# Chapter 5
# Water Management Under Weather Uncertainty

## 5.1 Introduction

Water scarcity and the cost of treating and recycling waste water both represent constraints in operating coal-fired power plants. As the capacity of thermoelectric power generation increases in the USA (the Energy Information Administration estimates that thermoelectric power generation will grow 22 % by 2030), so does the importance of managing the water used in these plants. In a clean coal-fired power plant, water is consumed in makeups (water added to a closed cycle due to evaporation or product loss), in blowdowns (water added during the cooling cycle due to liquid removal), and in the generation process itself. The amount of water consumed varies with two ambient weather factors: the dry-bulb temperature (temperature as measured by a thermometer shielded from moisture) and the humidity of the outside air, both of which are subject to significant uncertainty, and vary with the season and geographical region. It is, therefore, critical to determine the optimal operating conditions for these plants, so as to minimize water consumption subject to stochastic weather conditions. In this chapter, it is demonstrated how the BONUS method can substantially simplify this problem for a pulverized coal (PC ) power plant. This chapter is based on work by Salazar et al. [44, 45].

## 5.2 The Pulverized Coal Power Plant

The specific PC power plant model referenced herein is based on Case 11 in the DOE/NETL's report on the cost and performance of fossil energy plants (NETL, 2010). The model is a supercritical steady-state flowsheet without carbon capture designed to generate 548 MW of electricity.

A pulverized coal power plant generates electricity in four steps (as shown in Fig. 5.1):



U. Diwekar, A. David, *BONUS Algorithm for Large Scale Stochastic Nonlinear Programming Problems,* SpringerBriefs in Optimization, DOI 10.1007/978-1-4939-2282-6_5

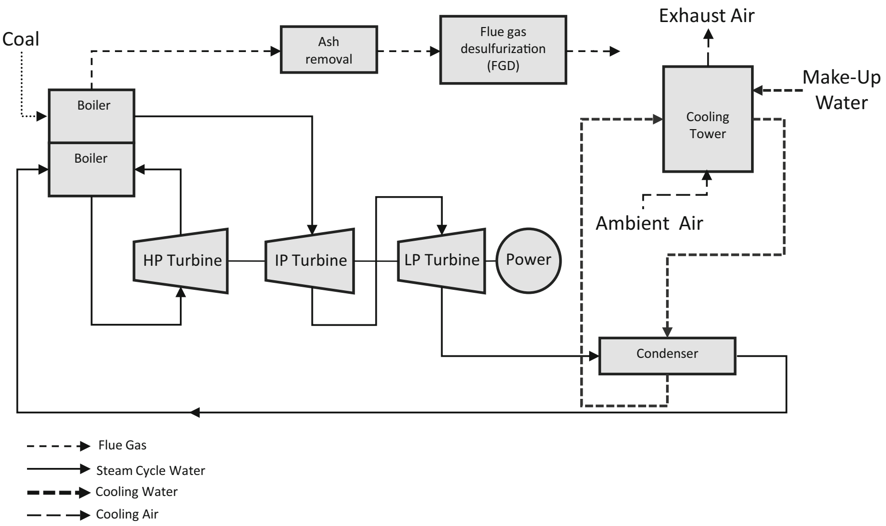


**Fig. 5.1** Schematic of PC power plant

1. Powdered coal is fed into the boiler's combustion chamber, where the combustion of coal produces steam.
2. The steam is fed into a series of high (HP), intermediate (IP), and low pressure (LP) turbines, causing the turbines to rotate at high speed.
3. The steam is cooled to condensation in a cooling tower.
4. The condensation is preheated with steam extracted from the turbines and returned to the boiler.

Subsequent to the generation process, the gaseous waste is passed through a flue gas desulfurization (FGD) unit prior to its atmospheric release. The FGD unit removes sulfur dioxide ($SO_2$) by combining the $SO_2$ with limestone slurry and oxygen to produce calcium sulfate (gypsum). The gypsum is then separated from the water, which is then recycled, yet a large amount of makeup water is still required to replace that lost in the desulfurization process.

Therefore, considering both the power generation process and the FGD unit, the areas of water consumption are:

- Water lost to evaporation in the cooling tower in the third step of the power generation process (EL)
- Water lost to drift in the cooling tower during the power generation process (D)
- Water used for "blowdown" in the cooling tower (B)
- Water used in the FGD for preparation of the limestone slurry and makeup (F)

The process performance parameters (generation, efficiency, emission, and water consumption) are simulated in Aspen Plus®, a chemical process modeling system from Aspen Technologies Inc. Aspen Plus® is commonly used for modeling power plants because of its capabilities in representing multiphase streams and handling complex substances such as coal [10]. In this case, Aspen Plus® takes the process design and operational parameters as its inputs and outputs the process performance parameters. Because the optimization techniques detailed in this chapter seek to find the optimal inputs to minimize or maximize performance parameters, the robustness of the Aspen Plus® model is critical to the reliability of the optimization results.

