Optimal Control of Carbon Dioxide Exchange Process in a Membrane Oxygenator Using Particle Swarm Optimization Approach

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Abstract. The aim of this study is to evaluate the performance of Zeigler-Nichols continuous cycling and particle swarm optimization (PSO) method in tuning the optimal gains for Proportional-Integral-Derivative (PID). PID controller is implemented to control the rate of CO2 elimination from a membrane oxygenator during extracorporeal blood purification process. The sweep gas flow rate is chosen as the manipulated variable to control arterial CO2 partial pressure (pCO2) in blood. The Zeigler-Nichols continuous cycling tuning method is employed for tuning purpose and the performance of each controller (P-only, PI and PID) are evaluated based on three performance indices, namely integral absolute error (IAE), integral squared error (ISE) and integral time absolute error (ITAE). Next, the optimization algorithm known as PSO is used to calculate the gain parameter that can produce the best control action. The robustness of these tuning methods is assessed for set point tracking and load disturbance rejection tests. Results indicated that the PID is seen as the best controller compared to the classical controllers such as P and PI when Zeigler-Nichols continuous cycling as the tuning method is implemented. However, further tests highlighted the PSO-PID strategy (PID parameters that are optimized by PSO) showed even better control responses compared to PID alone. Thus, it can be concluded that optimization strategy by PSO method is the best tuning method to be used in determining the controller parameters for the automation of extracorporeal circulation control for both set point tracking and load disturbance rejection tests.

Keywords: carbon dioxide removal, membrane oxygenator, PID tuning, Zeigler-Nichols continuous cycling tuning, particle swarm optimization.

1. Introduction

A huge leap in membrane technology which evolved from bubble oxygenator in 1970’s until the recent innovation of membrane oxygenator made from polymethylpentene (PMP) has resulted in vastly improved in gas exchange with great reduction in oxygenator failure rate. The main components of extracorporeal life support system consist of membrane oxygenator, pump and tubing circuits. During
the operation of membrane oxygenator in extracorporeal life support, the sweep gas adjustment is a must, since CO₂ clearance is dependent on the sweep gas flow rate (1, 2). The importance of manipulating the sweep gas by adjusting its flow rate was highlighted by Richard et al. (3) and Extracorporeal Life Support Organization (ELSO) (4), where sweep gas rate should be carefully adjusted in order to give a partial pressure of CO₂ (pCO₂) between 30-40 mm Hg. Thus, the gas flows to the oxygenator are manually adjusted until the optimum partial pressure in the arterial blood is achieved. This manual adjustment is performed by a perfusionist staff, which prone to human error and extreme workload to the staff (5). Hence, the idea of implementing an automated sweep gas flow rate adjustment using feedback control system seems to be the perfect solution for this problem. By this automated control, patient’s safety and efficacy of membrane oxygenator employment could be enhanced due to the fast control reference tracking of reasonable set points and good disturbance rejection by the implemented control system. It also will reduce the extreme workload of perfusionist, in addition to the correct decision making. Hence, in this study, the attention will be given to the oxygenator, in order to produce a self- automated control of CO₂ gas transfer in membrane oxygenator.

Automated control strategy on gas transfer process across membrane oxygenator were actively recruited for the past years and well-documented in previous studies, such as PI controller with gain scheduling (6-9), smith predictor with inner PI controller (9, 10), cascade control scheme that comprised of gain-scheduled PID and PI controller (11), PID controller (5, 12). Most of these studies were focusing on the automatic control of oxygen pO₂, with none or minor attention on pCO₂. In this study, the control strategy will be fully dedicated on the automatic control of pCO₂ using PID, with detail explanation on tuning process of PID gain using Ziegler-Nichols method and Particle Swarm Optimization (PSO) method. In addition, the approach of performance evaluation on PID controller differs from previous related studies, which the performance is evaluated in terms of integral absolute error (IAE), integral squared error (ISE) and integral time absolute error (ITAE). Dynamic responses using proposed controllers are then plotted for both set point tracking and load disturbance rejection tests to further study and analyse their individual control ability.

