Decentralised Control Optimisation for a Glass Furnace by SGA's

Kumaran Rajarathianm, J. Barry Gomm, Karl Jones, Ahmed Saad Abdelhadi

Abstract: *In this paper, the potential of standard genetic algorithms (SGAs) are presented to optimise the discrete PID parameters for multivariable glass furnace. Control oriented models of each multivariable glass furnace; glass temperature and excess oxygen are used to optimise the discrete controller with personalised cost function and adjusted boundaries by SGAs, individually. Well optimised discrete PID parameters by control oriented model are applied to realistic multivariable model by decentralised method.*
Key words: *Genetic Algorithms, Discrete Control Optimisation, and Decentralised Control.*

INTRODUCTION

Glass manufacturing processes have really long dynamics and are complex processes with high energy usage. Especially, large furnaces with multiple port burners cause the glass manufacturing industries to consume high energies in glass production. Most glass industries are operating at maximum daily through-put to fulfil the market requirement. Therefore, glass furnace operations are facing great challenges in reduction of fuel consumption by applying well tuned control strategies. Apart from high energy consumption, undesirable emission 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 was 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 percentage 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 is already operating in poor thermal conditions around the world. For such a complex multivariable process, the decentralised controls 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 the loop interactions.

A literature search reveals that there are several classified tuning methods suggested to tune decentralised controllers for multivariable processes such as Detuning method [2], Sequential design method [3], and Iterative method [4]. 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 method (EOP) was introduced [5]. But, the EOP method produces model approximation error due to the mathematical complications as the model dimensions increased. In recent years, to improve the entire control performance and robust stability, a systematical approach based on the generalised IMC-PID design method [6] and the reduced effective transfer function (RETF) by inverse response behaviour method [7] is introduced for multivariable process. But, both methods involve a complex mathematical approach to design the decentralised controllers.

However, a question always arises about the wellness of control optimisation and the flexibility due to the application constraints by those design methods. Standard Genetic algorithms (SGAs) are global search method by genetics evolution with higher performance in control optimization over traditional methods. Due to its superior self-adjustable ability, SGAs have been applied extensively in tuning the PID parameters for single-input single-output (SISO) systems [8], curve fitting [9], and fuzzy optimisation [10]. On the other hand, multiple-input multiple-output (MIMO) system is still an open research topic for optimising control parameters by SGAs. A promising decentralised controller by SGAs was proposed for multivariable process [11]. 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 break down was proposed [12].

This paper explores the potential of SGAs in optimising the discrete PID parameters by decentralised control technique for a multivariable process without further tuning required. Further, the minimisation of fuel consumption for multivariable glass furnace is analysed by decentralised technique while maintaining a desired glass temperature. The structure of this paper is as followed; first, a brief introduction is given about the identified control oriented and realistic models of the considered multivariable glass furnace. Second, a discussion of discrete PID parameter optimisation by decentralised technique by SGAs with boundary constraints and personalised cost function. Third, a discussion of applying decentralising control technique on a realistic model. The proposed methods are developed and tested in simulations based on Matlab/Simulink models.

INTRODUCTION OF MULTIVARIABLE GLASS PROCESS

Figure 1 illustrates the block diagram of multivariable glass furnace which consists of a 24 state-space furnace model 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 (Cp) and lower heat value (LHV) for determining the combustion energy, C_g is glass control, T_{SET} is primary temperature setting, AFR is air-fuel ratio, T_{amb} is ambient temperature, u is control output, $\dot{m}$ is fuel flow, T_g is glass temperature and EO_2 is excess oxygen.

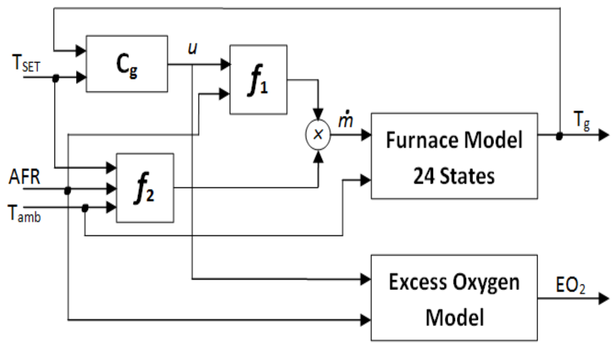

Figure 1: Block diagram of multivariable glass furnace

The realistic glass furnace model that identified and applied for further research here is representing a real plant of combustion chamber from Fenton Art Glass Company, USA [13]. This is an extended research work of radiative zone method by Holladay [14] and was identified to develop 24 state space variables (zones) model. The linearised energy balance equation is applied and modified with respective 24 state variables for each zones corresponding to temperatures.

