Adaptive Particle Swarm Optimization based System Identification and Internal Model Sliding Mode controller for Mass Flow System

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Abstract: An integrated mass flow meter and control valve forms the Mass Flow Controller (MFC) and is extensively used in semiconductor industries. In this work an Internal Model Sliding Mode Controller based on Adaptive Particle Swarm Optimization (IMSMC-APSO) is proposed to control the valve position in MFC. First step is to identify an open loop transfer function model for MFC through system identification via the data acquired from a real time mass flow controller. Optimal transfer function parameters are estimated through APSO and compared with PSO for better estimation accuracy. In second step IMSMC is designed for the identified transfer function model and an APSO optimally tunes the control parameters off-line. The control objective is to track a multi step flow trajectory instantaneously with high precision, under model uncertainties and pressure disturbances accounting the limitation on long sensor time constant. For the purpose of comparison a classical PI, a simple IMSMC are also designed. Simulation results show that IMSMC- APSO automated the controller tuning and improved the MFC performance in terms of settling time (average) by 11.45% and accuracy (ITAE) by 16.33%, 20.24% and 18.26% in normal condition, amid pressure disturbance and model uncertainty respectively compared to simple IMSMC.

Keywords: Internal model control, sliding mode control, Particle Swarm Optimization, Adaptive particle swarm optimization, system identification

1. INTRODUCTION

A special type of integrated mass flow meter and control valve is known as Mass Flow Controller (MFC) (Manuel and Viviana, 2010; Paolo et al, 2004).These are complex closed loop devices that monitor and control process gas in semiconductor, microelectronic and chemical process industries. Costumer's requirement on MFC performance is mainly inclined to higher accuracy and reduced settling time.

MFCs are considered to be long time constant/dead time system owing to the slow responding thermal sensor in comparison with the variations in flow rate of the process gas. These excessive sensor response time and modelling errors have significant effects on the performance of MFC as defined by standard SEMI EI7-00-0600 (Pierre, 2009).To ensure efficient working performance of MFC an effective automatic control system is needed. In the Proportional Integral (PI) controller designed by (Vyers, 1999) out flow is computed by controlling the estimated flow rather than the sensed flow this reduces the signal to noise ratio and system stability. Pierre designed a digital RST controller for mass flow system and demonstrated its efficiency. Though this controller is robust for modelling uncertainties, a phase advance filter is designed to compensate the dynamic effects of long time constant and to improve the 2% settling time of MFC. Finding out the filter coefficient is a multifaceted task (Pierre, 2009). In 2011 a Linear Quadratic Regulator (LQR) is designed for MFC, as the effect of long time constant is not compensated the transient behaviour is unsatisfactory (Jenita and Jeraldin, 2011).Advanced feed forward control scheme (Stephen, 2012) and controller gain scheduling technique (Junhua Ding, 2011) proposed to control MFC gives a reasonable performance only for predetermined operating conditions.

Systems with large time delay similar to MFC are susceptible to either very oscillatory or highly damped behaviour when affected by set point variation and external disturbance. The new predictive structures developed to decouple the disturbance from set point variations are practically unrealizable and are susceptible to modelling errors. Though Sliding Mode Controller (SMC) has proved to be robust against modelling uncertainties and disturbances its transient performance is too lethargic (Camacho and Smith, 2000; Camacho et al., 2003; Oscar et al., 2007). Since Internal Model Sliding Mode Controller (IMSMC) combines simple predictive structure with sliding mode control, it could be used for controlling the mass flow rate in MFC.

Performance of the Internal sliding mode controller for MFC proposed earlier is limited owing suboptimal tuning and lack of real time environment (Jenita and Jeraldin, 2012) .This work aims at identifying an open loop transfer function for MFC using system identification process via the data acquired from a real time mass flow controller. The parameters of the identified model are being estimated using

APSO with high estimation accuracy. For the identified model an IMSMC is designed and the control parameters are tuned off-line using APSO. Objective of the designed controller is to improve the settling time and precision of MFC amid external pressure disturbance and modelling uncertainties. Performance of APSO based IMSMC is compared with a classical PI and a simple IMSMC. Robustness analysis and pressure disturbance rejection test are done for the MFC controlled by IMSMC- APSO. System identification and APSO implementation are done in MATLAB/SIMULINK platform.

2. SYSTEM IDENTIFICATION

2.1 MFC system identification

A well known version of MFC uses a magnetic solenoid valve and a Thermal flow sensor where the output signal is a temperature difference produced by the flow across the heated stainless steel capillary tube (Paolo et al., 2006).When the time constant of the solenoid valve is neglected the effective mass flow rate (Y_m) is similar to the voltage applied to the control valve. The mathematical model of MFC allows the prediction of system dynamic response to changes in set point or input pressure variations (John et al., 2004).

The first principle models developed for Thermal Mass Flow Controller are based on rather complex heat transfer phenomenon. This complexity allows the investigator to use assumptions on sensor tube temperature, gas mean temperature, Nusselt number etc. (Sung and Seok, 2001; II Young et al., 2005; Dong-Kwon et al., 2007; Tae et al., 2009). So the numerical models presented do not reflect the real system behaviour furthermore the experimental validation on real plant is complex and expensive.

So system identification is used to identify the dynamic properties of MFC. In system identification process, a reliable mathematical model is built for a dynamic system from the experimentally generated input output data. These identified models are in close agreement with the physical reality and are used for control purpose(Rodriguez et al., 2008).A model in the form of transfer function with defined structure and unknown parameter value is suitable for system identification (Klemen et al., 2013).

