# Flexible Backup Supply and the Management of Lead-Time Uncertainty 

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## 1 Appendix

Proof of Proposition 1. 1) With a little algebra, we can get, if $1>r>0$ holds, then

$$
\begin{aligned}
R(\beta \mid r)= & \frac{1}{2} \frac{(\pi+h)^{2}-h^{2}}{\pi+h}\left(\beta T-\frac{\left(\pi r T-\left(c_{f}-c_{d}\right)\right)}{(\pi+h)^{2}-h^{2}}(\pi+h)\right)^{2}+\frac{1}{2} \pi r^{2} T^{2} \\
& +\frac{1}{2} h(1-r)^{2} T^{2}-\frac{1}{2} \frac{\left(\pi r T-\left(c_{f}-c_{d}\right)\right)^{2}}{(\pi+h)^{2}-h^{2}}(\pi+h)
\end{aligned}
$$

and if $r \geqslant 1$ holds, then

$$
\begin{aligned}
R(\beta \mid r)= & \frac{1}{2} \frac{(\pi+h)^{2}-h^{2}}{\pi+h}\left(\beta T-\frac{\left(\pi r T-\left(c_{f}-c_{d}\right)\right)}{(\pi+h)^{2}-h^{2}}(\pi+h)\right)^{2}+\pi r T^{2} \\
& -\frac{1}{2} \pi T^{2}-\frac{1}{2} \frac{\left(\pi r T-\left(c_{f}-c_{d}\right)\right)^{2}}{(\pi+h)^{2}-h^{2}}(\pi+h)
\end{aligned}
$$

Therefore $R(\beta \mid r)$ is minimized when $\beta T-\frac{\left(\pi r T-\left(c_{f}-c_{d}\right)\right)}{(\pi+h)^{2}-h^{2}}(\pi+h)=0$. This leads to our part 1) conclusion in view of the boundary conditions for $\beta$.
2) $\beta^{*}>0$ hold if and only if $\pi r T-\left(c_{f}-c_{d}\right)>0$; and $\beta^{*}<1$ hold if and only if $\frac{\left(\pi r T-\left(c_{f}-c_{d}\right)\right)}{(\pi+h)^{2}-h^{2}}(\pi+h)<T$. This leads to our part 2) conclusion.
3) Part 3) conclusion is true because $\left(c_{f}-c_{d}\right)>0$ and $\frac{\pi+h}{\pi+2 h}<1$.

Proof of Algorithm 1. We first examine the situations where $\underline{l_{f}} \leqslant T$ holds. We will analyze the cases defined in (8). For the case $\beta<\frac{l_{f}}{T}, r \leqslant 1$, since it is obvious that the optimal $l_{f}$ is $\underline{l_{f}}$, we focus on the decision for $\beta$. It can be seen that $R\left(\beta, l_{f}^{*} \mid r\right)$ is linear in $\beta$ with the first order
derivative

$$
\frac{\partial R\left(\beta, l_{f}^{*} \mid r\right)}{\partial \beta}=T\left(-\pi\left(r T-\underline{l_{f}}\right)+\left(c_{f}-c_{d}\right)\right)
$$

Thus, when $r T \leqslant \frac{c_{f}-c_{d}}{\pi}+\underline{l_{f}}$, the optimal $\beta$ is 0 ; when $r T>\frac{c_{f}-c_{d}}{\pi}+\underline{l_{f}}$, the optimal $\beta$ is $\frac{l_{f}}{\bar{T}}$.
For the case $\beta \geqslant \frac{l_{f}}{\bar{T}}, r \leqslant 1$, it can be seen that $R\left(\beta, l_{f} \mid r\right)$ is convex in $l_{f}$ with the first order derivative

$$
\frac{\partial R\left(\beta, l_{f} \mid r\right)}{\partial l_{f}}=(\pi+h) l_{f}-h \beta T
$$