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 numerical data from an industrial furnace by 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 glass temperature and EO_2 models for control optimisation. The identified transfer functions by GAs are;

For EO_2 Realistic Model,

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

For EO_2 Control Oriented Model,

$$\frac{\Delta EO_2(s)}{\Delta AFR(s)} = \frac{1.6}{150s+1} e^{-174s} \tag{2}$$

For Glass Temperature Control Oriented Model,

$$\Delta Tg(s) = \frac{4488.4}{199200s+1} \cdot \Delta \dot{m} + \frac{-0.9834}{199200s+1} \cdot \Delta T_{SET} \tag{3}$$

DISCRETE PID PARAMETERS OPTIMISATION BY SGAs

In general, a discrete PID controller can be described by an input–output relation expressed as [15],

$$G(z) = K_c\left(1 + \frac{1}{T_i}\frac{T}{2}\frac{(z+1)}{(z-1)} + T_d\frac{1}{T}\frac{(z-1)}{z}\right) \tag{4}$$

where T is the sampling time, and K_c, T_i and T_d denote the proportional gain, the integral gain and derivative gain, respectively. Equation (4) is expressed in the position form of the algorithm by applying finite difference approximations. For more accurate approximations the trapezoidal and backward rules are applied here to develop the discrete expressions for integral and derivative, respectively.

As illustrated in flowchart (Figure 2) and theories of the SGAs, at initial state, the chromosomes of an array of variable values to be optimised are defined:

$$Chromosome = \left\{\left(\underbrace{K_P, K_I, K_D}_{Tg}\right), \left(\underbrace{K_P, K_I, K_D}_{EO_2}\right)\right\} \tag{5}$$

The coding selection was done based on the mutation rate (M_{rate}). According to [16], the binary code converges faster when $M_{rate} > 0.6$. Thus, the binary coding was selected to encode the discrete controller parameters into binary string to generate the initial population randomly in the beginning. The length of chromosome is determined based on the binary precision:

$$2^{m_j - 1} < \left(b_j - a_j\right) \times 10^4 \leq 2^{m_j} - 1 \tag{6}$$

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

$$x_j = a_j + Dec \times \frac{\left(b_j - a_j\right)}{2^{m_j} - 1} \tag{7}$$

where x_j is the respective real value of chromosome and *Dec* is decimal value of respective binary string. A complete simulated system response of each PID set and its initial fitness value is evaluated by using 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

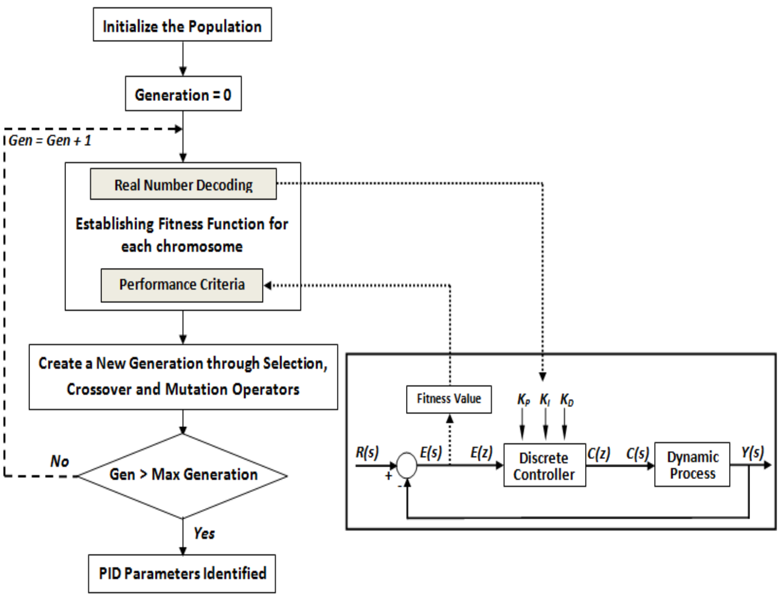

Figure 2: Flow chart of control optimisation by SGAs

rate (S_{rate}), crossover (X_{rate}) and mutation (M_{rate}) to produce a fitter chromosome for the next generation.