MFC model is a combination of control valve and a thermal flow sensor. The dynamics of the control valve is modelled as a first order transfer function with steady gain K_0 and time constant n_o.

$$G_0(s) = \frac{Y_M(s)}{U(s)} = \frac{K_0}{(n_0 s + 1)} \tag{1}$$

When greater accuracy is needed in utilizing the results of the experimental data to determine the dynamics of thermal flow sensor a second order system with time delay is employed as transfer function.

$$G_1(s) = \frac{Y(s)}{Y_M(s)} = \frac{K_1 e^{-n_3 s}}{(n_1 s + 1)(n_2 s + 1)} \tag{2}$$

n_1 and n_2 sensor time constant ,n_3- delay time, K_1-sensor constant

Dynamic response of the thermal flow sensor for a temperature step from T_{min} to T_{max} is given as

$$T(\tau) = T_{\min} + (T_{\max} - T_{\min})\left[1 - \frac{n_1}{n_1 - n_2}\exp\left(-\frac{\tau - n_3}{n_1}\right) + \frac{n_2}{n_1 - n_2}\exp\left(-\frac{\tau - n_3}{n_2}\right)\right]$$
$$n_1 \neq n_2 \; ; \; \tau \geq n_3 \tag{3}$$

Overall transfer function is the combination of control valve transfer function and thermal flow sensor transfer function.

2.1.1 Optimization problem formulation in MFC parameter estimation

The transfer function between the mass flow rate Y*(s)* and the applied voltage to the control valve *U(s)* is

$$\frac{Y(s)}{U(s)} = \left[\frac{k}{(n_0 s + 1)(n_1 s + 1)(n_2 s + 1)} e^{-n_3 s}\right] \tag{4}$$

n_0 -- valve time constant, n_1, n_2 - sensor time constants , n_3 - delay time, k - sensor gain. Parameter vector to be estimated is $[n_0 \; n_1 \; n_2 \; n_3 \; k]$.

Parameter estimation in MFC is stated as minimization of a cost function SSE which measures the fitness of the model with respect to the given experimental data set subject to some constraints.

$$SSE = \sum_{K=1}^{N} [y_{\exp}(k) - y(k)]^2 \tag{5}$$

$y_{\exp}(k)$- Experimentally measured output. $y(k)$- Model output; *N*-length of the data;

The constraints on system parameters are

All the time constants and the sensor gain are positive ($0 < k, n_0, n_1, n_2, n_3$).

The valve response time is shorter with respect to temperature sensor response time ($n_o < n_1$ *and* n_2)

Influence of the time constant n_1 is small enough to improve system accuracy ($n_1 < n_2 ; n_1 \neq n_2$).

Combination of these three constraints is stated as $0 < n_0 < n_1 < n_2$

The parameter estimation problem is formulated as the optimization problem as

Minimize

$$J_{(SSE)} = \sum_{K=1}^{N} [y_{\exp}(k) - y(k)]^2 \tag{6}$$

Subject to constraints

$$\begin{aligned} n_0^{\min} &< n_0 < n_0^{\max} \\ n_1^{\min} &< n_1 < n_1^{\max} \\ n_2^{\min} &< n_2 < n_2^{\max} \\ n_3^{\min} &< n_3 < n_3^{\max} \\ k^{\min} &< k < k^{\max} \end{aligned} \tag{7}$$

2.2 Experiment design and parameter estimation

This experimental work aims to estimate the MFC transfer function parameters. The experimental arrangement is shown in Fig.1.The sensor tube is a stainless steel tube of length 95mm. A heater of length 14mm is fixed centrally on the sensor tube and two Pt 100 RTDs are fixed on either side equidistance. The heater is powered by a constant power of 1W by a stable DC supply. Solenoid valve is compact proportional type with repeatability 3% and hysteresis less than 10% powered by 0-12V DC. Response time of the solenoid valve is less than 0.1 sec where as response time of sensor tube varies between 10sec to 30sec. Operating fluid is chosen as Nitrogen at a pressure of 1psi because of its increased usage as calibration gas in semiconductor fabrication process. Temperature difference between upstream and downstream RTD is zero at zero flow rate. The temperature signals from the thermal flow sensor are directly measured using data acquisition unit NI Compact DAQ.

Now the solenoid valve attached to the upstream section of the sensor tube is suddenly opened by applying a step input of 0-5V (input data).Temperature gradient between the upstream and downstream RTD were acquired and recorded from the start of the gas flow through the sensor tube. This temperature gradient is linearly dependent on the mass flow rate of the nitrogen gas passing through the sensor tube (Viswanatha et al., 2002).The experiment was repeated three times and three sets of data were recorded .The average of the three sets of data were utilized for parameter estimation. A total of 117 data samples were collected with a sample time of 5 sec. A plot of this input voltage and output temperature data samples with respect to time is shown in Fig.2. In MFC temperature gradient between the sensor Y (t) is the controlled variable and the voltage applied to the solenoid valve is the manipulated variable U (t).

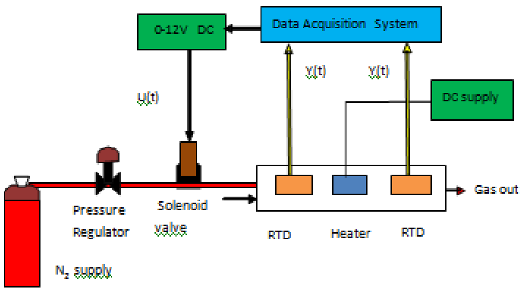


Fig. 1. Experimental setup for Mass Flow Controller.

