한국에너지공학회(1997년도)
추계학술발표회 논문집 pp.17-23

Data reconciliation and optimization of utility plants for energy saving

Moo Ho Lee, Jeong Hwan Kim, Chonghun Han[1], Kun Soo Chang,
Automation Research Center and Chemical Engineering Department,
Pohang University of Science and Technology

Seong Hwan Kim
Hyundai Information Technology Co. Ltd

Sang Hyun You
Hyundai Petrochemical Co. Ltd

Abstract

A methodology for on-line data reconciliation and optimization has been proposed to minimize the energy cost of a utility system. As industrial data tend to be corrupted by noise or gross error, fast and robust data reconciliation technique is essential for the on-line optimization of utility system. Thus, we propose the hierarchical decomposition approach that can be applicable to on-line data reconciliation and optimization. As this approach divides whole system into several subsystems and removes the nonlinearity of constraint systematically, it handles complexity of system easily and shows good performance in accuracy and computation speed. Through case studies, we prove that this methodology is a good candidate for on-line data reconciliation and optimization.

INTRODUCTION

In chemical industries, the optimal operation of an industrial utility plant is a very important problem in terms of efficiency and cost. The utility plant supplies steam and electricity to the processes. However, there are many factors that affect the optimal operation of the utility plant. Energy demand from each process varies depending on each process conditions. Electricity cost is a function of time, consumption and peak demand. The boiler operation cost changes according to the fuel type, boiler load and excess amount of oxygen. The turbine efficiency changes with turbine throughput. To satisfy the time-varying energy demands and the optimal operation of the plant simultaneously, we need an on-line optimization system that can meet the demand changes and ensure the optimal opeation. An on-line optimization system consists of process models, gross error detection, data reconciliation, parameter estimation and process optimization.

Measurement data tend to be contaminated by random or gross error and don't satisfy mass and energy balances or model equations. As this discrepancy between measurement data and model equation results in the failure of on-line optimization based on measurement data, data reconciliation is important to perform on-line optimization. Data reconciliation is also necessary to estimate system parameters such as boiler efficiency, heat transfer coefficient of heat exchanger which can be used for process maintenance (Papalexandri et al., 1996). Several efficient data reconciliation methods have been proposed (Hodouin and Everell, 1980; Crowe, 1986; Simpson, 1988). However, these methods are limited to linear system or bilinear system, although data reconciliation problem for industrial plant is usually nonlinear. Thus SQP (Successive Quadratic Programming) is commonly used for data reconciliation of nonlinear system (Pierucci *et al.*, 1996; Islam *et al.*, 1994; Tjoa and Biegler, 1991).

Many researchers have studied the optimization and optimal design of utility system. Their research can be classified into two categories: thermodynamic approach based on thermodynamic analysis of system performance (Nishio et al., 1980; Nishio et al., 1985; Chou and Shih, 1987) and mathematical optimization method such as

---

[1] Author to whom all correspondence should be addressed, E-mail: chan@vision.postech.ac.kr

linear programing(LP) (Petroulas and Reklaitis, 1984; Boulilloud, 1969), mixed integer linear programming(MILP) (Papoulias and Grossmann, 1983; Marechal and Kalitventzeff, 1991), nonlinear programming(NLP) (Foster 1987; Prokopakis and Maroulis, 1996) and mixed integer nonlinear programming(MINLP) (Papalexandri et al., 1996; Petracci et al., 1991). LP showed good result when only material balance was concerned without energy balance. As energy balance is required to take into account thermal conditions, Clark and Helmick (1980) treated both material and energy balance using iterative linear programming. Papoulias and Grossmann(1983) used MILP to represent thermal condition and usage of units as discrete variables in optimal synthesis of utility plant.

NLP or MINLP approaches are desirable for the complete representation of utility system. However, they did not answer the question of efficient handling of the complexity, which leads to several difficulties such as local minimum, initial guesses of the values, more computation time. Thus, we need an on-line optimization system that can handle the complexity efficiently while satisfying the required speed and robustness of the solutions. Although data reconciliation is performed prior to on-line optimization for an industrial utility system, most papers for opimization of utility system did not cover data reconciliation. Thus, we propose hierarchical data reconciliation and optimization approach and apply it to the data reconciliation and optimization of utility plant in this paper.

