

# Process Goose Queue Methodologies with Applications in Plant-wide Process Optimization

Jingwen Huang

College of Information Science and Technology, Beijing University of Chemical Technology, Beijing 100029, China  
Email: huangjw@mail.buct.edu.cn

Hongguang Li

College of Information Science and Technology, Beijing University of Chemical Technology, Beijing 100029, China  
Email: lihg@mail.buct.edu.cn

**Abstract**— Inspired by biologic nature of flying wild geese, a so-called process goose queue (PGQ) technique oriented for plant-wide optimization is established. Taking advantage of this ad-hoc structure of flying geese, a plant-wide process can be decomposed into several hierarchically connected PGQs along the direction of the objective function generation. In line with this thought, plant-wide process optimization is accordingly identical with the following and tracking issues between leading and following geese. Followed by this philosophy, related theoretical definitions and modeling principles together with enabling algorithms are explicitly introduced. With the characteristics of evolutionary optimization, PGQ approach is able to overcome the algorithmic deficiencies associated with conventional optimizations. To demonstrate the feasibility and validity of the contributions, TE process is employed as the case study.

**Index Terms**—plant-wide process, process optimization, process goose queue (PGQ)

## I. INTRODUCTION

Traditionally, plant-wide process optimization approaches can be classified into two relatively distinct categories in terms of architecture: global or centralized architecture and decentralized architecture. The global approaches associate overall processes with economic objectives and optimize them based on rigorous models. Therein, the main impacts on optimization performance arise from model complexity and nonlinearity, as well as heavy computational burden due to enormous manipulated variables involved. Even though applications of flow-sheet simulation tools such as DMCPlus, CLP and RTO of AspenTech, as well as Profit Optimizer and Profit Max of Honeywell are increasingly extensive, it is acknowledged that the corresponding optimization solutions suffer both far from analytics and hard to understand. Alternatively, the decentralized approaches decompose large-scale optimization problems into

several sub-systems mutually coordinated. Darby and White [1] exemplified that decentralized architectures could achieve the same performances with those of the global ones. Taking into account of physical structures and coupling factors among the subsystems, Sobieski[2] presented a generalized multilevel optimization approach named multidisciplinary design optimization (MDO), which is concerned with complex systems exhibiting challenges with three typical MDO architectures subsequently exploited, including concurrent subspace optimization (CSSO), collaborative optimization (CO) and Bi-Level Integrated System Synthesis (BLISS). MDO methods are widely applied to non-process industries. For example, Duddeck & Fabian[3] applied MDO to control system designs for car bodies and Silva & Valceres [4] employed MDO to those for gas turbine engines. However, most of existing researches highlight mechanical structures but rarely deal with interconnection characteristics of process variables. Another research issue of decentralized optimization focuses on hierarchical multi-objective optimization together with multi-layer optimization algorithm, in which the problems are firstly decomposed into a multi-system and subsequently dealt with using multi-objective programming, as addressed in references [5],[6]. However, owing to the demands for separable or approximately separable objectives, the above-cited method is apt to cause considerable systematic deviations in the presence of severe nonlinear relations between the global objective and sub-objectives. A popular approach at present is to recognize the weights of sub-objectives which can then be used to approximate the global objective. However, in the presence of severe nonlinear relationship between global objectives and sub-objectives, the solutions derived from this method can be far away from the actual optima.

Plant-wide industrial processes are actually connections of a variety of basic operational units which are considered as dynamic systems constituted by output process variables and input process variables. Inspired by

Corresponding author: Hongguang Li; Tel.: 86-10-64434797; Fax: 86-10-64442932.

the philosophy of flying goose queue, a certain kinds of operational units could be regarded as a goose so that the plant-wide process could be identified as a goose queue. The principle of pursuing optimal set points in plant-wide process is similar to the mechanism of flocks of geese self-organizing into V-formation. In line with this thought, we came up with a novel idea of “process goose queue (PGQ)” [7] to reconfigure plant-wide processes, thereby optimizing them in terms of economic perspectives. With the PGQ methodology, optimization model can be decomposed organically according to goose queue formation. The transformation of the subsystem optimum objective value can refer to the transfer mechanism of optimal position of through upwash models. Thus, the optimum operating points can be achieved based on the pursuing principle among geese in V-formation. As for inseparable objectives, the PGQ approaches could enjoy theoretically lossless decomposition to achieve decentralized optimization schemes.

The remainder of this paper is organized as follows. Section 2 briefly discusses the mechanism of flocks of geese self-organizing into V-formation. Section 3 proposes fundamental definitions and adjusting rules of PGQ along with an illustrative example. In Section 4 plant-wide process optimization problems are formulated based on multi-layer PGQ metrics and enabling algorithms of multi-layer PGQ for plant-wide process optimization are introduced. In Section 5, TE process is employed as a case study for exemplifying the applications. Section 6 concludes the contribution and assesses the future prospects.

