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PID Controller Tuning for a Multivariable Glass Furnace Process by Genetic Algorithm

Kumaran Rajarathinam James Barry Gomm Ding-Li Yu Ahmed Saad Abdelhadi
Mechanical Engineering and Materials Research Centre, Control Systems Group, School of Engineering,
Liverpool John Moores University, Byrom Street, Liverpool, L3 3AF, UK

Abstract: Standard genetic algorithms (SGAs) are investigated to optimise discrete-time proportional-integral-derivative (PID) controller parameters, by three tuning approaches, for a multivariable glass furnace process with loop interaction. Initially, standard genetic algorithms (SGAs) are used to identify control oriented models of the plant which are subsequently used for controller optimisation. An individual tuning approach without loop interaction is considered first to categorise the genetic operators, cost functions and improve searching boundaries to attain the desired performance criteria. The second tuning approach considers controller parameters optimisation with loop interaction and individual cost functions. While, the third tuning approach utilises a modified cost function which includes the total effect of both controlled variables, glass temperature and excess oxygen. This modified cost function is shown to exhibit improved control robustness and disturbance rejection under loop interaction.

Keywords: Genetic algorithms, control optimisation, decentralised control, proportional-integral-derivative (PID) control, modified cost function, multivariable process, loop interaction.

1 Introduction

Glass manufacturing processes have very long dynamic response time and are complex processes with high energy usage. Especially, large furnaces with multiple port burners cause glass manufacturing industries to consume high energies in glass production. Most glass industries are operating at maximum daily throughput to fulfil the market requirement. Therefore, glass furnace operations are facing great challenges in reducing fuel consumption by applying well tuned control strategies. Apart from high energy consumption, undesirable emissions from glass industries is another setback to consider as the entire world is greatly concerned about green house effects. Tight environmental regulations are now applied to reduce gases and particles that are undesirable emissions associated with burning fossil fuels.

Generally, the glass industries are operating within the emission guideline which is regulated by environmental agencies[1]. Thus, most glass industries are not emphasising on continuous monitoring and control strategies for emissions. At maximum operating conditions, the likelihood of producing undesirable emission is high. If there is any occurrence of sudden undesirable disturbances, this can result in more problems for existing furnaces which may be already operating in poor thermal conditions around the world. The control of excess oxygen emissions, as well as glass temperature, is therefore also considered in this paper.

For such a complex multivariable process, a decentralised control strategy is generally applied and has always been in the attention of many researchers for developing a precise control strategy to enhance the performance of multivariable processes. However, difficulties are encountered in designing the decentralised control due to loop interactions.

A literature search reveals that there are several classified tuning methods suggested to tune decentralised controllers for multivariable processes such as detuning[2], sequential design[3], independent design[4] and iterative[5] methods. These tuning methods have achieved a certain degree of success in the design approach. However, these tuning methods do exhibit weaknesses and can suffer in compensating the couplings between loop interactions of a multivariable system. To improve the compensation of loop interactions, the effective open-loop (EOL) method was introduced[6]. The EOL method considers all other loop interactions while adapting the i-th control parameters for the i-th EOL. But, the EOL method produces model approximation error, due to mathematical complications, as the model dimensions are increased. Thus, the EOL method is mainly applicable for low dimension models. Another successful approach is that of relay auto-tuning, which is a combination of single loop relay auto-tuning and the sequential tuning method[7]. This method appears to perform well, but a multivariable system with large multiple dead time exhibits poor performance. In recent years, to improve the entire control performance and robust stability, a systematical approach based on the generalised internal model control, proportional-integral-derivative (IMC-PID) design method[8] and the reduced effective transfer function (RETF) by inverse response behaviour method[9] have been introduced for multivariable processes. But, both methods involve a complex mathematical approach to design the de-

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centralised controllers. In general, a question always arises about the wellness of control optimisation and the flexibility, due to the application constraints, of these design methods.

Standard genetic algorithms (SGAs) are global search methods by genetics evolution with higher performance in optimisation over traditional methods[10−12]. Due to their superior self-adjustable ability, SGAs have been applied extensively in tuning the PID parameters for single-input single-output (SISO) systems[13−15], curve fitting[16] and fuzzy optimisation[17]. On the other hand, application to multiple-input multiple-output (MIMO) systems is still an open research topic for optimising control parameters by SGAs. A promising decentralised controller by SGAs was proposed for a multivariable process[18]. The controller performance was defined by closed-loop response in terms of time-domain bounds for both reference following and loop interactions. An integrity theorem with SGAs to enhance the closed-loop system stability when certain loops are failing or breaking down was proposed[19]. Recently, improved convergence of genetic algorithms was achieved by introducing the multi-objective evolutionary algorithm (MOEA) which combines two fitness assignment methods (global rank and dominance rank)[20].