After the completion of genetic operator process, the new set binary string of each chromosome in the population is required to be decoded into real values and propagated again to the discrete PID controller to evaluate for a new fitness value. This process will be repeated until the end generation where the optimal fitness is attained. Since no previous information of genetic operator exists for T_g and EO_2 control optimisation, the dynamic random variations of genetic operators were tested for enhancing searching mechanism, individually. Table 1 illustrates the selected genetic operator parameters for both T_g and EO_2.

Table 1: Selected genetic operators of T_g and EO_2

Genetic Operators	***T_g (^oK)***	***EO_2 (%)***
No. of individuals	50	50
Max. No. of Generation	30	50
Generation Gap	0.6	0.7
Precision of Binary Rep.	4	4
Selection	SUS	SUS
Crossover	Single Point, 0.6	Single Point, 0.7
Mutation	Binary Rep., 0.7/Lind	Binary Rep., 0.7/Lind

PERFORMANCE CRITERION FORMULATION

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

i. For T_g; Overshoot < 2%, Settling time (T_S) ≈ 5hrs.
ii. For EO_2; Overshoot < 2%, Settling time (T_S) ≈ 7min.

Standard objective functions (ISE and IAE) are insufficient to attain the desired response characteristics. Thus, to improve the searching mechanism, the boundary constraint is introduced by improved bound. For better selection of improved bound values, the conventional (Ziegler-Nichols and Direct Synthesis) tuning methods are analysed to identify PID values. With identified PID values, the b_j and a_j are adjusted accordingly to ensure an optimal solution for desired response characteristics.

Figure 3 and table 2 illustrate that the SGAs with parameter vectors of improved bound PID, $K_P \in [0:1], K_I \in [0:0.01], K_D \in [0:50]$ of EO_2 has better dynamic response and higher degree of accuracy while reducing the performance criterion by adapting the fitness value. Initial optimisation of PID parameters using conventional techniques provides better suggestion of improved bound range than assigning the bound range randomly. By limiting the b_j of K_P, the SGA consolidates well within the boundary constraint with K_I to converge to the global minima.

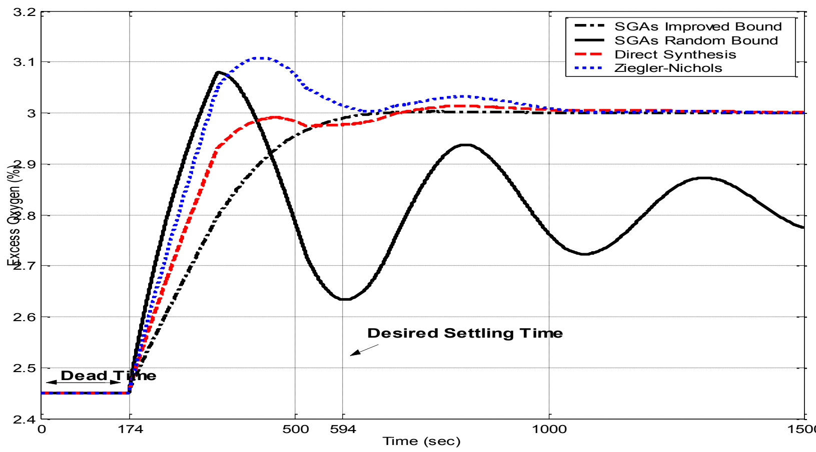

Figure 3: SGA's random and improved boundaries of EO_2 responses with conventional techniques.

However, figure 4 and table 4 illustrate an overshoot of 10% (1555^{o}K) occurred in the transient

Table 2: PID parameters for EO_2 by tuning methods

Tuning Methods	***K_P***	***K_I***	***K_D***	***ISE***	***IAE***	***T_s (2%)***
Ziegler-Nichols	1.38	0.0038	65.88	-	-	14min
Direct Synthesis	1.137	0.0034	74	-	-	14.5min
Random Bound SGAs	2	0	36.67	119.8	355.6	-
Improved Bound SGAs	0.7685	0.0043	32.27	83.26	187.7	7.1min

response with long settling time of 30hrs for T_g with improved boundaries. SGAs optimise closest to the b_j to attain the desired response characteristics, but failed to achieve global minima. To enhance the searching mechanism for the control parameters and achieve global minima the personalised cost function is applied. The weighting factor (λ) is added with input term of cost function to minimise the fast rising effect of transient response. The personalised cost functions applied is given by relation,

$$J_i(IAE + \lambda ISU) = \int_{t=0}^{t=\max} \left(\left| YoutN(t) - 1550 \right| + \left(\lambda u^2 \right) \right) dt \qquad (8)$$

where $YoutN(t)$ is the model output and u is the controller output. The selection of optimal value of λ is done by trial and error technique. As illustrates in table 3, the weighting factor associated with the desired response characteristics was set to be λ = 400 to give more emphasis to the set point tracking objectives.