Therefore the decision rule on $l_{f}$ for given $\beta$ is: to choose $l_{f}=\frac{h}{\pi+h} \beta T$ if $\frac{h}{\pi+h} \beta T \geqslant l_{f}$, and to choose $\underline{l_{f}}$ otherwise. The value of $R\left(\beta, l_{f} \mid r\right)$ at the optimal $l_{f}$, denoted by $R\left(\beta, l_{f}^{*} \mid r\right)$, is accordingly given below

$$
\begin{aligned}
R\left(\beta, l_{f}^{*} \mid r\right)= & \left(c_{f}-c_{d}\right) \beta T+\frac{1}{2} \pi(r T-\beta T)^{2}+\frac{1}{2} h(T-r T)^{2} \\
& +\left\{\begin{array}{cl}
\frac{1}{2} \pi\left(\underline{l}_{\underline{f}}\right)^{2}+\frac{1}{2} h\left(\beta T-\underline{l}_{f}\right)^{2} & \text { if } \beta T \geqslant l_{\underline{f}}, \frac{h}{\pi+h} \beta T<\underline{l}_{f}, r \leqslant 1 \\
\frac{1}{2} \frac{\pi h}{\pi+h}(\beta T)^{2} & \text { if } \beta T \geqslant \underline{l_{f}}, \frac{h}{\pi+h} \beta T \geqslant \underline{l_{f}}, r \leqslant 1
\end{array}\right.
\end{aligned}
$$

The first order derivative for $R\left(\beta, l_{f}^{*} \mid r\right)$ with respect to $\beta$ can be obtained as follows

$$
\frac{d R\left(\beta, l_{f}^{*} \mid r\right)}{d \beta}=\left\{\begin{array}{cl}
\left(\left(c_{f}-c_{d}\right)+(\pi+h) \beta T-h l_{\underline{f}}-\pi r T\right) T & \beta T \geqslant \underline{l_{f}}, \frac{h}{\pi h} \beta T<\underline{l_{f}}, r \leqslant 1 \\
\left(\left(c_{f}-c_{d}\right)+\frac{\pi h}{\pi+h} \beta T+\pi \beta T-\pi r T\right) T & \beta T \geqslant \underline{l_{f}}, \frac{h}{\pi+h} \beta T \geqslant \underline{l_{f}}, r \leqslant 1
\end{array}\right.
$$

Based on the expression above, it can be seen that with a little algebra, $R\left(\beta, l_{f}^{*} \mid r\right)$ is convex in $\beta$ over $[0, r]$ for given $r$. Therefore the optimal $\beta$ can be determined from the first order condition given above. Particularly, we have: a) if $r T<\frac{c_{f}-c_{d}}{\pi}+\underline{l_{f}}$, then the optimal $\beta$ is 0 . This is because $\frac{d R\left(\beta, l_{f}^{*} \mid r\right)}{d \beta}>0$ for $\left.\beta \in[0, r] ; \mathrm{b}\right)$ if $r T$ is greater than $\frac{c_{f}-c_{d}}{\pi}+\underline{l_{f}}$ and less than $\frac{c_{f}-c_{d}}{\pi}+\frac{(\pi+h)^{2}-h^{2}}{\pi h} l_{f}$, then the optimal $\beta T$ is $\frac{\pi}{\pi+h}(r T)+\frac{h}{\pi+h} \underline{l_{f}}-\frac{c_{f}-c_{d}}{\pi+h}$, which is less than $r T$. This is because $\frac{d R\left(\beta, l_{f}^{*} \mid r\right)}{d \beta}$ is negative at $\beta=\left(\frac{c_{f}-c_{d}}{\pi}+\underline{l_{f}}\right) / T$ and is positive at $\beta=\left(\frac{c_{f}-c_{d}}{\pi}+\frac{(\pi+h)^{2}-h^{2}}{\pi h} \underline{l_{f}}\right) / T$; c) if $r T$ is greater than $\frac{c_{f}-c_{d}}{\pi}+\frac{(\pi+h)^{2}-h^{2}}{\pi h} \underline{l_{f}}$, then the optimal $\beta T$ is $\frac{\pi+h}{(\pi+h)^{2}-h^{2}}\left(\pi r T-\left(c_{f}-c_{d}\right)\right)$, which is less than $r T$, since $\frac{d R\left(\beta, l_{f}^{*} \mid r\right)}{d \beta}$ is negative at $\beta=\left(\frac{c_{f}-c_{d}}{\pi}+\frac{(\pi+h)^{2}-h^{2}}{\pi h} \underline{l_{f}}\right) / T$.

