OPTIMAL SENSOR SELECTION FOR SUCCESSFUL REAL-TIME OPTIMIZATION

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Abstract: In Real-Time Optimization (RTO) systems, the performance of the RTO depends strongly on the selection of measured variables and of sensors used for their measurements. Many studies have investigated the selection of variables (e.g., Krishnan, *et al*., 1992; Fraleigh, *et al*., 1998). This study extends previous work by considering the error in the implementation of the RTO results due to imperfect sensors used in process control. A practical optimal sensor design strategy based on nonlinear closed-loop Monte-Carlo simulations is developed. Case study results demonstrate that the implementation error can be essential for determining the appropriate sensors.

Keywords: Sensor design; Implementation error; Real-time optimization; Uncertainty; Closed-loop; Monte-Carlo simulation;

1. INTRODUCTION

Significant economic benefits can be obtained by applying operational optimization to chemical units or plants (Marlin and Hrymak, 1997). During the past ten years, with the development of numerical methods and computing power, many successful industrial applications of real-time optimization (RTO) have been reported (van Wijk and Pope, 1992; Bailey *et al*., 1993; Brewer and Lopez, 1998).

The various existing process optimization techniques can be classified into two general categories: direct search and model-based optimization (Garcia and Morari, 1981). Direct search methods explore the plant response surface directly for the optimum operating conditions through a series of plant experiments, while model-based methods use process models to estimate the plant optimum. This paper concentrates on model-based process optimization systems.

A typical model-based RTO system is composed of several subsystems: process data validation, model update, economic optimization, and RTO results implementation. A general structure for the model-based RTO system is shown in Fig. 1.

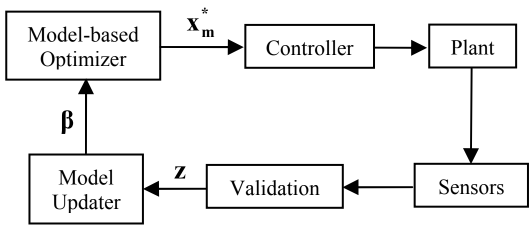

Fig. 1 General structure of RTO system

From Fig. 1, it can be seen that, in real-time optimization systems, feedback is applied to compensate for model errors and unmeasured disturbances. As a result, the performance of the RTO depends strongly on the selection of measured variables and of sensors used for their measurements. Several studies have investigated the selection of variables (Kage and Joseph, 1990; Krishnan *et al*., 1992; Zhang, 1998). These studies, however, only consider the parameter updater as an isolated system rather than examining the effect of measurements on the RTO performance. Fraleigh *et al.* (1998) considered the whole closed-loop RTO system and developed a sensor system design cost criterion which allows the designer to compare various measurement combinations with respect to uncaptured profit due to setpoint variance and bias.

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This study extends previous work by considering the error in the implementation of the RTO results due to imperfect sensors used in process control. A practical optimal sensor design strategy based on nonlinear closed-loop Monte-Carlo simulations is developed. Sensor design candidates are evaluated in terms of true plant economic performance with consideration of various typical uncertainties experienced in industrial processes. The optimal sensor design strategy is illustrated with a distillation optimization example. Simulated case studies show that considering implementation error can be essential for determining the appropriate sensors.

In the next section, methods for optimal sensor design are briefly described. A design strategy based on closed-loop Monte-Carlo simulations is then presented with considering several critical issues in sensor selection problem. Section 3 contains the problem formulation and case study design. Case study results are presented in Section 4. The final section are the conclusions.

2. OPTIMAL SENSOR SELECTION FOR RTO SYSTEMS

For illustrative purpose in the following discussion, the closed-loop RTO system of Fig. 1 is simplified to include only three major subsystems shown in Fig. 2. Here it is assumed that the process measurements $\mathbf{z}$ are corrupted by random, zero-mean, stationary noise N and the process controllers are capable of implementing the calculated setpoints.