Table 3: Weighting factor identification

λ	*Set-Point Error*	*IAE*	*λISU*	*T_S (2%)*
100	1.847e4	8.783e2	1.759e4	1.9hrs
250	4.456e4	1.510e3	4.306e4	3.7hrs
350	6.173e4	1.799e3	5.993e4	4.6hrs
400	7.029e4	1.922e3	6.836e4	4.9hrs
550	9.585e4	2.324e3	9.352e4	6.2hrs
850	1.467e5	2.918e3	1.438e5	7.6hrs
1000	1.721e5	3.192e3	1.689e5	8.3hrs

Simulation results (Figure 4 and Table 4) illustrate that the SGAs with personalised cost function, IAE + λISU (equ. 8) has higher level of optimisation mechanism and better dynamic response than improved bound. The application of λ with ISU has suppressed the oscillatory behaviour of glass temperature response by smoothes the controlled variable responses. Overall desired response characteristics, which are reduction of set-point error, overshoot and settling time, are achieved with the IAE + λISU.

Table 4: PID parameters for T_g by tuning methods

Tuning Methods	*K_P*	*K_I*	*K_D*	*Set-point Error*	*Ts (2%)*
Direct Synthesis	2.235e-3	5.15e-5	3.563	$1.981e^5$	40hrs
Improved Bound SGAs	3.675e-3	2.54e-5	6.322	$8.438e^4$	30hrs
Weighting Factor SGAs	9.863e-3	9.461e-6	7.358	$7.029e^4$	4.9hrs

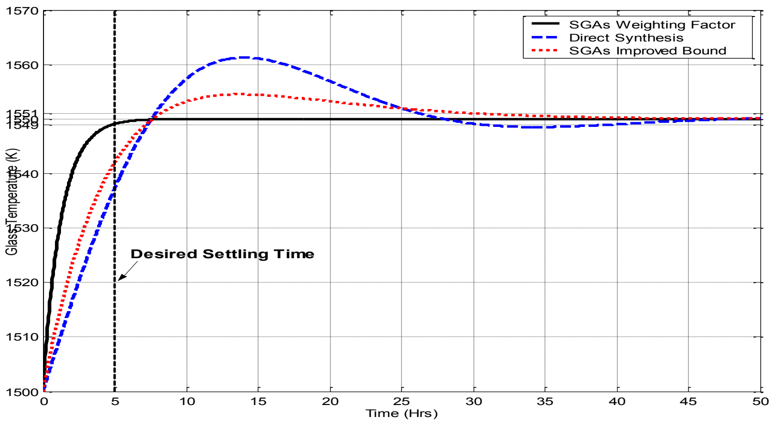

Figure 4: SGA's improved boundaries and λ of T_g responses with conventional Techniques.

DISCRETE CONTROL STRATEGIES ON REALISTIC MODEL BY DECENTRALISED TECHNIQUE

Discrete PID controllers would be applied in loop interactions associated with the 2x2 multivariable glass furnace processes as shown in figure 5. Individually optimised discrete control parameters by SGAs with the respective control oriented models are applied in the decentralising control scheme at the multivariable realistic models. By applying closed-loop step input on both EO_2 and T_{SET} will be tested to

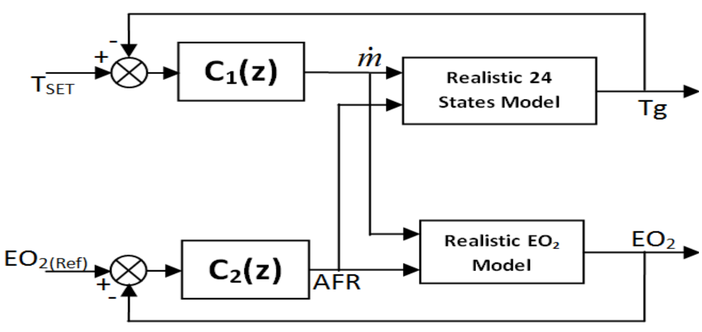

Figure 5: 2-input, 2-output multivariable glass furnace under closed-loop discrete PID controller

analyse the affect of loop interaction within the realistic models on fuel consumption and thermal efficiency. Under closed-loop steady-state glass temperature (T_{SET} = 1550°K), air ratio 17.2 (0.05028 kg/s) and the fuel consumption is 0.002923 kg/s.