The PID algorithm functions to drive the controller output in the direction that force the process variable towards the set point until it reaches the desired set point. For this purpose, a closed-loop of PID operation is constructed based on the output obtained from process plant. Hence it must be tuned properly based on the various tuning methods that been introduced, since these PID parameters will contribute to high impact on stability and performance of control system (13-15).

The equation of PID is generally given as:

\[ u(t) = K_p e(t) + K_i \int_0^t e(t) dt + K_d \frac{d}{dt} e(t) \]  

Where \( K_p \) is proportional gain, \( K_i = K_p/T_i \), \( K_d = K_p \times T_d \), \( T_i \) is integral time constant and \( T_d \) is derivative time constant.

There are some classic tuning methods available today, such as Ziegler-Nichols (for open and closed loop systems), Thyreus-Luyben, damped-oscillation, Cohen and Coon, Internal Model Control (IMC) and minimum error criteria (IAE, ISE and ITAE) methods (16), which later been improved by powerful optimization-based synthesis method by considering closed-loop stability region with respect to \( K_p, K_i \) and \( K_d \) (17), event-based PID controller (18) or using computer intelligence approach as in genetic algorithm (GA) and PSO.

PSO algorithm is an evolutionary computational technique that was introduced by Kennedy and Eberhart (19), and remain relevant to be used until today (20-22). PSO started with a random distribution of set of particles (potential solutions), which later followed by the improvement of solution according to a quality measure (fitness function) (23). This improvisation strategy is performed through moving the particles around the search space through a set of simple mathematical equations that model some inter-particle communications (23). The particle’s movement is based on concept of ‘at each time step,
velocity changing (accelerating) for each particle towards its pbest (best position) and gbest (best particle) locations’ (for global version of PSO) (24).

There are some known advantages of using PSO compared to GA, even both of them are most common optimization techniques. Since PSO interact in group enhances, rather than detracts from progress towards the solution, PSO seems to be simpler algorithm than GA (25). In addition, PSO has memory, which is absent in GA. Without this ability, any changes in genetic population will lead to the destruction of previous problem knowledge, except when elitism is implemented, even though in this case only one or small number of individuals will retain their identities. In contrast, for PSO, individuals who fly past optima are maintained to return towards them, so that knowledge of good solution is retained by all particles (25). Due to these advantages, PSO was selected to be employed as optimization strategy, with the hypothesis that PID gain that is tuned by PSO algorithm will produce the best performance as compared to controllers which are tuned using Zeigler-Nichols continuous cycling method, mainly for closed-loop systems.

2. Methodology

It was proven from our previous reported study (26), total flow rate of sweep gas that enters the membrane oxygenator are the determinant factor for rate of pCO\textsubscript{2} exchange in oxygenator. This findings also were advocated by other previous studies, either by simulation studies (27), in vitro studies Federspiel and Hattler (28), (29) or even in vivo studies (30-32). Thus, in this present study, controller output is the sweep gas flow rate that been supplied to the process plant, while pCO\textsubscript{2} value that obtained from the process plant is considered as process output. This pCO\textsubscript{2} value then is used as an input value to PID controller. By using this approach, a closed loop control system is designed to automatically adjust the sweep gas flow rate by considering the response of pCO\textsubscript{2} measurement to the previous change of this controller output (33) to maintain the setpoint of pCO\textsubscript{2} during CO\textsubscript{2} gas transfer through membrane oxygenator.

2.1. Modelling of CO\textsubscript{2} transfer

In this study, simulations were conducted based on the comprehensive mathematical model of respiratory model that been developed by Hill et al. (34), which then extended by Hexamer and Werner (35) to suit with its context on membrane oxygenator design. This model described mathematically the process of gas diffusion process (O\textsubscript{2} and CO\textsubscript{2}) in membrane oxygenator with consideration on three compartments: gas (g), plasma (pl) and red blood cell (rbc). The simulation on this model also had been reported in our previous study (26), which also included open loop-loop test findings.