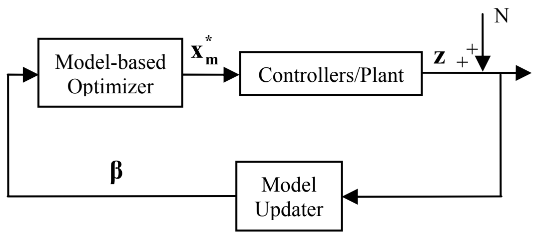

Fig. 2 Simplified RTO system

Generally, two approaches can be used for optimal sensor design: linear approximation and Monte-Carlo simulation. Linear approximation method was developed by Forbes and Marlin (1996). The central idea is based on the fact that each element of Fig. 2 can be considered as a nonlinear map. For arbitrarily small deviations from the plant optimum, the nonlinear maps of each element can be represented by their first-order approximations. The resulting system of linear equations can be reduced to an iterative relationship in perturbations to the predicted optimum setpoints ($\boldsymbol{\delta}\mathbf{x}_\mathbf{m}^*$):

$$\boldsymbol{\delta}\mathbf{x}_\mathbf{m}^*(k) = \left(\frac{d\mathbf{x}_\mathbf{m}^*}{d\boldsymbol{\beta}}\frac{d\boldsymbol{\beta}}{d\mathbf{z}}\frac{d\mathbf{z}}{d\mathbf{x}}\right)_{\mathbf{x}_\mathbf{p}^*,\boldsymbol{\beta}^*,\mathbf{z}^*} \boldsymbol{\delta}\mathbf{x}_\mathbf{m}^*(k-1) + \left(\frac{d\mathbf{x}_\mathbf{m}^*}{d\boldsymbol{\beta}}\frac{d\boldsymbol{\beta}}{d\mathbf{z}}\right)_{\boldsymbol{\beta}^*,\mathbf{z}^*} N(k) \tag{1}$$

where $\mathbf{x}_\mathbf{p}^*$ is the plant optimum setpoints; $\boldsymbol{\beta}^*$ and $\mathbf{z}^*$ are model parameters and process measurements at the plant optimum, respectively; k is the iteration counter.

For RTO system excited by process noise and with $\boldsymbol{\delta}\mathbf{x}_\mathbf{m}^*(0) = \mathbf{0}$, the setpoint covariance matrix $Q_{\mathbf{x}_\mathbf{m}^*}$ is:

$$Q_{\mathbf{x}_\mathbf{m}^*} = \sum_{i=0}^{\infty} \left(\frac{d\mathbf{x}_\mathbf{m}^*}{d\boldsymbol{\beta}}\frac{d\boldsymbol{\beta}}{d\mathbf{z}}\frac{d\mathbf{z}}{d\mathbf{x}}\right)^i_{\mathbf{x}_\mathbf{p}^*,\boldsymbol{\beta}^*,\mathbf{z}^*} \left(\frac{d\mathbf{x}_\mathbf{m}^*}{d\boldsymbol{\beta}}\frac{d\boldsymbol{\beta}}{d\mathbf{z}}\right)_{\boldsymbol{\beta}^*,\mathbf{z}^*} Q_\mathbf{z} \left[\left(\frac{d\mathbf{x}_\mathbf{m}^*}{d\boldsymbol{\beta}}\frac{d\boldsymbol{\beta}}{d\mathbf{z}}\frac{d\mathbf{z}}{d\mathbf{x}}\right)^i_{\mathbf{x}_\mathbf{p}^*,\boldsymbol{\beta}^*,\mathbf{z}^*} \left(\frac{d\mathbf{x}_\mathbf{m}^*}{d\boldsymbol{\beta}}\frac{d\boldsymbol{\beta}}{d\mathbf{z}}\right)_{\boldsymbol{\beta}^*,\mathbf{z}^*}\right]^T \tag{2}$$

where $Q_\mathbf{z}$ is the given covariance matrix of process measurements.

Thus, by using differential sensitivity analysis, a closed-loop RTO system shown in Fig. 2 can be represented by a linear approximation. The sensor design candidates can be evaluated by studying the setpoints covariance matrix $Q_{\mathbf{x}_\mathbf{m}^*}$.

Although the linear approximation method has been demonstrated to be effective for small-scale process problems (Fraleigh, 1998), when applied to large-scale optimization systems, it may be impractical due to the potentially intense computational expense associated with the derivative calculations. Another shortcoming of this method is that the design procedure is based on linear approximation of the closed-loop RTO system, which means the analysis is only locally valid and the range of validity is unknown.

Monte-Carlo simulation, on the other hand, is a relatively straightforward method. Instead of performing linear sensitivity analysis, it evaluates design candidates by closed-loop RTO simulations. Given the sensor noise and typical uncertainties, the entire closed-loop RTO system can be simulated by considering the interaction of the three major subsystems shown in Fig. 2.