## II. SELF-ORGANIZATION V-FORMATION OF FLOCK OF GESE

Goose queue refers to a flock of flying wild geese lined an instinctively V-shaped formation in mass migration, whose principal benefit lies in the increased flying efficiency, as shown in Fig.1. It is reported that geese in a V-formation may conserve 12–20 % of the energy they would need to fly alone [8], [9], [10]. A flying goose could generate an upward pressure known as upwash beneficial for a following goose maintaining its altitude and save energy. As a result, leading goose serves as the leader of the queue while following geese are responsible for following and keeping the V-formation. Cattivelli [11], [12] focused on the self-organizing V-formation of flocks of geese, thereby using a model,  $f(x,y)$ , to describe the upwash generated by a flying goose. Assuming that the wingspans of all geese are constant and the upwash functions are convex, an optimum position  $(x_{opt}, y_{opt})$  is available which could maximize the upwash as shown in Fig. 2. Every goose located at position  $(x_k, y_k)$  in the V-formation experiences the overlap upwash through  $\sum_{l=1}^N f(x_k - x_l, y_k - y_l)$ , by which the optimum position  $(x_{opt}, y_{opt})$  could be achieved. The

underlying point behind this mechanism lies in that geese could measure the upwash and communicate with their neighbors.

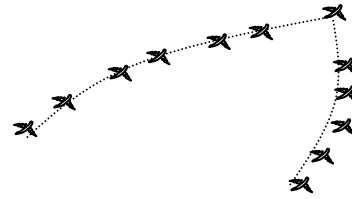


Figure 1 V-formation of flying geese.

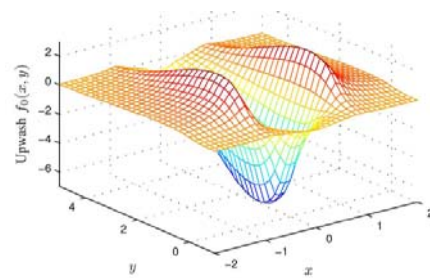


Figure 2 Upwash generated by a goose.

In simulation, Fig.3 [11] shows the resulting goose formations at different time instants, where the goose flock converges to a V-shape formation through 500 iterations or so. Goose located at position  $(x_k, y_k)$  measures the upwash with respect to the reference geese so that to pursue an optimum position  $(x_{opt}, y_{opt})$ . After that a new estimate of the best relative position with other geese is achieved.

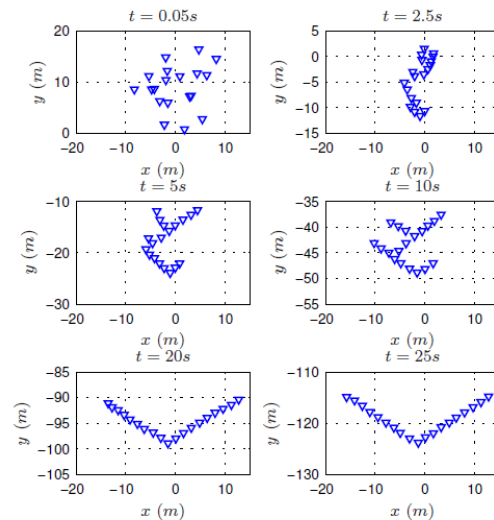


Figure 3 Goose positions at different time instants.

A steady-state V-formation is shown in Fig. 4, where the red dots indicate the positions of the geese. Notice that every goose flies in such a way that the generated upwash overlaps with the upwash from its leading goose.

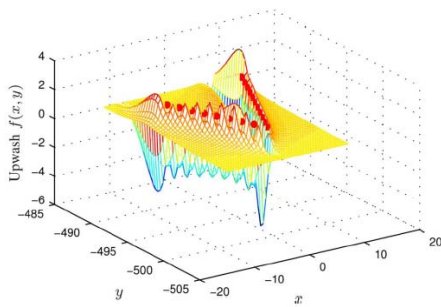


Figure 4. Upwash generated by geese in steady-state.

### III. PROCESS GOOSE QUEUE

Generally, steady-state relationship among the basic operational units of a plant-wide process can be described by following equation:

$$Y = g(S, X) \tag{1}$$

where,  $Y, S, X$  and  $g$  indicate sets of the output state variables, input state variables, manipulated variables and steady-state relationship functions, respectively. Instead, we accordingly propose PGQ approaches with following descriptions.

