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Determination of Optimum Target Values for Production Processes under Two-Stage Screening Procedure

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2단계 검사절차를 이용한 생산공정의 최적 평균 및 검사 기준값의 결정

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This paper considers the problem of determining the optimum target values of the quality characteristic of interest Y and the screening limits of a surrogate variable X which is correlated with Y under two-stage screening procedure. In the two-stage screening procedure, X is measured first to decide whether an item should be accepted, rejected or additional observations should be taken. If it is difficult to decide on the result of measured value of X, Y is then observed to classify the undecided items.

Assuming that Y and X are jointly normally distributed, a model is constructed which involves selling and reduced prices, production, inspection, and penalty costs. Methods of finding the optimum process mean and the screening limits are presented. A numerical example and analysis of the results are also presented.

1. Introduction

As a result of advances in automated manufacturing systems, sensoring technology and automatic inspection equipment, complete inspections are increasingly popular in industries in order to improve the outgoing quality of its products. Suppose that there is a lower specification limit L for the quality characteristic Y of interest. All items are subjected to acceptance inspection and those with $Y < L$ are reprocessed or sold at a discount. Such quality characteristics include filling weights and volume.

Items produced by a production process may deviate from the process mean because of variations in materials, labor and operation conditions. The process mean may be adjusted to a higher value in order to reduce the proportion of the nonconforming items. Using a higher process mean, however, may result in a higher production cost. Therefore, a process parameter μ for the process mean is to be selected so that the expected profit per item is maximized.

This problem has been studied by several researchers. Springer [1] and Bettes [2] considered a filling process where upper and lower specification limits were given. The optimal target value was obtained in order to minimize the reprocessing cost and material costs for overfilled and underfilled items. Golhar [3] studied a canning process in which underfilled cans are emptied and refilled so that it would be sold in the primary market. Al-Sultan [4], Boucher and Jafari [5], and Carlsson [6] discussed situations in which the items are subjected to lot-by-lot acceptance sampling rather than complete inspections. Arcelus and Rahim [7] considered the problem of determining simultaneously target values for variable and attribute quality characteristics. Chen and Chung [8] considered an economic model for determining the most profitable target value and optimum measuring precision level for a production process.

In all these studies, inspection is performed on the quality characteristic Y of interest (performance variable). In some situations, it is impossible or not economical to directly inspect the characteristic Y. In such cases, the use of a variable X(surrogate variable) which is highly correlated with Y is attractive, especially when inspecting the surrogate variable is relatively less expensive than Y. In a cement plant, for example, the weight of a cement bag which is difficult to measure directly due to the high-speed packing may be used as a performance variable. The milli ampere(mA) of the load cell is strongly correlated with the weight of a cement bag and does not require special effort to measure. Hence it can be considered as the surrogate variable (Bai and Lee [9]). The idea of selecting the screening limit on X has been studied by many researchers. Bai and Lee [9] and Tang and Lo [10] presented economic models that determine the process mean and the screening limit on X when inspection is based on X instead of Y for situations where items with $Y \geq L$ are sold at a fixed price and items with $Y < L$ are scrapped or reprocessed, respectively. Lee and Jang [11] developed a procedure to select economically target values for a production process where an item is sold in one of two markets with different profit/cost structures or scrapped.

In applications where quality assurance is critical the outgoing quality improvement may be more important than the reduction in the inspection cost. Since a surrogate variable is not perfectly correlated with Y, some conforming items may be rejected and excluded from shipment while some nonconforming items may be accepted for shipment. These decision errors are likely to occur when the value of a surrogate variable is close to the screening limits. Consequently, in this situation, there may be an economic advantage to reduce the errors by observing the performance variable even though the inspection may be expensive. Of course, this can be done only when the inspection of the performance variable is not destructive. Based on this, Tang [12] proposed an economic two-stage screening procedure where the surrogate variable is used in the first stage and the performance variable is used in the second stage. The screening limits are determined by minimizing the total cost associated with the screening procedure. Bai *et al.* [13] considered an economic two-stage screening procedure with a prescribed outgoing quality in logistic and normal models.