Similar spirit above can be applied to analyze the cases for $r>1$. For the case $\beta<\frac{l_{f}}{\bar{T}}, r>1$, it is obvious that the optimal $l_{f}$ is $\underline{l_{f}}$. Regarding the decision for $\beta$, we can get: if $r T \leqslant \frac{c_{f}-c_{d}}{\pi}+\underline{l_{f}}$ holds, then the optimal $\beta$ is 0 ; if $r T>\frac{c_{f}-c_{d}}{\pi}+\underline{l_{f}}$ holds, then the optimal $\beta$ is $\frac{l_{f}}{T}$.

For the case $\beta \geqslant \frac{l_{f}}{\bar{T}}, r>1$, the optimal $l_{f}$ is $\underline{l_{f}}$ if $\frac{h}{\pi+h} \beta T<\underline{l_{f}}$ holds, and is $\frac{h}{\pi+h} \beta T$ otherwise.

The value of $R\left(\beta, l_{f} \mid r\right)$ at the optimal $l_{f}$, denoted by $R\left(\beta, l_{f}^{*} \mid r\right)$, is

$$
\begin{aligned}
& R\left(\beta, l_{f}^{*} \mid r\right)=\left(c_{f}-c_{d}\right) \beta T+ \\
& \left\{\begin{array}{c}
\frac{1}{2} \pi\left(\underline{l_{f}}\right)^{2}+\pi\left(\underline{l_{f}}-\beta T\right)\left(r T-\underline{l_{f}}\right)+\frac{1}{2} \pi\left(T-\underline{l}_{\underline{f}}\right)^{2}+\pi(r T-T)\left(T-\underline{l_{\underline{f}}}\right) \text { if } \beta<\frac{l_{f}}{\bar{T}}, r>1 \\
\frac{1}{2} \pi(T-\beta T)^{2}+\pi(T-\beta T)(r T-T)+\frac{1}{2} \pi\left(\underline{l_{f}}\right)^{2}+\frac{1}{2} h\left(\beta T-\underline{l}_{\underline{f}}\right)^{2} \quad \text { if } \beta T \geqslant l_{f}, \frac{h}{\pi+h} \beta T<l_{f}, r>1 \\
\frac{1}{2} \pi(T-\beta T)^{2}+\pi(T-\beta T)(r T-T)+\frac{1}{2} \frac{\pi h}{\pi+h}(\beta T)^{2} \text { if } \beta T \geqslant \underline{l_{f}}, \frac{h}{\pi+h} \beta T \geqslant \underline{l_{f}}, r>1
\end{array}\right.
\end{aligned}
$$