SYSTEM DESCRIPTION AND MODELING

Our system is the industrial utility plant of Hyundai Petrochemical™ in Korea. The utility system consists of two parts: steam generation part and steam distribution part. Five boilers produce super-heated high pressure steam (XPS) in 101 kg/cm^{2}g by burning two types of fuels, B-C oil and PFO (process fuel oil). Each boiler can supply maximum 150 tons/hr XPS to steam distribution part. XPS is used by two turbines to generate electricity and is released as high pressure steam (HPS) in 43 kg/cm^{2}g, medium pressure steam (MPS) in 11 kg/cm^{2}g and low pressure steam (LPS) in 3.3 kg/cm^{2}g through nine letdown valves. This utility system has two turbines to generate electricity that is used to meet the site demand. The first turbine that produces 36MWh in maximum has one extraction stream from the turbine to HPS header. The second turbine that generates 61MWh in maximum has two extraction streams: one from turbine to HPS header and the other from turbine to MPS header. Two turbines supply 97MWh using about 690 tons/hr XPS as an input flow. The utility system has to satisfy the demands for HPS, MPS, LPS, and electricity from a variety of processes. The required quality for each steam is determined based on temperature, pressure and flowrate. When the generated electricity is not enough to meet the demand, the electricity can be purchased from an electrical power company. The demand change for steam and electricity are shown in Figure 1. The process values such as flowrate, temperature, pressure are collected, monitored, and controlled by DCS(Distributed control system).

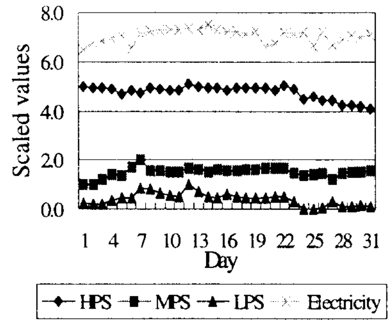

Figure 1. Demand change for steam and electricity.

Most popular models for on-line data reconciliation and optimization are equation-based ones rather than modular-based ones, because equation-based models offer the flexible selection of decision variables and possibility of using the same models for both reconciliation and optimization. As an industrial utility plant handles a variety of streams such as steam, electricity and water and has many complex and nonlinear unit processes such as boilers and turbines, the utility system model becomes complex nonlinear. The utility model that is based on mass and energy balance is can be represented as follows.

Mass balance is

$$\sum_{i=1}^{s} \alpha_i^k F_i = 0,\ k = 1,..,n \text{ and } i = 1, \ldots, s. \quad (1)$$

Where k is a node number or a process unit and i is a stream number. The α_i^k represents the state of stream, input, output, or unrelated stream of *k-th* node. Thus, α_i^k has 1 for input, -1 for output and 0 for unrelated stream. F_i is flowrate of *i-th* stream. An energy balance is

$$\sum_{i=1}^{s} \alpha_i^k F_i H_i - Q^k - W^k = 0, \qquad (2)$$
$$k = 1, ..., n \text{ and } i = 1, ..., s$$

Where H_i is an enthalpy of *i-th* stream and a function of temperature and pressure. Q^k and W^k are a heat and a work generated by unit *k*. As the pressure of each stream is fixed as a desired value for stable operation, we assume that the enthalpy is a function of temperature only.

Besides mass and energy balance equations, we have to obtain characteristic equations to represent boiler efficiency and generated electricity using the measurement data from plant. It is very important to represent boiler efficiency that changes according to heat load, or produced steam load (Cho 1978).

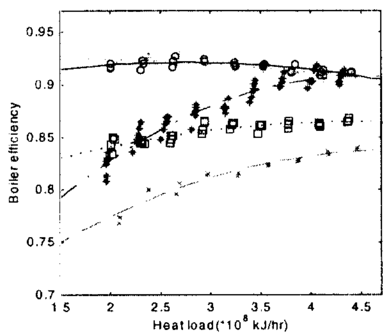

Figure 2. Boiler efficiency according to heat load (Operation data, o :boiler 1, + :boiler 2, * :boiler 3, x :boiler 4, • boiler 5, Curves are characteristic equations)

The efficiency of *l-th* boiler can be expressed as follows.

$$\eta_l = a_l Q_{trans}^2 + b_l Q_{trans} + c_l, \ l = 1, ..., m . \qquad (3)$$

Where Q_{trans} is a heat flowrate, that is transferred by boiler to produce XPS, and a_l, b_l and c_l are coefficients. We obtain the coefficients for the boiler efficiency equation (3) using operation data. As shown in Figure 2, the efficiency of boiler varies with heat load and five boilers have different efficiency equations respectively.

