Chapter 7
Sensor Placement Under Uncertainty for Power Plants

7.1 Introduction

This chapter demonstrates the use of the BONUS method, in combination with kernel density estimation (KDE), to calculate Fisher information. This concept is then applied to the problem of sensor placement in an integrated gasification combined cycle (IGCC) power plant, and how BONUS significantly reduces computational resources while contributing to an appropriate solution is shown. This chapter is derived from the work by Lee and Diwekar [28].

7.1.1 The Integrated Gasification Combined Cycle Power Plant

The IGCC power plant is a cleaner way of getting electricity from coal compared to the pulverized coal (PC) plant described in earlier chapters. IGCC consists of three main elements: the air separation unit (ASU), the gasification plant, and the power block, as shown in Fig. 7.1 [35]. Power is produced in the IGCC power plant as follows:

1. The ASU separates ambient air into oxygen (O_2) and nitrogen (N_2). The oxygen is used primarily to produce fuel gas in the gasification plant, while most of the nitrogen is used to dilute fuel gas and reduce nitrous oxide (NO_x) levels in the power plant's combustion turbine.
2. The gasification plant converts coal or other solid fuel (e.g., petroleum coke or biomass) into fuel gas and high pressure steam by reacting with the O_2 produced by the ASU in several steps.
   a) The coal is received and stored in the plant in the form of coal fines, finely powdered solid material.
   b) Coal fines are mixed with water and ground into a viscous slurry.
   c) The coal slurry and oxygen react in the gasifier to produce:

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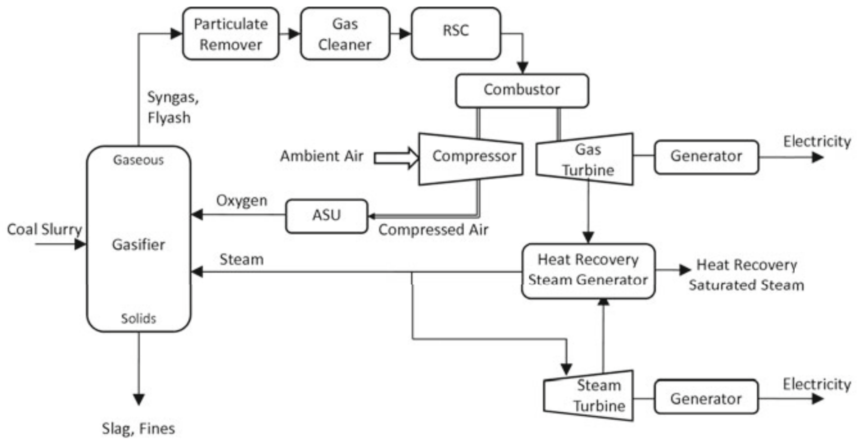

Fig. 7.1 The integrated gasification combined cycle power plant

- Syngas, a synthetic gas composed of hydrogen (H_2), water vapor (H_2O), carbon monoxide (CO), and carbon dioxide (CO_2)
- Slag, the residual mineral matter from coal not converted to syngas, which afterward flows down the gasifier walls, solidifies into an inert glassy frit with little carbon content, and is removed as waste
- Flyash, partially gasified residual carbon that exits the gasifier within the syngas stream

Both slag and flyash are undesirable byproducts of the reaction. The gasifier typically operates at a temperature and pressure around 1645 K and 2760 KPa.

d) The syngas is cooled in a radiant syngas cooler (RSC), then passed through a high pressure steam generator and gas cooler. The efficiency of this steam generation step may be improved by employing hot gas desulfurization to reduce nitrous oxide (NO_x) emissions.
e) Intensive water scrubbing removes flyash and other particulate matter from the syngas.
f) COS is converted to H_2S and removed from the syngas.
g) Selective catalytic reduction (SCR) removes NO_x from the process.

3. The power block generates electricity from the fuel gas, nitrogen, and high pressure steam.
   a) The fuel gas powers a combustion turbine.
   b) A heat recovery steam generator (HRSG) uses the gas turbine exhaust gas to generate both high and low pressure steam.
   c) The high and low pressure steam powers additional turbines, generating electricity.