This paper investigates the potential of SGAs for optimising the discrete-time PID controller parameters in a decentralised control scheme for a multivariable glass furnace. The paper enhances and expands on initial results presented in [21]. The structure of this paper is as follows. First, an introduction is given about the considered multivariable glass furnace process and the models used for the controller optimisation studies. Second, the approach to optimisation by SGAs of discrete PID controller parameters is presented, with considerations to boundary constraints and particular cost functions. Third, investigations are presented on loop interaction effects and control robustness for the multivariable glass furnace, with controllers optimised by three SGAs tuning approaches. The proposed methods are developed and tested in simulations based on Matlab/Simulink models.

2 Multivariable glass furnace process and modelling

Fig. 1 illustrates the block diagram of the realistic multivariable glass furnace considered in this research, which consists of a state-space furnace model of 24 states with feedback loop and excess oxygen model. f_1 and f_2 are algebraic expressions, f_1 includes controller output and saturation, f_2 includes specific heat C_p and lower heat value (LHV) for determining the combustion energy, T_{SET} is the primary temperature setting, AFR is air-fuel ratio, T_{amb} is ambient temperature, $\dot{m}$ is fuel flow in mass, T_g is glass temperature, and EO_2 is excess oxygen.

The realistic glass furnace model that is identified and applied for further research here is representing a real plant combustion chamber from Fenton Art Glass Company, USA[22]. The furnace model is an extended research work by Holladay[23] using a radiative zone method to develop the 24 state space variables (zones) model. The linearised energy balance equations are applied and modified with respect to the 24 state variables for each zone corresponding to temperatures. For example, the energy balance equation of combustion zone $\alpha1$ can be written as

$$Ca_{\alpha1}\frac{\mathrm{d}Ta_{\alpha1}}{\mathrm{d}t} = Qa_{\alpha1} = Qbw_{\alpha1} + Qc_{\alpha1} + Qsw_{\alpha1} + Qa_{\alpha2} + Qg_{\beta1} + Qg_{\beta2} + Qg_{\chi1} + Qg_{\chi2} + Qg_{\delta1} + Qg_{\delta2} + Q_{in}. \quad (1)$$

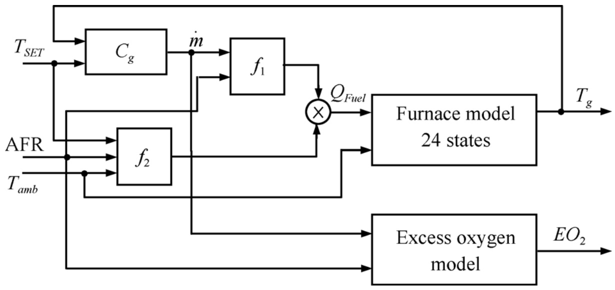

Fig. 1 Block diagram of realistic multivariable glass furnace process model

A literature survey reveals that there is no EO_2 realistic model for a glass furnace available for research. The realistic EO_2 model designed for research here was developed using collected data from an industrial furnace by an open-loop step response technique. SGAs were applied for identification of a higher order transfer function (3rd order) as a realistic model for EO_2, and control oriented models for both T_g and EO_2 for control optimisation. The identified transfer functions by SGAs are as follows:

For EO_2 realistic model,

$$\frac{\Delta EO_2(s)}{\Delta AFR(s)} = \frac{1.613}{50.3s^3 + 149.6s^2 + 142.7s + 1}\mathrm{e}^{-173s}. \quad (2)$$

For EO_2 control oriented model,

$$\frac{\Delta EO_2(s)}{\Delta AFR(s)} = G_{EO_2}(s) = \frac{1.6}{150s + 1}\mathrm{e}^{-174s}. \quad (3)$$

For glass furnace temperature control oriented model,

$$\Delta T_g(s) = G_{T_g1}(s)\Delta\dot{m}(s) + G_{T_g2}(s)\Delta T_{SET}(s) = \frac{4\,488.4}{1.992\times10^5 s + 1}\Delta\dot{m}(s) + \frac{-0.983\,4}{1.992\times10^5 s + 1}\Delta T_{SET}(s). \quad (4)$$

According to the collected data of EO_2, the model is designed based on a step input of air-fuel ratio (AFR ratio is 17.2:1 in mass). Changes in fuel flow $\dot{m}$ cause corresponding changes in air flow through the AFR. Since $\dot{m}$ does not alter the AFR and it is the AFR that affects EO_2, there will be no effect on the EO_2 when $\dot{m}$ is changed. However, any variation in air-fuel ratio will affect the outputs of f_1 and f_2 (Fig. 1) which leads directly to changes in $\dot{m}$ and hence, T_g. Therefore, the multivariable glass furnace process has single loop interaction from AFR to T_g under closed-loop influences. The identified control oriented model of the interaction was

$$\frac{\Delta T_g(s)}{\Delta AFR(s)} = G_{AFR}(s) = \frac{-61.5}{2\times10^5 s+1}. \tag{5}$$

The dynamics of the glass furnace process are therefore, represented by the following low order 2×3 transfer function matrix which is used for controller optimisation.