To represent the generated power from a turbine, we obtain the relation of generated power (P) as a function of input and extraction flowrates as follows

$$P_j = d_j F_{input} + e_j F_{ext} + g_j, \ j = 1, ..., q \qquad (4)$$

Where F_{input} and F_{ext} are flowrates of input and extraction of turbine, and d_l, e_l and g_l are coefficients. We obtain the coefficients using operation data and the result is shown in Figure 3.

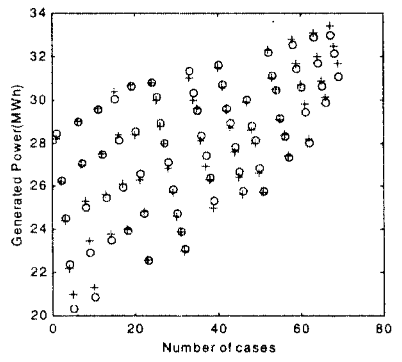

Figure 3. Comparison of operation data and characteristic equation in generated power
(+ :operation data, o : characteristic equation)

HIERARCHICAL ON-LINE DATA RECONCILIATION AND OPTIMIZATION

As process demands for steam and electricity change several times a day and many decision variables are involved in determing control parameters to minimize the cost of utilty system, on-line data reconciliation and optimization system is necessary for successful energy management as shown in Figure 4. DCS receives process data from utility system and give controls. Data reconciliation supplies reconciled data for optimization and process monitoring. Reconciled data involve measument data, gross error detection, and paramerter estimation such as boiler efficiency, heat transfer coefficent of heat exchanger. Process demand and fault are monitored by process monitoring system and optimization gives optimal setpoints to process controllers. A fast and robust optimization approach is needed for successful on-line data reconciliation and optimization.

We propose a hierarchical on-line data reconciliation and optimization for an industrial utility plant based on hierarchical decomposition approach (HDA). If a large and complex system is decomposed into several subsystems that are almost independent of each other and easy to solve, we can easily solve the whole system by solving the subsystems and combining the sub-solutions to generate the final solution. In reality, however, two difficulties exist for HDA: a) the interaction between connected subsystems which causes the discrepancy between state values for the connection stream, b) a coordination when we combine subsolutions into a final solution. The proposed approach introduces the classification of process variables into three categories: a) *common variable* (CV): a state variable for an interconnection stream between two connected subsystems, e.g. flowrate, pressure, temperature of the interconnection variable between interconnected subsystems, b) *linearization variable* (LV): a variable which linearizes balance equations when its value is given, e.g. ether flowrate or temperature in equation (2), or efficiency, heat transfer coefficient, c) *internal variable* (IV): variables of subsystems.

We represent our strategy as shown in Figure 5. We decompose a system into several subsystems. If the values for *coordinating variables*, which consist of common and linearization variables, are given, each subsystem becomes independent and linear like the subsystem 2 in Figure 5. When most of variables for a subsystem are related to nonlinearity, we can solve this subsystem using nonlinear programming method instead of making subsystem linear like the subsystem 1 in Figure 5.

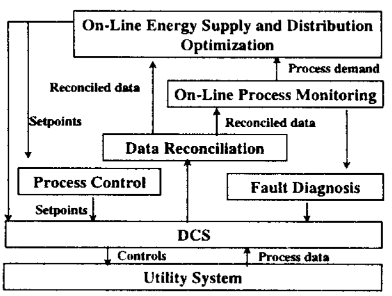

Figure 4. On-line data reconciliation and optimization

During optimization, at the upper level, since the coordinating variables are related to nonlinearity or the interconnection between two subsystems, they should be optimized using more robust nonlinear optimization algorithms such as SQP. After the values of coordinating variables are determined at upper level, coordinating variables become pre-specified parameters for each subsystem. At the lower level, each subsystem has only linear constraints and is optimized easily by relatively simple optimization techniques such as LP and least square(LS). The objective function values of subsystems at the lower level optimization are transferred to the upper level optimization.