2.2. PID tuning and automated control

Closed loop control was conducted using P-only, PI, PID and PID that been optimized by PSO. This control strategy involved 2 stages, namely tuning and automated controlling. Ziegler-Nichols continuous cycling method was implemented to tune the best PID tuning parameter setting. Ziegler-Nichols method started with the determination of critical value for controller gain ($K_c$) and ultimate period ($P_u$) that produce a continuous oscillation of control loop, according to the tuning procedure described in (36-38), followed with the tuning of $K_p$, $T_i$ and $T_d$. Gain for $K_p$, $T_i$ and $T_d$ that were obtained from this method were tabulated in Table 1.

| Controllers | P-only | PI | PID | PSO-PID |
|-------------|--------|----|-----|---------|
| $K_p$       | 450.00 | 405.00 | 540.00 | 599.75 |
| $T_i$       | -      | 0.98 | 0.59 | 1 X $10^3$ |
| $T_d$       | -      | -   | 0.15 | 0.29 |

Table 1: Gain for $K_p$, $T_i$ and $T_d$
In addition to Ziegler-Nichols continuous cycling method, PSO optimization then is implemented to tune $K_p$, $T_i$ and $T_d$, so that the efficiency of both tuning methods can be compared. PSO algorithm is used to tune the gains of the best controller offline, using the same mathematical modelling that previously described. Next, the accuracy of the entire controllers is calculated based on the quantitative analyses, which are IAE, ISE and ITAE.

$$IAE = \int_0^{\infty} |e(t)| dt$$  \hspace{1cm} (2)

$$ISE = \int_0^{\infty} e^2(t) dt$$  \hspace{1cm} (3)

$$ITAE = \int_0^{\infty} t|e(t)| dt$$  \hspace{1cm} (4)

2.3. Particle swarm optimization (PSO)

In this study, number of populations selected is 25; with maximum iteration are 15 iterations. All the parameters such as population size, maximum iteration and weight associated to the fitness function used in this simulation are tested heuristically by changing it until the optimum parameters for optimal performance is achieved. Currently, there is no general method to determine the optimum parameters, since the selection of these variables is a problem dependent phenomenon and varies from problem to problem. Nevertheless, there are some references that were taken as our guidelines which discussed this topic (39-41).

The fitness function for minimization is:

$$J(K_p,T_i,T_d) = \omega_1(IAE) + \omega_2(ISE) + \omega_3(ITAE)$$  \hspace{1cm} (5)

Where, $\omega_1 = 0.2$, $\omega_2 = 0.4$ and $\omega_3 = 0.4$

In this PSO algorithm, both position and velocity of the particle was updated using the equations:

$$v_{id}^{n+1} = w. v_{id}^n + c_1. rand. (p_{id}^n - x_{id}^n) + c_2. rand. (p_{gd}^n - x_{id}^n)$$ \hspace{1cm} (6)

$$x_{id}^{n+1} = x_{id}^n + v_{id}^{n+1}$$ \hspace{1cm} (7)

Where $i_{th}$ particle is represented as $x_i = (x_{i1}, x_{i2}, ..., x_{id})$. The best previous position (giving the minimum fitness value) of any particle is represented as $p_i = (p_{i1}, p_{i2}, ..., p_{id})$, which is called $p_{best}$. The index of the best particle among all particles in the population then is represented by the symbol $g$, called as $g_{best}$. The velocity for the particle $i$ is represented as $v_i = (v_{i1}, v_{i2}, ..., v_{id})$. The $c_1$ and $c_2$ are two positive constants (acceleration constants), which $c_1 = c_2 = 2$, $w$ is inertia weight factor. Next, $rand(\ )$ is random function between 0 and 1, while $n$ denotes iteration.