#### Definition1 (PGQ)

A Process Goose Queue (PGQ) is a 4-tuple,  $PGQ = (L, F_S, F_M, A)$ , where,

- $L$  is the process leading goose (PLG) such that  $\{L|L \subset Y\} \neq \emptyset$ , represented as  $(L)$  ;
- $F_S$  is the supervised following goose (SFG) such that  $F_S \subset S$  represented as  $(F_S)$  ;
- $F_M$  is the manipulated following goose (MFG) such that  $\{F_M|F_M \subset X\} \neq \emptyset$ , represented as  $(F_M)$  ;
- $A$  is the information arc (IA) such that  $\{A|A \subseteq (L \times (F_S \cup F_M)) \cup (A \subset g)\} \neq \emptyset$ , represented as inverted V;
- $F_S \cap F_M = \emptyset$  ,  $L \cap F_M = \emptyset$  ,  $L \cap F_S = \emptyset$  ,  $L = A(F_S, F_M)$

The graphical description of a PGQ is illustrated in Fig.5, where, the PLG ( $L$ ), SFG ( $F_S$ ) and MFG ( $F_M$ ) represent output process variables,  $Y$ , input process state variables,  $S$ , and input process manipulated variable,  $X$ , respectively.  $A$ , corresponds to the process steady-state models,  $g$ .

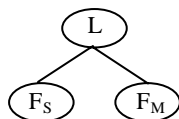


Figure 5. A PGQ (process goose queue)

Let's take a look at an example of the Williams-Otto reactor [13] which is a jacketed CSTR as shown in Fig.6.

It is operating at a temperature  $Tr$  as well as reactant flows  $F_a$  and  $F_b$ , where a six-component product,  $z$ , is produced.

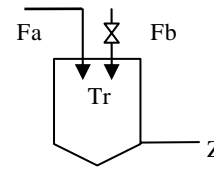


Figure6. Williams-Otto reactor

Based on PGQ techniques, the output state variables  $Z$ , input state variables  $F_a$ , manipulated variables  $F_b$  and  $Tr$  are equivalent to PLG, SFG, MFG, respectively, as shown in Fig.7, where a steady-state model between the output and inputs corresponds to IA of the PGQ.

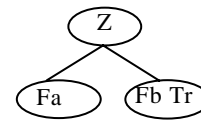


Figure 7. A PGQ for Williams-Otto reactor

#### Definition 2(Optimum operating states)

Optimum operating states refer to an ideal PGQ configuration in which a PLG operating at an ideal trajectory is followed by an optimum V-formation constituted by a SFG and a MFG, as described by:

$$L^* = A(F_S^*, F_M^*) \tag{2}$$

In practical industrial processes, optimum operating state could be destroyed by uncertain disturbances, which is in desperate need of adjustment to recover. Motivated by this idea, two alternative adjustment rules associated with a PGQ are specified as follows.

#### Rule 1 (PLG driven adjustment)

Once a PGQ operates away from its normal trajectory, PLG would try to adjust its position autonomously back to an ideal one. At the same time, SFG and MFG would operate in consistent with the activities of PLG, formulating an adapted V-formation. This kind of adjustment implies solving the following optimization problems.

$$\begin{aligned} & \min_{F_M, F_S} (L^* - L)^2 \\ \text{s.t. } & L = A(F_S, F_M) \\ & F_{SL} \leq F_S \leq F_{SU} \\ & F_{ML} \leq F_M \leq F_{MU} \end{aligned} \tag{3}$$

#### Rule 2 (SFG driven adjustment)

Once the V-formation of PGQ deviates from an optimum one due to SFG failing to follow it, MFG would try to adjust its position autonomously to formulate a new

optimum formation. At the same time, PLG would slightly shift its position to survive the adjustment of MFG. This kind of adjustment implies solving the following optimization problems.

$$\begin{aligned} & \min_{F_M} (L^* - L)^2 \\ \text{s.t. } & L = A(F_S^*, F_M) \\ & F_{ML} \leq F_M \leq F_{MU} \end{aligned} \quad (4)$$

Referring back to the above-mentioned example, if a new target of any component of z is demanded, the rule 1 would be launched to implement the adjustment; if  $F_S=[F_a]$  deviates from the optimum operating state, the rule 2 would be triggered to implement the adjustment.

IV. PROCESS OPTIMIZATION

A. Plant-wide PGQ for Process Optimization

In order to cope with plant-wide processes, a multi-layer PGQ structure should be established additionally.

Definition 3 (Multi-layer PGQ)

A multi-layer PGQ consists of several PGQs which are organized in a hierarchical architecture. Therein, the PGQs are characterized by  $PGQ_i=(L_i, F_{Si}, F_{Mi}, A_j)$ , where,  $i=1, \dots, m$ , indicates the depth index, the SFG of an upper PGQ may serve as the PLG of the neighbored lower PGQ in terms of increased depth index. The graphical description of a multi-layer PGQ is exemplified in Fig.8.

