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Research paper

Decentralized Non-Derivative Algorithm for Real-Time Optimising Control of Large-Scale Industrial Processes

Normah Abdullah[1], Cheong Tau Han [2], Mohd. Jailani Mohd. Nor[3], Sallehuddin Mohamed Haris[3*]

[1]Department of Chemical and Process Engineering, Faculty of Engineering and Built Environment, National University of Malaysia, 43600 Bangi, Selangor, Malaysia
[2]Faculty of Education, Campus Intech, Universiti Teknologi Mara, Shah Alam SS17, Selangor, Malaysia
[3]Department of Mechanical and Materials Engineering, Faculty of Engineering and Built Environment, National University of Malaysia, 43600 Bangi, Selangor, Malaysia
**Corresponding author E-mail: sallehmh@ukm.edu.my*

Abstract

Designing controller systems for large-scale processes in a centralized form are faced with computational burden due to the large number of decision variables involved, however these difficulties can be overcome by decentralization or decomposition of the optimal control problems into smaller sub-systems in a hierarchical manner. Hence, this paper presents a decentralized adaptive real-time optimizing (RTO) control scheme for determining and maintaining the optimum steady-state operating conditions for inter-connected large scale industrial processes. The proposed strategy extends the applicability of the centralized non-derivative algorithm and by structuring it hierarchically in a decentralized fashion as in the Integrated System Optimisation and Parameter Estimation (ISOPE) technique. The proposed algorithm has been formulated in two different ways of utilising the available measurement from the plants: the first method employs input-output feedback and the second method uses only output feedback. The simulation examples are provided to illustrate and compares the methods in which the results show that the algorithm with input-output structure performs better with less number of set-point changes and faster convergence. Since the algorithm is designed in the decentralize form, the computation difficulties may adequately be dealt with.

Keywords: *Coordination; decentralize; large-scale processes; optimal control; real-time optimisation*.

1. Introduction

In a large industrial process which generally consists of interconnected subsystems, optimal operation is typically addressed by a hierarchical structure. The upper level, also called Real-Time Optimization (RTO), whose task is to obtain the optimum operating condition for lower-level controllers that include basic control and multivariable predictive control [1]. A complex processing plants can be difficult to maintain in a centralized fashion so decentralized and hierarchical approach are often favored by engineers and managers [2]. A centralized control system is extremely expensive and difficult to implement because of huge computational burden and high communication cost [3]. Since the late1970s, there have several developments in RTO to drive the process to its optimum point, modifier adaptation is one of the schemes that have been proposed which can handle considerable plant-model mismatch by applying empirical bias and gradient-corrections to the objective and constraint functions in an iterative optimization procedure [4,1]. The non-derivative method (NDM) is an example of modifier adaptation scheme which does not require derivative of the real process [5] and this method belong to a class of algorithm known as ISOPE [6,7,8,9,10]. NDM also exhibits higher rate of convergence and requires less set-points changes to converge to optimum set-points compared to other ISOPE algorithms with the same class of algorithm which does not require derivative of real process. The NDM method employs the curve fitting technique to construct an approximate linear model which can match the output at each iteration and match the required derivatives of reality at the optimum point. In this current study, the applicability of this centralized NDM is extended to decentralized form by hierarchically structuring the NDM in decentralized fashion as in ISOPE algorithm [11].

2. Methodology

The proposed decentralized algorithm will be known as decentralized non-derivative method (DNDM). The proposed DNDM employs model base on curve fitting technique and has two level structures: the first level, the optimization problem is decomposed into several interactive sub-systems and while at the second level, the coordinating strategy is introduced where coordination of the overall control system is performed. The algorithm is hierarchically structured and the DNDM is in a form suitable for application to a large-scale industrial process which consisting of a collection of interconnected sub-processes. Various structures have been developed for the decentralized ISOPE algorithms which depend upon the type of information feedback available from the real process and the manner in which the information is utilized [8] and some of these structures have been extended to augmented ISOPE which extended its applicability to non-

linear processes [12]. In this study, the consideration is given to the single loop structure with employs two different feedbacks information: the first single loop structure employs input-output feedback and the second structure utilizes only output feedback. The proposed algorithm is structured hierarchically which is of an iterative type and utilize information feedback from the real process and price decomposition to cater for model reality differences and process complexity, respectively.
If the controlled system together with its follow-up controllers is described in a decomposed manner by the set of subsystem input-output equations [13]: $y_i = F_{*i}(c_i, u_i) \ \ i \in 1, N$