Equation (6) is used to calculate particle’s new velocity based on its previous velocity and the distances of its current position from its own best experience (position) and the group’s best experience. Next, the particle moves to a new position according to equation (7). The whole process flow of PSO algorithm implemented in this study was summarized in form of flowchart as in Figure 1 (42):
The PSO algorithm then is applied in complement with PID controller in MATLAB/SIMULINK environment, which is further referred as PSO-PID. The structure for PSO-PID is depicted in Figure 2. Note that the PID controller that has been used in this study is a direct acting controller, based on the open-loop simulation results obtained in previous study (26).
2.4. Robustness tests

In order to further evaluate the robustness of the proposed controllers in dealing with model uncertainty, some process parameters are altered, according to its two assigned tasks, which are set point tracking and load disturbance rejection tests:

2.4.1. Set point tracking

For set point tracking task, the set point was set as 40 mm Hg at t=0 until t=29.99 s, then adjusted to 42 mm Hg from t= 30 s to t=70s. At t= 70.01s, the set point was returned back to its initial value, which is 40 mm Hg. This is to see the ability of the controllers to control the process variable accordingly to the desired set point in order to minimize the error between simulated pCO\textsubscript{2} and set point.

2.4.2. Load disturbance rejection

To assess the ability of the proposed controller in rejecting load disturbance, a load of 0.5 L/min was introduced to process plant at t=30s to t= 70s. This test was conducted due to the fact that a good controller will take action to bring the process variable back toward the desired set point in case of load disturbance on the process that cause the deviation.

3. Results

3.1. Robustness of PID control: set point tracking

For quantitative analysis, IAE, ISE and ITAE were calculated to evaluate the accuracy of P-only, PI, PID and PSO-PID controllers during set point tracking. Performance indices such as IAE, ISE and ITAE for these controllers were calculated and presented in Table 2.

Table 2: Performance indices for P-only, PI, PID and PSO-PID controller for set point tracking

| Performance index | P-only | PI  | PID  | PSO-PID |
|-------------------|--------|-----|------|---------|
| IAE               | 1.83   | 1.68| 1.37 | 0.54    |
| ISE               | 0.70   | 0.69| 0.69 | 0.69    |
| ITAE              | 105.90 | 95.42| 74.68| 21.19   |
Based on these findings, it can be concluded that PID is the best controller among the classic PID controller, such as P-only, PI and PID, with 1.37 IAE, 0.69 ISE and 74.68 ITAE. The competitive performance of PID that obtained from this study was agreed with the results reported by Sadati et al. (12) during maintaining nominal range of pO_2 in membrane oxygenator.

Tuning of PID using Ziegler-Nichols continuous cycling method is a heuristic method that considers the experience in manual tuning of controller designer. This classical tuning method then was improved by PSO optimization technique in order to get better controlling performance. While comparing both tuning methods, it was evident from Table 2 that PSO-PID performed better than PID (tuned by Ziegler-Nichols continuous cycling method), which produced significantly lower IAE, ISE and ITAE with 0.54, 0.69 and 21.19, respectively. In fact, this proposed controller can produce the best performance result compared to other controllers to control the process.

In addition to calculation of performance indices, the simulated pCO_2 for entire controllers were plotted in one graph to see the dynamics of process variable in response to the controller’s action, as illustrated in Figure 3.

Figure 3. Comparison of simulated pCO_2 for different type of controllers for setpoint tracking

Figure 3 shows responses of process variable (pCO_2) and controller output (sweep gas flow rate) with a step change of pCO_2 set point for P-only, PI, PID and PSO-PID controller and close-up graph as inset. From Figure 3, the presence of highest offset for P-only controller was clearly seen, as compared to PI
and PID controller. Slight overshoot and error that were obtained for PI controller also similar with the plotted process variable reported by Wartzek et al. (9) and Walter et al. (11). Both authors used the mathematical model of membrane oxygenator by Hexamer and Werner (35), as in this study. For the same figure (Figure 3), very small error (less than 0.001) was observed for this PSO-PID controller. This observation verifies our hypothesis that the performance of PID control action can be improved using PSO algorithm as tuning method in determining gain for P, I and D.