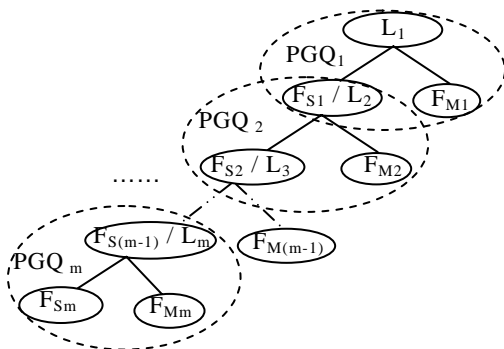


Figure 8. A multi-level PGQ

In fact, process optimization could be identified as a procedure of adjusting manipulated variables to minimize or maximize economic goals subjecting to the constraints of process models. What's more, the fact that actual formations of process models involved in a plant-wide process optimization depend on the connections of operational units accounts for particular hierarchical decompositions of process models, as shown in Fig.9.

Specifically, the economic objective function of a plant-wide optimization problem can be expressed in terms of direct related process state variables and manipulated variables. Accordingly, an additional concept about the objectives of a multi-layer PGQ is presented as

follows.

Definition 4 (PGQ-Objective) :

A PGQ-Objective is equivalent to an economic objective function of a plant-wide process, characterized by

$$P = \min \varphi(P_{S1}, P_{S2}, \dots, P_{Sj}, P_M) \quad (5)$$

$(j = 1, 2, \dots, n)$

where,  $P_{Sj}$  and  $P_M$  are process state variables and manipulated variables respectively.

Referring back to definition 1,  $P_{Sj}$  and  $P_M$  could be similarly considered as PLG and MFG of a PGQ, respectively. The graphical descriptions of a PGQ-Objective are shown in Fig.10. In this context, the procedures towards establishing a plant-wide PGQ for process optimization are summarized as follows.

(1) A plant-wide process is decomposed into several operational units / areas corresponding to the PGQs using sequential modular approaches. In the presence of a tree-structural plant-wide process, the multi-layer PGQs are consistent with the connections of the process operational areas. Otherwise, additional modeling treatments such as block segmentation, staggered breaks, and convergence calculation should be carried out before the multi-layer PGQs are obtained.

(2) Construct the economic objective functions with respect to the related process state variables  $P_{Sj}$  which serve as PLG ( $L_{ij}$ ) and manipulated variables  $P_M$ .

(3) Connect each  $P_{Sj}$  ( $L_{ij}$ ) with a multi-layer PGQ. Thus, a plant-wide PGQ could be realized, whose exemplary graphical description is shown in Fig.11.

