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# Neural Network-based Model Predictive Control with CPSOGSA for SMBR Filtration

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**ABSTRACT**

This paper presents the development of neural network based model predictive control (NNMPC) for controlling submerged membrane bioreactor (SMBR) filtration process.The main contribution of this paper is the integration of newly developed soft computing optimization technique name as cooperative hybrid particle swarm optimization and gravitational search algorithm (CPSOGSA) with the model predictive control. The CPSOGSA algorithm is used as a real time optimization (RTO) in updating the NNMPC cost function. The developed controller is utilized to control SMBR filtrations permeate flux in preventing flux decline from membrane fouling. The proposed NNMPC is comparedwith proportional integral derivative (PID) controller in term of the percentage overshoot, settling time and integral absolute error (IAE) criteria. The simulation result shows NNMPC perform better control compared with PID controller in term measured control performance of permeate flux.



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## 1. INTRODUCTION

Membrane bioreactor (MBR) is an efficient technology in wastewater treatment process. The combination of membrane technology and biological process reactor is an answer for high quality effluent in wastewater treatment. Membrane filtration process is very important element in MBR system this is the place where separation process is occur. However, MBR struggle with a few limitations such as membrane fouling and high energy consumption during filtration process. A fouling phenomenon is caused by many factors such as colloidal, particulate, and solute materials. Membrane fouling is a complex process, affected by many parameters, including the operation, influent properties, and the membrane itself [1]. Fouling can lead to a membrane clogging, resulting in that the membrane pore will be blocked by solid material. Fouling will affect the overall performance of a filtration system in short and long term operation, by inducing high filtration resistance, as a result of the compact formation of fouling on the membrane surface[2]. The clogging on the membrane also will reduce the permeate flux output and the same time the overall system efficiency will be effected. Several membrane cleaning techniques were introduced to control fouling development such as relaxation, backwash, airflow and chemical cleaning. A part from that, manipulation of flux flow rate is very important in membrane filtration system. It can be utilize to reduce fouling by adjusting the permeate set point when necessary [3].

Controlling a permeate flux at different set point is a challenging task because the pressure of the filtration due to fouling phenomena is different at different set point. Higher set point will result of higher pressure. Higher filtration pressure is due to the filtration resistances that increase at the higher flux flow rate.Even though MBR technology is introduce for many years ago, the application of control system in MBR system still not mature. At the moment, open loop control system still implement in many MBR plant [4]. Application of advance control system for SMBR process is very challenging task and needs a lot of understanding of the system operation and dynamic. Some successful implementation of close loop control has shown that the application of controller has gives improvement to the system and process. Proportional integral derivative (PID) controller is still the main controller used in many industries. This controller is very popular because of its simplicity and simple to understand. In addition, the controller is very stable and easy to be tuned. Curcio et al [5] presents the PI and PID control application to the UF membrane filtration process. Simulation of the system was done using hybrid neural network model. The controllers were used to control the permeate flux of the filtration process. The controllers were tuned using zigler-nichols (ZN) and ITAE tuning methods. The authors found ITAE tuning method is more robust both in regulator and servo problem in preventing flux decline during filtration process. PID controller was used for permeate flux control in submerged anaerobic membrane bioreactor [6]. However, PID controller was found produce high overshoot at the initial filtration cycle that can cause poor filtration performance. This is cause by the ON and OFF stages in the filtration system. In order to solve this problem, fixed frequency with PID controller was introduce to control the permeate pump.

Nonlinear Model predictive control (NMPC) is an effective model based controller for many applications such as in [7],[8] and [9]. This technique is very effective since many of the process are nonlinear. Neural network based model predictive control (NNMPC) is among the popular NMPC technique in literature. This controller employed neural network as a prediction model in the controller design. This work employed the NNMPC technique to control the SMBR filtration permeate flux. The NNMPC is design with cooperative particle swarm optimization with gravitational search algorithm (CPOSGSA) as a real time optimization (RTO) for the MPC cost function minimization. The CPSOGSA optimization algorithm is new and efficient technique for optimization for many types cost function. Integration of this optimization technique in MPC will produce reliable and effective NNMPC.