Compared to linear approximation approaches, Monte-Carlo simulation does not approximate the sensitivity of the loop elements and hence provides more accurate results for optimal sensor design problem. This advantage is significant especially when the systems considered are highly nonlinear. In addition, it can be applied in most of the commercial available optimization system products. In this paper, closed-loop Monte-Carlo simulation method is employed for the optimal sensor design with several important issues to be recognized.

The first is the impact of implementation error on the RTO performance when the process control system enforces the RTO results. No previous study has considered this factor. In industrial practice, high accuracy sensors may not be available or might not be economically justified. In this case, the implementation error has to be considered. It's a trade-off between sensor cost and plant profit: when high accuracy sensors are not used, RTO performance might be degraded by selecting relatively lower accuracy sensors instead.

Another important issue in optimal sensor design is the design strategy. To make the design decision quickly, a screening method is also proposed. The motivation for incorporating the screening method in design strategy is that in industrial practice, there are usually many, say, tens or even hundreds of design candidates to be evaluated. To make the important design decisions quickly, the screening method can be used to eliminate some of the design candidates before testing the best candidate on closed-loop Monte-Carlo simulations. The detailed strategy is described in the following steps:

1. Assume high accuracy sensors are available, perform closed-loop Monte-Carlo simulations without considering implementation error;
2. Assume high accuracy sensors are not available, set proper error level for each of the individual setpoints;
3. Use screening method to evaluate the design candidates. Detailed procedure is given below:
   a) For each design candidate, randomly select one or several sets of setpoints from previous closed-loop RTO iteration points;
   b) For the selected set of setpoints:
      i) Generate the implementation error according to the error level given in 2. and add it to the setpoints;
      ii) Run plant Monte-Carlo simulations;
   c) Eliminate some of the design candidates by comparing their RTO performance;
4. Test the design candidates that pass step 3 by closed-loop Monte-Carlo simulations with implementation error.

By following the design steps stated above, we can get both of the optimal sensor design results with/without implementation error, with reduced computing time.

It should be noted that the RTO performance should be calculated based on the plant model, not on the model used by the optimizer. This practice arises from the fact that due to model/plant mismatch, the optimum setpoints predicted by the optimizer don't necessarily guarantee an optimum performance in the true plant. Since we are more concerned about economic profit of the true plant, it is essential to evaluate the sensor design candidates in terms of the plant performance.

3. PROBLEM FORMULATION AND CASE STUDY DESIGN

3.1 Process description

The case study considered is a deisobutanizer from Sunoco Sarnia hydrocracker plant (Bailey *et al*., 1993). It is a 65 bubble cap tray distillation column, operating at approximate 500kPa, which separates isobutane from normal butane. The nominal feed conditions are given in Table 1.

Table 1 Deisobutanizer feed conditions

Composition (mol %)	Propane (C_3)	3.83
	iButane (iC_4)	63.76
	Butane (nC_4)	28.22
	iPentane (C_5)	4.19
Flow (Mmols/day)		6.424
Temperature (˚C)		94.8
Pressure (kPa)		1730.4

To match as closely as possible the behavior of the realistic distillation operation, the deisobutanizer model has been modified to include additional components, such as a total condenser model, flooding correlations, and pressure drop correlations, *etc*.

There are 32 ideal trays in the final model with one feed flow that enters the tower on tray 14. The model has 488 equations which are written in an equation-based format. All the variables are scaled by selecting appropriate engineering units. The case studies are solved using MINOS in GAMS (Brooke *et al*., 1998).

3.2 Problem formulation

Model updater Mathematically, the model updater is a special type of nonlinear optimization problem, in which there is no distinction between independent and dependent variables. The process model $\mathbf{h}$ can be expressed in terms of measured variables $\mathbf{x^m}$, unmeasured variables $\mathbf{x^u}$, fixed parameters $\boldsymbol{\alpha}$ and estimated parameters $\boldsymbol{\beta}$ (the data in Table 1 except pressure), as given in (3):

$$\mathbf{h}\left(\mathbf{x^m}, \mathbf{x^u}, \boldsymbol{\alpha}, \boldsymbol{\beta}\right) = \mathbf{0} \tag{3}$$

Many formulations are available for the model updater. In this study, we consider both of the data reconciliation and parameter estimation in model updater. Naturally, we have considered the gross errors in process measurements that have been identified and removed prior to the updating phase.