A high efficiency combined cycle helps lower SO_2, NO_x, and particulate levels, reducing the environmental impact of the IGCC plant power generation process.

7.1.2 Measurement Uncertainty

Monitoring every process variable contained in the IGCC plant operations using a complete network of sensors would prove to be both costly and, due to the inability of obtaining measurements within harsh environments, technically infeasible. At the same time, however, controlling the operating conditions is essential to maintaining the efficiency of the power generation process. Therefore, some process variables must be estimated from related process variables for which direct measurements are more easily taken.

Gasifier temperature provides an illustrative example. Because the gasifier operates at extreme temperature and pressure, standard thermocouples cannot be used to take direct measurements. This makes it difficult to both determine and maintain a target operating temperature. However, the durability of the gasifier decreases at higher temperatures, while slag output increases at lower temperatures, thus a variation in either direction from the optimal temperature increases both cost and environmental impact. Therefore, gasifier temperature must be inferred by measuring related process variables. In this case, the methane production rate depends on both gasifier temperature and fuel composition, allowing measurements of the methane production rate and fuel composition, which are more easily obtained in practice, to be used to estimate gasifier temperature.

The large number of process variables and the complex relationships among them generate a significant challenge in determining which variables should be directly measured and which should be estimated, or "indirectly measured." Each direct measurement requires the use of a sensor, and the network of online sensors is defined as the full set of sensors used. The problem herein is to design a network of online sensors so as to minimize the overall costs, including purchase, deployment, and maintenance, associated with that network, while enabling a sufficient level of process control. As part of a stochastic optimization problem, the decision to either observe or estimate each process variable results from the uncertainty surrounding the true values of the process variables in the form of system and measurement noise.

To solve the cost-minimization problem, the IGCC power plant is modeled in Aspen Plus® to quantify the variability of downstream process variables as a result of variability in a set of input process variables, such as coal and oxygen flow rates, gasifier temperature, and gasifier pressure. Using the known measurement distributions of online sensors that are a priori assumed to be part of the sensor network, the downstream process variability is captured using Fisher information, as detailed in the next section. The Fisher information is then used within the objective function to determine which of the downstream process variables should be observed or physically measured through the placement of candidate sensors.

7.2 Fisher Information and Its Use in the Sensor-Placement Problem

Fisher information is a statistical measure established in the field of information theory by Ronald Fisher [11]. For a set of independent and identically distributed (IID) observations, $x_1, x_2, ..., x_n$, resulting from n outcomes of a random variable, $X = X_i, i = 1, 2, ..., n$, Fisher information captures the amount of information the set of observations contains about some unknown parameter, θ_x, upon which the probability distribution of X, $p_x(x)$, depends. It does this by quantifying the expected change in the distribution due to a change in the parameter value, θ_x. The expression for Fisher information, I_x, is commonly given as [12]

$$I_x(\theta_x) = E^X\left[\left(\frac{1}{p_{X|\Theta_x}(X|\theta_x)}\frac{\partial p_{X|\Theta_x}(X|\theta_x)}{\partial \theta_x}\right)^2\right], \tag{7.1}$$

where the distribution $p(X|\theta_x)$ is the likelihood of x given the parameter θ_x.

In the sensor-placement problem, a high level of Fisher information for a downstream variable indicates the ability to accurately estimate the value of an upstream variable on which the downstream variable depends. Because Fisher information is additive ($I_{X,Y}(\theta) = I_X(\theta) + I_Y(\theta)$), a single Fisher quantity may be calculated for the entire system. Thus, the goal is to decrease the overall sensor cost by determining the optimal sensor locations to maximize the amount of information about the system's true state.

7.3 Computation of Fisher Information

Using the Aspen Plus® environment, a comprehensive model of the highly nonlinear IGCC process is used to simulate the steady-state performance of the ASU, gasifier, and power generation processes. This Aspen model is used to estimate the set of unmeasured variables using the data acquired from the process variables directly measured through the network of sensors physically deployed within the plant.