In this paper, we consider the problem of jointly determining the optimum process mean of the quality characteristic of interest and screening limits of the surrogate variable under two-stage screening procedure. In the two-stage screening, a surrogate variable is inspected first to decide whether an item should be accepted, rejected or additional observations should be taken. If it is difficult to decide on the result of measured value of X, the performance variable is then observed to classify the undecided items. The optimum process mean and screening limits of the correlated variable are jointly determined by maximizing the profit function which involves selling and reduced prices and production, inspection, and penalty costs. In section 2, we present a two-stage screening procedure for a production process and develop methods of finding the optimum process mean and screening limits of the surrogate variable. A numerical example and analysis of results are given in section 3.

2. Two-Stage Screening Procedure

Suppose that the performance variable Y is normally distributed with unknown process mean μ_y and known variance σ_y^2. We assume that surrogate variable X given $Y = y$ is normally distributed with mean $\lambda_1 + \lambda_2 y$ and variance σ^2 where λ_1 and λ_2 are known constants. λ_2 is assumed to be positive so that X and Y have a positive relationship. It can be easily shown that (X, Y) follow a bivariate normal density function with means $(\mu_y = \lambda_1 + \lambda_2 \mu_y, \mu_y)$, variances, $(\sigma_x^2 = \lambda_2^2 \sigma_y^2 + \sigma^2, \sigma_y^2)$, and correlation coefficient $\rho = \{\lambda_2^2 \sigma_y^2 / (\lambda_2^2 \sigma_y^2 + \sigma^2)\}^{1/2}$ (see Tang and Lo [10]). All items are inspected prior to shipment to determine whether they satisfy a lower specification limit L on Y or not.

The two-stage screening procedure is as follows:

First stage *: Take a measurement x of X for each incoming item. The item is (i) accepted if $x \geq \omega_1$, (ii) undecided if $\omega_2 \leq x < \omega_1$, and (c) rejected if $x < \omega_2$, where $\omega_1 \geq \omega_2$.*

Second stage *: For the case (ii) in the First stage, observe y of Y and (i) accept if $y \geq L$, and (ii) reject if $y < L$.*

Here, ω_1 and ω_2 are screening limits for X. If the surrogate variable X is negatively correlated with Y, we then use a screening variable $-X$ rather than X. Note that there are no misclassification errors at the second stage because all the undecided items are inspected with the performance variable.

Items with $Y \geq L$ are sold at a fixed price a to the primary market, and items with $Y < L$ are sold at a reduced price $\gamma (< a)$ to the secondary market. Since X is not perfectly correlated with Y, some items with $Y < L$ may be sold to the primary market. The errors of accepting items with $Y < L$ incur penalty cost $d (\geq a)$ which includes costs of identifying and handling the defective items, and service and replacement costs. The production cost per item is linear in Y, that is, $b + cy$ where b and c are constants, and c_y and c_x denote the inspection cost per item for the performance and surrogate variables, respectively.

Therefore, the profit function $P(x, y; \mu_y, \omega_1, \omega_2) \equiv P_T$ is

$$
\begin{aligned}
P_T = \; & a - b - cy - c_x, \quad X \geq \omega_1, \; Y \geq L \\
& a - b - cy - c_x - d, \quad X \geq \omega_1, \; Y < L \qquad (1) \\
& a - b - cy - c_x - c_y, \quad \omega_2 \leq X < \omega_1, \; Y \geq L \\
& r - b - cy - c_x - c_y, \quad \omega_2 \leq X < \omega_1, \; Y < L \\
& r - b - cy - c_x, \quad X < \omega_2
\end{aligned}
$$