$$\begin{aligned} \underset{\mathbf{x^m},\mathbf{x^u},\boldsymbol{\beta}}{Min} \quad & \left(\mathbf{x^m} - \mathbf{z}\right)^T Q_{\mathbf{z}}^{-1} \left(\mathbf{x^m} - \mathbf{z}\right) \\ s.t. \quad & \mathbf{h}\left(\mathbf{x^m}, \mathbf{x^u}, \boldsymbol{\alpha}, \boldsymbol{\beta}\right) = \mathbf{0} \end{aligned} \tag{4}$$

Model-based optimizer Model-based optimizer provides optimum operation policy based on the updated model and an economic objective function. The objective function accounts for the profit/cost of plant operation. Generally, it is a function of product profit and the costs of energy and raw materials. In this study, a nonlinear objective function based on plant cost is employed (Seferlis, 1995). It includes the cost of the utilities and the differential value of the components in the two product streams. The model-based optimizer can be stated as follows:

$$\begin{aligned} &\underset{\mathbf{x^i},\mathbf{x^d}}{Min}\ \Phi = C_B Q_B + C_D Q_D + C_{hk} x_{D,hk} D + C_{lk} x_{B,lk} B \\ &s.t. \qquad \mathbf{h}\left(\mathbf{x^i},\mathbf{x^d},\boldsymbol{\alpha},\boldsymbol{\beta}\right) = \mathbf{0} \\ &\qquad\quad\ \ \mathbf{g}\left(\mathbf{x^i},\mathbf{x^d},\boldsymbol{\alpha},\boldsymbol{\beta}\right) \le \mathbf{0} \end{aligned} \tag{5}$$

where Φ is the plant cost (\$/d); $\mathbf{x^i}$ are the optimization variables; $\mathbf{x^d}$ are the dependent variables; $\boldsymbol{\alpha}$ are the fixed parameters; $\boldsymbol{\beta}$ are the updated parameters; $\mathbf{g}$ are the inequality constraints account for the product quality specifications; Q_B and Q_D are the reboiler and condenser duties (TJ/d); $x_{D,hk}$ is the heavy key component in the top product; $x_{B,lk}$ is the light key component in the bottom product; D , B are the top and bottom products (Mmol/d), respectively; C_B , C_D , C_{hk} , C_{lk} are the cost coefficients. The values of the cost coefficients are given in Table 2.

Table 2 Cost coefficients for objective function

C_B	C_D	C_{hk}	C_{lk}
2.40	0.40	15000	15000

There are three optimization variables in the model-based optimizer, one of which is the overhead pressure, the other two are either component compositions or tray temperatures, depending on the case scenarios (See Table 3).

Plant After the three optimization variables are determined, the degrees of freedom of the plant is zero, and the plant simulation can be performed by solving the following equations.

$$\mathbf{h}\left(\mathbf{x^i},\mathbf{x^d},\boldsymbol{\alpha},\boldsymbol{\beta}\right) = \mathbf{0} \tag{6}$$

3.3 Case study design

As we know, for a distillation tower, there are usually three possible positions for the composition analyzers: on the top product, on the bottom product, or on the feed, leading to 8 analyzer combinations available for the distillation RTO system. As on-line composition analyzers are expensive, it is necessary to determine which combination is the best for the distillation operation.

Setpoints are selected to match measurements available. For each case scenario, there are three setpoints, one of which is the overhead pressure, the other two are either component compositions or tray temperatures, depending on the corresponding analyzer and measurement sets. As previously stated, the updated parameters $\boldsymbol{\beta}$ in this study are the feed composition, flow rate, and temperature.

The sensor design candidates, their setpoints, and measurement sets are given in Table 3. The other measurements are the common measurements that are based on the on-line process data currently available in the deisobutanizer operation and are used by all the design candidates.

