A control strategy for nonconventional column/rectifier configuration for composition control

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Abstract. Energy and cost saving can be accomplished by Nonconventional column/rectifier configuration. The design with a complex arrangement system needs an advance process control such as Model Predictive Control (MPC) to get the best responses control for composition. MPC which the objective function is optimized by Improved Particle Swarm Optimization (IPSO) is required and implemented for composition control. IPSO is used to get the best values of tuning for weighting in MPC. Integral Absolute Error (IAE) is used to indicate the value of control performance criteria. The results show that IPSO-MPC is better than MPC.

1. Introduction

The sequence multicomponent separation of three or more products is widely used in chemical processes industry. The conventional distillation column is usually performed in a sequence multicomponent separation [1]. The use of energy in conventional distillation column is big so that the alternative design is needed to achieve energy and cost saving. Many researchers have studied the alternative design of some sequence multicomponent separations such as divided wall column and nonconventional column/rectifier configuration [2]. Energy and cost saving can be accomplished by the sequence multicomponent separation of nonconventional column/rectifier configuration.

Nonconventional column/rectifier configuration does not use reboiler but still uses condenser. There are two columns, the first is the rectifier column and the second is the main column, the vapor side stream is taken out from the location under the feed tray of the main column then fed to the rectifier column [2]. Uwitonz et al present a recent study about nonconventional column/rectifier configuration then compare with conventional two column configuration with the direct sequence [3]. Some research are also reported by Kim et al and discuss about the rectifier column that is combined with the divided-wall column configurations and so do Young et al [4, 5]. Figueiredo et al also have done research about rectifier column in the separation of extractive distillation processes [6].

The implementation of the sequence multicomponent separation with nonconventional column/rectifier configuration is the demethanizer and the deethanizer column [2]. The demethanizer and the deethanizer column are widely used in gas industry processes. The demethanizer column is column that separates methane from natural gas and the deethanizer column is column which separates ethane from natural gas then the bottom of the deethanizer column is propane and the heavy
hydrocarbon components of natural gas. The purpose of the separation of methane and ethane is to make Liquefied Natural Gas (LNG) product [7].

The dynamic process system of the demethanizer and deethanizer plant with nonconventional column/rectifier configuration is a process with complicated system, so an advanced process control such as Model Predictive Controller (MPC) is required to satisfactorily perform in composition control [8]. MPC is designed by creating the products i.e. methane, ethane and propane as process variables, and making reflux rate of the rectifier and the main column, and energy from reboiler as manipulated variables and making the change of feed as disturbance variables [1]. The plant is assumed that pressure and level are already controlled for mass and heat balances of this process, so this study focus on composition control that is multivariable processes.

MPC has objective function that can be performed optimization to get optimal value [9]. Particle Swarm Optimization (PSO) is one type of metaheuristic optimizations. The inspired by various species to fulfill their demands, it was discovered by Kennedy and Eberhart [10, 11]. Many applications have applied it to solve many problems, even MPC also has been solved by PSO to get the optimal tuning of the weighting factor in objective function of MPC. PSO has been improved in algorithm to get the best value [12]. Fuad has studied about the improved PSO to perform optimization in MPC so that the best tuning of the weighting factor in objective function of MPC can be obtained [13].

2. Experimental section

2.1 Case study
The case studied of this configuration is based on the research of Luyben in figure 1. The plant is nonconventional column/rectifier configuration, from process flow diagram the feed is set on stage 2 of an eight-stage rectifier column that does not use reboiler but uses condenser. The vapor side stream from the main column that has 31 stages is retreated from stage 7 and entered in the bottom of the rectifier column [2]. Luyben has reported that specification was changed to be reasonable specification, the methane recovery was set at 99.64% and kept impurity of propane in the distillate of demethanizer column at 0.27 mol%, so that the required flow rate of the vapor side stream in this modified specification was set at 2950 kmol/hr. The rectifier column is the demethanizer column (Column 1), and the main column is the deethanizer column (Column 2), so the distillate of the rectifier column, the distillate of the main column and the bottom of the main column are methane, ethane, propane and the heavy hydrocarbon of the natural gas respectively.