Let S^{in} be the set of input variables, including coal and oxygen flow rate. Each variable in S^{in} follows a uniform distribution centered at its nominal value. A set of N_{samp} input variable operating conditions is generated using Hammersley sequence sampling, and the IGCC process is simulated in Aspen N_{samp} times. Each simulation generates a corresponding vector of points, S^{out}, that includes both intermediate and output process variables, such as syngas temperature and mass flow rate. S^{out} captures the nonlinear effects of the IGCC process, and the full set of S^{out} vectors generated from repeated simulations captures the variability of downstream process variables resulting from a uniformly distributed set of input variable sample points. Thus, a probability distribution can be generated for each intermediate and output variable that captures the variation in that variable due to variations in the input variables and the nonlinearity of the process behavior.

7.3.1 Reweighting Using the BONUS Method

Each time the network of sensors is altered, i.e., a sensor is added or removed from the online network, the underlying distributions of the process variables are altered, requiring a new computation of the Fisher information about each process variable. In this section, the BONUS algorithm is used to compare samples of the input variables taken from a uniformly distributed sample space to those taken from a new reference distribution in order to create a set of distribution weights that can be used to reweight the distribution functions of the intermediate and output variables. This reweighting approach eliminates the need to resimulate the IGCC process behavior in Aspen Plus for every possible combination of online sensors, thereby significantly reducing the overall computational time.

The BONUS reweighting scheme is implemented as follows:

1. Let $f_0(x_i)$ be the probability density function (PDF) associated with the base input distribution for the input variable $x_i, i = 1, 2, ..., S^{in}$.
2. A set of N_{samp} sample points uniformly distributed across a d-dimensional samples space is used to perform N_{samp} simulations of the IGCC process to generate $F_0(y_j)$, the base cumulative distribution function (CDF) associated with the intermediate or output variable $y_j, j = 1, 2, ..., S^{out}$, where $y_j = h(x_1, x_2, ..., x_{S^{in}})$ is the nonlinear transformation from the set of input variables, S^{in}, to the downstream variable y_j at iteration 0.
3. A new input distribution is defined, representing a change in sensor placement, such as a sensor placed at the location of this input variable. The redefined distribution, $f_t(x_i)$, at iteration t is used to create a set of weights

$$W_t(x_i) = \frac{f_t(x_i)}{f_0(x_i)}, i = 1, 2, ..., S^{in} \tag{7.2}$$

   that gives the likelihood ratio between the redefined and base distributions.
4. Given that the input variables act independently, the weights are used to construct the resulting distributions for the downstream intermediate and output variables at iteration t by multiplying the associated weights, $W_t(x_i)$, with the base distribution $f_0(y_j)$:

$$f_t(y_j) = f_0(y_j)\Pi_{i=1}^{S^{in}}(1 + \gamma_{ij}(W_t(x_i) - 1)), j = 1, 2, ..., S^{out}, \tag{7.3}$$

   where $\gamma_{ij} = 1$ if variable y_j is downstream of x_i and $\gamma_{ij} = 0$ if it is not.
5. The distribution is then normalized using

$$\hat{f}_t(y_j) = \frac{f_t(y_j)}{\sum_{n=1}^{N_{samp}} f_t(y_j(n))\frac{y_j(n+1)-y_j(n-1)}{2}}. \tag{7.4}$$

This reweighting approach can also be used when a sensor is placed at the location of an intermediate process variable to construct the resulting change in distributions of corresponding downstream variables. By eliminating the need to generate a new set of N_{samp} sample points through simulation of the IGCC process at each iteration, t, the BONUS reweighting algorithm provides an efficient method for calculating the Fisher information resulting from many different configurations of the online sensor network. Further, various underlying distributions corresponding to sensor accuracies can be readily analyzed without increasing the computational burden, and this approach can also be used for unmeasured disturbances to an input variable, such as a change in coal quality.