Based on the expression above, we can get the decision of the optimal $\beta T$. Particularly, we have: if $r T<\frac{c_{f}-c_{d}}{\pi}+\underline{l_{f}}$, then the optimal $\beta T$ is 0 ; if $r T$ is between $\frac{c_{f}-c_{d}}{\pi}+\underline{l_{f}}$ and $\frac{c_{f}-c_{d}}{\pi}+\frac{(\pi+h)^{2}-h^{2}}{\pi h} \underline{l_{f}}$, then the optimal $\beta T$ is $\frac{\pi}{\pi+h}(r T)+\frac{h}{\pi+h} \underline{l_{f}}-\frac{c_{f}-c_{d}}{\pi+h}$; if $r T$ is greater than $\frac{c_{f}-c_{d}}{\pi}+\frac{(\pi+h)^{2}-h^{2}}{\pi h} \underline{l_{f}}$, then the optimal $\beta T$ is $\frac{\pi+h}{(\pi+h)^{2}-h^{2}}\left(\pi r T-\left(c_{f}-c_{d}\right)\right)$. All of the optimal $\beta T$ have to be bounded above by $T$. Particularly, in case $\frac{\pi+h}{(\pi+h)^{2}-h^{2}}\left(\pi r T-\left(c_{f}-c_{d}\right)\right)>T$ and $r T>\frac{c_{f}-c_{d}}{\pi}+\frac{(\pi+h)^{2}-h^{2}}{\pi h} \underline{l_{f}}$, then the optimal $\beta T$ is $T$ with a cost of $\left(c_{f}-c_{d}\right) T+\frac{1}{2} \frac{\pi h}{\pi+h} T^{2}$ for $R\left(\beta^{*}, l_{f}^{*} \mid r\right)$ if $\frac{h}{\pi+h} T \geqslant \underline{l_{f}}$; and the optimal $\beta T$ is $T$ with a cost of $\left(c_{f}-c_{d}\right) T+\frac{1}{2} \pi\left(\underline{l_{f}}\right)^{2}+\frac{1}{2} h\left(T-\underline{l}_{f}\right)^{2}$ for $R\left(\beta^{*}, l_{f}^{*} \mid r\right)$ if $\frac{h}{\pi+h} T<\underline{l_{f}}$. In case that $\frac{\pi}{\pi+h}(r T)+\frac{h}{\pi+h} \underline{l_{f}}-\frac{c_{f}-c_{d}}{\pi+h}>T$ and $r T$ is between $\frac{c_{f}-c_{d}}{\pi}+\underline{l_{f}}$ and $\frac{c_{f}-c_{d}}{\pi}+\frac{(\pi+h)^{2}-h^{2}}{\pi h} \underline{l_{f}}$, then the optimal $\beta T$ is $T$ with a cost of $\left(c_{f}-c_{d}\right) T+\frac{1}{2} \pi\left(\underline{l_{f}}\right)^{2}+\frac{1}{2} h\left(T-\underline{l_{f}}\right)^{2}$ for $R\left(\beta^{*}, l_{f}^{*} \mid r\right)$.

We now examine the situations where $\underline{l}_{\underline{f}}>T$ holds. It is obvious that the optimal $l_{f}$ is $\underline{l_{f}}$. Recall that
$R\left(\beta, l_{f} \mid r\right)=\left(c_{f}-c_{d}\right) \beta T+\frac{1}{2} \pi(\beta T)^{2}+\pi(\beta T)\left(\underline{l_{f}}-\beta T\right)+\frac{1}{2} \pi(T-\beta T)^{2}+\pi(T-\beta T)(r T-T)$
It can be seen that with a little algebra, if $r T \leqslant \frac{c_{f}-c_{d}}{\pi}+\underline{l_{f}}$, then the optimal $\beta T$ is zero with a cost of $\frac{1}{2} \pi T^{2}+\pi T(r T-T)$ for $R\left(\beta^{*}, l_{f}^{*} \mid r\right)$; if $r T>\frac{c_{f}-\overline{c_{d}}}{\pi}+\underline{l_{f}}$, then the optimal $\beta T$ is $T$ with a cost of $\left(c_{f}-c_{d}\right) T+\frac{1}{2} \pi T^{2}+\pi T\left(\underline{l_{f}}-T\right)$ for $R\left(\beta^{*}, l_{f}^{*} \mid r\right)$.