Within this boiler/turbine/condenser cycle, water is lost to evaporation associated with the quantity of heat rejected at the cooling tower. To estimate the evaporation rate, an equilibrium-based model for the cooling tower (based on a scheme proposed by [15] is implemented in Aspen Plus® as what is known as a unit-operation-based model. Each "unit block" is a simulation unit that allows the user to define calculations not native to Aspen Plus®. Three unit blocks are used in this model, two flash separators and one heat exchanger. The first flash separator is used to determine the wet bulb temperature from the dry-bulb temperature and the humidity, while the second simulates the cooling tower itself. Specific details on the internal calculations of each of these blocks can be found in [44]. Using the design specifications and the calculator blocks, Aspen Plus® is able to determine the cold water temperature, circulating water flow rate, and air flow rate for a constant volume forced drift cooling tower, and thus calculate the water usage due to evaporation.

In addition to the evaporation losses, water is consumed due to both drift and blowdown. "Drift" refers to the water caught in the air leaving the top of the tower, estimated as 0.02 % of the water circulating through the cooling tower. It differs from evaporation in that the drift water remains in liquid form, while evaporation is the water that has been converted to steam, and thus the two types of loss are considered separately in calculations, though both contribute to the necessity of "makeups" and water that must be added to a closed cycle to compensate for losses.

Blowdown, by contrast, is water added to appropriately dilute corrosive substances. The amount of water consumed as blowdown (B) is estimated as

$$B = \frac{EL - (C - 1)D}{C - 1},$$

where C is the number of concentrating cycles (assumed to be 4), *EL* is the evaporation loss, and *D* is the drift loss.

The evaporation losses (ELs) are dependent on both temperature and humidity at the plant location, and because the drift and blowdown are calculated from the evaporation, all three are dependent upon operating conditions and weather factors. The water used in the FGD unit is dependent upon the conditions of the flue gas coming out of the boiler, which is, in turn, dependent on both the operating conditions and weather factors as well. The goal is, therefore, to determine the operating conditions that minimize the expected value of water consumption subject to the uncertainty in the ambient weather.

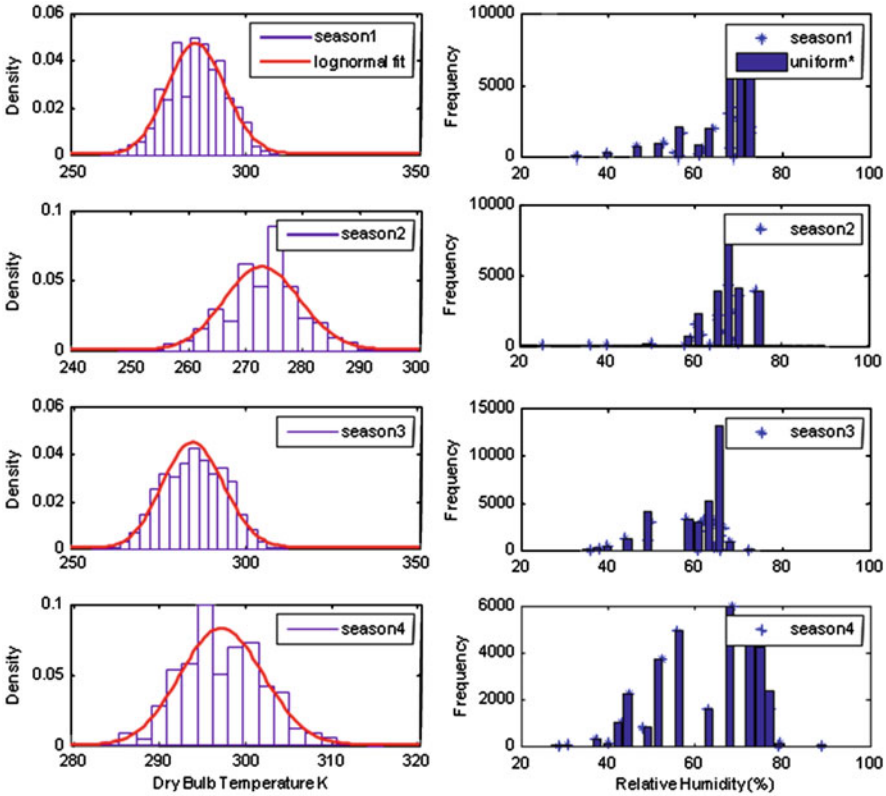


**Fig. 5.2** Probability density functions of four seasons (fall to winter from *top*) for dry-bulb temperature and relative humidity in eight US Midwestern cities