Simulation results of figure 6 and 7 illustrates that, under closed-loop step input of multivariable loop interaction are elaborated as follows:

1. EO_2 (2.45%) constant; T_{SET} = 1550°K to 1580°K – The fuel consumption is increased to 0.003034kg/s as an increase in T_{SET}. To obey an increase in fuel ratio, the air ratio is increased to 0.05218kg/s while maintaining AFR (17.2) and EO_2.
2. EO_2 (2.45%) constant; T_{SET} = 1550°K to 1530°K – The fuel consumption is decreased to 0.002811kg/s as a decrease in T_{SET}. To obey a decrease in fuel ratio, the air ratio is decreased to 0.04834kg/s while maintaining AFR (17.2) and EO_2.
3. T_{SET} (1550°K) constant; EO_2 = 2.45% to 3% – The AFR is increased to 17.78 as an increases in EO_2. To obey an increase in AFR, the air ratio and fuel ratio are increased to 0.0531kg/s and 0.002987kg/s while maintaining T_{SET}.
4. T_{SET} (1550°K) constant; EO_2 = 2.45% to 2% – The AFR is decreased to 16.75 as a decreases in EO_2. To obey a decrease in AFR, the air ratio and fuel ratio are decreased to 0.04732 kg/s and 0.002824kg/s while maintaining T_{SET}.

Simulation results reveals that any change in T_{SET} is varying the fuel consumption and excess air accordingly while sustaining the EO_2. As shown in figure 6, the both closed-loop step-up and step-down responses of EO_2 completely overlapped and describes that the responses are not affected at all by loop interaction of C_g as illustrated in figure 1. But, the $\Delta\dot{m}$ loop interaction is still needed to EO_2 model for AFR synchronisation.

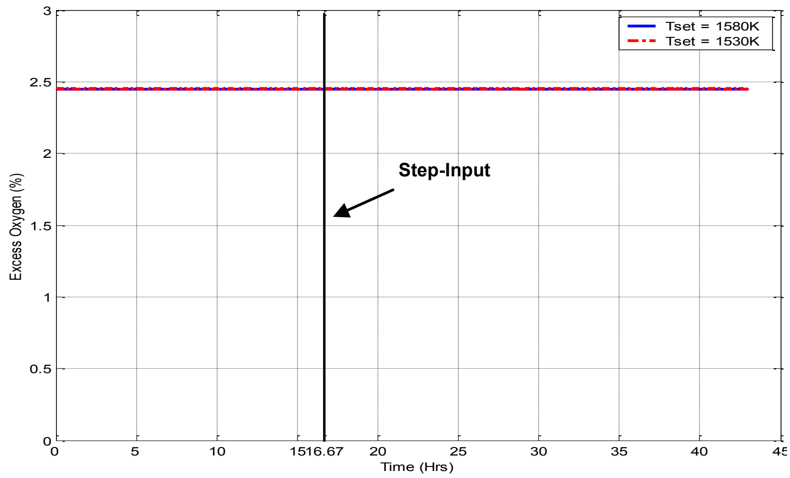

Figure 6: Closed-loop transient responses of EO_2

On other hand, any variations in EO_2 have an insignificant affect glass furnace process. According to realistic glass furnace model in figure 1, the AFR has a weak loop interaction with glass temperature model through nonlinear algebraic expression of f_1. Simulation results as in figure 7 reveals that when step inputs of EO_2 are changed at 16.67hrs, the T_g response is varies about 1°K under close-looped condition. Due to nonlinearity effect of f_1 and long dynamic responses the AFR, air ratio and fuel ratio are changed accordingly to sustain the T_g after 2hrs of step inputs.