![Figure 1 Process flow diagram (PFD) nonconventional column/rectifier configuration.](image-url)
2.2 Improved particle swarm optimization (IPSO)

Particle Swarm Optimization (PSO) is metaheuristic optimization that influenced by various species to fulfil their demands, it was discovered by Kennedy and Eberhart. The detailed algorithm is shown as figure 2 below [14]:

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**Figure 2.** The detailed algorithm of Particle Swarm Optimization (PSO).
For updating velocity and position for the particles $v_{k+1}(i), x_{k+1}(i)$ as equation (1) and equation (2) below [12, 15]:

$$v_{k+1}(i) = \omega v_k(i) + rand_1 c_1 \left(P_{best}(i) - x_k(i)\right) + rand_2 c_2 \left(G_{best}(i) - x_k(i)\right)$$  \hspace{1cm} (1)

$$x_{k+1}(i) = x_k(i) + v_{k+1}(i)$$  \hspace{1cm} (2)

where $v_{k+1}(i)$ is updating velocity of the particles, $v_k(i)$ is current velocity of the particles, $x_k(i)$ is current position of the particles, $x_{k+1}(i)$ is updating position of the particles, $\omega$ is inertia weight, $rand_1$ and $rand_2$ are the uniformly distributed random number, $c_1$ and $c_2$ are acceleration weight, $P_{best}(i)$ is the current position for individual particle where the best evaluation value was got by searching from history and $G_{best}(i)$ is the current position where the best evaluation value was got by among all the particles. Kawai et al have purposed for improving PSO by changing the inertia weight $\omega$ as equation (3) below [12]:

$$\omega = (\omega_1 - \omega_2) \times \frac{(\text{max iter} - \text{iter})}{\text{max iter}} + \omega_2$$  \hspace{1cm} (3)

2.3 Model Predictive Control (MPC)

Model Predictive Control (MPC) is an advance control that can solve difficult multivariable control problem. MPC can be calculated by the flowchart as in figure 3 below [8]. Model Predictive Control usually is operated in state space, for matrix of nonconventional column/rectifier configuration as equation (4) below:

$$\begin{bmatrix} \text{SP} \\ \text{C1} \\ \text{C2} \\ \text{C3} \end{bmatrix} = \begin{bmatrix} \text{RR}_1 \\ \text{GP}_{11} & \text{GP}_{12} & \text{GP}_{13} \\ \text{RR}_2 \\ \text{GP}_{21} & \text{GP}_{22} & \text{GP}_{23} \\ \text{Q_{reb}} \\ \text{GP}_{31} & \text{GP}_{32} & \text{GP}_{33} \end{bmatrix} \begin{bmatrix} \text{Feed} \\ \text{Gd}_1 \\ \text{Gd}_2 \end{bmatrix}$$  \hspace{1cm} (4)

$G_p$ is transfer function with FOPDT Model and need to change transfer function into state space model. Let equation (5) below:

$$G(s) = \frac{Y(s)}{U(s)} = \frac{K_p}{\tau s + 1} e^{-\theta s} = \frac{b_0}{a_2 s + 1}$$  \hspace{1cm} (5)

So it becomes equation (6) below:

$$a_1 \dot{y} + a_2 y = b_0 u$$

$$x_1 = y$$

$$\dot{x}_1 = -a_2 y + \frac{b_0}{a_1} u$$  \hspace{1cm} (6)
Equation (6) becomes a state space model as equation (7) below:

\[ x = Ax + Bu \]
\[ y = Cx + Du \]

\[ \begin{bmatrix} \dot{x}_1 \\ x_1 \end{bmatrix} = \begin{bmatrix} -a_2 \\ a_1 \end{bmatrix} \begin{bmatrix} x_1 \\ u \end{bmatrix} + \begin{bmatrix} b_0 \\ a_1 \end{bmatrix} u \]
\[ y = x_1 \]

\[ A = \begin{bmatrix} -a_2 \\ a_1 \end{bmatrix}, B = \begin{bmatrix} b_0 \\ a_1 \end{bmatrix}, C = [1], D = [0] \]  \hspace{1cm} (7)

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**Figure 3.** The Flowchart of MPC calculation.