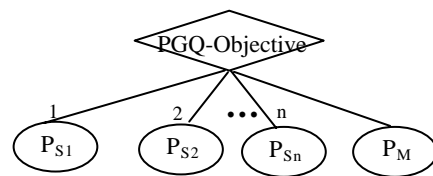


Figure 10. A PGQ (process goose queue)-Objective

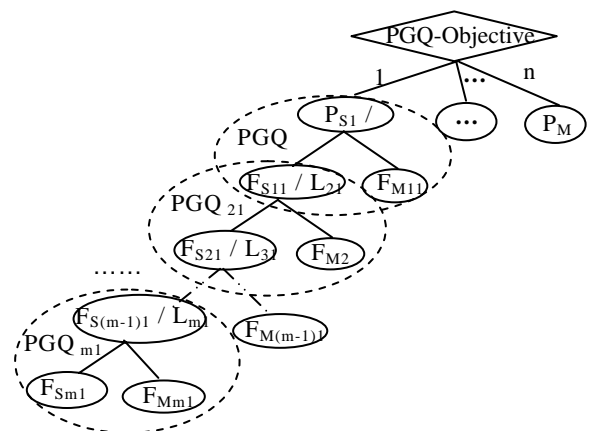


Figure 11. A plant-wide PGQ

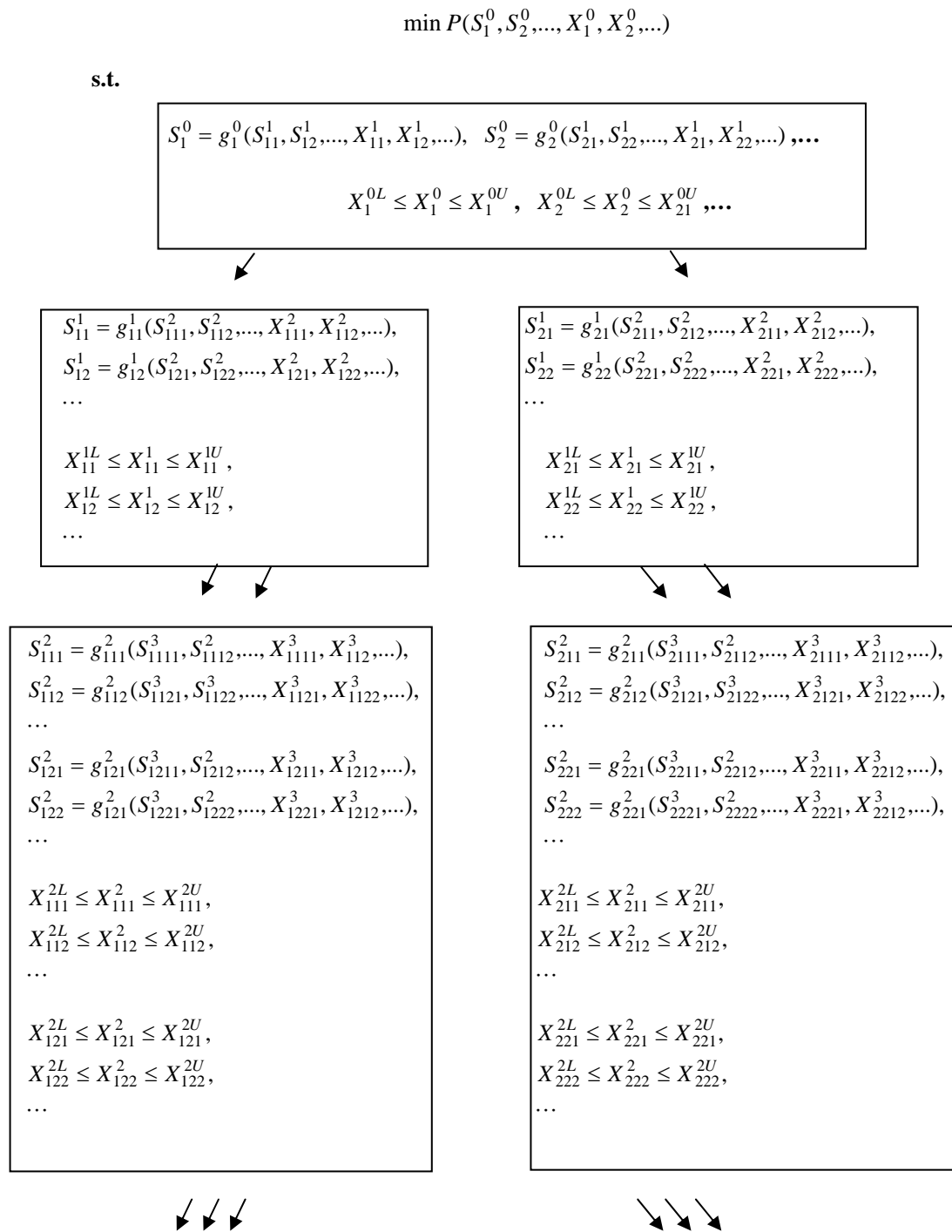


Figure 9 Decompositions of a plant-wide process optimization problem

**B. Implement of Plant-wide PGQ Optimization Algorithms**

According to the fundamental description of the PGQ, plant-wide process optimization is equivalent to implementing PLG autonomous adjustment rule in corresponding multi-layer PGQs. Therefore, solving a plant-wide optimization problem can be converted into implementing multi-layer PGQ optimization

algorithms which involves three kinds of interconnected tasks, such as assignment of a PGQ-Objective, configuration of the multi-layer PGQ formations and achievement of a PGQ-Objective, described as follows.

(1) *Assignment of a PGQ-Objective:* A PGQ-Objective could be achieved by means of assignment of optimum points of process state variables

$P_{S_j}(j=1,2,\dots,n)$  and manipulated variable set  $P_M$  involved, which could be implemented by applying rule 1 (PLG driven adjustment), i.e. solving the following optimization problem.

$$\begin{aligned} \min_{P_{S_1}, \dots, P_{S_n}, P_M} & \varphi(P_{S_1}, P_{S_2}, \dots, P_{S_n}, P_M) \\ \text{s.t.} & P_{S_{jL}} \leq P_{S_j} \leq P_{S_{jU}} \quad (j = 1, 2, \dots, n) \\ & P_{M_L} \leq P_M \leq P_{M_U} \end{aligned} \quad (6)$$

(2) Configuration of the multi-layer PGQ formations:

It supposed that there is a couple of multi-layer PGQ associated with a PGQ-Objective for a practical problem. For simplicity's sake, we only consider the treatment of one multi-layer PGQ. Starting off with  $i=1$ , rule 1 (PLG driven adjustment) is stepwise applied to  $PGQ_i$  at an increasing index  $i$ , which implies solving the following optimization problem (Noting  $F_{S0}=P_S$ ).

$$\begin{aligned} \min_{F_{S_i}, F_{M_i}} & (F_{S_{i-1}}^* - L_i)^2 \\ \text{s.t.} & L_i = A_i(F_{S_i}, F_{M_i}) \\ & F_{S_{iL}} \leq F_{S_i} \leq F_{S_{iU}} \\ & F_{M_{iL}} \leq F_{M_i} \leq F_{M_{iU}} \quad (i = 1, 2, \dots, m) \end{aligned} \quad (7)$$

(3) Achievement of a PGQ-Objective: From the PGQ with the largest depth index to the PGQ-Objective, we should update the achievement of PLG associated with each PGQ with respect to the optimum solutions (process variables) configured in step (2) until that of the PGQ-Objective.