## 2. RESEARCH METHOD

### 2.1. Process Modeling

The artificial neural network (ANN) model with recurrent structure is applied where the past output and input is used to predict the current output. This structure is also known as nonlinear auto regressive with exogenous input (NARX). Figure 1 presents the model structure employed in this work.

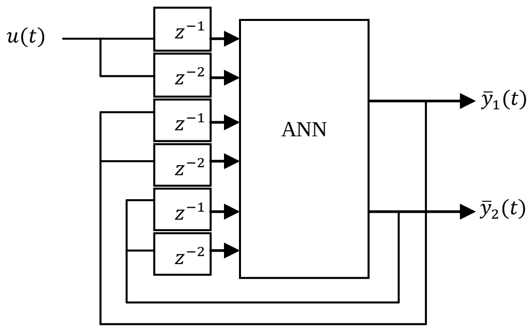


Figure 1. Neural Network Structure

$u(t)$ is the voltage applied to the permeate pump while, $\bar{y}_1(t)$ and $\bar{y}_2(t)$ is the predicted permeate flux and TMP respectively. $z^{-1}$is the delay operator.The experimentswere carried out in single tank submerged membrane bioreactors, with working volume of 20 L palm oil mill effluent (POME) taken from Sedenak Palm Oil Mill Sdn. Bhd. in Johor, Malaysia. The working temperatures for the bioreactors were at 29 ± 1 °C. The plant was operated with 120 second permeate and 30 second for relaxation period. The airflow rate is maintained around 6-8 LPM. Figure 2 shows the pilot plant setup for the experiment. The data plant was controlled and monitored using National Instruments, LabVIEW 2009 software with NI USB 6009 interfacing hardware.Table 1shows the list of instruments used in the pilot plant development.

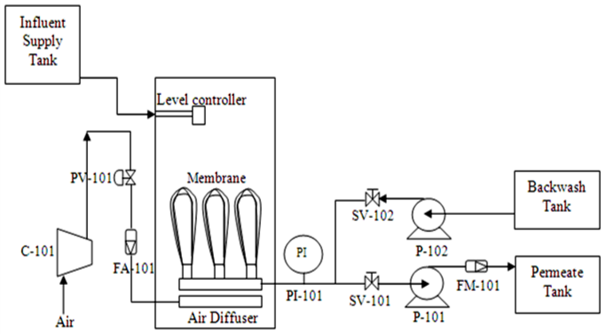


Figure 2. Schematic Diagram of the Submerged MBR

Table 1. List of Instruments/Parts

| Tag No | Description |
|---|---|
| C-101 | 20L 2HP Air compressor |
| PV-101 | Proportional Valve |
| FA-101 | Airflow Sensor |
| PI-101 | Pressure Transducer |
| SV-101 | Solenoid Valve Permeate Stream |
| SV-102 | Solenoid Valve Backwash stream |
| P-101 | Peristaltic Pump |
| P-102 | Diaphragm Pump |
| FM-101 | Liquid Flow Meter |
| Membrane | Hollow Fiber Membrane |

In this work, Polyethersulfone (PES) material with approximately 80-100kda pore size membrane was used in the filtration system. The data collection as shown in Figure 3 is performed using random step test to the permeate pump. This will excite the dynamic of the filtration process. 70 percent of the data is used to construct the neural network model using selected training method, while another 30 percent is used for testing the neural network accuracy.

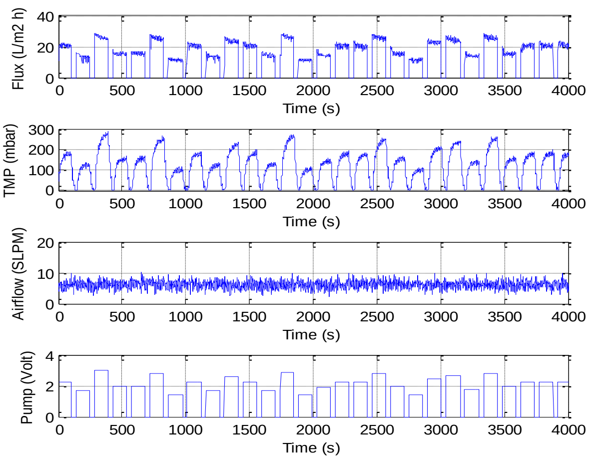


Figure 3. Experiment data

## 2.2. CPSOGSA Algorithm

The CPSOGSA is an effective optimization technique that can provide optimal solution for many applications. Fundamental approach of the algorithm is to allow more groups with different advantages to search for the best solution. With this method, it is less possibility for the algorithm to trap at the local minima.The cooperative technique in this work is described by the interaction between master and slaves.