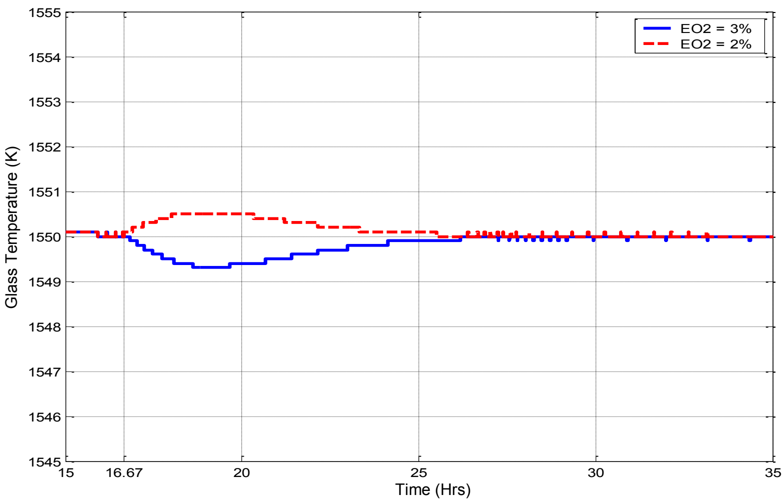

Figure 7: Closed-loop transient responses of T_g

Under open-loop condition, an increase and a decrease in air ratio is appeared a reduction and a rise in glass temperature, respectively. In actual condition, high excess air ratio will blow-away the heat from combustion chamber [17]. Simulation results of figure 8 and table 5 illustrates that by reducing the EO_2, the overall steady-state fuel consumption is reduced about 3.4% while sustaining the glass temperature set-point at 1550^{o}K.

According to the environmental agencies combustion guideline, the maximum permitted level of EO_2 is 3%. The optimum thermal efficiency of combustion process is within the range of 1.5% to 3% of EO_2, which is equivalent about 10% to 20% of excess air. Thus, reducing the EO_2 within the optimum region and automatic monitoring of excess oxygen model will be beneficial for minimising the undesirable emissions and fuel consumption while sustaining the thermal efficiency of combustion.

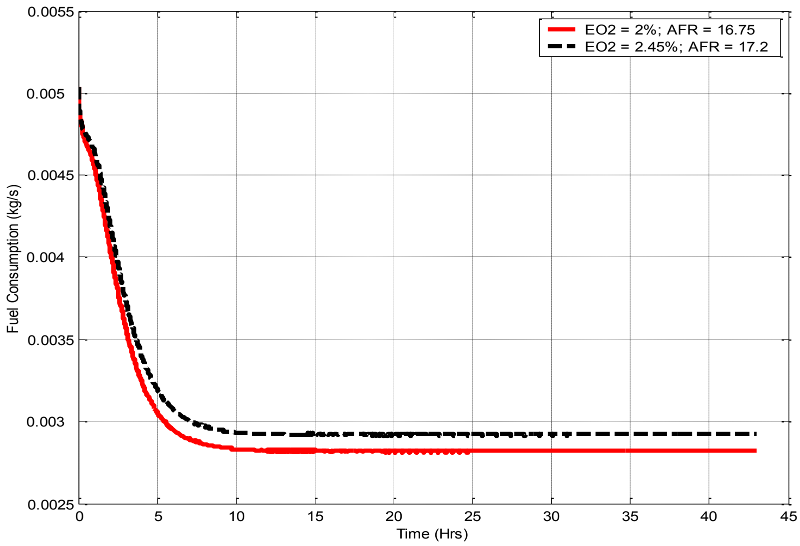

Figure 8: Fuel ratio consumption response of EO_2

Table 5: Simulation result of fuel consumption

***EO_2* (%)**	***AFR* (Mass)**	***Closed-Loop Steady State Fuel Flow (kg/sec)***	***Fuel Consumption (kg) (24 Hrs Operation)***
2.45	17.2	0.002923	252.55
2	16.75	0.002824	243.99

CONCLUSIONS AND FUTURE WORK

An application of SGAs in optimising the discrete PID controllers for realistic multivariable glass furnace has been demonstrated. According to the desired response characteristics, the control parameters optimisation is enhanced with personalised cost function and improved searching boundaries. The loop interaction within realistic multivariable glass furnace is compensated with well optimised PID parameters by SGAs in decentralised technique. An automatic continuous monitoring of EO_2 would enhance the overall performance of multivariable glass furnace. Future work will be carried out in optimising discrete controller for the extended multivariable realistic model in multistage model by SGAs.

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