where $F_{*i} = C_i \text{ x } U_i \to Y_i \ \ i \in 1, N$ is the i-th subsystem input-output mapping and N denotes the number of subsystems. C_i, U_i, and Y_i are finite dimensional spaces. The variables c_i, u_i, and y_i are the i-th subsystem control, interaction input and interaction output, respectively, and also $c_i \in C_i$, $u_i \in U_i$ and $y_i \in Y_i$ .The subsystems are interconnected with assumed structure equations: $u_i = H_i y = H_{ij} y_i \ \ i \in 1, N$, where H_i and H_{ij} are interconnected matrices. Let us denote

$$c \triangleq (c_1, \ldots, c_N) \triangleq C_1 \text{ x} \ldots \text{x } C_N \triangleq C_i$$
$$u \triangleq (u_1, \ldots, u_N) \triangleq U_1 \text{ x} \ldots \text{x } U_N \triangleq U_i$$
$$y \triangleq (y_1, \ldots, y_N) \triangleq Y_1 \text{ x} \ldots \text{x } Y_N \triangleq Y_i$$

then the subsystem equations and interactions can be written in the global form:

$$y = F_*(c, u), \ u = Hy \qquad (1)$$

where
$$F_* : C \text{ x } U \to Y$$
$$F_*(c, u) = (F_{*i}(c_1, u_1), \ldots, F_{*N}(c_N, u_N))$$
$$H = \{H_{ij}\}_{i, j = N}$$
Assuming that for each $c \in C$ there exits only one solution of the equation: $y = F_*(c, Hy)$. The global system mapping is given by: $K_* = C \to Y$, i.e $y = (K_{*i}(c), \ldots, K_{*N}(c))$. In practice, approximate models are used due to uncertainty of the real system relations. Each subsystem is assumed to be subjected to local constraints
$$(c_i, u_i, y_i) \in CUY_i \triangleq \{c_i, u_i, y_i)\} \in C_i \text{ x } U_i \text{ x } Y_i : G_{ij}(c_i, u_i, y_i) \leq 0, j \in J_i\}$$
These constraints can be written jointly as:
$$(c, u, y) \in CUY \triangleq \{(c, u, y)$$

$$\in CxUxY : G(c, u, y) \leq 0\} \qquad (2)$$

where
$$G(c, u, y) \triangleq G_i(c_1, u_1, y_1), \ldots, G_N(c_N, u_N, y_N),$$
$$G_i(c_i, u_i, y_i) \triangleq G_{i1}(c_1, u_1, y_1), \ldots, G_{ij}(c_i, u_i, y_i)$$
with each subsystem, a known local performance function:
$$Q_i : C_i \text{ x } Y_i, \ Y_i \to R^1, \ \ i \in 1, N$$

The overall performance index of the system is assumed to have the additive form:

$$Q(c, u, y) = \sum_{i=1}^{N} Q_i(c_i, u_i, y_i) \qquad (3)$$

The system optimizing control problem (OCP) can be defined

$$\min_{c,u,y} Q(c, u, y)$$
s.t.
$$y = F_*(c, u) \quad u = Hy$$

$$(c, u, y) \in CUY = \{G(c, u, y) \leq 0\} \qquad (4)$$

where
$$G(c, u, y) = [G_1(c_1, u_1, y_1), \ldots, G_N(c_N, u_N, y_n)]$$

2.1 Description of the DNDM

Using the similar approach as the centralized NDM [5], the DNDM is formulated based on the multiple linear straight equation, $y_i = Ax_i + Bu_i + C_i$, where A is the matrix gradient of set-points, B is the matrix of gradient of inputs and C is the correction factor. Matrix A and B are calculated using the finite different approximation and $C = y_i - Ax_i + Bu_i$. The single loop technique with output feedback measurements will be known as DNDM1 and can be presented as follows:

Step 1. Choose $\{v^{-1}, v^{0}\} \in C$, $\{w^{-1}, w^{0}\} \in U$, $\varepsilon > 0$ Set $i = 0$, $F_*(v^{-1})$ has been achieved.

Step 2. Measure the reality output $y = F_*(v^i)$ at the point $v^{-1} \in C$ and $w^{-1} \in U$.

Step 3. Construct the linear function

$$F(c,u,v^{i-1},v^i,w^{i-1},w^i) = (K^i)^T c + (J^i)^T u + B^i \qquad (5)$$

To fit the function $F_*(c,u)$ passing through the points $\{v^{i-1}, v^1\} \in C$, $\{w^{i-1}, w^1\} \in U$.

Step 4: Solve the subproblem

$$\min\,[Q(c,u,F(c,u,v^{i-1},v^i,w^{i-1},w^i)) + \rho/2\left\|c - v^i\right\|^2 + \rho/2\left\|u\text{-}w^i\right\|^2 + p^T(u - HF(c,u,v^{i-1},v^i,w^{i-1}w^i))] \qquad (6)$$

where $\rho > 0$ is a penalty coefficient. Let u^i and c^i be the solution. If $c^i = v^i$, $u^i = w^i$, then v^i, w^i is the solution and the algorithm is terminated. Otherwise go on.