1. Acquire new data (CV, MV, and DV values)
2. Update model predictions (output feedback)
3. Determine control structure
4. Check for ill-conditioning
5. Calculate set points/targets (steady-state optimization)
6. Perform control calculations (dynamic optimization)
7. Send MVs to the process
So for $G_{p11}$ will give the value of $A_{11}, B_{11}, C_{11}$, and got all parameters of matrix as equation (8) below:

$$A = \begin{bmatrix}
A_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & A_{12} & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & A_{13} & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & A_{21} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & A_{22} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & A_{23} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & A_{31} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & A_{32} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}$$

$$B = \begin{bmatrix}
B_{11} & 0 & 0 \\
B_{12} & 0 & 0 \\
B_{13} & 0 & 0 \\
0 & B_{21} & 0 \\
0 & B_{22} & 0 \\
0 & B_{23} & 0 \\
0 & 0 & B_{31} \\
0 & 0 & B_{32} \\
0 & 0 & B_{33} \\
\end{bmatrix}$$

$$C = \begin{bmatrix}
C_{11} & 0 & 0 & C_{12} & 0 & 0 & C_{13} & 0 & 0 \\
0 & C_{21} & 0 & 0 & C_{22} & 0 & 0 & C_{23} & 0 & 0 \\
0 & 0 & C_{31} & 0 & 0 & C_{32} & 0 & 0 & C_{33} \\
\end{bmatrix}$$

$$D = \begin{bmatrix}
D_{11} & D_{12} & D_{13} \\
D_{21} & D_{22} & D_{23} \\
D_{31} & D_{32} & D_{33} \\
\end{bmatrix}$$

For calculating MPC the value of state variable for instant sampling for $k_i, k_i \geq 0$ is $x(k_i)$ so the future state variable becomes equation (9) below:

$$x(k_i + 1|k), x(k_i + 2|k), x(k_i + 3|k), ..., x(k_i + m|k), ..., x(k_i + N_p |k)$$  \(9\)

For future control trajectory as equation (10) below:

$$\Delta u(k_i), \Delta u(k_i + 1), \Delta u(k_i + 2), ..., \Delta u(k_i + N_c - 1)$$  \(10\)
where \( x(k_i + m|k_i) \) is predicted state variable at sampling \( k_i + m \), and \( N_c \) is Control Horizon, and \( N_p \) is predictive horizon. So the model of state space as equation (11) and equation (12):

\[
x(k_i + 1|k_i) = Ax(k_i) + B\Delta u(k_i)
\]

\[
x(k_i + 2|k_i) = Ax(k_i + 1|k_i) + B\Delta u(k_i + 1)
\]

\[
\vdots
\]

\[
x(k_i + N_p|k_i) = A^{N_p}x(k_i) + A^{N_p-1}B\Delta u(k_i) + A^{N_p-2}B\Delta u(k_i + 1) + \ldots + A^{N_p-N_c}B\Delta u(k_i + N_c - 1)
\]

(11)

and

\[
y(k_i + 1|k_i) = CAx(k_i) + CB\Delta u(k_i)
\]

\[
y(k_i + 2|k_i) = CA^2x(k_i) + CAB\Delta u(k_i) + CB\Delta u(k_i + 1)
\]

\[
y(k_i + 3|k_i) = CA^3x(k_i) + CA^2B\Delta u(k_i) + CAB\Delta u(k_i + 1) + CB\Delta u(k_i + 2)
\]

\[
\vdots
\]

\[
y(k_i + N_p|k_i) = CA^{N_p}x(k_i) + CA^{N_p-1}B\Delta u(k_i) + CA^{N_p-2}B\Delta u(k_i + 1) + \ldots + CA^{N_p-N_c}B\Delta u(k_i + N_c - 1)
\]

(12)

Predicted variable is formulated as state variable \( x(k_i) \) and future control variable \( \Delta u(k_i + j) \) with \( j = 0, 1, \ldots, N_c - 1 \), so matrix vector is got as equation (13) below:

\[
Y = \begin{bmatrix} y(k_i + 1|k_i) & y(k_i + 2|k_i) & y(k_i + 3|k_i) & \ldots & y(k_i + N_p|k_i) \end{bmatrix}^T
\]

\[
\Delta U = \begin{bmatrix} \Delta u(k_i) & \Delta u(k_i + 1) & \Delta u(k_i + 2) & \ldots & \Delta u(k_i + N_c - 1) \end{bmatrix}^T
\]

(13)

The dimension of \( Y \) is \( N_p \) and \( \Delta U \) is \( N_c \). The final equation as equation (14) below [16]:

\[
Y = Fx(k_i)\Phi\Delta U
\]

\[
F = \begin{bmatrix} CA \\
CA^2 \\
CA^3 \\
\vdots \\
CA^{N_p} \end{bmatrix}
\]

\[
\Phi = \begin{bmatrix} CB & 0 & 0 & \ldots & 0 \\
CAB & CB & 0 & \ldots & 0 \\
CA^2B & CAB & 0 & \ldots & 0 \\
\vdots \\
CA^{N_p-1}B & CA^{N_p-2}B & CA^{N_p-3}B & \ldots & CA^{N_p-N_c}B \end{bmatrix}
\]