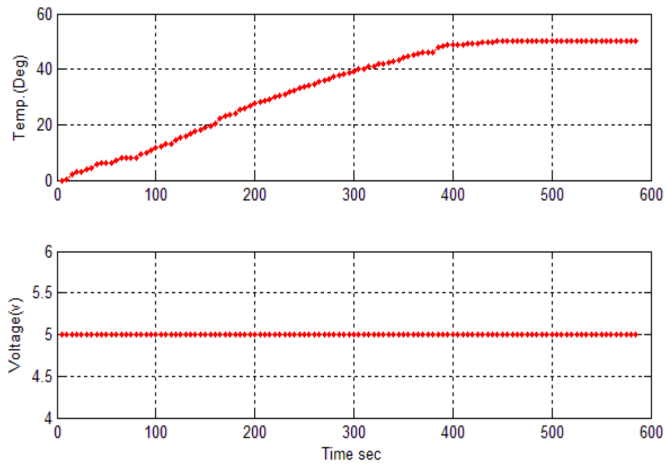


Fig. 2. Experimental response of MFC to a step input of (0-5V) valve voltage.

2.3 Parameter estimation using APSO

These unknown parameters may be estimated by numerous techniques. Conventional parameter estimation involves recursive least square, nonlinear least square, instrumental variable method, correlative function method, Voltera series, Weiner series and wavelets. These estimation methods suffer from shortcomings such as large estimation errors, more computational complexity, unrealistic assumptions, trapping in local minima and need for enormous input –output data. (Hamidreza et al., 2010; Asan et al., 2013). So heuristic optimization approaches like Genetic algorithms (GA) (Kristinsson and Dumont, 1992; Valarmathi et al., 2009) , Particle swarm optimization (PSO) and their variants are deemed to be powerful approaches (Xiaoning and Jeffery, 2011; Wenxin et al., 2011; Alireza and Hamidreza, 2011). PSO first introduced by Kennedy and Eberhart is a parallel, flexible, robust, stochastic optimization algorithm and find its application in many industrial applications. (Zamani et al., 2009; Kennedy and Eberhart, 1995; Eberhart and Kennedy, 1995). In this work Adaptive particle swarm optimization a variant of PSO is used for parameter estimation.

Adaptive Particle Swarm Optimization (APSO) is an variant of Particle Swarm Optimization (PSO) and this uses a dynamic adaptive inertia weight based on a measure called Adjacency Index (AI) characterised by the nearness of individual fitness to the real optimal solution. This rationally balances the global extrapolation and local exploitation abilities of PSO. Advantages of APSO are low estimation error, providing globally-optimum solution and fast convergence. Using this algorithm for system identification helps in avoiding modelling errors in MFC transfer function. In this work an Adaptive Particle Swarm Optimization (APSO) is utilized for estimating the parameters of the MFC transfer function from experimentally generated input output data with high estimation accuracy.

The APSO algorithm minimizes the SSE value so that the actual system parameters are accurately estimated. Parameter vector to be estimated is $[n_0\, n_1\, n_2\, n_3\, k]$. Each particle in the population is preset as a set of probable solution to the system identification problem. The system parameter linked with each particle is used to evaluate the SSE criterion. APSO optimizes the model parameters so that SSE is minimized, to give maximum estimation accuracy.

3. CONTROLLER DESIGN

3.1 Internal Model Sliding Mode Controller (IMSMC)

Unlike the classical PID controller IMSMC can handle time delay and constraints on manipulated variable guaranteeing closed loop stability (Mwembeshi et al., 2004). When the system model incorporates a time delay the IMC structure predicts the delay free model response and generates a feedback signal equivalent to the error between the system model and delay free model response. Controller compares this prediction with the reference to take a suitable control action (Amjad et al., 2010). Systems with sliding modes have proven to work satisfactorily in the presence of external disturbances and uncertainties. Once the states of the controlled system enter the sliding mode the system dynamics depends on the dynamics of the sliding surface and are independent of uncertainties and disturbances (Utkin , 1977, 1992; Hung et al., 1993; Edwards and Spurgeon, 1998; Young et al., 1999; Yu and Kaynak, 2009)

A simplified First Order Plus Time Delay (FOPTD) model of the original MFC system can be used to design IMSMC controller. The transfer function between the mass flow rate Y*(s)* and the applied voltage to the control valve *U(s)* is approximated to a FOPTD model.

$$\frac{Y(s)}{U(s)} = \frac{K_f}{\tau_f s+1} e^{-\tau_{0f} s} \quad ; G(s) = G^+(s) G^-(s); \tag{8-9}$$

$$G^-(s) = \frac{K_f}{\tau_f s+1} \quad ; G^+(s) = e^{-\tau_{0f} s} \tag{10-11}$$

The FOPTD model is decomposed into invertible part $G^-(s)$ and non-invertible part $G^+(s)$.The invertible part $G^+(s)$ contains the time delay element that lead to instability and realizability problems. The non-invertible part $G^-(s)$ contains the elements that can be used for controller design. Thus IMC technique eliminates all the elements in MFC that produces an unrealizable controller. To design SMC a sliding surface is defined to characterize the desired system dynamics, along which the system slides to reach the desired state.