Putting all the above together yields the proof for Algorithm 1.
Proof of Proposition 2. With a little algebra, we can decompose $\bar{V}_{\text {II }}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ as follows

$$
\begin{equation*}
\bar{V}_{\mathrm{II}}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)=\bar{V}_{\mathrm{II}}^{1}\left(Q_{1} \mid \xi_{0}, l, \widetilde{T}\right)+\bar{V}_{\mathrm{II}}^{2}\left(Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)+\left(c_{f}-c_{n}\right)(T-\widetilde{T}) \tag{13}
\end{equation*}
$$

where

$$
\begin{equation*}
\bar{V}_{\mathrm{II}}^{1}\left(Q_{1} \mid \xi_{0}, l, \widetilde{T}\right)=\left(c_{f}-c_{d}\right) Q_{1}+\frac{1}{2} \frac{\pi h}{\pi+h} Q_{1}^{2}+\frac{1}{2} \pi\left(\xi_{0}-Q_{1}\right)^{2} \tag{14}
\end{equation*}
$$

$$
\begin{align*}
\bar{V}_{\mathrm{II}}^{2}\left(Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)= & -\left(c_{f}-c_{d}\right) Q_{2}+\frac{1}{2} \frac{\pi h}{\pi+h}\left(T-\widetilde{T}-Q_{2}\right)^{2}  \tag{15}\\
& +\left\{\begin{array}{cl}
\frac{1}{2} h\left(\widetilde{T}+Q_{2}-\xi_{0}\right)^{2} & \text { if } Q_{1}<\xi_{0} \leqslant \widetilde{T}+Q_{2} \\
-\frac{1}{2} \pi\left(\widetilde{T}+Q_{2}-\xi_{0}\right)^{2} & \text { if } Q_{1} \leqslant \widetilde{T}+Q_{2}<\xi_{0}
\end{array}\right.
\end{align*}
$$

The first order derivatives of $\bar{V}_{\text {II }}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ with respect to $Q_{1}$ and $Q_{2}$ are, respectively,

$$
\begin{gather*}
\frac{\partial \bar{V}_{\mathrm{II}}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)}{\partial Q_{1}}=\left(c_{f}-c_{d}\right)+\frac{\pi h}{\pi+h} Q_{1}+\pi\left(Q_{1}-\xi_{0}\right)  \tag{16}\\
\frac{\partial \bar{V}_{\mathrm{II}}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)}{\partial Q_{2}}=-\left(c_{f}-c_{d}\right)+\frac{\pi h}{\pi+h}\left(\widetilde{T}+Q_{2}-T\right)  \tag{17}\\
\\
+\left\{\begin{array}{cl}
h\left(\widetilde{T}+Q_{2}-\xi_{0}\right) & \text { if } Q_{1}<\xi_{0} \leqslant \widetilde{T}+Q_{2} \\
-\pi\left(\widetilde{T}+Q_{2}-\xi_{0}\right) & \text { if } Q_{1} \leqslant \widetilde{T}+Q_{2}<\xi_{0}
\end{array}\right.
\end{gather*}
$$

Based on the expressions above (13), (14), (15), (16) and (17), we see that the following properties hold: 1) $\bar{V}_{\text {II }}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ is separable in $Q_{1}$ and $Q_{2}$; and, $\bar{V}_{\text {II }}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ is convex in $Q_{1}$; 2) $\bar{V}_{\text {II }}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ is concave in $Q_{2}$ for $\widetilde{T}+Q_{2}<\xi_{0}$ and is convex in $Q_{2}$ for $Q_{1}<\xi_{0} \leqslant \widetilde{T}+Q_{2}$. Furthermore, by the expressions for $Q_{1}\left(\xi_{0}\right)$ and $Q_{2}\left(\xi_{0}\right)$ and the expressions above, it can be seen that $Q^{U C} \widehat{=}\left(Q_{1}\left(\xi_{0}\right), Q_{2}\left(\xi_{0}\right)\right)$ is the unique local minimizer of (10) without constraints.