(14)
The working of MPC is based on predictions of set point tracking over both past of the measurements from output variables and manipulated variables, so that the objective function of MPC can be derived as the following equation (15):

\[
\min J(k) = \sum_{j=1}^{N_c} w_{i,j} \left( y_j(k+i+1|k) - r_j(k+i+1) \right)^2 + \sum_{j=1}^{N_p} w_{i,j}^w \Delta u_j(k+i+1|k) + \sum_{j=1}^{N_p} w_{i,j}^{\Delta u} \Delta u_j(k+i+1|k)
\]

(15)

Ławryn´czuk has purposed the objective function of MPC as Quadratic Cost in the following equation (16) [9]:

\[
\min J(k) = \sum_{j=1}^{N_c} w_{i,j} \left( y_j(k+i+1|k) - r_j(k+i+1) \right)^2 + \sum_{j=1}^{N_p} w_{i,j}^w \Delta u_j(k+i+1|k) + \sum_{j=1}^{N_p} w_{i,j}^{\Delta u} \Delta u_j(k+i+1|k)
\]

(16)

where \( N_p \) is predictive horizon, \( N_c \) is control horizon, \( w^r \) is weighting factor from output variable of reference tracking, \( y_j(k+i+1|k) \) is prediction trajectory, \( r_j(k+i+1|k) \) is reference trajectory, \( w^{\Delta u} \) weighting factor from manipulated variable of increment suppression, \( \Delta u_j(k+i+1|k) \) is increments of the manipulated variable.

2.4 Integral Absolute Error (IAE)

IAE is one of control performance criteria and defined as equation (17) below:

\[
IAE = \int_0^\infty |e(t)| dt
\]

(17)

with \( e(t) \) is error between set point and process variable.

3. Research procedures

The research method of this study consists five steps, the first step is simulation mass and energy balance in steady state of plant by using Aspen Plus v10.0, the model of rigorous model is Radfrac model that the first column is without reboiler then the second is using reboiler, the next is validation the result of the simulation with Process Flow Diagram (PFD) data. The second step is making the steady state model of plant to the dynamic model with Aspen Plus Dynamic (APD) v10.0 using pressure driven. In APD the pressure of the rectifier and the main column, the reflux drum level of the rectifier and main column, and the sump level of the rectifier and the main column are Single Input Single Output (SISO) system. The SISO systems use conventional Proportional Integral Derivative (PID) controller. The MIMO controller is designed by creating the mass fractions of the products i.e. methane (C1) in top product of rectifier column, ethane (C2) in top product of main column and propane (C3) in bottom of main column as process variables, making reflux rate of the rectifier and the main column, and energy from reboiler are manipulated variables and the change of feed is disturbance variables as in figure 4 below.

The next step test is performed to get the First Order and Dead Time (FOPDT) to get matrix of Transfer Function 3x3. The dynamic system of the plant is Multiple Input Multi Output (MIMO) process, so that the plant needs MIMO controls system to keep the condition of steady state to the dynamic. The matrix of Transfer Function 3x3 is defined as equation (18) and equation (19) below:
The third step is designing Model Predictive Controller (MPC) as Figure 4 [8]. The model of MPC is created by using Linear Time Invariant (LTI) state space model from transfer function matrix 3x3. The matrix of the transfer functions is approached by Relative Gain Array (RGA) for analyzing the pairing of multivariable process control problems [17]. The RGA for square system is defined as matrix Δ, and the RGA for each element as $\lambda_{ij}$, $\hat{\lambda}_{ij}$ is determined as the following equation (20), equation (21), equation (22) and equation (23):

$$SP \quad RR_1 \quad RR_2 \quad Q_{reb} \quad Feed$$

$$[C1] = \begin{bmatrix} 0.03987 e^{-2.3s} \\ 48.63s + 1 \\ 54s + 1 \\ 37.24s + 1 \end{bmatrix} \begin{bmatrix} 0.0125 e^{-2s} \\ 43.68s + 1 \\ 50.3s + 1 \\ 39.5s + 1 \end{bmatrix} \begin{bmatrix} -0.0204 e^{-2.5s} \\ 37s + 1 \\ 33s + 1 \\ 48s + 1 \end{bmatrix} = \begin{bmatrix} 0.01446 e^{-4s} \\ 40.3s + 1 \\ 17.4s + 1 \\ 58.7s + 1 \end{bmatrix} F$$