For the first order system in equation (6) the sliding surface is proposed as

$$s(t) = e_m(t) + \lambda \int_0^t e(t) dt \tag{12}$$

λ is the tuning parameter selected by the designer to determine the performance of MFC on the sliding surface and *e(t)* is the tracking error.

$$e_m(t) = r(t) - y_m(t)$$
$$e(t) = r(t) - Y(t) \tag{13}$$

r(t) - Reference mass flow rate.

Y(t) -Mass flow rate from nonlinear system model.

$y_m(t)$ - Estimated mass flow rate from approximated FOPTD model

The control objective is to guarantee that the controlled variable is driven to its set point value, which implies that *e(t)* and $\frac{de(t)}{dt}$ must be zero. This condition is satisfied if $\frac{ds(t)}{dt} = 0$.

Once the sliding surface is chosen the control law that drives the controlled variable to its set point value is to be designed satisfying equation (12).

A continuous part $u_c(t)$ and a discontinuous part $u_d(t)$ constitute the control law *u(t)*

$$u(t) = u_c(t) + u_d(t) \tag{14}$$

$$u(t) = \frac{\tau_f}{K_f}\left[\frac{y_m(t)}{\tau_f} + \lambda e(t)\right] + K_d \frac{s(t)}{|s(t)| + \delta} \tag{15}$$

K_d , λ and δ are the tuning parameters where K_d increases the aggressiveness, λ increases the integral effect in sliding surface and δ reduces the chattering problem respectively. Initial set of tuning parameters are suggested as

$$K_d = \frac{0.1}{K_f}; \quad \lambda = \frac{0.5}{\tau_f}; \quad \delta = 0.68 + 0.12 |K_f| K_d \lambda \tag{16–18}$$

3.2 Optimal tuning of IMSMC using APSO (IMSMC-APSO)

To solve the problem encountered in MFC by fixed operating point and to optimize the IMSMC control parameters a self tuning technique is used. Self tuning control is an adaptive control that changes some control parameters according to different operating condition in which the system operates. To optimize the MFC performance in terms of precision and settling time IMSMC parameters $K_d, \lambda, \delta, K_f$ *and* τ_f are tuned optimally using APSO. This control structure is referred as IMSMC-APSO and is in Fig.2.This automates as much of the tuning process as possible. Upper and lower bound of the parameters K_d, λ *and* δ are found from the knowledge of initial set of tuning equations (14-16) and K_f *and* τ_f from process reaction curve method respectively and listed in Table-4. This ensures that stability dictum of the system $G^-(s)$ is not violated. APSO evaluates individual particle based on its ability to track a predetermined multi step set point trajectory.

The fitness function is given as $f = \frac{l}{1+J}$. Here *J* is the criterion to be minimised. For multistep reference it is difficult to evaluate the performance based on classical transient and steady state performance similar to rise time, settling time and overshoot so the criterion chosen for minimisation is Integral Time Absolute Error (ITAE)

$$ITAE = \int_0^t t\left|r(t) - Y(t)\right|dt \tag{19}$$

r(t)-reference mass flow trajectory and *Y(t)* - the output flow trajectory.

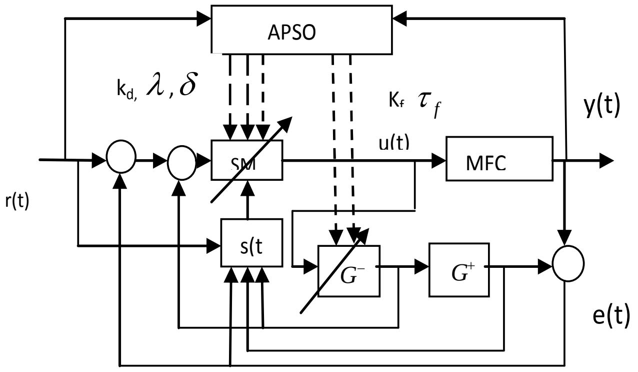


Fig. 3. IMSMC controller tuning via APSO.

4. RESULTS AND DISCUSSION

4.1 MFC system identification

Design variables allow one to acquire a best estimate of the system parameter using APSO. Table. 1 gives the parameter upper and lower bounds for the individuals and Table. 2 gives the initialization variables. Parameter estimation was also performed using classical methods such as Recursive Least Square (RLSarx), Nonlinear least square (NLarx) and Prediction Error Method (PEM). Fig. 4 shows the comparison of classical parameter estimation with PSO and APSO based estimation and its corresponding estimation error curve is shown in Fig 5. For each method the %fit was found and tabulated in Table.4.It is seen that PSO based methods give better fitness compared to classical methods. Furthermore the %fit shows that APSO outperforms PSO in parameter estimation. Estimated parameters in Table. 3 are used to form the identified transfer function model of MFC. It is concluded that the transfer function model corresponding to APSO estimated parameters gives the minimum estimation error compared to PSO estimation. The reason is APSO identified system gives a globally optimum solution thereby improving the estimation accuracy where as PSO system gives reduced estimation accuracy owing to premature convergence.

Table 1. Upper and lower bounds for the individuals used in APSO system identification.

Para-meters	K_1	n_o	n_1	n_2	n_3
Range	[0.1 5]	[0.1 1]	[1 20]	[21 50]	[.1 5]

Table 2. Initialization of design variables in APSO system identification.

