

Online Companion for

**“COMMITMENT OF ELECTRIC  
POWER GENERATORS UNDER  
STOCHASTIC MARKET PRICES”**

**OPERATIONS RESEARCH**

Volume 51, Number 6,  
November-December 2003

**Jorge Valenzuela  
Auburn University**

and

**Mainak Mazumdar  
University of Pittsburgh**

## APPENDIX

### A-1. Normal Approximation of $p_{mn}(r,t)$

Using the central limit theorem, the joint distribution of  $X_m(r)$  and  $X_n(t)$  can be approximated by a bivariate normal distribution. Thus,

$$p_{mn}(r,t) = \int_{a_m(r)}^{a_n(t)} \phi_2(z_1, z_2; \rho_{mn}(r,t)) dz_1 dz_2 \quad (\text{A-1})$$

where

$$a_j(s) = -E[X_j(s)] / \sqrt{V[X_j(s)]} \quad (\text{A-2})$$

$$E[X_j(s)] = \theta_s - \sum_{i=1}^j c_i p_i \quad (\text{A-3})$$

$$V[X_j(s)] = \sigma_s^2 + \sum_{i=1}^j c_i^2 p_i q_i \quad (\text{A-4})$$

$$\rho_{mn}(r,t) = \text{Cov}[X_m(r), X_n(t)] / \sqrt{V[X_m(r)] \times V[X_n(t)]} \quad (\text{A-5})$$

$$\text{Cov}[X_m(r), X_n(t)] = \sigma_{r,t} + \sum_{i=1}^{\min(m,n)} c_i^2 p_i q_i e^{-\delta_i |t-r|} \quad (\text{A-6})$$

### A-2. Edgeworth (Gram-Charlier) Approximation of $p_{mn}(r,t)$

The approximate expression for  $p_{mn}(r,t)$  using the bivariate Edgeworth expansion for the joint distribution function of  $X_m(r)$  and  $X_n(t)$  in which only the terms involving cumulants up to the third order is retained is given by:

$$\begin{aligned} p_{mn}(r,t) &= \int_{a_m(r)}^{a_n(t)} \phi_2(z_1, z_2; \rho_{mn}(r,t)) \times \left[ 1 + \frac{1}{6} \frac{K_{30}}{K_{20}^{3/2}} H_{30}(z_1, z_2; \rho_{mn}(r,t)) \right. \\ &+ \frac{1}{2} \frac{K_{21}}{K_{20} K_{02}^{1/2}} H_{21}(z_1, z_2; \rho_{mn}(r,t)) + \frac{1}{2} \frac{K_{12}}{K_{20}^{1/2} K_{02}} H_{12}(z_1, z_2; \rho_{mn}(r,t)) \\ &\left. + \frac{1}{6} \frac{K_{03}}{K_{20}^{1/2}} H_{30}(z_1, z_2; \rho_{mn}(r,t)) \right] dz_1 dz_2 \quad (\text{A-7}) \end{aligned}$$

Here,  $K_{kl}$  is the cumulant of order  $(k,l)$  of  $[X_m(r), X_n(t)]$ , and  $H_{ij}$  the bivariate Hermite polynomial. When only cumulants up to the third order are considered, the Gram-Charlier and the Edgeworth series give identical expansions.

### A-3. Large Deviation Approximation of $p_{mn}(r,t)$

When tail probabilities are involved, a better approximation is given by the large deviation approximation. Exponential tilting is used here to convert the tail region into a central region and then approximate the tilted distribution by a bivariate normal distribution. Let the exponentially tilted distribution of  $\mathbf{X}=[X_m(r), X_n(t)]$  for a given vector  $\mathbf{S}=(s_1,s_2)$  be:

$$dF^{\mathbf{S}}(\mathbf{X};m,n,r,t)=e^{\mathbf{S}\mathbf{X}-K(\mathbf{S};m,n,r,t)} dF(\mathbf{X};m,n,r,t) \quad (\text{A-8})$$