7.3.2 Calculating the Fisher Information from Kernel Density Estimation

As discussed in Chap. 3, KDE is a nonparametric method of estimating the PDF of a random variable based on a finite data sample. In this case, the finite data sample consists of the set of operating parameters estimated in Aspen PLUS for each input sample. The KDE technique estimates the PDF through the use of following formula:

$$p(y_n) = \sum_{m=1}^{N_{samp}} \frac{1}{\sqrt{2\pi}} exp\left(-\left(\frac{y_n - y_m}{h}\right)^2\right), \tag{7.5}$$

at each sample point $y_n, n = 1, 2, ..., N_{samp}$, where σ^2 is defined as the variance of the set of samples $\{y_1, y_2, ..., y_N\}$ and $h = 1.06\sigma/N_{samp}^{1/5}$.

Assume that the shift-invariant property holds for a small $\epsilon > 0$ change in the parameter θ_y (the mean value of a given y), i.e., $p(y_n \pm \epsilon)$ can be calculated from (7.5) by replacing y_n with $y_n \pm \epsilon$ on the right side of the equation. This is a viable assumption at IGCC process operating conditions near their means, as the plant is operated within a chemically stable region. Once the kernel density functions $p(y_n + \epsilon)$ and $p(y_n - \epsilon)$ are calculated from (7.5), they can be used to generate an approximation of the first-order derivative, $\partial p(y_n)/\partial \theta_y$, given by

$$\frac{\partial p(y_n)}{\partial \theta_y} \approx \frac{(p(y_n + \epsilon) - p(y_n - \epsilon))}{2\epsilon}. \tag{7.6}$$

The Fisher information is then obtained by substituting (7.6) into the discrete approximation of (7.1) to obtain

$$I_y(\theta_y) = \sum_{n=1}^{N_{samp}} (y_n - y_{n-1}) \frac{\left(\partial p(y_n)/\partial \theta_y\right)^2}{p(y_n)}, \tag{7.7}$$

which constructs a series of right-hand rectangles at $\frac{\left(\partial p(y_n)/\partial \theta_y\right)^2}{p(y_n)}$ to approximate the integral function in the expectation.

The following section applies Fisher information as a metric of observation order (the degree to which a given sensor network can monitor and control the system) within an optimization problem for placing sensors in various locations throughout the IGCC plant, subject to sensor cost constraints.

7.4 The Optimization Problem

The objective of the sensor-placement problem is to maximize the amount of information about the IGCC process from a network of sensors, given a set of budget constraints. Because it is desirable to minimize the variability of the unmeasured process variable estimations, the Fisher information should be maximized.

The resulting optimization problem is a nonlinear stochastic (binary) integer problem where the objective function consists of the overall Fisher information (with the goal of maximization) and the constraints consist of limits on the cost of sensor placement. Formally, this is given as

$$\max_{w_j \in \mathbb{W}} \sum_{j=1}^{S^{out}} f_j(\mathbf{w}, \mathbf{Y}) w_j, \tag{7.8}$$

$$s.t \sum_{j=1}^{S^{out}} C_j w_j \leq B, \tag{7.9}$$

$$w_j \in 0, 1, \quad j = 1, 2, ..., S^{out}, \tag{7.10}$$

where C_j is the cost associated with the purchase, deployment, and maintenance of sensor j and B is the total sensor budget. The binary variable w_j represents the decision to place or not place sensor j in the network of online sensors, with 0 representing the absence of sensor j and 1 representing its presence, and $\mathbb{W}$ constitutes the set of all feasible sensor networks that is given.