Swarm size	Number of iterations	Accelerating co-efficient	Inertia weight W_I	α
100	100	C_1=C_2=2	Linearly decreasing	0.4

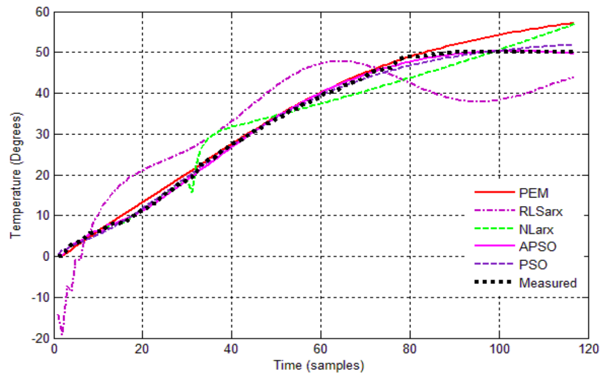


Fig. 4. Response of models identified through RLarx, NLarx, PEM, PSO and APSO.

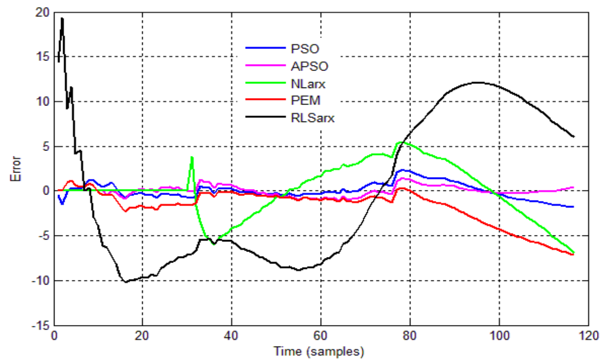


Fig. 5. Error curve for models identified through RLarx, NLarx, PEM, PSO and APSO.

Table 3. Estimated parameters of MFC transfer function via APSO system identification.

Parameter	Symbol	Estimated parameters PSO	Estimated parameters APSO	Units
Valve time constant	n_o	0.10000	00.1000	sec
Sensor time constant	n_1	16.1000	16.0020	sec
Sensor time constant	n_2	43.8000	45.0100	sec
Delay time	n_3	3.00000	3.00700	sec
Sensor gain	K	0.4259	0.60892	$°c/°c$

Table 4. FIT% for models identified through RLarx, NLarx, PEM, PSO and APSO.

Method	Model	FIT%
Classical	RLSarx	49.65
	NLarx	72.33
	PEM	81.12
PSO based	PSO	94.83
	APSO	97.74

Transfer function model estimated using PSO is given as

$$\frac{Y(s)}{U(s)} = \left[\frac{0.4259}{(0.1s+1)(16.1s+1)(43.8s+1)} e^{-3s}\right] \quad (20)$$

Transfer function model estimated using APSO is

$$\frac{Y(s)}{U(s)} = \left[\frac{0.60892}{(0.1s+1)(16.002s+1)(45.01s+1)} e^{-3.007s}\right] \quad (21)$$

The estimation error is calculated using SSE criterion and it is seen that APSO estimated transfer function gives the minimum SSE so this is chosen as the MFC transfer function. From here onwards for the rest of the paper the APSO estimated transfer function in equation (21) is considered to be the MFC transfer function or MFC system.

4.2 Controller design for MFC

The MFC system is tested against a step input of 1slpm gas flow and a multi step set point trajectory of 0-40%-50% - 60%-70%-50% in gas flow is for full scale with the three controllers PI, simple IMSMC and IMSMC-APSO and their performances are compared. To test the controller performance an input is applied to the MFC and mass flow rate at the output side is compared with the reference to generate the error signal.

4.2.1 IMSMC design for MFC

The transfer function between the mass flow rate Y*(s)* and the applied voltage to the control valve *U(s)* is approximated to a FOPTD model.

$$\frac{Y(s)}{U(s)} = \frac{0.05}{26s+1} e^{-3.007s} \quad (22)$$

$$G^-(s) = \frac{0.05}{26s+1} \qquad G^+(s) = e^{-3.007s} \quad (23)$$

$$K_d = \frac{0.1}{0.05} = 2; \qquad \lambda = \frac{0.5}{26} = 0.0192; \quad (24)$$

$$\delta = 0.68 + 0.12|0.05|2*0.0192 = 0.6802$$

4.2.2 APSO in optimal tuning of IMSMC

To optimize the MFC performance in terms of precision and settling time IMSMC parameters $K_d, \lambda, \delta, K_f$ *and* τ_f are tuned optimally using APSO. Design variables and the upper and lower bound for the individuals used for IMSMC-APSO are listed in Table.5 and Table.6 respectively

Table 5. Upper and lower bounds for the individuals used in IMSMC-APSO controller tuning.

Parameters	K_d	λ	δ	K_f	τ_f	τ_{of}
Range	[0 5]	[0 1]	[0 1]	[0 1]	[0 30]	[0 5]

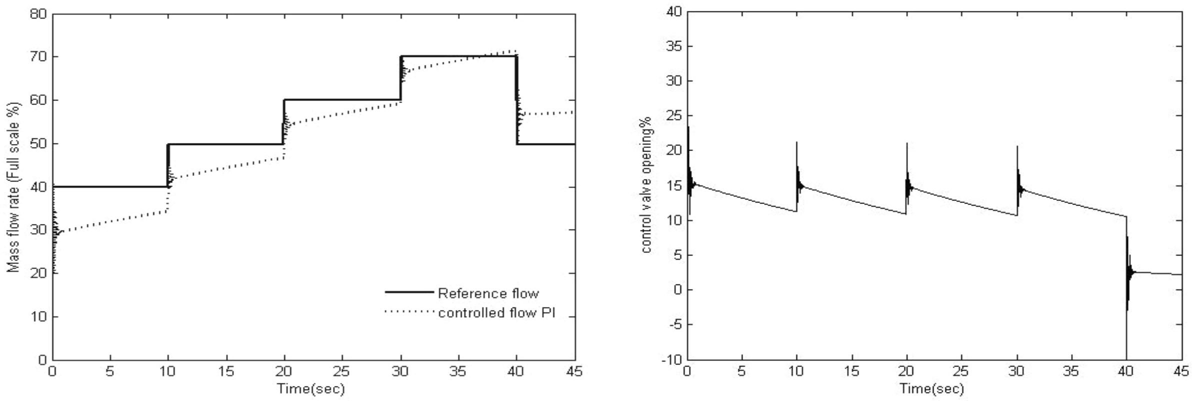
Table 6. Design variables in APSO controller tuning.