Table 3 Sensor design candidates

	Setpoints			Measurements					
				x_D		x_B		x_{fd}^{*}	others
1	x_{D,nC_4}	x_{B,iC_4}	P_{ov}	x_{D,C_3}	x_{D,nC_4}	x_{B,iC_4}	x_{B,C_5}	x_{fd}	
2	x_{D,nC_4}	x_{B,iC_4}	P_{ov}	x_{D,C_3}	x_{D,nC_4}	x_{B,iC_4}	x_{B,C_5}	---	F_{fd} ,
3	x_{D,nC_4}	T_{25}	P_{ov}	x_{D,C_3}	x_{D,nC_4}	---	---	x_{fd}	F_D , F_B ,
4	x_{D,nC_4}	T_{25}	P_{ov}	x_{D,C_3}	x_{D,nC_4}	---	---	---	F_R , F_{st} ,
5	T_5	x_{B,iC_4}	P_{ov}	---	---	x_{B,iC_4}	x_{B,C_5}	x_{fd}	T_2 , T_5 ,
6	T_5	x_{B,iC_4}	P_{ov}	---	---	x_{B,iC_4}	x_{B,C_5}	---	T_{18} , T_{25} ,
7	T_5	T_{25}	P_{ov}	---	---	---	---	x_{fd}	T_{31} , P_{ov}
8	T_5	T_{25}	P_{ov}	---	---	---	---	---	

*all components measured

In Table 3, x_D , x_B , x_{fd} are the compositions of top product, bottom product and feed; P_{ov} is the overhead pressure; F_{fd} , F_D , F_B , F_R , F_{st} are the flow rates of feed, top product, bottom product, reflux and steam to boiler, respectively; T_i are the tray temperature measurements.

In this case study, all the measurements have zero-mean white noise added to the true plant values; the noise on each of the individual measurements is not correlated, nor is the noise autocorrelated in time. The standard deviations for the measurements are 3% for flow rates, 0.5% for pressures, 5% for compositions, and 0.5°C for temperatures; the percentages are of the base case value.

Besides measurement noise, process disturbances are also considered. As feed composition variation is the major disturbance in distillation operation, four typical feed composition disturbance cases are investigated in this paper. Table 4 lists these disturbance cases.

Table 4 Disturbance cases

		Case1	Case2	Case3	Case4
Feed Comp. (mol %)	x_{fd,C_3}	5.06	3.83	10.03	9.03
	x_{fd,iC_4}	58.00	41.22	59.56	59.56
	x_{fd,nC_4}	14.07	50.76	26.22	23.22
	x_{fd,C_5}	22.87	4.19	4.19	4.19

Model/plant mismatch is another typical uncertainty experienced in optimization. In this study, structural model/plant mismatch is introduced in the number of ideal trays in the RTO system model. The feed tray number and tray temperature measurements are also changed proportionally to the total ideal tray number.

Table 5 Model/plant mismatch

	True Plant	RTO System
Tray No.	32	29
Feed Tray No.	14	13
Tray Temp. Measurements	2	2
	5	4
	18	16
	25	23
	31	28

4. CASE STUDY RESULTS

The 8 design candidates stated above are evaluated by using the strategy developed in this study. In each case scenario the simulated data are obtained by taking 300 closed-loop RTO iterations with each iteration involving model updater, model-based optimizer and plant, of which 100 iterations are for the base case, the other 200 are for the disturbance case. The disturbance is introduced at the 100th closed-loop RTO iteration.

RTO performance is calculated for each case. As a measure of the loss in economic performance of the RTO system due to imperfect optimization, the additional cost, that is, the offset between the mean value of the simulated data and the minimum value of the true plant cost is used to evaluate the design candidates. As any setpoints other than the plant optimum setpoints will lead to degraded plant performance, which in turn, yield higher plant cost, the offset is always positive, and the smaller the magnitude of the offset, the better the RTO performance. Fig. 3 illustrates the offset data of candidate 6 in disturbance case 1 without considering implementation error.

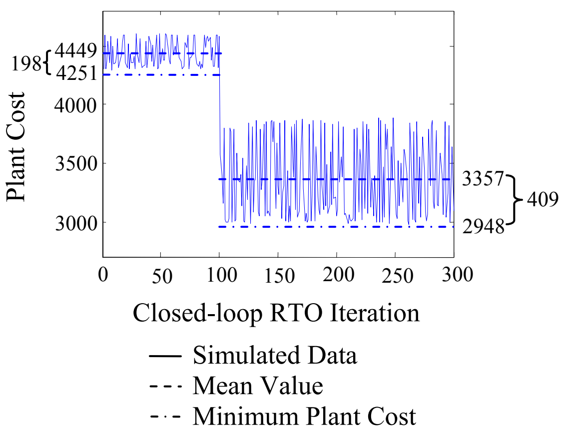

Fig. 3 RTO Performance Evaluation

To evaluate the design candidates, first, we perform closed-loop RTO simulations without considering the implementation error. In this case it is assumed that perfect sensors are available in the deisobutanizer operation. The design results are given in Table 6. It should be noted that the base case data in Table 6 are averaged from those of the base cases in the four disturbance cases.