7.4.1 *Defining the Objective Function*

The objective term $f_j(w, Y)$ is a function of the Fisher information resulting from the network of sensors, $\mathbf{w} = \{w_j \in \{0, 1\}, j = 1, 2, ..., S^{out}\}$ and the set of random variables $\mathbf{Y} = \{Y_j, j = 1, 2, ..., S^{out}\}$ associated with the measurement uncertainties in the intermediate and output process variables. This function is designed by first assuming that the information related to a process variable is always greater if a sensor is placed online at that specific location (i.e., more is known about Y_j when $w_j = 1$). Let $I^s_{Y_j}(\theta_{y_j} | w_k = 1)$ represent the Fisher information of θ_{y_j} resulting from a sensor placed at location $K = 1, 2, ..., S^{out}$, and let $I^{ns}_{Y_j}(\theta_{y_j} | w_k = 0), k = 1, 2, ..., S^{out}$ represent the Fisher information of θ_{y_j} resulting from no sensors placed in the network of intermediate and output variables, such that $I^s_{Y_j}(\theta_{y_j} | w_k = 1) \geq I^{ns}_{Y_j}(\theta_{y_j}), j = 1, 2, ..., S^{out}$ (this inequality states that the information about variable j that is known when there is a sensor measuring variable k is greater than or equal to the information about variable j that is known when there is *not* a sensor measuring variable k). A candidate objective function can then be defined as

$$f_j^A(\mathbf{w}, \mathbf{Y}) = 1 - \frac{I_{Y_j}^{ns}(\theta_{y_j})}{I_{Y_j}^{s}(\theta_{y_j}|w_j = 1)}, \tag{7.11}$$

where $0 \leq f_j^A(\mathbf{w}, \mathbf{Y}) \leq 1$. This function normalizes the Fisher information for each process variable between zero and one. Values of $f_j^A(\mathbf{w}, \mathbf{Y})$ close to zero correspond to the smallest change in information gained from placing a sensor at location j, while values close to one correspond to the largest change. It is therefore possible to optimize the placement of sensors across many variable attributes, including mass-flow, temperature, and pressure, for example, by determining which set of sensors provides the largest total gain in estimation of the dynamic system.

However, this function does not capture the potential effects of placing a sensor in the network upstream of location j. If location k is upstream of location j (i.e., Y_j is dependent on Y_k), then information gained by placing a sensor at location k increases the amount of information available about Y_j. A second candidate objective function that takes this into account is

$$f_j^B(\mathbf{w}, \mathbf{Y}) = \sum_{k=1}^{S^{out}} \left(1 - \frac{I_{Y_j}^{ns}(\theta_{y_j})}{I_{Y_j}^{s}(\theta_{y_j}|w_k = 1)}\right), \tag{7.12}$$

which captures the overall effect that placing (or not placing) a sensor has on all other process variables by summing the resulting information gained at all locations by placing a sensor at location k. The Fisher information is given as $I_{Y_j}^{s}(\theta_{y_j}|w_k = 1) = I_{Y_j}^{ns}(\theta_{y_j})$ if variable j is not downstream of variable k, and it can be seen that, in this case, the right-hand side of Eq. (7.12) reduces to zero. Otherwise, if j *is* downstream of variable k, $I_{Y_j}^{s}(\theta_{y_j}|w_k = 1)$ can be computed using the BONUS reweighting scheme.

7.4.2 The IGCC Power Plant

For the IGCC power plant studied, a set of eight sensors, S^{in}, measures the input process variables given in Table 7.1. The objective is to determine the placement of sensors across a set of 24 sensors, S^{out}, measuring intermediate and output variables $y_1, y_2, ..., y_{24}$ given in Eq. 7.2, as well as the nominal operating conditions. A schematic of potential sensor locations is given in Fig. 7.2.

For each intermediate and output process variable, three types of sensors are assumed to be available, with accuracies (six standard deviations) of $\pm 5\,\%$, $\pm 2.5\,\%$, and $\pm 1\,\%$, with sensors of higher accuracy incurring a higher cost than those of lower accuracy. The optimization problem is therefore slightly modified to include the consideration of multiple sensor types. Let the binary variable $w_{j,\tau} = 1(0)$ correspond to the decision to place a sensor of type $\tau = 1, 2, 3$ at location j. The problem can then be formulated as

Table 7.1 Input process variables

x_i	Description	Nominal	Units
1	Oxygen flow rate entering ASU	157,392	kg/h
2	Coal slurry flow rate	192,922	kg/h
3	Air flow rate to gas turbine compressor	2,962,683	kg/h
4	Recycled HRSG steam temperature	414	K
5	Recycled HRSG steam pressure	526	KPa
6	Recycled HRSG water temperature	369	K
7	Gasifier temperature	1644	K
8	Gasifier pressure	2806	KPa