If $Q_{1}=Q_{2}$, then the first-order derivative of $\bar{V}_{\text {II }}\left(Q_{2}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ is

$$
\begin{align*}
\frac{\partial \bar{V}_{\mathrm{II}}\left(Q_{2}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)}{\partial Q_{2}}= & \frac{\pi h}{\pi+h} Q_{2}+\frac{\pi h}{\pi+h}\left(\widetilde{T}+Q_{2}-T\right)+\pi\left(Q_{2}-\xi_{0}\right)  \tag{18}\\
& +\left\{\begin{array}{cl}
h\left(\widetilde{T}+Q_{2}-\xi_{0}\right) & \text { if } Q_{2}<\xi_{0} \leqslant \widetilde{T}+Q_{2} \\
-\pi\left(\widetilde{T}+Q_{2}-\xi_{0}\right) & \text { if } Q_{2} \leqslant \widetilde{T}+Q_{2}<\xi_{0}
\end{array}\right.
\end{align*}
$$

The expression above implies that $\bar{V}_{\text {II }}\left(Q_{2}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ is piecewise convex in $Q_{2}$. Based on (18), we can get the expression for the minimizer of $\bar{V}_{\text {II }}\left(Q_{2}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$. This turns out that $Q^{O A} \widehat{=}\left(Q_{2}^{O A}, Q_{2}^{O A}\right)$ is the minimizer of $\Gamma_{\text {II }}\left(Q_{2}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$.

If $Q_{1}=\widetilde{T}+Q_{2}$, then $\bar{V}_{\text {II }}\left(\widetilde{T}+Q_{2}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ has an expression

$$
\left(c_{f}-c_{d}\right) \widetilde{T}+\left(c_{f}-c_{n}\right)(T-\widetilde{T})+\frac{1}{2} \frac{\pi h}{\pi+h}\left(\widetilde{T}+Q_{2}\right)^{2}+\frac{1}{2} \frac{\pi h}{\pi+h}\left(T-\widetilde{T}-Q_{2}\right)^{2}
$$

which is convex in $Q_{2}$. It can be easily verified that $Q^{B C} \widehat{=}\left(\widetilde{T}+Q_{2}^{B C}, Q_{2}^{B C}\right)$ is the minimizer of $\bar{V}_{\text {II }}\left(\widetilde{T}+Q_{2}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$. Similarly it can be shown that if $Q_{2}=0$, then $\bar{V}_{\text {II }}\left(Q_{1}, 0 \mid \xi_{0}, l, \widetilde{T}\right)$ is minimized at $Q^{C O} \widehat{=}\left(Q_{1}^{C O}, 0\right)$ satisfying

$$
Q_{1}^{C O}=\left\{\begin{array}{cc}
0 & \text { if } \pi \xi_{0} \leqslant\left(c_{f}-c_{d}\right) \\
\frac{\pi \xi_{0}-\left(c_{f}-c_{d}\right)}{\frac{\pi h}{\pi+h}+\pi} & \text { if } 0 \leqslant \frac{\pi \xi_{0}-\left(c_{f}-c_{d}\right)}{\frac{\pi h}{\pi h}+\pi} \leqslant \widetilde{T} \\
\widetilde{T} & \text { if } \frac{\pi \xi_{0}-\left(c_{f}-c_{d}\right)}{\frac{\pi h}{\pi+h}+\pi} \geqslant \widetilde{T}
\end{array}\right.
$$

, and that if $Q_{2}=T-\widetilde{T}$, then $\bar{V}_{\mathrm{II}}\left(Q_{1}, T-\widetilde{T} \mid \xi_{0}, l, \widetilde{T}\right)$ is minimized at $Q^{A B}=\left(Q_{1}^{A B}, T-\widetilde{T}\right)$ satisfying

$$
Q_{1}^{A B}=\left\{\begin{array}{cc}
T-\widetilde{T} & \text { if } \frac{\pi \xi_{0}-\left(c_{f}-c_{d}\right)}{\frac{\pi h}{\pi h}+\pi} \leqslant T-\widetilde{T} \\
\frac{\pi \xi_{0}-\left(c_{f}-c_{d}\right)}{\frac{\pi h}{\pi+h}+\pi} & \text { if } T-\widetilde{T} \leqslant \frac{\pi \xi_{0}-\left(c_{f}-c_{d}\right)}{\pi h} \leqslant T \\
T & \text { if } \frac{\pi \xi_{0}-\left(c_{f}-c_{d}\right)}{\frac{\pi h}{\pi+h}+\pi} \geqslant T
\end{array}\right.
$$