Then the expected profit per item is given by

$$
\begin{aligned}
E(P_T) = \; & \Phi(-\delta_1) + \{\Phi(\delta_1, -\eta; -\rho) \\
& \Phi(\sigma_2, -\eta; -\rho)\} - d\Psi(-\delta_1, \eta; -\rho) \qquad (2) \\
& + c_y\{\Phi(\delta_2) - \Phi(\delta_1)\} + \gamma\{\Psi(\delta_1, \eta, \rho)\} \\
& + \Psi(\delta_2, -\eta; -\rho)\} + (b + c(L - \eta\sigma_y)) - c_x
\end{aligned}
$$

where $\Phi(\cdot)$ and $\Psi(\cdot, \cdot; \rho)$ are the standard normal distribution function and standardized bivariate normal distribution function with correlation coefficient ρ, respectively, $\eta = (L - \mu_y)/\sigma_y$ and. $\delta_i = (\omega_i - u_x)/\sigma_x$, $i = 1, 2$. See the Appendix for detailed derivation.

The optimum values δ_1^*, δ_2^*, and η^* can be obtained by maximizing $E(P_T)$, $E(P_T)$ is a unimodal function of η, δ_i, and the optimum values η^* and δ_i^* satisfy $\partial E(P_T)/\partial \eta = 0$, $\partial E(P_T)/\partial \delta_i = 0$, $i = 1, 2$ conditions given by Eq. (3)~(5):

$$
\begin{aligned}
& -d\Phi(-\delta_1^* + \eta^*\rho)/(1-\rho^2)^{1/2} - (a - \gamma) \\
& \quad \{\Phi((\delta_1^* - \eta^*\rho)/(1-\rho^2)^{1/2} - \Phi((\delta_2^* - \eta^*\rho)/ \\
& \quad (1-\rho^2)^{1/2})\} + c\,\sigma_y = 0 \qquad (3)
\end{aligned}
$$

$$
\begin{aligned}
\delta_1^* &= \{\eta^* - (1-\rho^2)^{1/2} \Phi^{-1} \\
& \qquad (c_y/(d + \gamma - a))\}/\rho \qquad (4) \\
\delta_2^* &= \{\eta^* + (1-\rho^2)^{1/2} \Phi^{-1} \\
& \qquad (c_y/(a - \gamma))\}/\rho \qquad (5)
\end{aligned}
$$

See the Appendix for detailed derivations.

The optimum values δ_1^*, δ_2^*, and η^* can be obtained by solving these equations simultaneously, and computational approach such as Gauss-Seidal's iterative method can be used to obtain δ_1^*, δ_2^*, and η^*. The optimum process mean μ_y^* and the screening limits ω_1^* and ω_2^* on X are obtained by

$$
\mu_y^* = L - \eta^*\sigma_y, \qquad (6)
$$

$$
\omega_1^* = \mu_x + \delta_i^*\sigma_x, \text{ for } i = 1, 2 \qquad (7)
$$

3. Numerical Example

In this section, an example which originally appeared in Bai and Lee [9] is presented to illustrate the optimum solution procedures. Numerical studies are also performed to investigate the effects of σ_y, ρ, and c_y. IMSL [14] subroutines such as DNO- RIN, DNORDF, and DBNRDF are used to evaluate the inverse of the standard normal ditribution function and standard univariate and bivariate normal distribution functions, respectively.

Example: Consider a packing plant of cement factory. The plant consists of two processes; a filling process and an inspection process. Each cement bag processed by the filling machine is moved to the loading and dispatching phases on a conveyor belt. Inspection is performed by CWFs (continuous weighing feeders). A CWF measures the mA (milli ampere) X of the load cell of the cement bag, which is positively correlated with the weight Y of the cement bag. From theoretical considerations and past experience, it is known that the variance of Y, $\sigma_y^2=(1.25\,\text{Kg})^2$, and that X for give $Y=y$ is normally distributed with mean $4.0+0.08y$ Y and variance $(0.05\,\text{mA})^2$. That is, X and are jointly normally distributed, with unknown means (μ_x, μ_y), known variances $\sigma_x^2=(0.112\,\text{mA})^2$, $\sigma_y^2=(1.25\,\text{Kg})^2$, and correlation coefficient $\rho=0.894$. The weight marked on each bag is 40Kg, and it is the lower specification limit. Suppose that the cost components and the specification limits for Y are $a=\$3.0$, $\gamma=\$2.25$, $c_0=\$0.1$, $c=\$0.06$, $c_y=\$0.04$, $c_x=\$0.004$, $d=\$6.5$, and $L=40$(kg).