ASU air separation unit, *HRSG* heat recovery steam generator

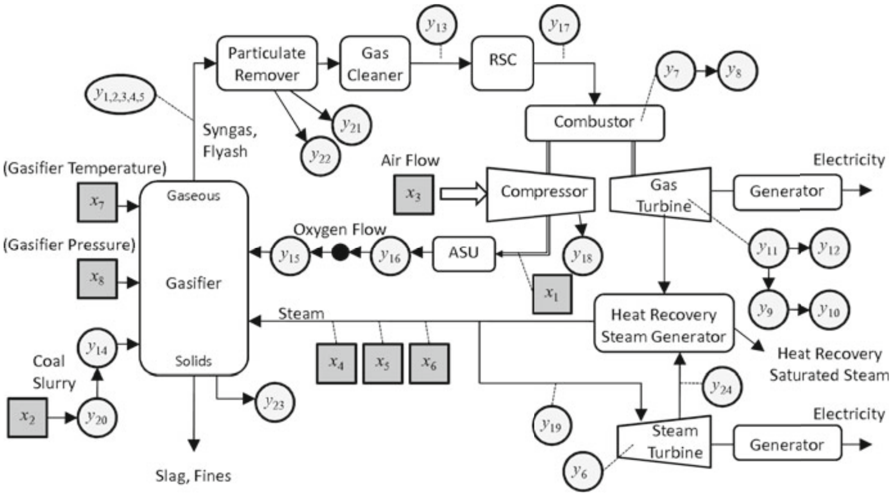

Fig. 7.2 Potential sensor locations in the IGCC power plant. *IGCC* integrated gasification combined cycle

$$\max_{w_{j,\tau}\in\mathbb{W}} \sum_{\tau=1}^{3}\sum_{j=1}^{24} f_{j,\tau}(\mathbf{w},\mathbf{Y})w_{j,\tau} \tag{7.13}$$

$$s.t \sum_{\tau=1}^{3}\sum_{j=1}^{24} C_{j,\tau}w_{j,\tau} \leq B, \tag{7.14}$$

$$\sum_{\tau=1}^{3} w_{j,\tau} \leq 1, \quad j = 1, 2, ..., 24 \tag{7.15}$$

$$w_{j,\tau} \in \{0, 1\}, \quad j = 1, 2, ..., 24, \ \tau = 1, 2, 3, \tag{7.16}$$

where $f_{j,\tau}(\mathbf{w}, \mathbf{Y})w_{j,\tau}$ is a function of the Fisher information when a sensor of type τ is placed at location j. Constraint (7.15) ensures that no more than one type of sensor is used at each location.

7.4.3 Problem Approach

The problem was approached in five steps:

1. A set of $N_s = 800$ operating conditions was generated across a uniform 8-dimensional sample space, corresponding to a set of 8 input variables varied $\pm 10\,\%$ of their nominal operating conditions using the Hammersley sequence sampling method.
2. For each set of operating conditions, the corresponding intermediate and output variable conditions were generated using the steady-state model developed in the Aspen Plus® simulation environment.
3. A distribution function was constructed from these sets of sample points using the KDE technique, which serves as the base distribution for the BONUS reweighting scheme.
4. The distribution function for $Y_j, j = 1, 2, \ldots, 24$ was constructed using BONUS by reweighting the base distribution of Y_j obtained from the Aspen simulations by the ratio of the sensor distribution of $X_i, i = 1, 2, \ldots, 8$ to the base distribution of X_i, provided that Y_j is downstream of each X_i. The resulting distribution at each Y_j corresponds to the variability of estimating Y_j if no sensors are placed across the set of intermediate and output variable locations.
5. The Fisher information given no sensors at the intermediate and output variable locations, $I^{ns}_{Y_j}(\theta_{y_j})$ is calculated as described above.

