Optimal Energy Commitments with Storage and Intermittent Supply

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We formulate and solve the problem of making advance energy commitments for wind farms in the presence of a storage device with conversion losses, mean-reverting price process, and an auto-regressive energy generation process from wind. We derive an optimal commitment policy under the assumption that wind energy is uniformly distributed. Then, the stationary distribution of the storage level corresponding to the optimal policy is obtained, from which the economic value of the storage as the relative increase in the expected revenue due to the existence of storage is obtained.

Key words: Markov Decision Process, Dynamic Programming, Energy

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1. Introduction

The emphasis on renewables, such as the goal set by the Department of Energy to have 20 percent of electric power from wind by 2030, has raised the importance of efficiently managing wind, and understanding the factors that affect the cost of using wind. Currently, wind energy accounts for a small fraction in the market and the grid operators allow the wind energy producers to deliver any amount of energy they produce at a given time. However, as the share of wind energy in the market grow, such a policy will become impractical, and grid operators will need to make commitments on the amount of wind energy that will be delivered in advance. Unfortunately, making commitments is complicated by the inherent uncertainty of wind. This uncertainty can be mitigated by the presence of storage, which also introduces the dimension of losses due to the conversion needed to store and retrieve energy. This paper derives an optimal policy for the case in which at time $t$, we
make commitments on the amount of energy we deliver during the time interval \([t, t+1]\). That is, we participate in a day ahead market in which we commit once a day, or we participate in an hour ahead market where we make commitments every hour.

In this paper, we derive an optimal policy for making energy commitments in the presence of storage and storage conversion losses. We assume that we are a small player in a large market, making it possible to sell all of the energy we produce as long as we make advance commitments. The problem has cosmetic similarities with classical inventory problems (storing product to meet demand), but with some fundamental differences. Inventory problems are typically trying to control the supply of product to meet an exogenous demand (Axsäter (2000), Zipkin (2000)). In our problem, we have exogenous supply (energy generated from wind) to meet demand by making advance commitments. We may store energy when it exceeds the commitments we have made, but we may incur significant conversion losses. In addition, the capacity of the storage device is limited.

In this paper, we assume that in order to participate in the spot market, a wind farm operator must sign a contract in advance and promise to deliver a predetermined amount of electricity. However, wind velocity cannot be predicted with any certainty and hence electricity production from wind cannot be scheduled, imposing challenges to the management of wind energy power systems. To alleviate the difficulties and allow the energy utilization to be more effective, attaching an energy storage system to the wind turbine is desirable (Castronuovo and Lopez (2004), Korpaas, et al. (2003), Garcia-Gonzalez, et al. (2008), Brunetto and Tina (2007), Ibrahim, et al. (2008)). Storage allows the operator to convert the electricity generated from the wind turbine to potential energy when the actual electricity production is higher than the desired level of production, and then convert it back to electricity when the actual electricity production is lower than the desired level of production. Storage is an insurance that allows the operator to make advance commitments without assuming too much risk; when the electricity produced from the wind turbine falls short of the commitment, the potential energy in storage can be used to compensate for the gap and fulfill
the commitment. The conversion loss associated with the storage can be seen as the marginal cost of the insurance.

Operating a wind farm with storage requires solving for the amount of electricity to commit to sell at a given time based on the forecast of the electricity generating capacity of the wind turbines and the spot market price of the electricity while trying to maximize the expectation of the cumulative profit over time. As of this writing, this problem has not been properly solved. One problem that is similar to the one described above is the problem of reservoir operation, which also involves managing a storage with random supply. Nandalal and Bogardi (2007) is an excellent reference for dynamic programming (DP) based solutions for the reservoir problem. The difference between the problem of wind farm operation presented in this paper and the problem of reservoir operations comes from the notion of advance commitments.

The goal of a wind farm operator is to maximize the cumulative profit over time by computing the amount of electricity to commit to sell during the time interval \([t, t + 1)\) at each time \(t\). Brown and Matos (2008), Brunetto and Tina (2007), Castronuovo and Lopez (2004), and Korpaas, et al. (2003) attempt to solve the problem by solving a deterministic optimization problem given a particular sample path over a finite horizon and then averaging the results over the sample paths. The sample paths are drawn from a fixed \((T + 1)\)-dimensional distribution describing the electricity generated from the wind farm during the time interval \([t, t + 1)\) for each \(t = 0, 1, \ldots, T\). However, this approach does not produce a valid, admissible policy. In practice, we need a policy that allows the wind farm operator to compute at time \(t\) the amount of electricity to commit to sell during the time interval \([t, t + 1)\) based on the state of the environment at time \(t\). The objective of this paper is to find such a policy and analyze it.