For the two-stage screening procedure, we obtain $\eta^*=-1.787$, $\delta_1^*=-0.782$, and $\delta_2^*=-2.807$ from Eq. (3)~(5). Therefore the optimum process mean and screening limits for X are

$$\mu_y^* = L\eta^*\sigma_y = 40.0-(-1.787\times1.25) = 42.234(\text{Kg})$$

$$\omega_1^* = \mu_x+\delta_1^*\sigma_x = 4.0+0.08\times42.234+(-0.782\times0.112) = 7.291(\text{mA})$$

$$\omega_2^* = \mu_x+\delta_1^*\sigma_x = 4.0+0.08\times42.234+(-2.807\times0.112) = 7.064(\text{mA})$$

and $E(P_T)=\$0.3235$.

(i) Effects of σ_y : Let Model I and Model II be the single-stage screening procedures. In the Model I inspection is performed on the performance variable Y, and in the Model II inspection is performed on the surrogate variable X. Let Model III be the two-stage screening procedures. Expected profits of the three models are shown in <Figures 1> and

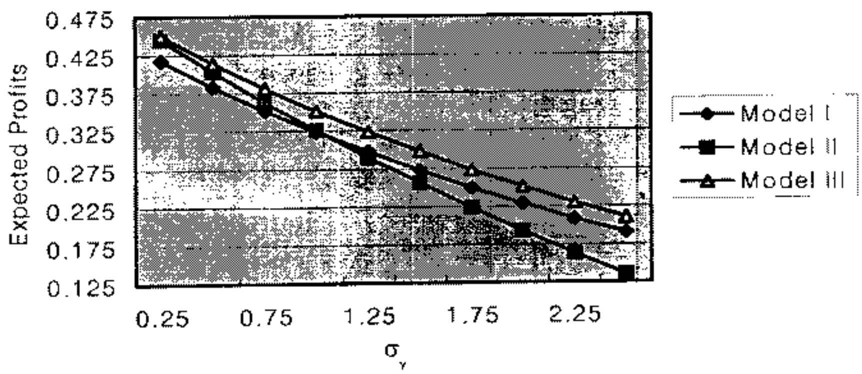

Figure 1. Expected profits as a function of σ_y.

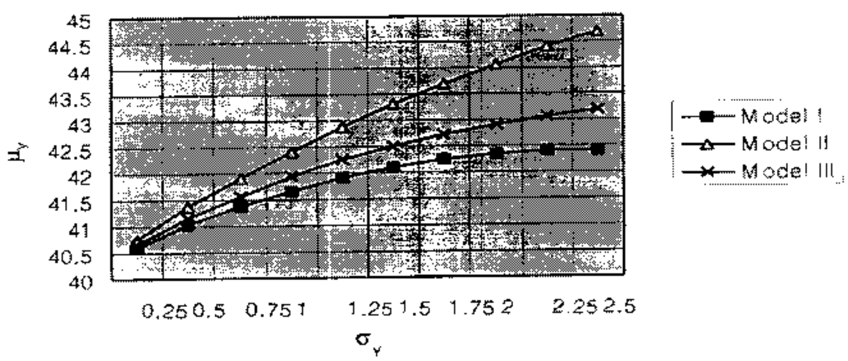

Figure 2. Process means as a function of σ_y.