Table 6 Sensor design offsets without implementation error

		Base	Case1	Case2	Case3	Case4
True Cost		4251	2948	4514	3982	3761
Cost Offset ($/d)	1	153	92	165	143	133
	2	151	90	163	141	131
	3	73	57	94	69	69
	4	40	27	53	37	42
	5	62	51	61	92	90
	6	198	409	136	381	397
	7	21	96	20	219	223
	8	116	459	77	333	385

From Table 6, it can be seen that candidates 1 - 5 consistently perform well in all the case studies. Candidates 6 - 8, on the other hand, yield significantly higher plant cost. Thus in the case where perfect sensors are available, design candidates 1 - 5 are recommended and 3 - 5 perform slightly better than 1 and 2.

In the subsequent studies, it is assumed that the perfect sensors are not available and hence the implementation error should be considered with appropriate implementation error. The implementation error level is the same as that of the sensor noise defined in Section 3.3. To reduce the computing time, instead of performing closed-loop RTO simulations directly, a screening method is first used to eliminate some of the design candidates. In this study, we select four sets of intermediate setpoints, say, 20th, 40th, 60th, 80th iteration points from the previous simulated data, and carry out 100 open-loop plant simulations for each set of setpoints. The offset data used to evaluate the design candidates are obtained by averaging the simulated data that are generated from the four sets of setpoints. Table 7 gives the screening results on base case. The intermediate setpoints come from the simulated data that produce the base case results in Table 6.

Table 7 Sensor design offsets by screening method

		20th	40th	60th	80th	Average
Cost Offset ($/d)	1	152	158	158	155	156
	2	148	148	165	157	155
	3	166	202	161	228	189
	4	190	178	212	153	183
	5	1692	2385	2667	2505	2312
	6	1319	2143	2058	2146	1917
	7	1498	1767	2068	1689	1756
	8	1623	2017	1727	1951	1830

Comparing Table 6 and 7, significant cost increases are observed in candidates 5 - 8, while the offset changes in 1 and 2 are negligible. Though RTO performance of 3 and 4 are worse, they are still acceptable. Thus by using the screening method, we can directly eliminate design candidates 5 - 8 without performing closed-loop RTO simulations.

To test and evaluate the design results in Table 7, further closed-loop RTO simulations are performed on design candidates 1 - 4 in order to give the design decisions with the consideration of implementation error. Table 8 gives the final sensor design results. From Table 8, it is clearly shown that design candidates 1 - 2 perform better than 3 - 4. Thus in the cases where perfect sensors are not available, design candidates 1 - 2 are recommended.

Table 8 Sensor design offsets with implementation error

		Base	Case1	Case2	Case3	Case4
True Cost		4251	2948	4514	3982	3761
	1	156	93	164	146	132
Cost Offset	2	154	92	165	143	134
($/d)	3	203	149	326	165	160
	4	176	128	226	185	150

Comparing the sensor design results with and without implementation error, it can be seen that the implementation error critically affects the design decisions. For example, candidate 5 would be the preferred design if implementation errors were not considered because it has a close approach to the best performance and only one costly analyzer. However, we see in Table 7 that this design gives very high costs with implementation errors. In addition, we see that the capital cost for three analyzers is not justified by the performance reported for candidate 1 in Table 8. Therefore, candidates 2 - 4, which all use two analyzers, remain as viable candidates. From Table 8, candidate 2 has the lowest cost and therefore, is the preferred design when considering implementation error.

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6. CONCLUSIONS

Optimal sensor design provides a systematic way for selecting sensors of the RTO systems. In this paper, the importance of the implementation error to sensor selection problem is studied. A practical sensor design strategy based on nonlinear closed-loop Monte-Carlo simulations is developed. The strategy incorporates a screening method to eliminate some of the design candidates in a preprocessing phase, which helps to make the important design decisions in a timely manner.

A series of case studies based on a distillation column have been performed with typical uncertainties experienced in industrial processes. The case study results demonstrate that the explicit consideration of implementation error is especially important for the cases where high accuracy sensors are not available or are very costly. It is also shown that this factor can be essential for correctly determining the appropriate sensors.

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