$$\begin{bmatrix} \Delta T_g(s) \\ \Delta EO_2(s) \end{bmatrix} = \begin{bmatrix} G_{T_g1} & G_{T_g2} & G_{AFR} \\ 0 & 0 & G_{EO_2} \end{bmatrix} \times \begin{bmatrix} \Delta\dot{m}(s) \\ \Delta T_{SET}(s) \\ \Delta AFR(s) \end{bmatrix}. \tag{6}$$

For a more complete control realisation of the EO_2 process, the realistic model transfer function (2) is associated with an AFR conversion model and EO_2 look-up table as illustrated in Fig. 2. The AFR conversion model was particularly designed to convert the real value of AFR(mass) to respective AFR(volumetric) based on the methane gas law. The transfer function (2) and AFR conversion model are linear. But, the EO_2 look-up table exhibits some nonlinear effects due to the methane chemical relationship between the stoichiometric AFR(volumetric) input and EO_2(%) output.

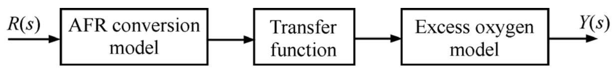

Fig. 2 Block diagram of complete realised EO_2 model

3 Discrete PID parameters optimisation by SGAs

In general, a classical PID controller can be described as an input–output relation expressed as

$$u(t) = K_c\left(e(t) + \frac{1}{T_i}\int e(t)\,\mathrm{d}t + T_d\frac{\mathrm{d}e(t)}{\mathrm{d}t}\right) \tag{7}$$

where u is the control signal, e is the error signal, and K_c, T_i and T_d denote the proportional gain, the integral gain and derivative gain, respectively. By using finite difference approximations, (7) is expressed as its discrete equivalent in positional form. For more accurate approximations, the trapezoidal and backward rules are applied here to develop discrete expressions for the integral and derivative terms, respectively ($K_I = \frac{1}{T_i}$),

$$G_c(z) = \frac{U(z)}{E(z)} = K_c\left(1 + K_I\frac{T}{2}\times\frac{z+1}{z-1} + T_d\frac{1}{T}\times\frac{z-1}{z}\right). \tag{8}$$

3.1 Performance criterion formulation

The performance criteria for both T_g and EO_2 are formulated individually under closed-loop SISO control based on the following desired response characteristics.

1) For T_g, overshoot $\leq 2\%$, settling time $(t_s) \approx 5\,\mathrm{h}$.

2) For EO_2, overshoot $\leq 2\%$, settling time $(t_s) \approx 7\,\mathrm{min}$.

3) For both variables, zero steady state error to a constant set point.

3.2 SGAs configuration

The SGAs approach used for optimisation of the PID controller parameters is shown in Fig. 3. As illustrated in the flowchart of the SGAs, at initial state, the chromosomes of an array of variable values to be optimised are defined as

$$\text{Chromosome} = \{\underbrace{(K_c\,K_I\,T_d)}_{T_g},\ \underbrace{(K_c\,K_I\,T_d)}_{EO_2}\}. \tag{9}$$

Binary coding was selected to encode the discrete controller parameters into binary strings to generate the initial population randomly in the beginning. The length of each chromosome (Lind) is determined based on the binary precision or resolution:

$$\mathrm{res}_j = \frac{b_j - a_j}{2^{m_j}-1} \tag{10}$$

where m_j is the number of bits, b_j is the upper boundary, and a_j is the lower boundary of each individual chromosome′s searching parameter. Each chromosome′s binary string is converted into an associated real value of PID parameter to propagate to the discrete PID controller. The decoding process into a real value is done as

$$x_j = a_j + Dec\times\frac{b_j - a_j}{2^{m_j}-1} \tag{11}$$

where x_j is the respective real value of the chromosome′s search parameter and Dec is the decimal value of the respective binary string. A complete simulated system response of each PID set and its initial fitness value is evaluated by using a defined objective function.

According to the chromosome′s fitness value by a defined objective function, a new generation (offspring) is produced by the process of genetic operators. The genetic operators manipulate the binary strings of the chromosomes directly, by means of selection rate (S_{rate}), crossover rate (X_{rate}) and mutation rate M_{rate} to produce fitter chromosomes for the next generation. After completion of the genetic operator process, the new set of binary strings for each chromosome in the population is required to be decoded into real values and propagated again to the discrete PID controller to evaluate the new fitness values. This process is sequentially repeated until a maximum number of generations is reached, where the optimal fitness is attained. Due to no previous information available for genetic operator values for both T_g and EO_2 control optimisation, several experiments were conducted where variations of the genetic operator values were tested individually for enhancing the searching mechanism. Table 1 illustrates the selected genetic operator parameters for both T_g and EO_2.