V. CASE STUDIES

Since TE process (Tennessee Eastman Process) [14], shown in Fig.12, was proposed by Downs and Vogel (1993), it has been widely circulated in the literature as a case study due to attractive challenging properties. TE process involves five major operational units including a two-phase reactor, a partial condenser, a separator, a stripper and a compressor, in which two products are created from four reactants, an inert component B and a byproduct F, denoted by a total of eight components, A, B, C, D, E, F, G, and H instead.

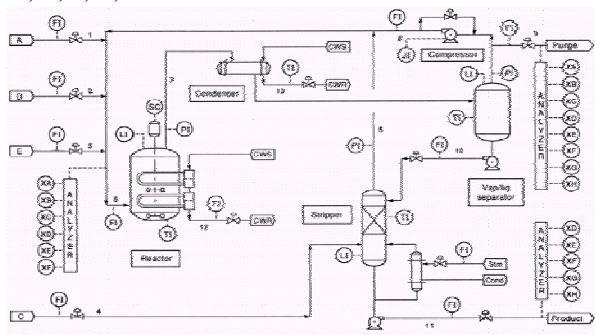


Figure 12 TE process

There are 12 manipulated variables and 41 state

variables involved in the process. Specifically, the manipulated variable vector  $F_M$  contains 10 variables,  $F_M=[F_1, F_2, F_3, F_4, F_8, F_9, F_{10}, F_{11}, T_{cr}, T_{cs}]$ , where,  $F_i$  is the molar flow rate of stream  $i$  [kmol/h] ( $i=1,2,\dots,11$ ),  $T_{cr}$  and  $T_{cs}$  are temperatures of the reactor and separator. Here, the objective function corresponds to the hourly operating cost ( $C_{tot}$ ) in \$/h which is aimed to be minimized. Therein, the reactant and product losses in terms of the purge and product streams, steam cost and compressor power cost and is measured by (8).

$$\begin{aligned} C_{tot} = & F_9 \sum_{\substack{i=A \\ i \neq B}}^H C_{i, cst} X_{i,9} + F_{11} \sum_{i=D}^F C_{i, cst} X_{i,11} \\ & + 0.0536 W_{cmp} + 0.0318 F_{steam} \end{aligned} \quad (8)$$

Based on the steady-state first-principle models, TE process can be developed into a plant-wide PGQ which includes two multi-layer PGQs as shown in Fig.13, in which the corresponding notations are listed in Table I. As a result, the following steps are implemented to solve the plant-wide PGQ optimization problem.

TABLE I.

CORRESPONDING PGQ NOTATIONS FOR TE PROCESS

PGQ	SFG/ PLG	MFG
PGQ-Objective	$P_{S1}/L_{11}=[X_{i,9}]$ $P_{S2}/L_{12}=[X_{i,11}]$	$P_{M3}=[F_9 F_{11}]$
PGQ <sub>11</sub>	$F_{S11} / L_{21}=[P_s T_s]$	$F_{M11}=[F_{10} F_8]$
PGQ <sub>21</sub>	$F_{S21}/ L_{31}=[T_R]$	$F_{M21}=[T_{CS}]$
PGQ <sub>31</sub>	$F_{S31}/L_{41}=[F_R P_R L_R]$	$F_{M31}=[F_{12} T_{CR}]$
PGQ <sub>41</sub>	0	$F_{M41}=[F_1 F_2 F_3]$
PGQ <sub>12</sub>	$F_{S11} / L_{21}=[T_{str} P_{str}]$	$F_{M12}=[F_4]$
PGQ <sub>22</sub>	$F_{S11} / L_{21}=[P_s, T_s]$	$F_{M22}=[F_{10}]$
PGQ <sub>32</sub>	$F_{S21}/ L_{31}=[T_R]$	$F_{M32}=[T_{CS}]$
PGQ <sub>42</sub>	$F_{S31}/L_{41}=[F_R P_R L_R]$	$F_{M42}=[T_{CR}]$
PGQ <sub>52</sub>	0	$F_{M52}=[F_1 F_2 F_3]$

(1) Assignment of the PGQ-Objective: Referring to the optimization scheme carried out by Ricker [15], compressor and steamer are specified at the OFF positions. The state variables  $x_{i,9}$  and  $x_{i,11}$  and the manipulated variables  $F_9$  and  $F_{11}$  involved in the objective function are selected as  $P_S$  and  $P_M$ , respectively. Table II presents assignment of the optimum points associated with the problem.