<2> for selected values of σ_y for 0.25 (0.25) 2.50. <Figure 1> shows that the expected profit decreases as σ_y increases. The computational results agree with our intuition that expected profit for the two-stage screening procedure is somewhat more profitable than that of the single-stage screening procedures. Expected profit of Model II is larger than that of Model I if σ_y takes a smaller value, but expected profit of Model II is smaller than that of Model I if σ_y takes a larger value. We also know that μ_y^* tends to increase as σ_y increases as shown in <Figure 2>.

(ii) Effects of ρ : The expected profit per item, the optimum process mean, and the screening specification limits on X are given in <Figure 3> for selected values of ρ for 0.650 (0.025) 0.975. <Figure 3> shows that expected profits of Model II and Model III increase as ρ increases. Expected profits of Model III is greater than that of Model II and the difference in the expected profits tends to decrease as ρ increases, this computational results agree with our intution.

(iii) Effects of c_y: The inspection proportions of stage 1 and stage 2 are given in <Figure 4> for selected values of c_y for 0.02 (0.005) 0.07. <Figure 4> shows that the inspection proportion of stage 1 tends to increase, and the inspection proportion of stage 2 tends to decrease as c_y increases.

4. Concluding Remarks

We have developed economic selections of the

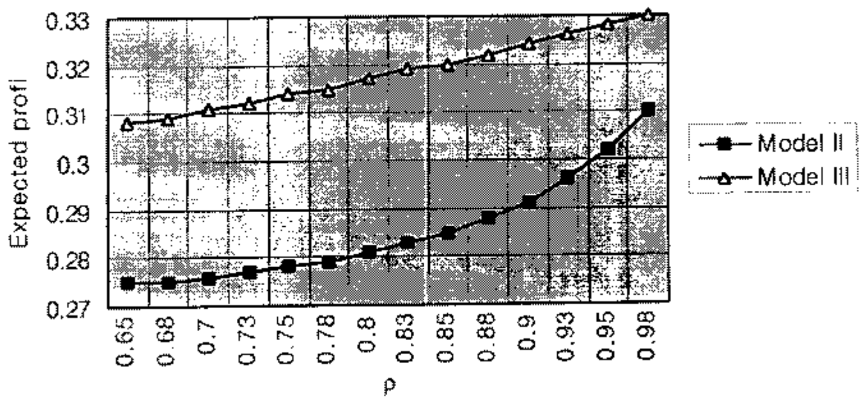

Figure 3. Expected profits as a function of ρ.

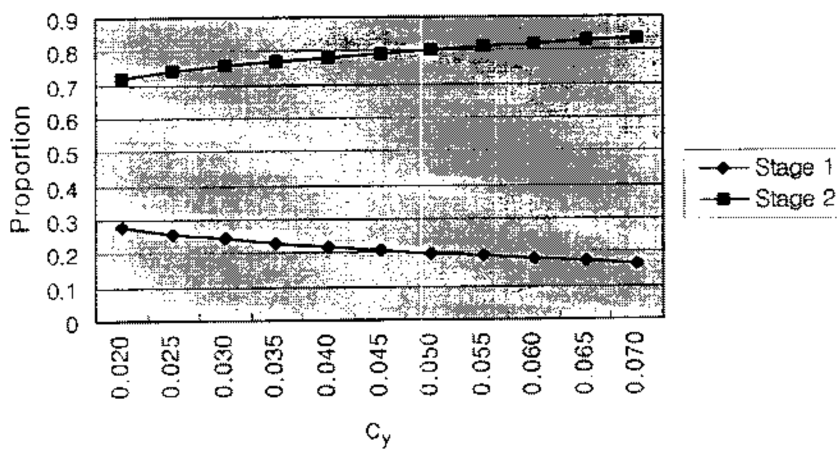

Figure 4. Proportion of inspection as a function of c_y.

optimum mean value of the quality characteristic of interest and the screening limits of a variable which is correlated with the quality characteristic of interest under two-stage screenings. A profit model is constructed under the assumption that the quality characteristic of interest. Concluding Remarksrest and the surrogate variable are jointly normally distributed. The optimum process mean and screening limits are jointly determined by maximizing the expected profit which involves the selling and reduced prices and the production, inspection and penalty costs. The solution is shown to be unique and optimum. However, closed form expressions for the optimum values are not obtained and numerical search algorithms such as Gauss-Seidel's iterative method is used. Numerical results show that the expected profit decreases as σ_y increases, and the process mean and screening limits on the correlated variable tend to increase as σ_y increases. Expected profit for the two-stage screening procedure is somewhat greater than that of the single-stage screening procedures.