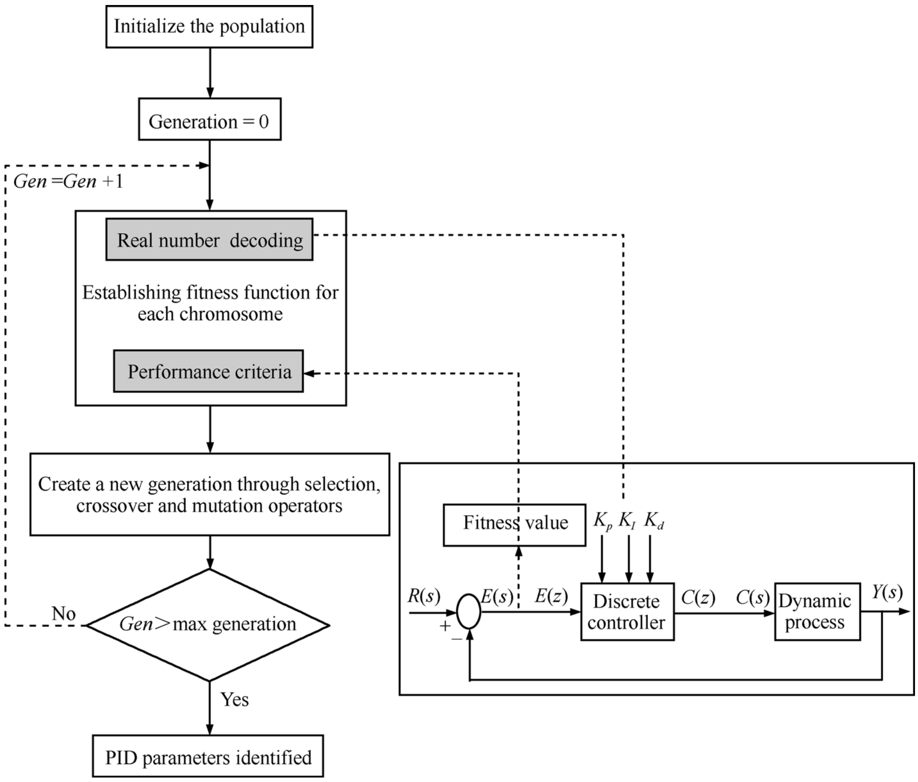

Fig. 3 Flow chart of control optimisation by SGAs

Table 1 Genetic operators of T_g and EO_2

Genetic operators	T_g (K)	EO_2 (%)
Number of individuals	50	50
Maximum number of generation	30	50
Generation gap	0.6	0.7
Precision of binary representation	6	6
Selection	SUS	SUS
Crossover	Single point, 0.6	Single point, 0.7
Mutation	Binary representation, $0.6/L_{ind}$	Binary representation, $0.6/L_{ind}$

3.3 Objective function and boundary constraint formulation

The control oriented models of both T_g and EO_2 were used individually to identify the optimum objective function and searching boundaries to achieve the performance criteria. In the first attempt, initial guesses were made for the search boundaries in the SGAs. Improved boundary constraints were subsequently introduced. For better selection of improved boundary values, conventional tuning methods (Ziegler-Nichols and direct synthesis) were analysed to identify PID values. With these identified PID values, b_j and a_j were adjusted accordingly to ensure an optimal solution for the desired response characteristics.

Two objective functions, integral absolute error (IAE) and integral squared error (ISE),

$$J_i\,(IAE) = \sum_{k=0}^{\max} |e(k)| \tag{12}$$

$$J_i\,(ISE) = \sum_{k=0}^{\max} e^2(k) \tag{13}$$

were used to compare and improve the set-point error for EO_2. Fig. 4 and Table 2 illustrates that the SGAs with parameter vectors of improved bound PID, $K_c \in [0,\ 1]$, $K_I \in [0,\ 0.01]$, $T_d \in [0,\ 50]$, for EO_2 have better dynamic response and higher degree of accuracy while reducing the performance criterion by adapting the fitness value. Initial optimisation of PID parameters by conventional techniques provides a better suggestion of improved bound ranges than assigning the ranges randomly or arbitrarily. By limiting b_j of K_c, the SGA consolidates well within the boundary constraints for K_I and T_d to converge to the global minimum.

However, Fig. 5 and Table 3 illustrate an overshoot of 10% (1 555 K) occurred in the transient response with a long settling time of 30 h for T_g with improved boundaries. SGAs optimised close to the b_j to attain the desired response characteristics, but failed to achieve a global minimum. To enhance the searching mechanism for the control parameters and achieve a global minimum, a modified cost function is applied. A weighting factor λ applied to the integral squared process input (controller output) term u (ISU) is added to the cost function to reduce the fast rising effect of the transient response. The modified cost function applied for T_g is given by the relation,

$$J_i\,(IAE+\lambda ISU)=\sum_{k=0}^{\max}|Tg(k)-1\,550|+\lambda u^2(k) \qquad (14)$$

where k is the sampling number and u is the controller output. The selection of an optimal value of λ is done by trial and error technique by varying λ in the range [100, 1 000]. The weighting factor associated with the desired response characteristics was set to $\lambda = 400$ to give more emphasis to the set point tracking objectives.