where  $F(x;m,n,r,t)$  is the bivariate c.d.f. of the random vector  $\mathbf{X}$ , and

$$K(\mathbf{S};m,n,r,t)=\ln E[e^{\mathbf{S}\mathbf{X}}] \quad (\text{A-9})$$

Then, the value of  $p_{mn}(r,t) = \int_0^{\infty} \int_0^{\infty} dF(\mathbf{X};m,n,r,t)$  can be expressed as a function of the distribution

function  $F^{\mathbf{S}}(\mathbf{X};m,n,r,t)$  as

$$p_{mn}(r,t) = e^{K(\mathbf{S};m,n,r,t)} \int_0^{\infty} \int_0^{\infty} e^{-\mathbf{S}\mathbf{X}} dF^{\mathbf{S}}(\mathbf{X};m,n,r,t) \quad (\text{A-10})$$

Next, the central limit theorem is used to approximate  $F^{\mathbf{S}}(\mathbf{X};m,n,r,t)$  by a normal distribution  $\Phi_2[\mathbf{X};\mathbf{B},\Sigma]$  with appropriately determined mean vector  $\mathbf{B}$  and covariance matrix  $\Sigma$ . Thus, we obtain

$$p_{mn}(r,t) = e^{K(\mathbf{S};m,n,r,t)} \int_0^{\infty} \int_0^{\infty} e^{-\mathbf{S}\mathbf{X}} d\Phi_2(\mathbf{X};\mathbf{B},\mathbf{O}) \quad (\text{A-11})$$

The constant vector  $\mathbf{S}$  is now chosen so that the lower limits of the integrals is the expected value of the random variable  $\mathbf{X}^S$  whose distribution function is  $F^S(\mathbf{X};m,n,r,t)$ . This reduces to the following system of equations (assuming  $m>n$ ):

$$\theta_r + \sigma_r^2 s_1 + \sigma_{r,t} s_2 - \frac{n}{i=1} \frac{c_i p_i g_{r,t}(q_i, q_i, \delta_i) e^{-s_1 c_i} - c_i p_i f_{r,t}(p_i, q_i, \delta_i) e^{-(s_1 + s_2) c_i}}{q_i f_{r,t}(q_i, p_i, \delta_i) + p_i g_{r,t}(q_i, q_i, \delta_i) e^{-s_1 c_i} + q_i g_{r,t}(p_i, p_i, \delta_i) e^{-s_2 c_i} + p_i f_{r,t}(p_i, q_i, \delta_i) e^{-(s_1 + s_2) c_i}} - \frac{m}{i=n+1} \frac{c_i p_i e^{s_1 c_i}}{q_i + p_i e^{-s_1 c_i}} = 0 \quad (\text{A-12})$$

$$\theta_t + \sigma_t^2 s_2 + \sigma_{r,t} s_1 - \frac{n}{i=1} \frac{c_i p_i g_{r,t}(p_i, p_i, \delta_i) e^{-s_2 c_i} - c_i p_i f_{r,t}(p_i, q_i, \delta_i) e^{-(s_1 + s_2) c_i}}{q_i f_{r,t}(q_i, p_i, \delta_i) + p_i g_{r,t}(q_i, q_i, \delta_i) e^{-s_1 c_i} + q_i g_{r,t}(p_i, p_i, \delta_i) e^{-s_2 c_i} + p_i f_{r,t}(p_i, q_i, \delta_i) e^{-(s_1 + s_2) c_i}} = 0 \quad (\text{A-13})$$

where  $f_{r,t}(a_i, b_i, \delta_i) = a_i + b_i e^{-\delta_i |r-t|}$  and  $g_{r,t}(a_i, b_i, \delta_i) = a_i - b_i e^{-\delta_i |r-t|}$

Let  $\mathbf{S}_0 = [s_1, s_2]$  denote the roots of equations A-12 and A-13. Then, Equation A-11 can be rewritten as

$$p_{mn}(r, t) = \int_0^{\mathbf{X}} e^{K(\mathbf{S}_0; m, n, r, t)} e^{-\mathbf{S}_0 \mathbf{X}} d(\mathbf{X}; \mathbf{0}, \mathbf{O}) \quad (\text{A-14})$$