## 5.3 Parameter Uncertainty

Dry-bulb temperature and dew point data for US urban centers is available at the DOE's energy efficiency and renewable energy program (EERE) website (http://www1.eere.energy.gov). Two years of dry-bulb temperature and dew point data, spanning September 2005 through August 2007, was averaged for eight major Midwestern US cities (Chicago, Detroit, Indianapolis, Minneapolis, St. Louis, Des Moines, Kansas City, and Cincinnati). This dry-bulb temperature data was organized into bins and histograms were generated for each season. For each bin, the corresponding dew point values were averaged to calculate values for relative humidity, and thus histograms could be generated for this parameter as well. The frequency distributions for dry-bulb temperature and humidity are shown in Fig. 5.2.

The probability distribution of the dry-bulb temperature was fitted to a lognormal distribution and the relative humidity was fitted to a modified uniform distribution (in which the range is divided into different intervals within which all values have an equal likelihood of occurrence). A distribution was created for each of the four seasons, using the eight-city average. It is notable that both parameters have larger variations during fall and spring than during winter and summer. This variability will, in turn, result in a higher variability for water consumption in these seasons.

Once the probability distribution functions are estimated, stochastic simulation and optimization are carried out as follows:

1. Efficiently sample the probability functions of dry-bulb temperature and relative humidity to generate a set of scenarios that accurately represent potential realizations of uncertainty.
2. Propagate uncertainity by executing the whole plant simulation for every scenario and record the water consumption in each.
3. Analyze the resulting distribution of water consumption and choose either the expected value or standard deviation (the first or second moment) as the objective function for stochastic optimization.

## 5.4 Problem Formulation

The objective of this problem is to minimize the expected value (**E**) of water consumption in the PC power plant, expressed as the sum of the evaporation losses (EL), drift losses (D), blowdown losses (B), and FGD consumption (F). The deterministic input parameters, $x$, are the design and operational conditions of the units, and the stochastic input parameters, $u$, are the uncertain weather conditions.

Further, let $Q$ represent the total heat rejected by the cycle and $P$ represent the amount of power generated, both dependent on $x$ and $u$. Similarly, evaporation loss (EL) depends on the total heat rejected by the cycle (Q), drift (D) depends on (EL), and blowdown B depends on both D and EL, while water consumption in the FGD unit also depends on $x$ and $u$. Thus, the following equations may be introduced: $Q = f(x, u)$, $P = h(x, u)$, $EL = g_1(x, u)$, $D = g_2(x, u)$, $B = g_3(x, u)$, and $F = g_4(x, u)$, where the set of functions, $f$, $h$, and $g_i$ represent "black-box" calculations in Aspen Plus®, i.e., the exact nature of the functions is proprietary, and knowledge of such is unimportant to the problem formulation and solution.

The problem can therefore be represented as

$$\begin{aligned}
&\min_{x_d} \mathbf{E}(g(x_d, u)) \\
&s.t. \\
&h(x_d, u) - P^* = 0 \\
&ME(x_d, u) = 0,
\end{aligned}$$

where $P^*$ is the fixed generation of electricity and $ME$ is the material and energy balance of the operating unit. Thus, the first constraint ensures that the required amount of electricity is generated and the second ensures that mass and energy balances are respected. Because the functions $f$, $ME$, and $h$ are highly nonlinear, this problem is extremely computationally complex, and a method such as the BONUS algorithm is needed to make the problem tractable.