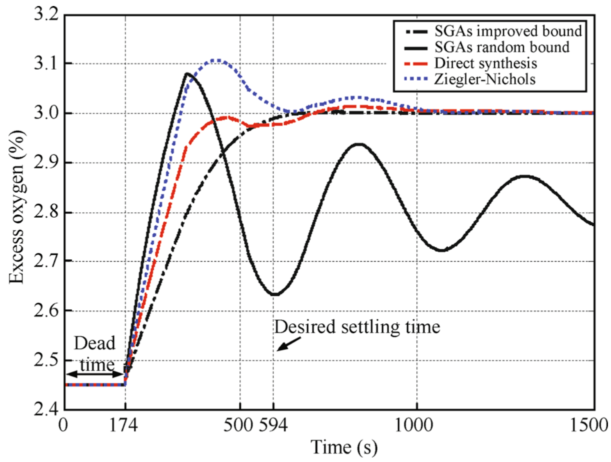

Fig. 4 Responses of EO_2 for conventional techniques and SGAs with random and improved boundaries

The simulation results in Fig. 5 and Table 3 illustrate that the SGA with modified cost function, $IAE + \lambda ISU$ (14), has a higher level of optimisation mechanism and better dynamic response than the improved searching bound alone. Application of λ with ISU has suppressed the larger overshoot behaviour of the glass temperature response by smoothing the controller output. Overall desired response characteristics, which are reduction of set-point error, overshoot and settling time, are achieved for T_g with the $IAE + \lambda ISU$ cost function.

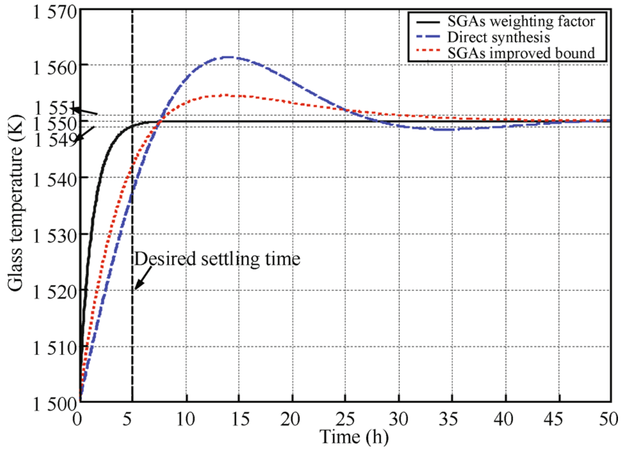

Fig. 5 Responses of T_g for a conventional technique and SGAs with improved boundaries and weighting factor

4 Simulation results of decentralised control strategies by SGAs

The optimisation of discrete decentralised control strategies is analysed by three SGAs tuning approaches, associated with the 2×2 control oriented multivariable glass furnace model as illustrated in Fig. 6. The three SGAs tuning approaches are applied in closed-loop step input tests. The three tuning approaches are:

SGAs-1: The discrete PID values of both T_g and EO_2 are optimised individually with their respective closed-loop control oriented model (independently) without loop interactions as discussed in Section 3.3.

SGAs-2: The discrete PID values of both T_g and EO_2 are optimised individually with their respective closed-loop control oriented model with loop interaction. ($C_1(z)$ is

Table 2 PID parameters for EO_2 by different tuning methods

Tuning method	K_c	K_I	T_d	ISE	IAE	t_s (2%)
Ziegler-Nichols	1.38	0.003 8	65.88	103.8	268.6	14 min
Direct synthesis	1.137	0.003 4	74	92.84	231.7	14.5 min
Random bound SGAs	2	0	36.67	119.8	355.6	35.8 min
Improved bound SGAs	0.768 5	0.004 3	32.27	83.26	187.7	7.1 min

Table 3 PID parameters for T_g by different tuning methods

Tuning method	K_c	K_I	T_d	Set-point error	t_s(2%)
Direct synthesis	2.235×10^{-3}	5.15×10^{-5}	3.563	1.981×10^{5}	40 h
Improved bound SGA	3.675×10^{-3}	2.54×10^{-5}	6.322	8.438×10^{4}	30 h
Weighting factor SGA	9.863×10^{-3}	9.46×10^{-6}	7.358	7.029×10^{4}	4.9 h

optimised with respective cost function, $T_{SET} = 1\,500\,\text{K} \rightarrow 1\,550\,\text{K}$, $EO_{2(Ref)}$ is constant (2.45%), $C_2(z)$ = default value from SGAs-1 result, $C_2(z)$ is optimised with respective cost function, T_{SET} is constant (1 500K), $EO_{2(Ref)} = 2.45\% \rightarrow 3\%$, $C_1(z)$ = default value from SGAs-1 result.)