CASE STUDIES

The proposed methodology has been applied to the off-line reconciliation and optimization of an industrial utility plant of Hyundai Petrochemical™ in Korea. As the generation and the distribution of steam are treated independently assigning the flowrates and temperatures for the connection streams to common variables, the utility plant has been decomposed into two subsystems: the boiler subsystem and the steam distribution subsystem. The boiler block is composed of five boilers and the steam distribution block two turbines, four headers, nine letdown valves and two deaerators. As the boiler efficiency equation is a quadratic function of flowrates and enthalpies of several streams, it is not a good strategy to select all these variables as linearization variables and to make boiler subsystem have only linear constraints. To solve this problem, we solve the steam distribution subsystem using HDA with temperatures as linearization variables and then solve the boiler subsystem using SQP based on the values of common variables that are calculated at the optimization of steam distribution subsystem.

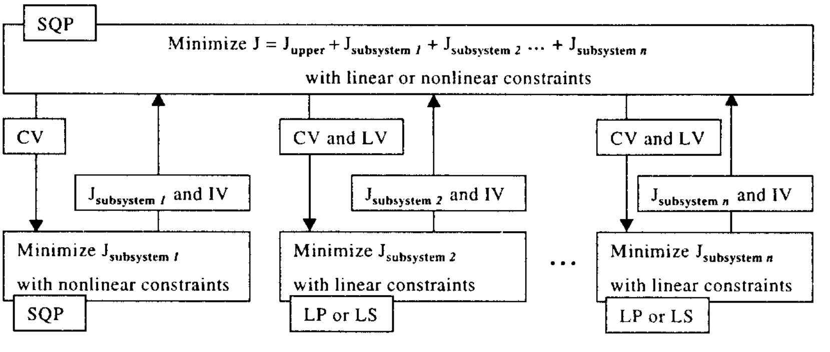

Figure 5. Optimization based on Hierarchical decomposition approach

Data reconciliation for utility system

HDA is used for the data reconciliation of a steam distribution subsystem. At upper level, temperature is optimized using SQP and its value is transferred into lower level optimization. At lower level optimization, as pressure can be specified as a fixed value and the value of temperature is determined at upper level optimization, equation (2) becomes linear for flowrate. As a result, the model for the steam distribution subsystem which consists of equation (1), (2), and (4) becomes linear. Data reconciliation problem for a linear system is well defined and easy to solve (Tamhane and Mah, 1985). The objective function for data reconciliation at lower level is

$$\underset{F}{\text{Minimize}}\ J_{lower} = \left(F - \tilde{F}\right) Q_{\tilde{F}}^{-1} \left(F - \tilde{F}\right)^{T} \qquad (5)$$

and constraints are equation (1), (2), and (4). Where $\tilde{F}$ is a measurement value vector for flowrates, F is a reconciled value vector which satisfies constraints, and $Q_{\tilde{F}}^{-1}$ is the inverse matrix of covariance of $\tilde{F}$. The objective function for data reconciliation at upper level is

$$\underset{T}{\text{Minimize}}\ J_{lower} = J_{lower} + \left(T - \tilde{T}\right) Q_{\tilde{T}}^{-1} \left(T - \tilde{T}\right)^{T}. \qquad (6)$$

Where $\tilde{F}$ and $\tilde{T}$ are measurement values of flowrate and temperature, and T and F are reconciled values. $Q_{\tilde{F}}^{-1}$ and $Q_{\tilde{T}}^{-1}$ are the inverse of covariance matrix of $\tilde{F}$ and $\tilde{T}$ respectively.

For the boiler subsystem, we use the SQP method due to its nonlinearity. As the boiler subsystem model is simpler than steam distribution subsystem model, data reconciliation of boiler subsystem is relatively easy. We have generated 20 sets of noisy data for simulation by adding white noise and used these data as measurement data. The result of data reconciliation shown in Table 1 is the average of 20 sets. The SQP shows the results from data reconciliation using SQP for the whole utility system and HDA shows the ones from data reconciliation using HDA. As shown Table 1, HDA shows better performance in objective function value and calculation time.