Step5: Update v^i, w^i by using the following equation

$$v^{i+1} = v^i + \varepsilon_v (c^i - v^i)$$

$$w^{i+1} = u^i + \varepsilon_w (u^i - w^i)$$

$$p^{i+1} = p^i + \varepsilon_p (u^i - Hy)$$

Set $i = i + 1$ and return to Step 2.

The single loop technique with input-output feedback measurement will be known as DNDM2 and for implementing the DNDM2, follows the similar steps 1 to 5 as above, accept the optimization problem (6) is modified by adding the term $\rho/2\left\|u - HK_*(v)\right\|^2$.

2.2 Case study examples

The following two examples are used as case study in the simulation work to investigate the behaviour of the DNDM1 and DNDM2, which are typical examples of large-scale industrial processes:

Example 1

Subsistem 1

$$y_1^* = c_1 - c_2 + 2u_{11} - 0.5c_1^2 + 0.5u_{11}(c_1 + c_2 - 2)$$

$$Q_1 = c_1^2 + (c_2 - 2)^2 + (u_{11} - 2)^2$$

$$C_1 \in \{1.006 - u_{11} - c_1 \le 0,\ |c_1| < 0.5,\ 0 \le c_2 \le 2.5\}$$

Subsistem 2

$$y_2^* = c_3 - c_4 + u_{21} - 3u_{22}$$

$$y_3^* = 2c_4 - c_5 - u_{21} + u_{22}$$

$$Q_2 = 4u_{21}^2 + u_{22}^2 + 2(c_3 - 2)^2 + c_4^2 + 3c_5^2$$

$$C_2 \in \{0 \le c_3 \le 2,\ |c_i| \le 0.5, i = 4,5\}$$

Subsistem 3

$$y_4^* = c_6 + 0.5u_{31}c_5 - 4u_{31}$$

$$Q_3 = (u_{31} - 1)^2 + (c_6 - 1)^2$$

$C_3 \in \{0.375 + 2.25c_6 - 2.75u_{31} - y_4 \geq 0, \ |c_6| \leq 0.5\}$

$$\begin{bmatrix} u_{11} \\ u_{21} \\ u_{22} \\ u_{31} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix}$$

Example 2
Subsistem 1

$y_1^* = 1.4c_1 - 0.6c_2 + 1.8u_{11}$

$Q_1 = c_1^2 + c_2^2 + 2(u_{11} - 2)^2 + (u_{12} - 3)^2$

$C_1 \in \{0.8 - 0.6u_{11} - c_2 \geq 0, \ |c_i| \leq 1, i = 1,2 \quad y_1 \geq 0\}$

Subsistem 2

$y_2^* = 1.3c_3 - 1.1c_4 + 1.1u_{21}$

$y_3^* = 2.3c_4 - 0.7c_5 + 1.1u_{21}$

$Q_2 = c_3^2 + c_4^2 + c_5^2 + (u_{21} - 1)^2$

$C_2 \in \{2.04 + 1.05u_{21} - c_3^2 - c_4^2 - c_5^2 \geq 0,$
$|c_i| \leq 1, i = 3,4,5 \ y_i \geq 0, i = 1,2,3\}$

$$\begin{bmatrix} u_{11} \\ u_{12} \\ u_{21} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

3. Results and discussion

Simulation studies have been performed on two examples taken from Liu and Roberts [5]. Selected results for Example 1 and 2 presenting the number of system iterations (IT) and number of set-point changes (IS) for all combination of the optimal values of $\varepsilon_v, \varepsilon_w$ and ε_p are given in Table 1 and 2, respectively, and while a suitable value of penalty coefficient ρ has been selected such that it improves the convergence of the algorithm. The real system performance, Q, for Examples 1 and 2 are 2.1405 and 5.9261, respectively.

Table 1: Comparison result for Example 1 for structure DNDM1 and DNDM2.

Parameter	$\rho = 0.3, \varepsilon_p = 0.25$ ε_v and $\varepsilon_w = 0.6$	$\rho = 10, \varepsilon_p = 0.1$ ε_v and $\varepsilon_p = 1.8$
	DNDM2	DNDM1
IT	27	42
IS	162	252
Q	2.140523	2.140529

The values of $\varepsilon_v, \varepsilon_w$ and ε_p are chosen as optimal when the smallest number of system iteration (IT) is produced at a prescribed final accuracy value of ε equal 0.001. Table 1 indicates that for the Example 1 at the optimal values of $\varepsilon_v, \varepsilon_w$ and ε_p for each structure, DNDM2 requires about 27 system iteration (IT), which is about half of those needed by the DNDM1.