(2) Configuration of the multi-layer PGQ formations: There are two multi-layer PGQs involved in this case. The optimum points  $L_{11}^*$  and  $L_{12}^*$  responsible for the PGQ-Objective are followed and tracked by PGQ<sub>11</sub> and PGQ<sub>12</sub>, attaining  $F_{S11} / L_{21}^*=[P_s=2700, T_s=92]$ ,  $F_{M11}=[F_{10}=37.2, F_8=0]$ ,  $F_{S12} / L_{22}^*=[P_{str}=3330, T_{str}=66.60]$ ,  $F_{M12}=[F_4=60.9]$ , where  $F_{S11}^*$  and  $F_{S12}^*$  serves as  $L_{21}^*$  of PGQ<sub>11</sub> and  $L_{21}^*$  of PGQ<sub>21</sub> respectively. Similarly, the rest PGQs are treated along with a minimum objective value 116\$/h expected, as listed in Table II.

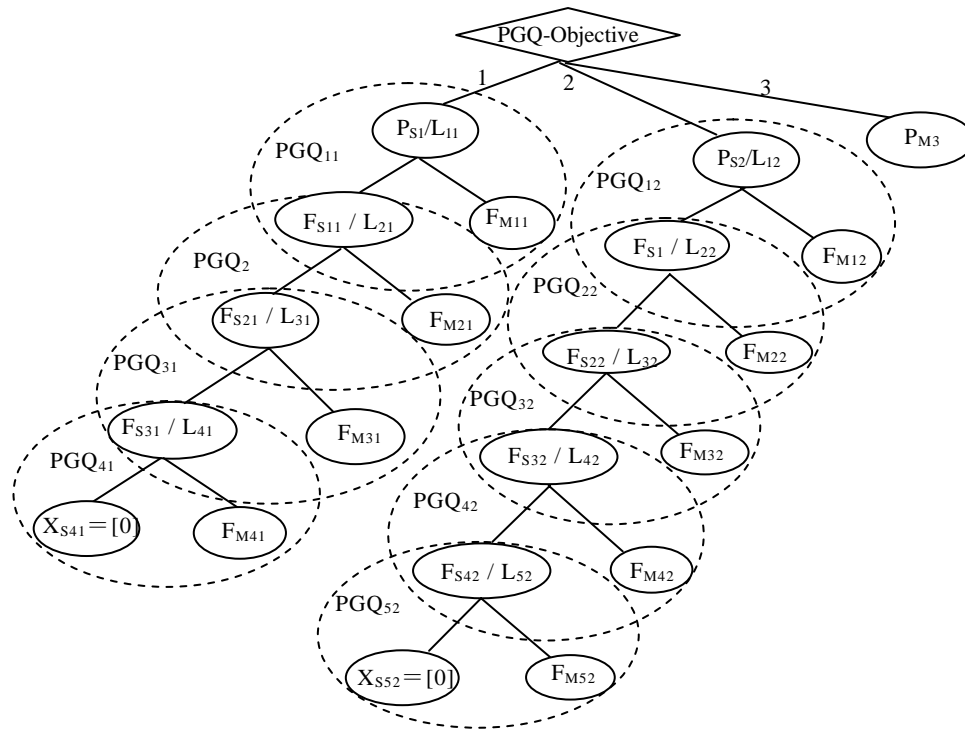


Figure 13. Plant-wide PGQ for TE process

TABLE II.

ASSIGNMENT OF THE OPTIMUM POINTS

Name of PGQ	SFG/PLG	MFG
PGQ-Objective	$P_{S1}/L_{11}^* = [X_{i,9(i=A,C,D,E,F,G,H)} = 32.63 \ 13.29 \ 0.89 \ 16.13 \ 6.675 \ 3.265]$ $P_{S2}/L_{12}^* = X_{i,11(i=D,E,F)} = [0.011 \ 0.575 \ 0.186]$	$P_{M3} = [F_9 = 24.2 \ F_{11} = 46.4]$
PGQ11	$F_{S11}^* / L_{21}^* = [P_s = 2700, T_s = 92]$	$F_{M11} = [F_{10} = 37.2 \ F_8 = 0]$
PGQ21	$F_{S21}^* / L_{31}^* = [T_R = 123.1]$	$F_{M21} = [T_{CS} = 13.0]$
PGQ31	$F_{S31}^* / L_{41}^* = [P_R = 2800, L_R = 65]$	$F_{M31} = [T_{CR} = 35.94]$
PGQ41	$F_{S41}^* = [0]$	$F_{M41} = [F_1 = 26.17 \ F_2 = 62.89 \ F_3 = 53.30]$
PGQ12	$F_{S12}^* / L_{22}^* = [P_{str} = 3330 \ T_{str} = 66.60]$	$F_{M12} = [F_4 = 60.9]$
PGQ22	$F_{S22}^* / L_{32}^* = [P_s = 2700, T_s = 92]$	$F_{M22} = [F_{10} = 37.2 \ F_8 = 0]$
PGQ32	$F_{S32}^* / L_{42}^* = [T_R = 123.1]$	$F_{M32} = [T_{CS} = 13.0]$
PGQ42	$F_{S42}^* / L_{52}^* = [P_R = 2800, L_R = 65]$	$F_{M42} = [T_{CR} = 35.94]$
PGQ52	$F_{S52}^* = [0]$	$F_{M52} = [F_1 = 26.17 \ F_2 = 62.89 \ F_3 = 53.30]$

(3) Achievement of the PGQ-Objective: Starting along the paths of PGQ41 → PGQ31 → PGQ21 → PGQ11 → PGQ-Objective and PGQ52 → PGQ42 → PGQ32 → PGQ22 → PGQ12 → PGQ-Objective, the two multi-layer PGQs are

implemented for the achievements. The resultant optimum solutions are listed in Table III, showing an actual objective value 118\$/h.