Appendix A : Derivation of Equation (2)

The expected profit per item is given by

$$\begin{aligned} E(P_T) &= \int_{\omega_1}^{\infty}\int_{L}^{\infty}(a-b-cy-c_x)f(x,y)dydx \\ &+ \int_{\omega_1}^{\infty}\int_{-\infty}^{L}(a-b-cy-c_x-d)f(x,y)dydx \\ &+ \int_{\omega_2}^{\omega_1}\int_{L}^{\infty}(a-b-cy-c_x-c_y)f(x,y)dydx \\ &+ \int_{\omega_2}^{\omega_1}\int_{-\infty}^{L}(\gamma-b-cy-c_x-c_y)f(x,y)dydx \\ &+ \int_{-\infty}^{\omega_2}\int_{-\infty}^{\infty}(\gamma-b-cy-c_x)f(x,y)dydx \end{aligned} \tag{A.1}$$

where $f(x, y)$ is the joint density function of X and Y.

Using the following relationships

$$\int_{\omega_1}^{\infty}\int_{-\infty}^{L}f(x,y)dydx = \Psi(-\delta_1,\eta;-\rho), \tag{A.2}$$

$$\int_{\omega_1}^{\infty}\int_{L}^{\infty}f(x,y)dydx = \Psi(-\delta_1,-\eta;\rho), \tag{A.3}$$

$$\int_{\omega_2}^{\omega_1}\int_{-\infty}^{L}f(x,y)dydx = \Psi(-\delta_2,-\eta;-\rho) - \Psi(-\delta_1,\eta;-\rho) \tag{A.4}$$

$$\int_{\omega_2}^{\omega_1}\int_{L}^{\infty}f(x,y)dydx = \Psi(\delta_1,-\eta;-\rho) - \Psi(-\delta_2,-\eta;-\rho), \tag{A.5}$$

equation (A.1) can be rewritten as

$$\begin{aligned} E(P_T) &= a\Phi(-\delta_1) + a\{\Psi(\delta_1,-\eta;-\rho) \\ &- \Psi(\delta_2,-\eta;-\rho)\} - d\Psi(-\delta_1,\eta;-\rho) \\ &+ c_y\{\Phi(\delta_2)-\Phi(\delta_1)\} + \gamma\{\Psi(\delta_1,\eta;\rho) \\ &+ \Psi(\delta_2,-\eta;-\rho)\} + (b+c(L-\eta\sigma_y)) - c_x. \end{aligned} \tag{A.6}$$

Appendix B : Derivation of Equations (3)~(5)

Using the following relationships

$$\partial\Psi(\delta_1,\eta;\rho)/\partial\delta_1 = \Phi\left(\frac{\eta-\delta_1\rho}{\sqrt{1-\rho^2}}\right)\phi(\delta_1) \tag{B.1}$$

$$\partial\Psi(\delta_1,\eta;\rho)/\partial\eta = \Phi\left(\frac{\delta_1-\eta\rho}{\sqrt{1-\rho^2}}\right)\phi(\eta) \tag{B.2}$$