The number of slave groups can be generated accordingly depending on the complexity of the optimization problem. Figure 4 shows the cooperative architecture between master and slave groups.

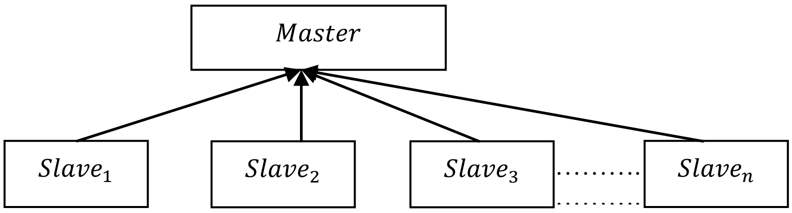


Figure 4. The cooperative architecture of the algorithm

Each of the slave groups will look for the best fitness and this fitness value will be compared among the slave group. The best fitness of the slave group will be compared again with the master group and the best fitness agent will be used for the velocity update calculation using equation (1).

$$V_M(t+1) = w \times V_M(t)c_3 + c_1 \times a \times rand_1 + c_2 \times \beta_1\big(gBest_{slave} - X_{id}(t)\big) \times rand_2 + c_3 \times \beta_2(gBest_{Master} - X_{id}(t)) \times rand_3 \quad (1)$$

Where $c_1$,$c_2$ and $c_3$ are the constant. $rand_1$,$rand_2$and $rand_3$are the normal distribution random number 0 to 1. $gBest_{slave}$is the best position from the slave groups while $gBest_{Master}$is the pest position from the master group.

The position update equation is given by:

$$X_m(t+1) = X_m + V_M(t+1) \quad (2)$$

The competitive between the slave and the master which adopted in [10] is also applied in this algorithm, where:

IF *gBest_slave>gBest_Master*
$\beta_1$*=1,* $\beta_2$*=0;*

IF *gBest_slave<gBest_Master*
$\beta_1$*=0,* $\beta_2$*=1;*

IF*gBest_slave=gBest_Master*
$\beta_1$*=0.5,* $\beta_2$*=0.5*

In this work two slave groups were utilize in the real time optimization (RTO) for the MPC function minimization. The first slave is the GSA algorithm that as developed in [11] and another slave is from inertia weight PSO algorithm.

The proposed framework of CPSOGSA can be described as the following steps:
Step1: Initialize the population of the slave and master groupsposition.

$$[x_{1,n}^{s1}, x_{2,n}^{s1}, \ldots\ldots x_{l,n}^{s1};\ x_{1,n}^{s2}, x_{2,n}^{s2}, \ldots\ldots x_{l,n}^{s2};\ \ldots\ldots;\ x_{1,n}^{sk}, x_{2,n}^{sk}, \ldots\ldots x_{l,n}^{sk};\ x_{1,n}^{M}, x_{2,n}^{M}, \ldots\ldots x_{l,n}^{M}]$$

Step 2: Evaluate the current fitness $f(b,w)$of the agents.
Step 3: Find the personal best and worst in each of the groups.

$$[p_{best,s1}^{i} = \min(fit^{i})\,;\ p_{best,s2}^{i} = \min(fit^{i});\ \ldots;\ p_{best,sk}^{i} = \min(fit^{i}); p_{best,M}^{i} = \min(fit^{i})]$$

$$[p_{worst,s1}^{i} = \max(fit^{i})\,;\ p_{worst,s2}^{i} = \max(fit^{i});\ \ldots;\ p_{worst,sk}^{i} = \max(fit^{i})\,;\ p_{worst,M}^{i} = \max(fit^{i})]$$

Step 4:.Find $\beta_1$and $\beta_2$using competitive algorithm.