## 5.5 Selection of Decision Variables

Of the assigned parameters that potentially influence water consumption, as detailed in the NETL report on cost and performance baselines for fossil energy plants [36], nine were selected as potential decision variables:

1. Boiler temperature: The temperature of the unit that burns coal particulate to initially heat water into steam.
2. Air excess: The amount of air present in the combustion chamber in excess of the theoretical minimum, used to ensure all coal particulate is exposed to sufficient air.
3. Reheater temperature: The temperature of the unit that reheats the steam between the high pressure turbine and the medium pressure turbine.
4. FGD efficiency: A measure of the rate of $SO_2$ removal in the FGD, influenced by the design parameters of the unit, such as surface area and absorption material.
5. $O_2/SO_2$ ratio: the ratio of oxygen to sulfur dioxide in the FGD unit.
6. $CaCO_3/SO_2$ ratio: The ratio of calcium carbonate to sulfur dioxide in the FGD unit.
7. Water content of FGD slurry: The amount of water added to limestone to produce the FGD slurry.
8. Pressure drop at high-pressure condenser 1: The difference in pressure between the steam exhausted from the turbines and that leaving the first condenser.
9. Pressure drop at high-pressure condenser 2: The difference in pressure between the steam exhausted from the first condenser and that leaving the second condenser.

These nine were selected based on the feasibility of implementation, i.e., these variables are most easily controlled in a practical setting. For example, the water content in the FGD slurry is easily modified through a change in operational policy.

To determine which of the nine operating parameters should be used as decision variables, a stochastic simulation was run in Aspen Plus®, as described in [8]. The ranges of potential decision variables were sampled from uniform distributions, and the model was run for each of the generated combinations, each time producing an output result in the form of a water consumption value. Partial rank correlation coefficients (PRCC) were then calculated as shown in Table 5.1. PRCC are a measure of the relationship between the output and input variables for a nonlinear function; thus the absolute value of the PRCC indicates the influence of the deterministic variable on water consumption. Five variables, air excess, reheater temperature, water content of FGD slurry, pressure drop at high-pressure turbine 1, and pressure drop at high-pressure turbine 2, were found to have the greatest impact on water consumption, and were therefore chosen as the decision variables for the stochastic optimization problem.

**Table 5.1** Partial rank correlation coefficients (PRCC) for relationship between potential decision variables and water consumption

| Potential decision variable | Partial ranked correlation coefficient |
|---|---|
| Air excess | *0.256642* |
| Reheater temperature | *0.228009* |
| FGD efficiency | −0.125901 |
| Boiler temperature | −0.018852 |
| $O_2/SO_2$ ratio | −0.021453 |
| $CaCO_3/SO_2$ ratio | −0.032031 |
| Water content of FGD slurry | *0.191058* |
| Pressure drop at high-pressure turbine 1 | *−0.294448* |
| Pressure drop at high-pressure turbine 2 | *−0.266594* |

## 5.6 Implementation of BONUS Algorithm

The BONUS algorithm was applied to this problem as follows:

1. A set of 600 scenarios based on the probability distributions of the uncertain inputs and uniform distributions for the decision variable was generated using a Hammersley sequence sampling technique.
2. The model was run for the scenarios generated in step 1 to calculate the value of the objective function and constraints for each set of input values, and a probability distribution was estimated using kernel density estimation for each.
3. The nonlinear optimizer (based on the sequential quadratic programming (SQP) algorithm) was initialized by selecting starting values for each decision variable.
4. The value of the objective function was estimated by first assuming a narrow normal distribution centered at the value chosen in Step 3, and then using this normal distribution, along with the initial uniform distribution of the decision variables and the corresponding outputs found in Step 2 used to calculate new values of the probability density functions according to the following formula:

$$p(u) = \frac{\frac{f(u)}{\widehat{f(u^*)}}}{\sum_{j=1}^{N_{samp}} \frac{f(u_j)}{\widehat{f(u_j^*)}}} p(u_j^*), \tag{5.1}$$

   where $N_{samp}$ is the number of samples taken in Step 1, $p(u_j^*)$ is the probability density function for the output distribution corresponding to the initial uniform input distribution, $f(u)$, and $\widehat{f(u)}$ is the probability density function of the updated input distribution. The latter is given by

$$\widehat{f(u)} = \frac{1}{N_{samp}h} \sum_{j=1}^{N_{samp}} \frac{1}{\sqrt{2\pi}} e^{\frac{1}{2}} \left( \frac{u - u_j}{h} \right)^2, \tag{5.2}$$

   where $h$ is the variance of the data set.