3.2. Robustness of PID control: Load disturbance rejection

The robustness of PID controller is further proven by its ability to reject any load disturbance subjected to the controller, as tabulated in Table 3. Once again, the best control performance was shown by PID controller which was tuned by PSO optimization. The trend is similar with set point tracking task, but with better IAE, ISE and ITAE performance indices. When comparing between these two tasks, it is clearly shown that all controllers that have been implemented in this study offered better performance and capability to reject load disturbance rather than set point tracking task.

Table 3: Performance indices for P-only, PI, PID and PSO-PID controller for load disturbance

| Performance index | P-only | PI     | PID    | PSO-PID |
|-------------------|--------|--------|--------|---------|
| IAE               | 0.91   | 0.77   | 0.56   | 0.01    |
| ISE               | 0.01   | 0.01   | 6 X 10^{-3} | 4.25 X 10^{-5} |
| ITAE              | 65.69  | 56.79  | 40.94  | 0.51    |

Control performance of each implemented strategies then are plotted to demonstrate their individual performance as depicted in Figure 4. There is small noticeable offset seen in P-only, PI and PID controller which indicate the steady-state error, while no offset was seen for PSO-PID. PSO-PID offers good adaptation to the load disturbance by bringing the process variable responses to the specified set point to achieve nearly perfect dynamics over the whole simulation period. This indicates the ability of the controller to suit the load that applied to the actuator. Prior to the applied load disturbance (t<30 seconds), the controller output for all four controllers were around 0.85 L/min. After the load disturbance (t≥30 seconds), the controller output was reduced to 0.35 L/min, in order to adapt the load of 0.5 L/min, which consequently reach the set point as 40 mmHg. This adaptive response clearly indicated robustness of the controllers used in this study.
4. Discussions

Robustness in this context is defined as the ability of the controller to tolerate with any change in process plant without disturbing the stability of feedback system. From the result obtained in previous section, PID controller became the best and most robust controller for both set point tracking and load disturbance rejection tasks. With the combination of proportional, integral and derivative control actions, steady state error, or mostly known as an ‘offset’ and undesirable oscillatory response can be significantly reduced. With the implementation of PSO in tuning the best gain for each parameter (P, I and D), the best performance of control action was developed and reported in this study.

PSO is an offline numerical optimization technique that solves the pre-stated mathematical programming problem (in terms of fitness function). In addition to its outshine performance, there are a few advantages of PSO approach, such as it does not require any practical experience of control engineers, its ability to handle complicated tasks and its ability to deal with large class of nonlinear systems. In addition to these advantages, the other factor to be considered here is the ability of the controllers to produce optimal tuning on the process variable.

According to Altmann (36), the main objectives of PID tuning are to minimize both IAE and ISE, to provide the fast control of PID controller, produce minimum wear and tear of controlled equipment and eliminate the overshoot at the start up. Thus, PID that was tuned by PSO algorithms was proven had fulfilled all the requirements, especially when it reduced IAE and ISE indices with no overshoot for both set point tracking and load disturbance rejection. This superb control ability implies that the proposed PSO approach is the best optimization method for PID parameter tuning and suitable to be applied in real system.
5. Conclusion

Tuning the parameter of PID controller with the Ziegler-Nichols continuous cycling method offered the best performance among the classic controllers, such as P-only and PI. As an improvement strategy, PSO algorithm was employed to tune the PID parameter, which reflects the greatest ability to control pCO₂ during extracorporeal circulation using membrane oxygenator as compared to the other tested controllers. This was proven by the reduction of around 83% for IAE and 72% for ITAE using PSO-PID, rather than PID controller alone without any optimization strategy. As for load disturbance rejection, the reduction of performance indices observed for PSO-PID compared with PID alone are higher with up to 98% for IAE and 99% for ISE and ITAE. Hence, to summarize the findings, PID controller recorded the best performance and robustness compared with P-only and PI when tuned with Ziegler-Nichols continuous cycling method, while PID that tuned by PSO approach performed better than PID with Ziegler-Nichols continuous cycling method.

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Conflict of interest
The authors declare that there is no conflict of interest relevant to the subjects of this article.

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