TABLE III.

FINAL OPTIMUM SOLUTIONS

Name of PGQ	SFG/ PLG	MFG
PGQ -Objective	$P_{S1}/L_{11} = [X_{i,9(i=A,C,D,E,F,G,H)} = 32.56 \ 13.61 \ 0.9162$ $15.71 \ 5.392 \ 6.703 \ 3.308 ]$ $P_{S2}/L_{12} = X_{i,11(i=D,E,F)} = [0.0142 \ 0.5880 \ 0.1782 ]$	$P_{M3} = [F_9 = 24.57 \ F_{11} = 46.41]$
PGQ <sub>11</sub>	$F_{S11}/L_{21} = [P_s = 2702.59 \ T_s = 92.15 ]$	$F_{M11} = [F_{10}=37.16 \ F_8=0]$
PGQ <sub>21</sub>	$F_{S21}/L_{31} = [T_R = 123.10]$	$F_{M21} = [T_{CS} = 13.89]$
PGQ <sub>31</sub>	$F_{S31}/L_{41} = [P_R = 2798.6 \ L_R = 65.23]$	$F_{M3} = [T_{CR}=35.97 ]$
PGQ <sub>41</sub>	$F_{S41} = [0]$	$F_{M4} = [F_1=26.11 \ F_2=62.98 \ F_3=53.08 ]$
PGQ <sub>12</sub>	$F_{S12} / L_{22} = [P_{str}=3329.88 \ T_{str} = 66.75]$	$F_{M12} = [F_4=60.65]$
PGQ <sub>22</sub>	$F_{S22} / L_{32} = [P_s = 2702.59 \ T_s = 92.15 ]$	$F_{M22} = [F_{10}=37.16 \ F_8=0]$
PGQ <sub>32</sub>	$F_{S32}/L_{42} = [T_R = 123.10]$	$F_{M32} = [T_{CS} = 13.89]$
PGQ <sub>42</sub>	$F_{S42}/L_{52} = [P_R = 2798.6 \ L_R = 65.23]$	$F_{M42} = [T_{CR}=35.97 ]$
PGQ <sub>52</sub>	$F_{S52} = [0]$	$F_{M52} = [F_1=26.11 \ F_2=62.98 \ F_3=53.08 ]$

VI. CONCLUSIONS

Inspired by biologic nature of flying goose queue, this paper proposed novel PGQ strategies for plant-wide modeling and optimization, contributing to overcoming the algorithmic deficiencies associated with conventional plant-wide process optimization. To offer PGQ theoretical foundations, key definitions and enabling algorithms have been explicitly. The benefits of the proposed strategies are demonstrated through a case study of TE process. It could be expected that advantages of the PGQ approaches towards plant-wide process optimization are potentially attractive in the following aspects.

(1) Focusing on inseparable objectives, the PGQ approaches could enjoy theoretically lossless decomposition to achieve decentralized optimization schemes.

(2) The PGQ methodology is accommodated to relatively simple nominal forms of the objective functions and process models. In contrast to conventional optimization methods which need to deal with enormous manipulated variables, the PGQ approaches could take advantage of more accurate process models by solving several small-scale PGQ optimization problems, which are more beneficial for effectively utilizing as much information of process variables as possible against modeling uncertainty.

(3) It is found that the algorithms related with the PGQs and PGQ-Objective could be launched independently, helping make options for appropriate optimization algorithms more flexible.

Anyway, to promote this research issue more attractive, an in-depth investigation on PGQ real-time optimization (RTO) approaches together with the applicability potential should be strongly advisable.

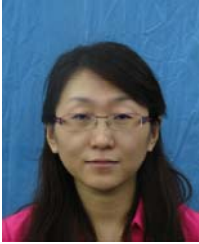
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**Jingwen Huang** was born in Shandong province, P. R. China in 1978. She received the M.S. degree in China University of Mining and Technology in 2003. At present, she is the part time Ph. D. candidate and Lecturer in Beijing University of Chemical Technology. Her research interests are process modeling, control and optimization.



**Hongguang Li** was born in Jilin Province, P. R. China in 1963. He received the Ph. D. degree in East China University of Science and Technology in 2004. At present, he is professor in Beijing University of Chemical Technology. His research interests are Modeling, control and optimization of chemical process as well as computer based intelligent control for industrial plants.