SGAs-3: The discrete PID value of both T_g and EO_2 are optimised together by multivariable closed-loop control oriented model with loop interaction. The optimised cost function is modified to include the total effect of T_g and EO_2 by adding the individual cost functions for both variables for each test as shown in (15). ($C_1(z)$ and $C_2(z)$ are optimised with modified cost function: $T_{SET} = 1\,500\,\text{K} \rightarrow 1\,550\,\text{K}$ at EO_2 = steady-state, $EO_{2(ref)} = 2.45\% \rightarrow 3\%$ at T_{SET} = steady-state (1 550K)).

$$\begin{aligned} J_{i(Tg)} &= (IAE + \lambda ISU)_{T_g} + IAE_{EO_2} \\ J_{i(EO_2)} &= 0 + IAE_{EO_2}. \end{aligned} \tag{15}$$

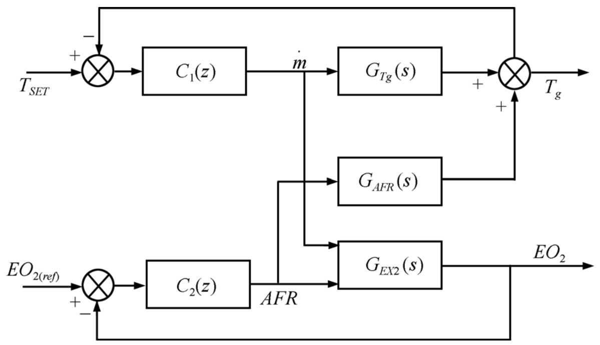

Fig. 6 2-input, 2-output multivariable control oriented model under closed-loop discrete decentralised PID control

Tables 4 and 5 compare the optimised PID parameters by the respective SGA tuning approaches of T_g and EO_2, respectively. As discussed in Section 2, any variation in $\dot{m}$ caused by T_{SET} and $EO_{2(Ref)}$ step inputs does not affect EO_2. Thus, Fig. 7 reveals that there is no change in EO_2 responses by SGAs-1 and SGAs-2. This can also be noticed in Table 5, where the PID parameters for these two approaches barely have a change.

On the other hand, Fig. 8 reveals that the optimised PID parameters by SGAs-1 are inadequate to achieve the desired performance criteria for T_g under loop interaction. As a result of the $G_{AFR}(s)'$s long dynamic time constant (2×10^5 s), the T_g response rise time (t_r) is lagged about 24 min, hence the settling time (t_s) has increased to 7 h and produced a steady-state temperature error of 1 K. In contrast, the SGAs-2 method consolidated better with loop interaction and $G_{AFR}(s)'$s dynamic time constant to maintain the desired performance criteria by increasing the K_c and K_I parameters accordingly.

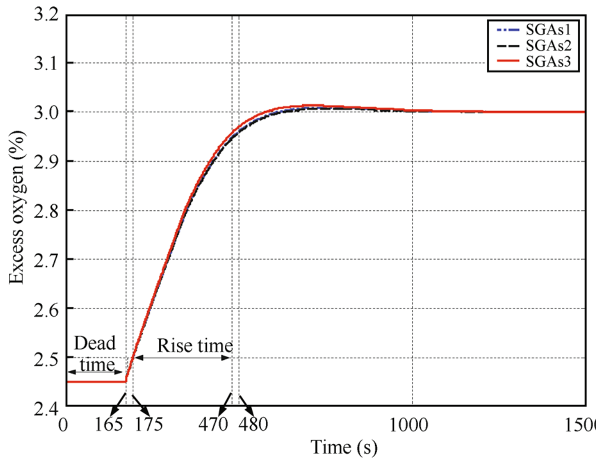

Fig. 7 EO_2 responses by three SGAs tuning approaches under loop interaction

The SGAs-3 tuning approach is tested by applying step inputs on both set points (T_g and EO_2) at two different time periods in one simulation with the modified (combined) cost function (15). Thus, the total simulation time has increased to optimise both sets of PID parameters. The simulation results of SGAs-3 for T_g are shown in Fig. 9. At $t_1 = 0$ h, $T_{SET} = 1\,500\,\text{K} \rightarrow 1\,550\,\text{K}$, $EO_2 = 2.45\,\%$ (constant). At t_2= 61.1 h, $T_{SET} = 1\,550\,\text{K}$ (constant), $EO_2 = 2.45\,\% \rightarrow 3\,\%$. From t_1 to t_2, technically the cost function of T_g ($IAE + \lambda ISU$) is optimising the PID parameters of $C_1(z)$ individually without any effect of the EO_2 cost function (IAE). Such a long time, gap between t_1 and t_2 is required in the optimisation considering the effect of $G_{AFR}(s)'$s long dynamic time constant (2×10^5 s). Up to t_1, there is no effect on EO_2 as this loop interaction is cancelled by the AFR relationship inherent in the process.

Table 4 Optimised PID parameters for T_g by decentralised techniques

Tuning approach	K_c	K_I	T_d	IAE+λISU	t_s (2%)
SGAs-1	9.863×10^{-3}	9.461×10^{-6}	7.358	7.029×10^4	4.9 h
SGAs-2	1.052×10^{-2}	1.371×10^{-5}	7.211	7.017×10^4	4.86 h
SGAs-3	1.108×10^{-2}	1.311×10^{-5}	7.892	7.007×10^4	4.84 h

Table 5 Optimised PID parameters for EO_2 by decentralised techniques

Tuning approach	K_c	K_I	T_d	IAE	t_s (2%)
SGAs-1	0.768 5	0.004 3	32.27	187.7	7.1 min
SGAs-2	0.767 9	0.004 27	32.84	188.9	7.1 min
SGAs-3	0.785 7	0.004 313	32.18	178.53	6.9 min