To verify the validity of the reweighting approach, the Fisher information was calculated two ways: first, by using a uniform distribution across each of the input variables as the input to the Aspen Plus® simulation, followed by use of the BONUS reweighting scheme, and second, by using a normal distribution across each of the input variables as the input to the Aspen Plus® simulation. There was no significant difference in the Fisher information calculated under each of the two methods. This is because the number of sample points and the sampling scheme used ensured adequate coverage of the 8-dimensional space, and the reweighting approach undergoes only one iteration when computing the Fisher information for a given set of input variable distributions. Thus, it is evident that the BONUS reweighting scheme is a useful approach for comparing sensor networks with contrasting variability, rather than rerunning the resource-intensive simulation in Aspen Plus® (Table 7.2).

Table 7.2 Intermediate and output process variables

y_j	Description	Stream[a]	Nominal	Units
1	Gasifier syngas flow rate	RXROUT	393,475	kg/h
2	Syngas CO flow rate	RXROUT	224,637	kg/h
3	Syngas CO_2 flow rate	RXROUT	88,051	kg/h
4	Syngas temperature	RXROUT	1644	K
5	Syngas pressure	RXROUT	2806	KPa
6	Low pressure steam turbine temperature	TORECIR	369	K
7	Gas turbine combustor burn temperature	POC2	1628	K
8	Gas turbine combustor exit temperature	POC3	1533	K
9	Gas turbine high pressure exhaust stream temperature	GTPC3	621	K
10	Gas turbine low pressure exhaust stream temperature	GTPC9	404	K
11	Gas turbine expander output temperature	GTPOC	872	K
12	Fluegas flow rate exiting gas turbine expander	6X	5,760,623	kg/h
13	Syngas flow rate after solids removal	RAWGAS	467,200	kg/h
14	Coal slurry flow rate entering gasifier	COALD	21,170	kg/h
15	Oxygen flow rate into gasifier	O2GAS	157,452	kg/h
16	Oxygen flow rate exiting ASU	GASIFOXY	157,452	kg/h
17	Acid gas flow rate	FUEL1	344,996	kg/h
18	Gas turbine compressor leakage flow rate	XCLEAK	2052	kg/h
19	Flow rate into high pressure steam turbine	TOHPTUR	621,421	kg/h
20	Coal slurry feed flow rate	COALFEED	192,922	kg/h
21	Slag extracted from syngas	SLAG	15,805	kg/h
22	Fines extracted from syngas	FINES	5363	kg/h
23	Gasifier heat output	QGASIF	2.47e7	Btu/h
24	Recycled HRSG[b] steam heat output	QRDEA	3.27e8	Btu/h

[a] Stream notation refers to DOE/NETL model [35]
[b] *HRSG* heat recovery steam generator

7.4.4 Results

Table 7.3 lists the computed objective values using the normalized function $f_j^B(\mathbf{w}, \mathbf{Y})$ from Eq. 7.12. As the sensor accuracy at a location increases, the value of f_j^B at that location increases due to the decrease in measurement variability, resulting in an increase in information pertaining to the true value of the variable at that location. Note that some variables, such as gasifier syngas flow rate (y_1) and fluegas flow rate exiting gas turbine expander (y_{12}), exhibit large increases in information when a

Table 7.3 Computed objective values, f_j^B, for each sensor type

Sensor j	Low accuracy	Medium accuracy	High accuracy
1	0.9100	8.6612	10.6078
2	9.8488	10.7561	10.9649
3	10.5601	10.8862	10.9898
4	7.8290	10.1407	10.8627
5	7.8989	10.1472	10.8613
6	0.1036	0.7760	0.9643
7	4.6106	5.6794	5.9470
8	3.7799	4.7002	4.9529
9	1.9262	1.9832	1.9981
10	0.9940	0.9989	1.0002
11	2.5901	2.9110	2.9845
12	0.0002	0.7054	0.9531
13	0.9188	6.2690	7.6865
14	12.4675	15.8420	16.8025
15	12.4553	15.8393	16.8083
16	13.3944	16.8241	17.8059
17	3.6553	6.2014	6.8691
18	0.9389	0.9849	0.9978
19	0.0002	0.0002	0.0002
20	13.4061	16.8267	17.8000
21	0.7492	0.9375	0.9902
22	0.7492	0.9375	0.9902
23	1.0002	1.0002	1.0002
24	0.0002	0.0002	0.0002