Swarm size	Number of iterations	Accelerating co-efficient	Inertia weight W_I	α
100	100	C_1=C_2=2	Linearly decreasing	0.7

System response for multi step set point trajectory of 0-40%-50%-60%-70%-50% in gas flow for full scale via PI controller is illustrated in Fig.6 (a). From the simulation it is seen that the system becomes noisy and its signal to noise ratio is greatly reduced, furthermore system stability is degraded. System instability is owing to the lack of ability of PI controller in handling time delay. Settling time is considerably long due to the slow responding sensor in comparison with the variations in flow rate of the process gas and the designed PI controller could not compensate for it. The control effort required to achieve this performance is displayed in Fig.6 (b).This shows a non smooth control i.e. frequent opening and closing of the solenoid valve indicative of a shorter life span of the valve

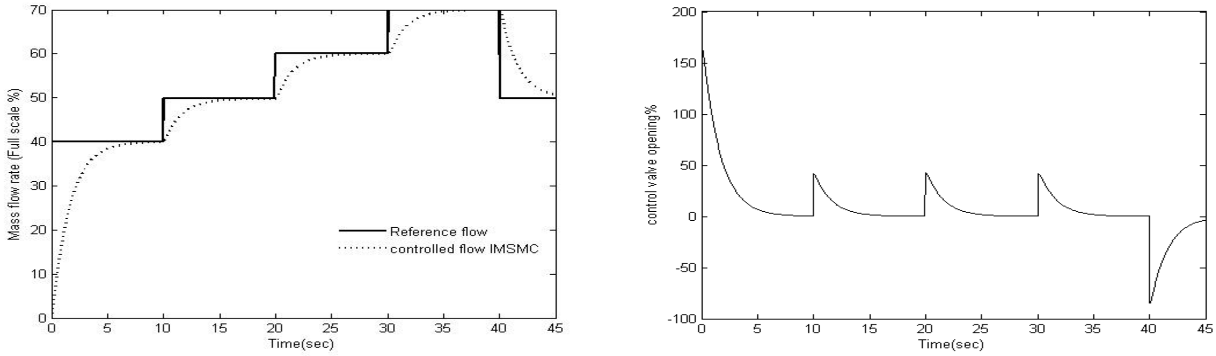
Performance evaluation of simple IMSMC based on multi step set point trajectory of 0-40%-50%- 60%-70%-50% in gas flow for full scale is shown in Fig.7 (a). Though the system performance has increased considerably it shows a highly damped behaviour prolonging system settling violating the major prerequisite of MFC. The parameters of IMSMC are selected by trial and error so they are likely to be inappropriate and are fixed. Designed IMSMC could handle time delay and improve the transient response, it gives a good but not an optimum performance this is attributable to the trade-off among the IMSMC tuning parameters. This could be solved by optimizing the control parameters of IMSMC structure. The control command required to achieve the performance is shown in Fig.7 (b). This gives a smoother control compared to PI but the control effort is excessive. Presence of excessive control action causes actuator saturation (Jeraldin and Sundaravadivelu, 2011).In addition the response time of the valve is long, once opened it takes approximately 3 seconds to fully close.

Design of IMSMC-APSO for multi step set point trajectory of 0-40%-50%- 60%-70%-50% in gas flow for full scale is exemplified through Fig.8(a).MFC tuned with IMSMC-APSO gives a highly precise and quick response with insignificant overshoot. Control effort required for the IMSMC-APSO is illustrated through Fig.8 (b).



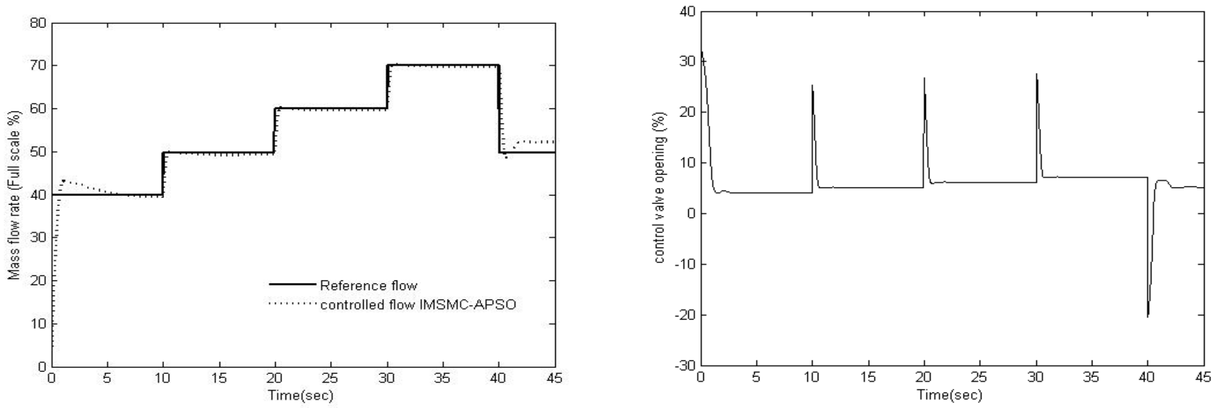
(a) (b)

Fig. 6. Performance of PI controller for a multi step trajectory (a) mass flow response (b) control signal.