Step 5: Calculate $a$ and $M$ using equations (10) and (16) in [11] (for groups that required this variables).
Step 6: Update velocity and position for all groups with master group by using equation (1) and (2).
Step 7: Compare if meet the optimization criteria. If not, return to step 2
Step 8: Return to the best solution

### 2.3. Neural Network Model Predictive Control

NNMPC is a model based control system which explicitly employs a neural network model to predict the process output at future time instant.The successful of this controller is much depends on the accuracy of the mode. This will ensure optimal output from the controller. The CPSOGSA algorithm is used to optimize input of the controller in order to minimize MPC cost function. This optimization process is repeated at every sampling interval. Figure 5 shows the MPC block diagram.

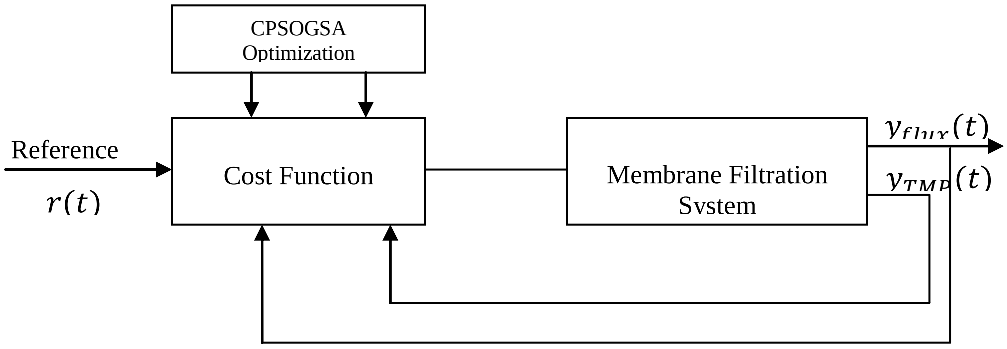


Figure 5. Block Diagram of the NNMPC for SMBR Filtration Process

The cost function of the NNMPC is given by:

$$J(p,m) = \left\{\sum_{k=1}^{p} \varphi\,[y(t+k) - r(t+k|t)]^2 + \sum_{k=1}^{m} \mu[\Delta u(t+k)]^2\right\} \quad (3)$$

where,$p$ is prediction horizon, $m$ is control horizon., $r$ is a set point.$\Delta u(t+k)$ is the change of input . $\varphi$ and $\boldsymbol{\mu}$ are the control weighting coefficient to add weight to the relative importance of the control and tracking errors. For the constrainted cases, the uppper and lower bound of the manipulted variables are given by:

$$\begin{aligned} &u_{min} \le u(t) \le u_{max} \\ &y_{min} \le y(t) \le y_{max} \\ &\Delta u_{min} \le u(t) - u(t-1) \le \Delta u_{max}. \end{aligned} \quad (4)$$

In this work, the input constrain is determine by the minimum and maximum permeate pump voltage from the critical flux test. In this work the minimum voltage ($u_{min}$) is set to 0, while the maximum voltage ($u_{max}$) is 3.5 volt.

Let the state of the system in each sampling interval, $k$ is defined as follows:

$$\hat{y}(k) = \begin{bmatrix} \hat{y}_0(k) \\ \hat{y}_1(k) \\ \vdots \\ \hat{y}_{n-1}(k) \end{bmatrix} \quad (5)$$

where $\hat{y}_i(k) = y(k+i)$ for $\Delta u(k+j) = 0\,; j \ge 0$

In this approach the neural network model is used to predict future outputs several steps in future over the prediction horizon($P$). This iterative technique is whereoutput from the first prediction $y(k+1)$ will be used as inputs for the next prediction in predicting $y(k+2)$, with this iterative procedure, the prediction of multiple output $P$ future steps can be done. The setting of the NNMPC parameters employed in this work is presents in Table 2.