$$[C2] = \begin{bmatrix} 0.0035 e^{-2.9s} \\ 0.01874 e^{-2.4s} \\ 0.0043 e^{-3.8s} \\ 0.001 e^{-4.8s} \end{bmatrix} \begin{bmatrix} e^{-2s} \\ 43.68s + 1 \\ 50.3s + 1 \\ 39.5s + 1 \end{bmatrix} \begin{bmatrix} -0.001 e^{-2.7s} \\ 37s + 1 \\ 33s + 1 \\ 48s + 1 \end{bmatrix} + \begin{bmatrix} 0.000998 e^{-4.5s} \\ 17.4s + 1 \\ -0.00976 e^{-4.8s} \\ 58.7s + 1 \end{bmatrix}$$

Figure 4. Model Predictive Control (MPC) for Nonconventional Column/Rectifier Configuration.
\[
\left( \lambda_j \right) = \left( \frac{\partial y_i}{\partial u_j} \right)_{\text{all loops open}}
\]

\[
\Delta = G(0) \otimes \hat{G}(0)
\]

\[
\Delta = \begin{bmatrix}
\lambda_{11} & \lambda_{12} & \lambda_{13} \\
\lambda_{21} & \lambda_{22} & \lambda_{23} \\
\lambda_{31} & \lambda_{32} & \lambda_{33}
\end{bmatrix} = \begin{bmatrix}
k_{11} & k_{12} & k_{13} \\
k_{21} & k_{22} & k_{23} \\
k_{31} & k_{32} & k_{33}
\end{bmatrix} \frac{1}{\det Adj G(0)}
\]

\[
\det = k_{11}k_{22}k_{33} + k_{13}k_{21}k_{32} + k_{12}k_{23}k_{31} - k_{13}k_{22}k_{31} - k_{12}k_{21}k_{33} - k_{11}k_{23}k_{32}
\]

The transfer functions of the plant are implemented in Simulink Matlab R2013a and used MPC controller. The fourth step is performed optimization by using improved PSO for tuning of the weighting factor in objective function of MPC. The value of weighting is just \( \omega_u \) or weighting factor from manipulated variable of increment suppression as this equation (24) below:

\[
\min J = \sum_{j=1}^{N} \left( w_{ij}^u \Delta u_j \right)^2
\]

then the value of \( \omega_u \) or weighting factor from manipulated variable of increment suppression is applied in MPC controller, \( \omega_u \) in matrix diagonal as equation (25) below:

\[
\omega_u = \text{diag} \left( w_{11}^u, w_{12}^u, w_{13}^u, \ldots, w_{N_p-1 \cdot N_y}^u \right)
\]

Then this matrix is calculated with \( \Delta U \) in equation (13) and minimize the objective function in equation (24). The last step is analyzing the response control systems of MPC without optimization and MPC which is performed optimization by using improved PSO.

4. Results and discussion

4.1 Relative Gain Array (RGA)

The value of the RGA 3x3:

\[
RGA = \begin{bmatrix}
0.9427 & 0.0557 & 0.0015 \\
0.0468 & 0.9126 & 0.0405 \\
0.0104 & 0.0316 & 0.9580
\end{bmatrix}
\]

The result of the RGA 3x3 is positive in diagonal so that the matrix of the transfer function is diagonally dominant. The pairing of the matrix should be used U1 to control C1, U2 to control C2 and U3 to control C3 as figure 5 below:
4.2 Simulation results

IPSO is used to get the optimal value of $w_{uv}$ or weighting factor from manipulated variable of increment suppression. The obtained value is 0.0276 then this value is applied in MPC controller with the value of $N_y$ or predictive horizon is 50 then $N_u$ or control horizon is 1. The simulation of composition control is performed by using Simulink Matlab software R2013a. The step change is done on methane (C1), (C2) and (C3) as process variables, then the results of the control system response are shown in figure 6 to figure 11 below:

Figure 5. The Result of relative gain array (RGA) pairing 3x3 from transfer function plant.
Figure 6. Response control of set point tracking from methane (C1) in top product of rectifier column for nonconventional column/rectifier configuration. The Value of settling time for MPC=60 minutes and IPSO-MPC=60 minutes. The Value of Integral Absolute Error (IAE) for MPC=28.7028 and for IPSO-MPC= 28.2465.