(a) (b)

Fig. 7. Performance of simple IMSMC for a multi step trajectory (a) mass flow response (b) control signal.



(a) (b)

Fig 8. Performance of IMSMC-APSO for a multi step reference trajectory (a) mass flow response (b) control signal.

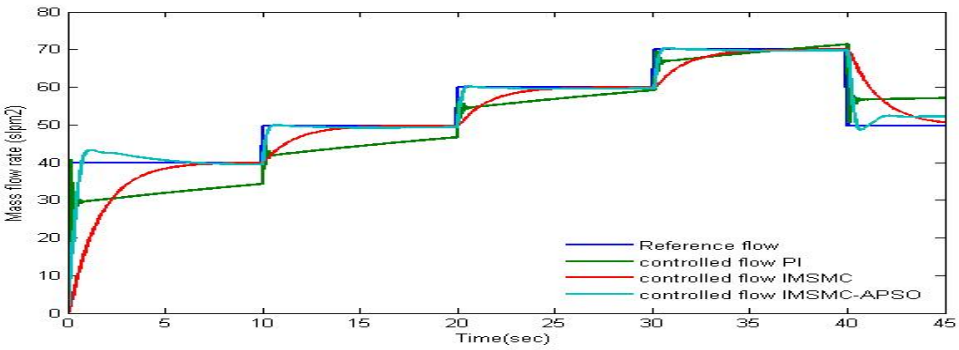


Fig. 9. Comparison of MFC response using PI, simple IMSMC and IMSMC-APSO.

IMSMC-APSO gives a smooth control with minimum effort of 30% compared to PI and IMSMC.Table.7 shows the control parameters of IMSMC and IMSMC–APSO used in multi step tracking.

A comparison of system response for multi step set point trajectory of 0-40%-50%- 60%-70%-50% in gas flow for full scale via PI controller, simple IMSMC and IMSMC–APSO are illustrated in Fig.9. It is seen that IMSMC-APSO tracks the reference trajectory instantly and precisely compared to PI and IMSMC.

Table 7. Control parameters of IMSMC and IMSMC-APSO used in multistep tracking.

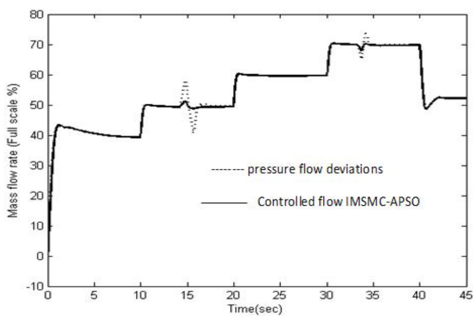
Parameters	**IMSMC**	**IMSMC-APSO**
K_d	2.0700	4.0605
λ	0.0292	0.0208
δ	0.6702	0.6802
K_f	0.0500	0.0246
τ_f	26.000	24.0067
τ_{0f}	3.000	3.01700

4.3 Pressure transient insensitivity of IMSMC-APSO

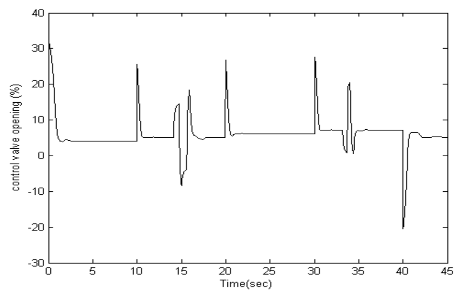
Sensitivity to pressure transients remains a chronic problem with semiconductor gas delivery system. These pressure perturbations stem from set point changes in MFCs sharing a common feed-line. A step change in the inlet pressure can result in a spike of inlet flow to the MFC that can be in the order of magnitude above or below the reference flow rate. A disturbance gas pressure variation acts as an additive signal on the sensor signal. To analyse the pressure transient insensitivity performance pressure perturbations are introduced in the form of pressure step changes. The MFC system with IMSMC –APSO is tested against disturbance.

An upward pressure perturbation of 3 psia at 15sec and a reverse pressure perturbation of 2 psia at 35 sec are introduced. Response of the systems controlled by IMSMC-APSO for this pressure transient is shown in Fig.10 (a) .From the response it is concluded that IMSMC –APSO have good disturbance rejection capability.

IMSMC-APSO controller action for the pressure disturbance is shown in Fig.10 (b). The IMSMC-APSO needs a lower controller effort compared to the IMSMC controller. In addition IMSMC-APSO returns the valve to equilibrium position more rapidly compared to IMSMC controller. For positive flow error the control valve reduces the flow and after the transient passes the valve opens again generating damped oscillations for few seconds until the system recovers equilibrium. Magnitude of flow error is independent of flow rate.



(a)



(b)

Fig. 10. Performance of IMSMC-APSO for pressure disturbance (a) mass flow response (b) control signal.