Table 2. NNMPC parameters

| Parameter | Value |
|---|---|
| Prediction Horizon, $p$ | 5 |
| Control Horizon, $m$ | 3 |
| Weight, $(\varphi,\mu)$ | 10 |
| Sampling time | 1 second |

## 3. RESULTS AND ANALYSIS

The simulation result for tow cycle filtration shows the filtration process without controller cause the flux decline at the end each of the cycle. The application of controller can maintain the permeate flux at the desired set point. However, high overshoot controller ill effect the filtration performance. From the result, it can be observed that the NNMPC perform better compare with the PID controller. The first cycle controller performance indicates the NNMPC controller produce only 1.17% of overshoot compared with the PID with 20.64%. The settling times of the controllers are 18.2 second for the NNMPC and 17.9 second for PID controller. In term of the accuracy of the controller the IAE shows NNMPC controller perform at 72.8 and the PID controller is at 114.2. Figure 6 shows the response of the controllers for two cycle filtration is shows in Figure 6.The step response performance of the controllers is presents in Table 3.

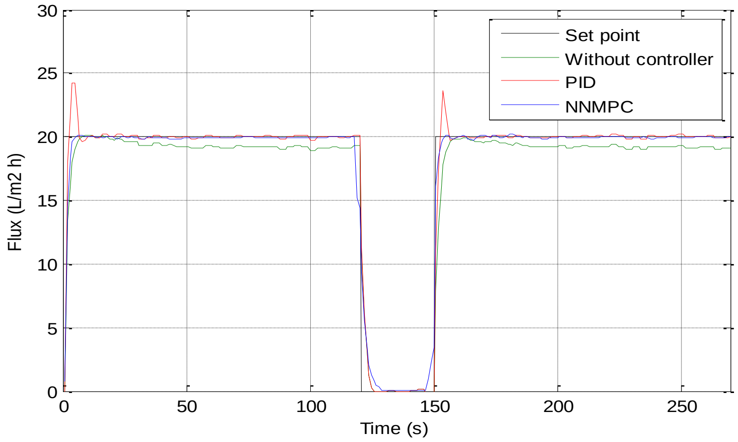


Figure 6. Performance Controller for Two Cycles

Table 3. Controller Performance at First Cycle

| Controller | %Overshoot | Settling Time (sec.) | IAE |
|---|---|---|---|
| PID | 20.64 | 17.9 | 114.2 |
| NNMPC | 1.17 | 17.2 | 72.8 |

The second simulation results is four cycles with change in set point. It can be observed, the NNMPC produce appropriate response at every set point tested. The PID controller produce high overshoot at higher set point and there is no excessive overshoot for set point 15L/m2 h which is in the forth cycle. Figure 7 shows the performance of the controllers for the set point change.

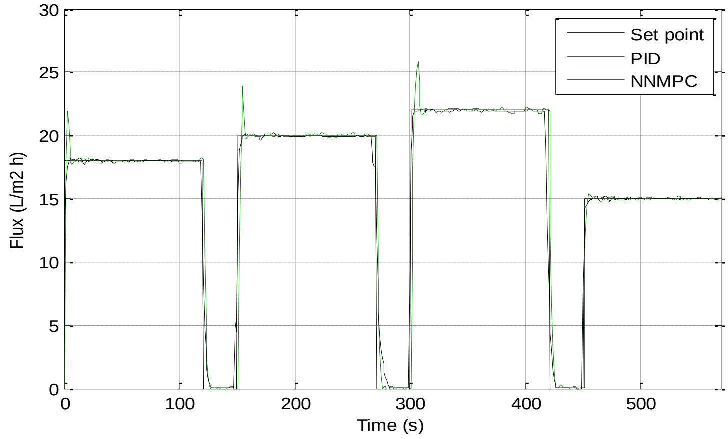


Figure 7. Four cycles with set point change

## 4. CONCLUSION

This paper presents the application of NNMPC with CPSOGSA for SMBR filtration control. The CPSOGSA algorithm performs as a RTO of the controller cost function within 1 second sampling time. This work utilized the neural network model the SMBR filtration process. The simulation result for two filtration cycles indicates the controller can prevent from flux decline during the filtration process. In term of the application of the controller it can be concluded the NNMPC controller perform better than the PID controller for especially for the overshoot and precision of the controller. Simulation for set point change indicates the NNMPC gives a good tracking at all set point without significant overshoot. Meanwhile, the PID controller also can track the set point; however there is an overshoot was observed at the high set point. Finally, the NNMPC with CPSOGSA is a good potential controller to be applied in many process control applications. However, further study needs to be done for applications that required much faster sampling time and RTO.

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