Figure 7. Response control of set point tracking from ethane (C2) in top product of main column for nonconventional column/rectifier configuration. The Value of settling time for MPC=60 minutes and IPSO-MPC=60 minutes. The Value of Integral Absolute Error (IAE) for MPC= 31.66 and for IPSO-MPC= 28.46.
Figure 8. Response control of set point tracking from propane (C3) in bottom product of main column for nonconventional column/rectifier configuration. The value of settling time for MPC= 50 minutes and IPSO-MPC= 48 minutes. The value of Integral Absolute Error (IAE) for MPC= 20.12 and for IPSO-MPC= 19.52.

Figure 9. Response control of disturbance rejection from methane (C1) in top product of rectifier column for nonconventional column/rectifier configuration. The value of IAE for MPC=0.372 and for IPSO-MPC=-0.361.
Figure 10. Response control of disturbance rejection from tracking from ethane (C2) in top product of main column for nonconventional column/rectifier configuration. The value of IAE for MPC = 0.28 and for IPSO-MPC = 0.26.

Figure 11. Response control of disturbance rejection from propane (C3) in bottom product of main column for nonconventional column/rectifier configuration. The value of IAE for MPC = 0.25 and for IPSO-MPC = 0.24.

The results show that the responses control of tracking set point from methane (C1), ethane (C2) and propane (C3) are better by using IPSO-MPC than MPC, and the all value of Integral Absolute Error (IAE) are better by using IPSO-MPC than MPC. The results also show that the responses control of rejecting disturbance from all of process variables i.e. methane (C1), ethane (C2) and propane (C3) are also better by using IPSO-MPC than MPC. Even the value is not significantly different but the result can show that MPC with performing optimization is better than without.
5. Conclusion
The composition control of multi variable processes with methane (C1) in top product of rectifier column, ethane (C2) in top product of main column and propane (C3) in bottom of main column as process variables, then reflux rate of the rectifier and the main column and energy from reboiler as manipulated variables, then the change of feed as disturbance variables for nonconventional column/rectifier has done by using MPC and IPSO-MPC. The Results show that over all responses control of tracking set points and rejecting disturbances from methane (C1), ethane (C2) and propane (C3) is better by using IPSO-MPC then MPC.

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Symbols Used
C1 \([kg\ kg^{-1}]\) mass fraction of methane
C2 \([kg\ kg^{-1}]\) mass fraction of ethane
C3 \([kg\ kg^{-1}]\) mass fraction of propane
c1, c2 \([-\]) acceleration coefficients
F \([kg\ hr^{-1}]\) feed of plant
Gd \([-\]) transfer functions of disturbance
Gp \([-\]) transfer functions of plant
G_{best}(i) \([-\]) the current position where the best evaluation value was got by among all the particles
max iter \([-\]) predefined maximal iteration
\Delta \([-\]) matrix RGA
N_c \([-\]) control horizon
N_p \([-\]) predictive horizon
P_{best}(i) \([-\]) the current position for individual particle where the best evaluation value was got by searching from history
Q_{reb} \([kJ\ hr^{-1}]\) duty of reboiler
RR_1, RR_2 \([kg\ hr^{-1}]\) reflux rate of the first and the second column
rand_1, rand_2 \([-\]) the uniformly distributed random number in interval [0,1]
r_j(k+i+1[k]) \([-\]) reference trajectory
SP \([kg\ kg^{-1}]\) set points of composition control
\Delta u_j(k+i[k]) \([-\]) increments
v_{k+1}(i) \([-\]) updating velocity of the particles
v_k(i) \([-\]) current velocity of the particles
w^{\Delta u} \([-\]) weighting factor from manipulated variable of increment suppression
\( w^3 \) \([-\]\) weighting factor from output variable of reference tracking
\( x_{k+1}(i) \) \([-\]\) updating position of the particles
\( x_k(i) \) \([-\]\) current position of the particles
\( y_j(k+i+1|k) \) \([-\]\) prediction trajectory

**Greek symbols**

\( \omega \) \([-\]\) the inertia weight
\( \lambda_{ij} \) \([-\]\) the RGA for each element

**Abbreviations**

APD aspen plus dynamic
FOPDT first-order plus dead time
IAE integral absolute error
IPSO-MPC improved particle swarm optimization-model predictive control
LNG liquefied natural gas
LTI linear time invariant
MIMO multiple input multiple output
MPC model predictive control
RGA relative gain array
SISO single input single output
PID proportional integral derivative
PSO particle swarm optimization

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