Fig. 1(a) and 1(b), compare the convergence performance index Q and price p for Example 1, at optimal values of $\varepsilon_v, \varepsilon_w$ and ε_p as indicates in Table 1, versus number of system iterations (IT). Table 1 also indicates that DNDM2 requires 162 set-point changes to achieve convergence which about half required by DNDM1

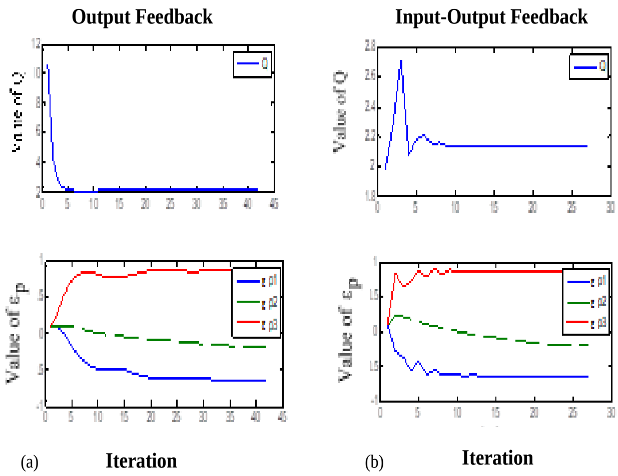

Fig. 1: Performance index and price of Example 1 verses IT for (a) DNDM1 (b) DNDM2

While, Table 2 and Fig. 2 show the comparative simulated results for DNDM1 and DNDM2 when applied to Example 2. Table 2 indicates a better performance is obtained with DNDM2 where 75 set-point changes are required compared to 210 set-point changes needed by DNMD1

Table 2: Comparison result for Example 2 for DNDM1 and DNDM2.

Parameter	$\rho = 0.3, \varepsilon_p = 0.6$ ε_v and $\varepsilon_w = 0.7$	$\rho = 10, \varepsilon_p = 0.1$ ε_v and $\varepsilon_w = 1.6$
	DNDM2	DNDM1
IT	15	45
IS	75	210
Q	5.926071	5.926099

Fig. 2(a) and 2(b), compare the convergence performance index Q and price p of Example 2, at optimal values of $\varepsilon_v, \varepsilon_w, \varepsilon_p$ and ρ as given in Table 2, versus number of system iterations (IT) for DNDM1 and DNDM2.

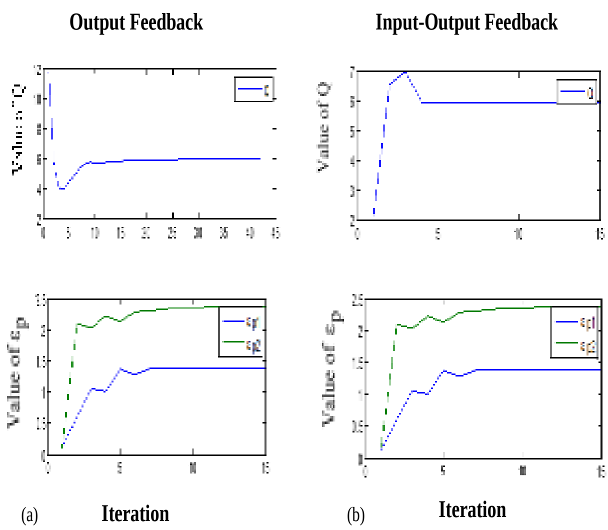

Fig. 2: Performance index and price of Example 2 verses IT for (a) DNDM1 (b) DNDM2

The simulated results obtained when both proposed DNDM1 and DNDM2 are applied on the two examples, demonstrate that DNDM2 is more efficient than DNDM1 since significant reduction in set-point changes required by DNDM2. The computation difficulties have been adequately deal because the control system structure of DNDM1 and DNDM2 are designed where the optimal control problems have been decomposed into smaller sub-systems in a hierarchical manner and the coordinating strategy is introduced where coordination of the overall control system is performed.

4. Conclusions

The decentralized non-derivative method has been formulated for two different structures: the first structure employs output feedback (DNDM1) and the second structure used only input-output feedback (DNDM2). The simulation examples illustrate and compare the methods in which the results show that the algorithm with input-output structure performs better with less number of set-point changes and faster convergence. Lower iterations mean lesser time is required in order to achieve the optimum control solution. Since the algorithm is designed in the decentralize form the computation difficulties may adequately be dealt with.

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