**Table 5.2** Minimization of average water consumption under uncertain air conditions for a 548 MW PC power plant located in the Midwestern US for four different seasons. (Water consumption estimates are reported in millions of pounds per hour)

| Season | Optimal values of decision variables | | | | |
|---|---|---|---|---|---|
| | Air excess % | RH temperature °F | FGD limestone fraction | HP1 pressure ratio | HP2 pressure ratio |
| Fall | 38.925 | 1160.8 | 0.31457 | 0.49 U | 0.61 L |
| Summer | 48.947 | 1174 | 0.42262 | 0.49 U | 0.66 L |
| Spring | 35.5 | 1096.5 | 0.22185 | 0.36 L | 0.61 L |
| Winter | 19.039 | 1141.9 | 0.30077 | 0.49 U | 0.79 U 2 |
| | Base case values of decision variables | | | | |
| All | 20 | 1157 | 0.3 | 0.365 | 0.637 |
| Season | Bonus estimate optimal objective function | Stochastic simulation estimate optimal objective function | Stochastic simulation base case objective function | Savings % | |
| Fall | 2.433 | 2.567 | 2.742 | 6.4 | |
| Summer | 2.622 | 2.702 | 3.194 | 15.4 | |
| Spring | 2.421 | 2.595 | 2.698 | 3.8 | |
| Winter | 2.331 | 2.384 | 2.463 | 3.2 | |

5. The decision variables were perturbed, and new estimates of the objective function and its derivative were calculated using the reweighting scheme.
6. Steps 3–5 were repeated until Kuhn–Tucker conditions were reached.

## 5.7 Results

The nonconvexity of the objective function required the SQP algorithm to be run for a variety of initial values for both reheater temperature and air excess. The nonlinear optimizer was run 61 times, and each nonlinear optimization took between 2 and 20 iterations, for a total of 519 iterations for each of the four seasons. Using the BONUS algorithm, results were derived in 4800 model evaluations per season. By contrast, a traditional framework for this stochastic optimization problem would have instead required at least 120 scenarios in the stochastic loop, for a minimum of 373,680 evaluations, nearly 78 times as many. The BONUS algorithm therefore saved 98.7 % of the computational time required to solve the problem.

Table 5.2 gives the optimal values of the decision variables and water usage estimations at (1) the optimal point using the BONUS algorithm, (2) the optimal point with a rigorous stochastic simulation, and (3) the base case with a rigorous stochastic simulation for each of the four seasons. The water consumption estimations are given as the expected values of the probability distributions approximated with BONUS or calculated via stochastic simulation. The savings in average water consumption at the optimal point, as compared to the base case, range from a low of 3.2 % in winter to 15.4 % in summer.

It is intuitive that the water consumption savings are greater in warmer seasons. In the relatively warm fall and summer seasons, the turbine pressure ratios 1 and 2 are pushed to their upper and lower limits, respectively (these two turbines define the feed-water temperature entering the boiler and the pressure at which steam is reheated). Operating the turbines at the limits of their pressure ratios, along with a higher reheater temperature, increases their thermodynamic generation capacity (work per mass of steam), reducing both required fuel and the steam flow rate. At the same time, these operating parameters have little effect on the heat rejection rate. By combining a reduction in the steam flow rate with a steady heat removal rate, water consumption is minimized in the warmer seasons, in which the cooling tower is least efficient. By contrast, in the cooler seasons (spring and winter), the cooling tower operates more efficiently and allows for reduced water consumption even when a large amount of heat must be removed at the condenser.

## 5.8 Summary

The BONUS algorithm can be used to efficiently optimize water consumption in a PC power plant. Uncertainty in air temperature and humidity affect the amount of water lost to evaporation, drift, blowdown, and makeup. Reheater temperature, air excess to the boiler, FGD slurry preparation water ratio, and pressure drops at the two high-pressure turbines are all operational variables that may be manipulated to minimize water consumption, but the highly nonlinear nature of the objective function and the power and mass balance constraints make this problem extremely computationally intensive under a traditional stochastic optimization framework. The BONUS algorithm reduces this computational intensity by 98.7 %, and shows that reductions of 3.2–15.4 % are possible, depending on the season, for a 548-MW plant in the Midwestern US.

## Notations

| | |
|---|---|
| $B$ | blowdown losses |
| $D$ | drift losses |
| $EL$ | evaporation losses (EL) |
| $f$, $h$, and $g_i$ | constraints using black-box models in Aspen Plus® |
| $f(u)$ | initial uniform input distribution |

| | |
|---|---|
| $\widehat{f(u)}$ | probability density function of the updated input distribution |
| $F$ | FGD consumption |
| $ME$ | material and energy balance of the operating unit |
| $N_{samp}$ | number of samples taken |
| $P$ | amount of power generated |
| $P^*$ | fixed generation of electricity |
| $p(u_j^*)$ | probability density function for the output distribution corresponding to the initial uniform input distribution |
| $Q$ | total heat rejected by the cycle |
| $x$ | set of deterministic input parameters (design and operational conditions) |
| $u$ | set of uncertain weather conditions |