Ordering terms, completing squares, and evaluating the integrals gives:

$$p_{mn}(r, t) = e^{K(s_1, s_2; m, n, r, t) + G(s_1, s_2; m, n, r, t, \rho)} {}_2(\alpha_1, \alpha_2, \rho(s_1, s_2; m, n, r, t)) \quad (\text{A-15})$$

Expressions for  $(\ )$ ,  $G(\ )$ ,  $\alpha_1$ , and  $\alpha_2$  have been derived to be

$$\rho(s_1, s_2; m, n, r, t) = \frac{K_{11}(s_1, s_2; m, n, r, t)}{\sqrt{K_{02}(s_1, s_2; m, n, r, t) K_{20}(s_1, s_2; m, n, r, t)}} \quad (\text{A-16})$$

$$G(\ ) = \frac{1}{2[1 - \rho^2]} \left\{ [\sigma_m(r) s_1 + \rho \sigma_n(t) s_2]^2 + [\rho \sigma_m(r) s_1 + \sigma_n(t) s_2]^2 + 2\rho[\rho \sigma_m(r) s_1 + \sigma_n(t) s_2][\sigma_m(r) s_1 + \rho \sigma_n(t) s_2] \right\} \quad (\text{A-17})$$

$$\alpha_1 = \sigma_m(r) s_1 + \rho \sigma_n(t) s_2 \quad (\text{A-18})$$

$$\alpha_2 = \rho\sigma_m(r)s_1 + \sigma_n(t)s_2 \quad (\text{A-19})$$

where

$$\sigma_m(r) = \sqrt{K_{20}(s_1, s_2; m, n, r, t)}, \sigma_n(t) = \sqrt{K_{02}(s_1, s_2; m, n, r, t)}, \text{ and } \rho = \rho(s_1, s_2; m, n, r, t)$$

The bivariate normal approximation to  $F^S(\mathbf{X}; m, n, r, t)$  is not likely to be very accurate in the tails. However, if  $s_1$  and  $s_2$  are positive the multiplier,  $\exp(-s_1x_1 - s_2x_2)$ , reduces the error of the bivariate normal approximation in the tails in Equation A-14. If either  $s_1$  or  $s_2$  turns out to be negative, the probability of the complement of the region is approximated instead. Three cases are identified:  $s_1$  is positive and  $s_2$  is negative;  $s_1$  is negative and  $s_2$  is positive;  $s_1$  and  $s_2$  are negative. The same change of variable previously used in the one-dimensional case is also used here, which gives the following equations:

Case 1: if  $s_1$  is positive and  $s_2$  is negative redefine  $s_2$  as  $-s_2$ , and use Equation A-20:

$$p_{mn}(r, t) = \Pr[X_m(r) \geq 0] - e^{K(S_0; m, n, r, t) + G(S_0; m, n, r, t, \rho)} \Phi_2(\alpha_1, -\alpha_2, -\rho) \quad (\text{A-20})$$

Case 2: if  $s_1$  is negative and  $s_2$  is positive redefine  $s_1$  as  $-s_1$ , and use Equation A-21

$$p_{mn}(r, t) = \Pr[X_m(r) \geq 0] + \Pr[X_n(t) \geq 0] + e^{K(S_0; m, n, r, t) + G(S_0; m, n, r, t, \rho)} \Phi_2(-\alpha_1, \alpha_2, -\rho) \quad (\text{A-21})$$

Case 3: if both  $s_1$  and  $s_2$  are negative redefine  $s_1$  as  $-s_1$  and  $s_2$  as  $-s_2$ , and use Equation A-22

$$p_{mn}(r, t) = \Pr[X_n(t) \geq 0] - e^{K(S_0; m, n, r, t) + G(S_0; m, n, r, t, \rho)} \Phi_2(-\alpha_1, -\alpha_2, \rho) \quad (\text{A-22})$$