{\mathrm{opt}}}$ and $T_{\mathrm{i}} < T_{\mathrm{i_{opt}}}$, where the index 'opt' indicates the optimal control parameter value. The second is a sluggishly-tuned controller with initial conditions $K_{\mathrm{c}} < K_{\mathrm{c_{opt}}}$ and $T_{\mathrm{i}} > T_{\mathrm{i_{opt}}}$. The gas-combustion system is treated as an integrating process and the limits of RDI calculation are set to $D_{\mathrm{IR,agg}} = 0.3$ and $D_{\mathrm{IR,slug}} = 0.5$.

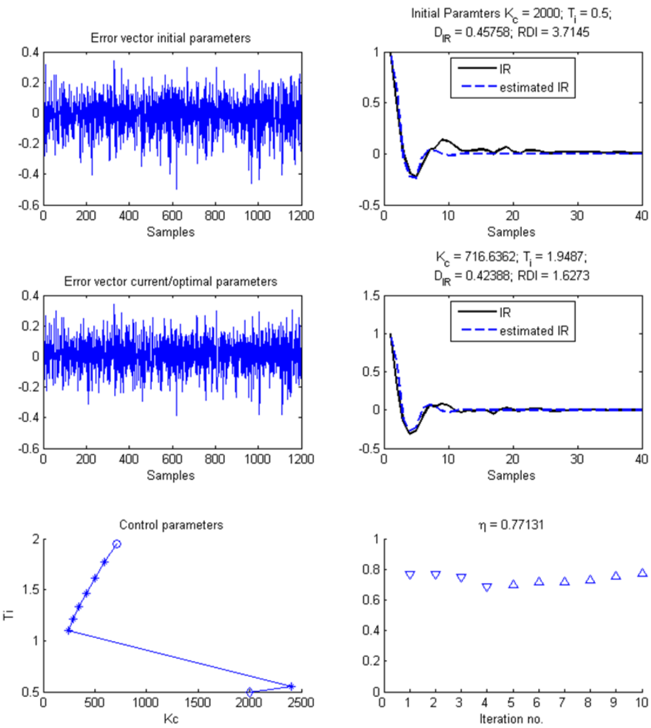

Fig. 6. Optimizations results for the initially aggressively-tuned gas temperature control loop

The auto-tuning routine was applied to the first case and the results are shown in Figure 6. The upper left time trend shows the preprocessed error vector with initial conditions. The middle right time trend shows the error vector after optimization was carried out. The time trends in the upper right of Figure 6 show the IR and the estimated IR before and the middle right time trend the results after the optimization. The lower left plot shows the history of control-parameter improvement during the iteration routine. Starting at the initial parameters $K_{\mathrm{c}} = 2000$ and $T_{\mathrm{i}} = 2\,\mathrm{s}$, shown by the diamond, until the optimal control parameters $K_{\mathrm{c}} = 716.6$ and $T_{\mathrm{i}} = 1.95\,\mathrm{s}$, shown by the circle. The lower right plot shows the development of HI with triangles. If the triangle direction is pointing up, η is increasing with respect to the previous iteration. A triangle pointing down shows a decreasing η.

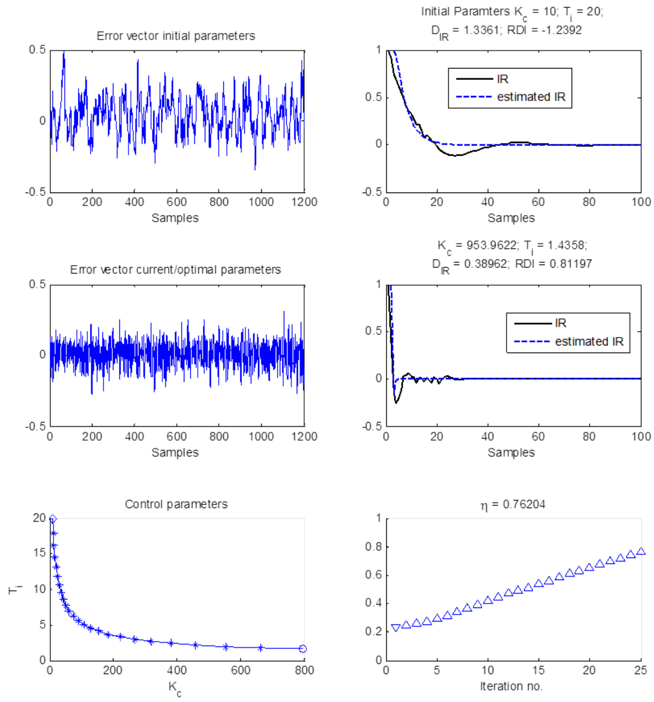

Fig. 7. Optimizations results for the initially sluggishly-tuned gas temperature control loop

Figure 7 shows the results of the sluggishly tuned controller, similarly organized as Figure 6. The initial parameter conditions are set to $K_{\mathrm{c}} = 10$ and $T_{\mathrm{i}} = 20\,\mathrm{s}$. Starting with the sluggishly tuned controller, the parameters are modified by the auto-tuning routine until the optimal parameters $K_{\mathrm{c}} = 954$ and $T_{\mathrm{i}} = 1.432\,\mathrm{s}$ are obtained.

D. Discussion of results

In both cases, the RDI auto-tuning routine converges to a solution near the optimal parameters region. The improvement of control performance is indicated by the increased value of HI and is satisfactory for further plant operation. In the case of the aggressively-tuned controller, an advanced strategy for parameters variation is carried out. In the second iteration step, the algorithm detects good controller performance, but parameter development runs in the wrong direction. Therefore, the parameter K_{c} is strongly reduced and T_{i} increased to make the control behavior more sluggish. However, the tuning results for the case of aggressive initial conditions is not as good as for the sluggishly tuned case. Possible reason is the furnace model that indicates open-loop behavior because of heating burner saturation. Also, due to the slow nature of the process, it was difficult to drive it to a highly aggressive behaviour of the oscillative type as in Figure 2 (top left). The area of optimum parameters is sensitive to the proportional part of controller and lies around $K_\mathrm{c} = 500$–1000 with a $T_\mathrm{i} = 1.2$–5 s.

VII. Conclusion

In this paper, a method to use the Harris index in combination with the relative damping index for a new CPM-based controller tuning is proposed. To improve closed-loop performance, the control parameters are changed systematically, based on operating data only. The proposed tuning method was applied to a simulation model of a steel annealing furnace to optimize the basic control loop. It turns out that the method works and leads to (near) optimal parameters, even for different starting values. The stability issue remains an open question. The application of the method thus requires *a-priori* knowledge of the parameter range, where the closed loop is assured to be stable.

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