Now, we are ready to show Proposition 2 is valid.
1). Since $\xi_{0} \geqslant T, Q_{2}+\widetilde{T} \leqslant \xi_{0}$ holds for any $Q_{2} \leqslant T-\widetilde{T}$. Thus $\bar{V}_{\mathrm{II}}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ is concave in $Q_{2}$. For any $Q_{1}, \bar{V}_{I I}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ could be minimized only at the boundary points of the feasible set $O A B C$. The minimum of $\bar{V}_{I I}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ could be achieved only at the four sides of the feasible set $O A B C$ illustrated in Figure ??. Since the minimum of $\bar{V}_{I I}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ on the four sides could only be achieved at one of the four points $Q^{O A}, Q^{C O}, Q^{B C}$ and $Q^{A B}$, respectively, part 1) follows.
2). Since $\xi_{0}<T$, there may exist $Q_{2}$ such that $Q_{2}+\widetilde{T}>\xi_{0}$ holds. Thus $\bar{V}_{I I}^{2}\left(Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ is concave-convex in $Q_{2}$. For any $Q_{1}, \bar{V}_{I I}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ could be minimized only at the boundary points of the feasible set $O A B C$ or $Q_{2}\left(\xi_{0}\right)$. If $Q^{U C} \widehat{=}\left(Q_{1}\left(\xi_{0}\right), Q_{2}\left(\xi_{0}\right)\right)$ falls outside the feasible set $O A B C$, then any interior point is dominated by some point on the four sides of the feasible region: $\overline{O A}, \overline{C O}, \overline{B C}$ and $\overline{A B}$; therefore, the minimum of $\bar{V}_{I I}\left(Q_{1}, Q_{2} \mid \xi_{0}, l, \widetilde{T}\right)$ could only be achieved at one of the four points $Q^{O A}, Q^{C O}, Q^{B C}$ and $Q^{A B}$. If $Q^{U C} \widehat{=}\left(Q_{1}\left(\xi_{0}\right), Q_{2}\left(\xi_{0}\right)\right)$ is an interior point of the feasible set $O A B C$, then any interior point is dominated by either $Q^{U C}$ or some point on the four sides. Thus, part 2) follows.

## Modeling parameters and their values for all the numerical examples

| Figure | Modeling parameters values |
| :--- | :--- |
| 1. | $\pi=1.8, h=.3, T=14, \xi \sim \operatorname{Gamma}(\mu, \theta), \mu=5, \theta=3, c_{f}-c_{d}=2$ |
| 2.a, 2.b | $\pi=1.8, h=.3, T=14, \xi \sim \operatorname{Gamma}(\mu, \theta), \mu=5, \theta=3$ |
| 3. | $\pi=1.8, h=.3, T=14, \xi \sim \operatorname{Gamma}(\mu, \theta), \mu=5, \theta=3$ or $5, c_{f}-c_{d}=2$ |
| 4.a, 4.b | $\pi=1.8, h=.3, T=14, \xi \sim \operatorname{Gamma}(\mu, \theta), \mu=5, \theta=3$ or $5, c_{f}-c_{d}=2$ |
| 6.a, 6.b | $\pi=1.8, h=.3, T=14, \xi \sim \operatorname{Gamma}(\mu, \theta), \mu=5, \theta=3$ or $5, c_{f}-c_{d}=2, c_{f}-c_{n}=1.5$ |
| 7.a, 7.b | $\pi=1.8, h=.3, T=14, \xi \sim \operatorname{Gamma}(\mu, \theta), \mu=5, \theta=3, c_{n}-c_{d}=1, l_{f}=5$ |
| 8 | $\pi=1.8, T=14, \xi \sim \operatorname{Gamma}(\mu, \theta), \mu=5, \theta=3, c_{f}=5, c_{n}=4, c_{d}=3$ |