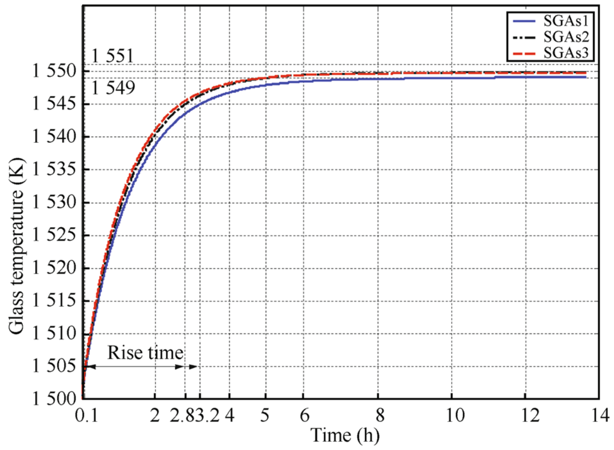

Fig. 8 T_g responses by three SGAs tuning approaches under loop interaction

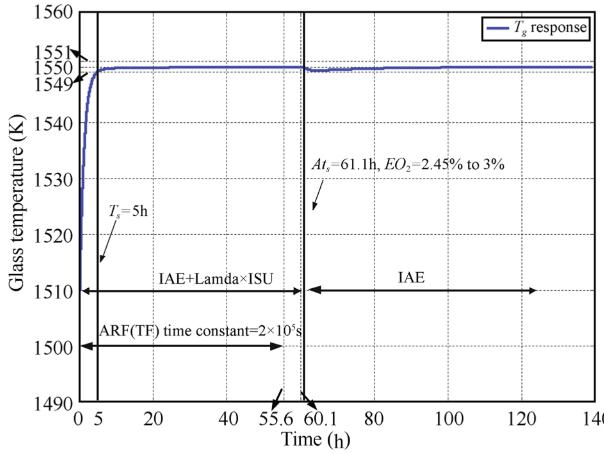

Fig. 9 T_g responses by SGAs-3 with modified (combined) cost function

From t_2, the total effect of T_g and EO_2 cost functions ($J_{i(T_g)}$) are compounded together in further optimisation of the $C_1(z)$ and $C_2(z)$ PID parameters. According to Fig. 9, T_g is reduced approximately to 1 549.2 K under loop interaction for the increase in EO_2 at t_2. To maintain the T_g response, the K_c parameter by SGAs-3 is increased about 5.31% from SGAs-2 (Table 4). But, the K_I parameter by SGAs-3 is reduced about 4.58% from SGAs-2. The effect of an increment and reduction of K_c and K_I is noticeable in Fig. 7 where both gain parameters are consolidating well to achieve a desirable response. Also, the EO_2 response and PID parameters vary by a smaller amount with the modified (combined) cost function ($J_{i(T_g)}$) as illustrated in Fig. 8 and Table 5. In the control of both variables, the SGAs-3 method achieves the smallest values of the cost functions and settling times (Tables 4 and 5).

The total set-point error of $J_{i(T_g)}$ is $7.024\,9 \times 10^4$. Technically, as there is no loop interaction from $\dot{m}$ to EO_2, the cost function of $J_{i(EO_2)}$ (15) is applied to identify the set-point error of EO_2. As a result, the set-point error of $J_{i(EO_2)}$ is 178.53. Also, the optimised PID parameters by $J_{i(T_g)}$ for EO_2 are very much similar to $J_{i(EO_2)}$. Thus, the set-point error of $IAE + \lambda ISU$ (T_g) is 7.007×10^4 by calculation.

As discussed in Section 2, a nonlinearity effect may appear in step input variations due to the methane chemical relationship between stoichiometric AFR (volumetric) and EO_2(%). Thus, the loop stability and control robustness are investigated further. Fig. 10 illustrates the robust responses of T_g for the three sets of optimised PID parameters (SGAs-1 to SGAs-3) under loop interaction for two EO_2 step input tests. The simulations of the two EO_2 step input tests are elaborated as follows:

1) EO_2, 2.45% $\rightarrow$ 3.45%: Initial steady state of T_g =1 550 K causes an initial reduction in T_g, 1 550 K $\rightarrow$ 1 548.7 K (approximately).

2) EO_2, 2.45% $\rightarrow$ 1.45%: Initial steady state of T_g = 1 550 K causes an initial increase in T_g, 1 550 K $\rightarrow$ 1 551 K (approximately).

The observed disturbances in T_g are caused by the changing AFR as a result of the EO_2 set points. To compensate the feedback error, controller $C_1(z)$ varies $\dot{m}$ accordingly to sustain T_g. In overall, the SGAs-2 method has 17.4% better control robustness than SGAs-1 (as measured by the IAE between T_g and the temperature set point). While, the SGAs-3 method has 4.36% better control robustness than SGAs-2.