4.4 Robustness Analysis of MFC

Although the IMSMC-APSO is designed for nominal operating conditions of MFC a satisfactory performance is desirable for other operating conditions also. Even a small discrepancy in sensor time constants 'n_1' and 'n_2' can create overshoot and increase the settling time Robustness analysis for MFC controlled by IMSMC-APSO were performed by varying thermal flow sensor time constants n_1 and n_2 in the range of -10% to +10% in steps of 5%. Flow responses of MFC controlled by IMSMC-APSO varying n_1 is shown in Fig. 11. It can be seen that deviation in settling time and accuracy are very small for selected system parameters. So it is concluded that the MFC controlled by IMSMC-APSO are robust to parameter uncertainty and modelling approximations.

Settling Time comparison of Mass flow system with IMSMC and IMSMC-APSO for multi step input is shown in Table.8. From the quantitative analysis it is seen that settling time has decreased by 11.45% in IMSMC –APSO compared to simple IMSMC.ITAE and ISE criterions are used to quantify the accuracy and tracking ability of the controller and its comparison is shown in Table .8. From the table it is seen that accuracy (ITAE) in IMSMC –APSO has increased by 16.33%, 20.24% and 18.26% in normal condition, amid pressure disturbance and model uncertainties respectively compared to simple IMSMC.

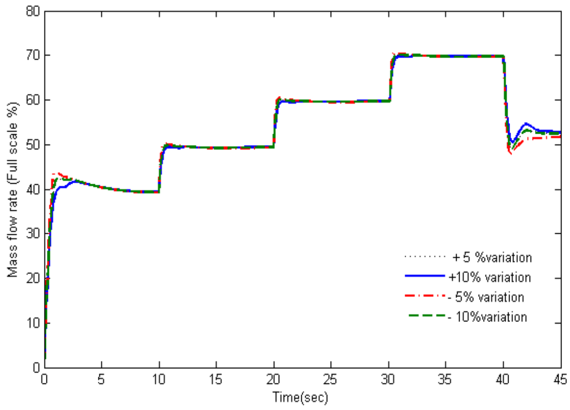


Fig. 11. Robustness analysis for IMSMC-APSO 'n_1' varying from –10% to +10% in steps of 5%.

Table 9. settling time comparison of Mass Flow Controller using IMSMC and IMSMC-APSO

Reference flow rate %	Settling Time (sec)		
	PI	IMSMC	IMSMC-APSO
0% -40%	-	6.90	0.65
40% -50%	-	5.2	0.45
50%-60%	10	5.05	0.40
60%-70%	10	5.5	0.50

Table 10. Performance measures of IMSMC and IMSMC- APSO as applied to MFC

Input	ITAE		ISE	
	IMSMC	IMSMC -APSO	IMSMC	IMSMC -APSO
Step (1slpm)	4.012	0.347	0.474	0.068
Multi step input (0%-40%-50%-60%-70%-50%) (Full Scale)	3.789	0.232	0.258	0.023
Multi step input with pressure transients (3psia upwards 2psia downwards)	3.907	0.193	0.279	0.050
Multi step input varying n_1 by ±10%	3.816	0.209	0.154	0.038

5. CONCLUSIONS

In this work an IMSMC-APSO controller has been proposed for an identified model of MFC to control the mass flow rate. First, through system identification a third order system with time delay and low damping ratio is identified as the open loop transfer function of MFC. To avoid modelling errors in the identified transfer function the system parameters are estimated optimally via APSO with 2% higher estimation accuracy compared to PSO. In second step a self tuning IMSMC –APSO is proposed to surmount the difficulty in fixed operating condition. The controller tracks the multi step flow trajectory with decreased flow deviation and settling time. The robustness analysis and pressure disturbance rejection test indicate that the proposed IMSMC –APSO could maintain a fixed mass flow rate regardless of system parameter (time constant) uncertainty and pressure disturbance. Furthermore an analysis on the required control effort proved that the control signal needed for operating IMSMC-APSO is reduced through 30% compared to PI and simple-IMSMC this avoids the actuator saturation caused by excessive control effort. Numerical simulation results validate that APSO is a rational candidate to be used for optimal system identification and IMSMC tuning.

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Appendix A

APSO ALGORITHM

Initially a population with a size of the particle is created. Each particle is associated with the velocity. Velocity of each particle is updated based on its own experience and the companion particle's experience. It is expected that the particles will fly towards better solution areas . Fitness of each particle is evaluated on the basis of objective function of optimization problem In APSO velocity of every particle in each iteration is given as

$$v_i^{k+1} = w_i^k v_i^k + c_1^k r_1\left(p_{best\ i}^k - x_i^k\right) + c_2^k r_2\left(g_{best}^k - x_i^k\right)$$

Where $p_{best\ i}^k$ - best previous position of the particle; x_i^k -position of the particle in kth iteration; g_{best}^k -best previous position among all the particle in kth iteration;

C_1 and C_2- acceleration coefficient; r_1 and r_2- random numbers in the range [0,1];

w_i^k - inertia weight for ith particle in kth iteration;

$$w_i^k = \frac{1}{1+e^{-(\alpha + A_i^k)^{-1}}}$$

; α – positive constant in the range [0, 1] ;(influences the rate of change of inertia weight)

$$A_i^k = \frac{F\left(p_{best\ i}^k\right) - F_N}{F\left(p_{best\ i}^k\right) - F_N} - 1$$

$F\left(p_{best\,i}^k\right)$ is the fitness of the best previous position of the kth particle and F_N real optimal solution

After calculating the velocity, the new position of the particle is given as

$$x_i^{k+1} = x_i^k + v_i^{k+1}$$

Until the predetermined generation is reached the velocity and position equations are updated