Table 1. Comparison of SQP and HDA for data reconciliation

	Objective function value	Number of iteration	CPU time(sec)
SQP	30.8	343	41
HDA	48.9	8667	746

The reconciled values for temperature and flowrate show smaller variance than measured values as shown in Figure 6 and 7. From data reconciliation, we obtain the information on boiler efficiency that cannot be measured directly as shown in Figure 8.

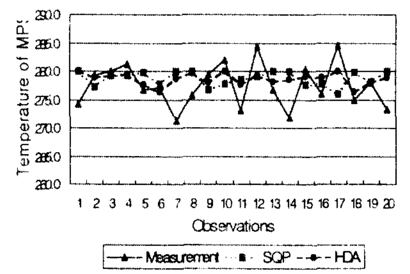

Figure 6. Data reconiclication of MPS temperature.

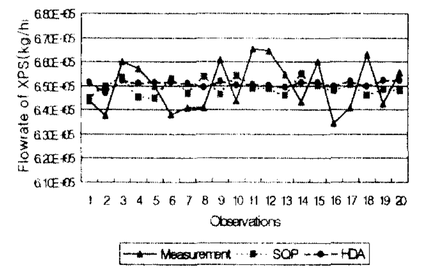

Figure 7. Data reconciliation of flowrate of HPS.

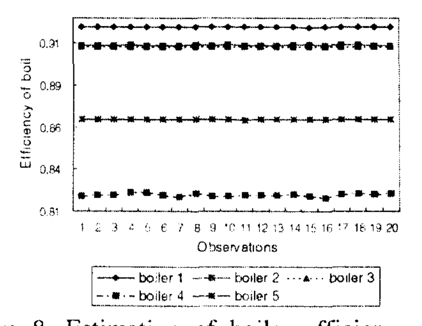

Figure 8. Estimation of boiler efficiency using data reconciliation.

Optimization for utility system

HDA is used for the on-line optimization of steam distribution subsystem like the case of data reconciliation. At the upper level optimization, temperature is determined using SQP and its value is transferred into lower level optimization. As constraint equations are linear functions of flowrate and electric power at lower level optimization, lower level optimization is a linear programming problem. The objective for lower and upper level optimization is to minimize heat flowrate Q_{trans} that is supplied by boiler subsystem.

$$\text{Minimize } J = Q_{trans} = F_{xps}H_{xps} - F_{bfw}H_{bfw} \qquad (7)$$

has equation(1), (2), (4) and steam and electricity demand as constraints. Where F_{xps} and F_{bfw} are flowrates of XPS and boiler feed water and H_{xps} and H_{bfw} are enthalpies of XPS and boiler feed water.

During the boiler subsystem optimization, we minimize the amount of fuel burned in five boilers producing heat flowrate which has been calculated from the optimization of the distribution subsystem using SQP. We perform optimization using SQP and HDA respectively for three cases and compare the results as shown in Table 2 and 3. The result of HDA shows the fuel cost is reduced by 5.4 – 9.2% compared with the current operation. The saved cost for fuel is shown in Table 2. Price of B-C Oil is 0.177 $/kg and annual operation hour is 8000.

Table 2. Optimization results for a utility system

Case number	Demand				Fuel(kg/hr)			Saving ($/yr)
	Power (kw)	HPS (ton/hr)	MPS (ton/hr)	LPS (ton/hr)	Operation	SQP	HDA	
1	94047	202	128	96	56212	53185	52771	4893866
2	91271	276	79	59	55140	52269	52032	4420266
3	94642	276	79	59	58046	53028	52734	418133

Table 3. Optimization result for case 1.