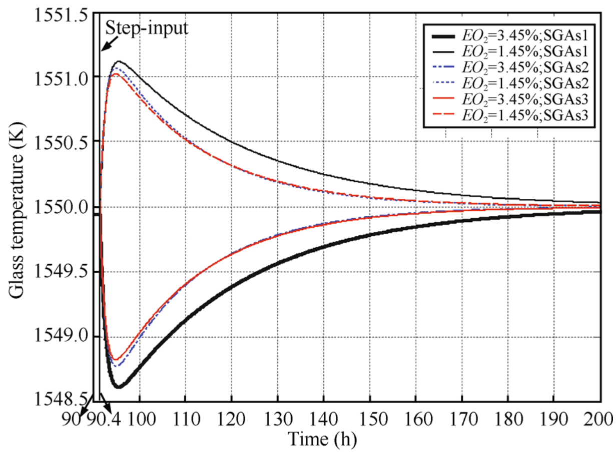

Fig. 10 Loop interaction of multivariable process under closed-loop discrete decentralised control strategy. Effect of $EO_{2(ref)}$ (Δ1%) on T_g

5 Conclusions

SGAs were applied successfully to identify low order, control oriented models of the plant to be used for subsequent controller optimisation. According to the desired response characteristics, the control parameters optimisation by genetic algorithms was enhanced with an improved cost function and improved searching boundaries. The loop interaction and control robustness within the realistic multivariable glass furnace model were compensated with well optimised PID parameters by SGAs in a decentralised PID control scheme. Lower values of the optimised cost functions and improved robustness to loop interactions were achieved when the controllers were optimised together.

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Kumaran Rajarathinam received the M. Sc. degree in electronic engineering from Liverpool John Moores University (LJMU), UK in 2011. He is currently a Ph. D. degree candidate in advanced control techniques with the Control Systems Group, Mechanical Engineering and Materials Research Centre (MEMARC), LJMU, UK.

His research interests include controller optimisation, process identification and genetic algorithms.

E-mail: K.Rajarathinam@2011.ljmu.ac.uk

ORCID iD: 0000-0001-8652-6940

James Barry Gomm received the B. Eng. (Hons) first class degree in electrical and electronic engineering, and the Ph. D. degree in process fault detection from Liverpool John Moores University, UK in 1987 and 1991, respectively. He joined the academic staff at LJMU in 1991 and is a reader in intelligent control systems. He was the co-editor of the book *Application of Neural Networks to Modelling and Control* (London, UK: Chapman and Hall, 1993) and has been the guest editor for several journal special issues including *Fuzzy Sets and Systems* and *Transactions of the Institute of Measurement and Control*. In 2011, he as the co-author, received the IFAC award for most cited paper in the journal *Engineering Applications of Artificial Intelligence*. He has published more than 130 papers in international journals and conference proceedings. He is a member of the IET and IEEE, and has served on an IET committee and organising committees of several conferences.

His research interests include neural networks for modelling, control and fault diagnosis of non-linear processes, intelligent techniques for control, system modelling and identification, adaptive systems and algorithms, analysis, control and stability of non-linear systems.

E-mail: j.b.gomm@ljmu.ac.uk (Corresponding author)
ORCID iD: 0000-0002-1777-8850

Ding-Li Yu received the B. Eng. degree from Harbin Civil Engineering College, China in 1982, the M. Sc. degree from Jilin University of Technology (JUT), China in 1986, and the Ph. D. degree from Coventry University, UK in 1995, all in control engineering. He was a lecturer at JUT from 1986 to 1990, a visiting researcher at University of Salford, UK in 1991, a post-doctoral research fellow at Liverpool John Moores University (LJMU) from 1995 to 1998. He joined LJMU Engineering School in 1998 as a senior lecturer and was promoted to a reader in 2003, then to professor of control systems in 2006. He is the associate editor of two journals, *International Journal of Modelling Identification and Control* and *International Journal of Information & Systems Sciences*. He organized two special issues in 2006, "Fault Detection, Diagnosis and Fault Tolerant Control for Dynamic Systems" and "Intelligent Monitoring and Control for Industrial Systems". He serves as a committee member of the IFAC Safe Process Committee, and has been an International Program Committee member for many international conferences. He is a fellow of IET and senior member of IEEE. He leads the Control Systems Research Group at LJMU. He has published more than 160 journal and conference papers and these papers have been cited more than 580 times.

His research interests include fault detection and fault tolerant control of bilinear and nonlinear systems, adaptive neural networks and their control applications, model predictive control for chemical processes and automotive engines, and real-time evaluations.

E-mail: d.yu@ljmu.ac.uk

Ahmed Saad Abdelhadi received the M. Sc. degree in electrical power and control engineering from Liverpool John Moores University (LJMU), UK in 2012. He is currently a Ph. D. degree candidate in nonlinear system identification and control with control Systems Group, Mechanical Engineering and Materials Research Centre, at LJMU, UK.

His research interests include modelling and control of nonlinear processes using neural and local model networks.

E-mail: a.s.abdelhadi@2012.ljmu.ac.uk.