more accurate sensor is used, while others, such as gas turbine low pressure exhaust steam temperature (y_{10}) and flow rate into high pressure steam turbine (y_{19}), show little improvement in Fisher information from use of a more accurate (and therefore costly) sensor.

Consider the case in which the total budget is $B = \$1,500,000$. The solution to the optimization problem places a network of low accuracy sensors at locations y_2, y_3, y_5, y_9, and y_{11}, and medium accuracy sensors at y_1, y_{14}, y_{15}, y_{16}, y_{17}, and y_{20} (thus y_4, y_6, y_7, y_8, y_{10}, y_{12}, y_{13}, y_{18}, and y_{19} are not directly measured). The resulting standard deviation in the IGCC power plant production and gasifier performance is provided in Table 7.4, in comparison with the standard deviation resulting from the baseline case in which no sensors are deployed across the intermediate and output process variable location. The significant reduction in variability for both gas turbine power production and total plant power production is immediately obvious.

Table 7.4 Measurement variation of the integrated gasification combined cycle (*IGCC*) power production and gasifier performance using the optimal sensor network versus no sensors deployed

IGCC power production	Nominal	Standard deviation Optimal (no sensors)	Units
Gas turbine power production	424.94	2.26 (43.11)	MWE
Steam turbine power production	251.97	0.71 (0.71)	MWE
Miscellaneous power consumption	– 67.41	0.25 (4.62)	MWE
Auxiliary power production	18.29	1.35 (1.35)	MWE
Total plant power production	591.22	2.16 (43.73)	MWE
Gasifier performance	Nominal	Standard deviation Optimal (no sensors)	Units
Oxygen flow rate	157,452	655 (13,386)	kg/h
Coal flow rate	192,922	803 (10,874)	kg/h
Slag flow rate	15,805	46 (1097)	kg/h
Fines flow rate	5363	16 (372)	kg/h
Syngas temperature	1645	370 (370)	K
Syngas pressure	2806	23 (234)	KPa

7.5 Summary

The use of the BONUS reweighting scheme can significantly reduce the computational resources required to calculate Fisher information, here used as a measurement of the variability of system parameters, given limitations on direct measurement of variables. This greatly improves the tractability of a nonlinear, stochastic integer program used to design a network of online sensors in an IGCC power plant, seeking to minimize variability while respecting budgetary constraints. In the case presented, measurement variability of total plant power production was reduced by over 95 %.

Notations

B	total sensor budget
C_j	cost associated with the purchase, deployment, and maintenance of sensor j
$f_0(x_i)$	probability density function (PDF) associated with the base input distribution for the input variable $x_i, i = 1, 2, \dots, S^{in}$
$F_0(y_j)$	base cumulative distribution function (CDF) associated with the intermediate or output variable $y_j, j = 1, 2, \dots, S^{out}$
$f_t(x_i)$	redefined input distribution
h	band width
I_x	Fisher information
N_{samp}	number of input scenarios generated using Hammersley sequence sampling

S^{in}	set of input variables, including coal and oxygen flow rate
S^{out}	set of intermediate and output process variables, such as syngas temperature and mass flow rate
t	iteration
w_j	decision variable for placement of sensor j in the network of online sensors, with 0 representing the absence of sensor j and 1 representing its presence
$\mathbb{W}$	set of all feasible sensor networks
$W_t(x_i)$	weight used in the BONUS algorithm that gives the likelihood ratio between the redefined and base distributions
x_i	observations
X	random variable

Greek letters

γ_{ij}	position indicator equal to 1 if variable y_j is downstream of x_i and $\gamma_{ij} = 0$ if it is not