the first derivatives of $E(P_T)$ with respect to η and δ_i, $i=1,2$, are

$$\begin{aligned} \frac{\partial E(P_T)}{\partial\eta} &= (a-r)\left[\Phi\left(\delta_2-\eta\frac{\rho}{\sqrt{1-\rho^2}}\right)-\Phi\left(\frac{\delta_1-\eta\rho}{\sqrt{1-\rho^2}}\right)\right. \\ &\cdot \emptyset(-\eta) - d\Phi\left(\frac{\delta_2-\eta\rho}{\sqrt{1-p^2}}\right) \\ &\cdot \phi(-\eta) - c\sigma_y \end{aligned} \tag{B.3}$$

$$\frac{\partial E(P_T)}{\partial\delta_1} = (d+\gamma-a)\varphi\left(\frac{\eta-\delta_1\rho}{\sqrt{1-\rho^2}}\right)\phi(\delta_1) + c_y\phi(\delta_1), \tag{B.4}$$

$$\frac{\partial E(P_T)}{\partial\delta_2} = (r-a)\Phi\left(\frac{-\eta+\delta_2\rho}{\sqrt{1-\rho^2}}\right)\phi(\delta_2) - c_y\phi(\delta_2), \tag{B.5}$$

The second partial derivatives of $E(P_T)$ with respect to η and δ_i, $i=1,2$, at $(\eta^*, \delta_1^*, \delta_2^*)$ are

$$\begin{aligned} \frac{\partial^2E(P_T)}{\partial\eta^2} &= \frac{(a-\gamma)\rho}{\sqrt{1-p^2}}\left[\phi\left(\frac{\delta_2-\eta\rho}{\sqrt{1-\rho^2}}\right)\right. \\ &+ \left.\phi\left(\frac{\delta_1-\eta\rho}{\sqrt{1-\rho^2}}\right)\right]\phi(-\eta) - \frac{d\rho}{\sqrt{1-\rho^2}}\phi \\ &\left(\frac{-\delta_1+\eta\rho}{\sqrt{1-\rho^2}}\right)\phi(\eta) \end{aligned} \tag{B.6}$$

$$\frac{\partial^2E(P_T)}{\partial\delta_1^2} = \frac{(a-d-r)\rho}{\sqrt{1-\rho^2}}\phi\left(\frac{\eta-\delta_1\rho}{\sqrt{1-\rho^2}}\right)\phi(\delta_1) \tag{B.7}$$

$$\frac{\partial^2E(P_T)}{\partial\delta_2^2} = \frac{(r-a)\rho}{\sqrt{1-\rho^2}}\Phi\left(\frac{-\eta+\delta_2\rho}{\sqrt{1-\rho^2}}\right)\phi(\delta_2) \tag{B.8}$$

$$\frac{\partial^2 E(P_T)}{\partial\eta\,\partial\delta_1} = \frac{(d+\gamma-a)}{\sqrt{1-\rho^2}}\,\phi\!\left(\frac{\eta-\delta_1\rho}{\sqrt{1-\rho^2}}\right)\phi(\delta_1) \quad \text{(B.9)}$$

$$\frac{\partial^2 E(P_T)}{\partial\eta\,\partial\delta_2} = \frac{(\gamma-a)}{\sqrt{1-\rho^2}}\,\phi\!\left(\frac{-\eta+\delta_2\rho}{\sqrt{1-\rho^2}}\right)\phi(\delta_2) \quad \text{(B.10)}$$

$$\frac{\partial^2 E(P_T)}{\partial\delta_1\,\partial\delta_2} = 0 \quad \text{(B.11)}$$

Since $d \geq a > \gamma$, it is clear that $\partial E(P_T)/\partial\eta^2 < 0$, $\partial^2 E(P_T)/\partial\partial_1^2 < 0$, $\partial^2 E(P_T)/\partial\delta_2^2 < 0$, at $(\eta^*, \delta_1^*, \delta_2^*)$ and therefore the Hessian matrix is negative definite. Hence, $(\eta^*, \delta_1^*, \delta_2^*)$ represents a maximum point of equation (2). Setting the partial derivatives of $E(P_T)$ with respect to η and δ_i, $i=1,2$, to zero, we obtain the equations (3)~(5).

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