		Initial	SQP	HAD
XPS	F	672000	650100	644800
	T	510	500	500
HPS	F	270000	263900	267200
	T	393	370	370
MPS	F	233500	216700	216100
	T	273	278	280
LPS	F	111000	96400	96000
	T	208	180	180
Letdown	F	0	0	0
XPS→HPS	T	393	370	370
Letdown	F	68000	67500	71100
HPS→MPS	T	273	278	280
Letdown	F	105000	96400	96000
MPS→LPS	T	208	180	180
Extraction	F	190000	176900	140300
Turbine1→LPS	T	395	410	410
Extraction 1	F	80000	80100	120000
Tubine2→MPS	T	395	410	410
Extraction 2	F	160000	149200	145000
Turbine2→LPS	T	270	270	270
Turbine1	p	35	37	29
Turbine2	p	58	57	65
XPS	F	100000	116800	115100
From boiler 1	T	510	493	495
XPS	F	100000	149900	150000
From boiler 2	T	510	480	539
XPS	F	100000	150000	149900
From boiler 3	T	510	540	492
XPS	F	100000	116900	114900
From boiler 4	T	510	499	480
XPS	F	100000	116500	114900
From boiler 5	T	510	480	480
BFW(boiler	F	500000	650100	644800
feed water)	T	120	140	140

F: flowrate(kg/hr), T: temperature(°C) and p: power(MWh)

CONCLUSIONS

As the conditions of utility system such as steam and electricity demands change according to time, on-line data reconciliation and optimization is needed to minimize the energy cost of utility system. We propose the hierarchical data reconciliation and optimization approach based on HDA for the application to industrial utility system. The proposed approach have significantly reduced the computation time and offered the modular structure which are easy to maintain and update for data reconciliation and optimization. We applied this approach to the data reconciliation and optimization of utility plant by off-line and show that it gives good performance in accuracy and computation speed enough to be applicable to on-line data reconciliation and optimization. We are going to apply this methodology to industrial utility system by on-line. The proposed methodology can be easily applied to on-line data reconciliation and optimization of various systems.

ACKNWLEDGMENT

Special thanks are owed to R & D Management Center for Energy and Resources under the Korea Energy Management Corporation for its financial support.

REFERENCES

Boulilloud, P., (1969), *Hydro. Proce.* Aug., 127.

Cho, C. H., (1978), *Instr. Tech.* Oct., 55.

Chou, C. and Shih, Y., (1987), *Ind. Eng. Chem. Res.* 26, 1100.

Clark, J. K. and Helmick, N. E., (1980), *Chem. Eng.* Mar., 116.

Crowe, C. M., (1986), *AIChE J.* 32, 616.

Foster, D., (1987), *Proc. Instn Mech. Engrs* 201, 201.

Hodouin D. and Everell M. D., (1980), *Int. J. Miner. Process* 7, 91.

Marechal, F. M. and Kalitventzeff, B., (1991), *Comp. Oriented Proc. Engng.* 185.

Nishio, M., Itoh, J., Shiroko, K., and Umeda, T., (1980), *Ind. Eng. Chem. Process Des. Dev.* 19, 306.

Nishio, M., I. Koshijima, K. Shiroko and Umeda, (1985), *Ind. Eng. Chem. Process Des. Dev.* 24, 19.

Papalexandri, K. P., Postikopoulos, E. N., Kalitventzeff, B and Dumont, M. N., (1996), *Comput. Chem. Eng.* 20, Suppl., S763.

Papoulias, S. A. and I. E. Grossmann, (1983) *Comput. Chem. Eng.* 7, 695.

Petracci, N. C., Brignole, E. A. and Eliceche, A. M., (1991), *Comp. Oriented Proc. Engng.* 387.

Petroulas, T. and G. V. Reklaitis, (1984), *AIChE J.* 30, 69.

Prokopakis, G. J. and Z. B. Maroulis, (1996) *Comput, Chem. Eng.* 20, Suppl., S623.

Pierucii, S., P. Brandani, E. Ranzi, A. Sogaro, (1996) *Comput. Chem. Eng.* 20, Suppl., S1539.

Islam, K. A., G. H. Weiss, J. A. Romagnoli, (1994) *Comput. Chem. Eng.* 18, Suppl., S217.

Simpson, D. E., M. G. Everett, V. R. Voller, (1988), *Appl. Math. Modeling* 12, 204.

Tamhane, A. C., and Mah, R. S. H., (1985), *Technometrics* 27, 409.

Tjoa, I. B. and L. T. Biegler, (1991) *Comput. Chem. Eng.* 15, 679.