The contributions of this paper are as follows. 1) We establish assumptions on the electricity price and the distribution of wind, size of the storage, and the decision epoch intervals that allow us to derive the optimal policy for energy commitment in a closed form and explain the implications of those assumptions. 2) Under those assumptions, we derive the optimal policy for advance
energy commitment in a simple, analytical form, when we have a storage with an arbitrary round-trip efficiency, and when electricity prices are mean-reverting. The optimal policy obtained under such assumptions resembles the optimal policy for the well-known newsvendor problem (Khouja (1999), Petruzzi and Dada (1999)).

3) We obtain the stationary distribution of the storage level corresponding to the optimal policy, from which we find the economic value of the storage as the relative increase in the expected revenue due to the existence of storage. 4) We test our policy using wind energy generated from truncated Gaussian distributions and demonstrate that the error introduced by assuming a uniform distribution for wind is reasonably small.

This paper is organized as follows. In §2, we model the wind energy storage problem as an MDP with continuous-state and control variables. In §3, we present our assumptions and the structural properties of the optimal value function of the MDP. In §4, the optimal policy for the infinite horizon problem for a storage with general round-trip efficiency is obtained. Then, the stationary distribution of the storage level corresponding to the optimal policy is obtained, from which the economic value of the storage as the relative increase in revenue due to existence of storage, is derived. In §5, we compute the economic value of storage using the wind speed data obtained from the North American Land Data Assimilation System (NLDAS) project (Cosgrove, et al. (2003)), and the electricity price data provided by a utility company. In §6, we summarize our conclusions.

2. Model

Operating a wind farm depends on two markets: the electricity spot market and the regulating market. We sell to the spot market and pay a penalty when we fail to meet our commitment. The grid operator buys energy from the regulating market when we fail to meet our commitment. In the spot market, the energy producers make their commitments to deliver (sell) electricity in advance while the regulating market is a marketplace for reserve energy in which the producers have the ability to sell electricity on a shorter notice than the spot market (Korpaas, et al. (2003), MacKerron and Pearson (2000), Morthorst (2003)). As a wind farm operator, when the electricity
production exceeds our expectation and we have an excess amount of electricity left over after fulfilling the contractual commitment, we store the excess amount. On the other hand, when the electricity production falls too short to meet the contractual commitment, we have to pay a premium, a penalty for failing to meet the commitment, while the producers in the regulating market make up for the gap. Therefore, if we commit too much, we can actually lose money. We have revenues from our sale on the spot market and costs from tapping into the regulating market when we fail to meet our commitment for delivery on the spot market (see Chapter 16 of MacKerron and Pearson (2000) for a detailed exposition of the market system).

At each time $t$, the market participants submit their bid for the supply and demand for electricity that must be delivered during the time interval $[t, t+1)$. The market overseer collects the bidding information and determines the spot market and the regulating market price for the time interval $[t, t+1)$ shortly after the participants submit their bids. Therefore, as a wind farm operator, we do not know what the prices will be when we are making our commitments.

We make the following assumptions. First, we assume that at each time $t$, we have a probability distribution of the electricity we will generate during the time interval $[t, t+1)$. Second, we assume that we are a small participant in the market such that the market can always absorb our supply and the effect of our bidding on the expected spot market and the regulating market prices of the electricity is negligible. Then, the prices can be treated as exogenous variables and we only need to determine the amount of electricity to commit to sell. Third, we assume that the spot market price of the electricity is mean-reverting and the ratio of the expected spot market price over the expected regulating market price is always less than the round-trip efficiency of our storage with the discount factor. Otherwise, the cost of using the storage, which can be measured by the conversion loss, will be greater than the expected cost of tapping into the reserve energy in the regulating market, annihilating the purpose of using a storage in the first place. The third assumption is crucial in maintaining the concavity of the optimization problem.
2.1. System Parameters

\( R_{\text{max}} = \) upper limit on the storage. \textit{(unit: storage energy capacity unit)}

\( \rho_R = \) coefficient used to convert the generated electricity to potential energy in the storage. \textit{(unit: storage unit / electricity unit)}

\( \rho_E = \) coefficient used to convert the potential energy in the storage to electricity. \textit{(unit: electricity unit / storage unit)}

Note that \(0 < \rho_E \rho_R < 1\), where \(\rho_E \rho_R\) denotes the round-trip efficiency. Throughout this paper, \(1 - \rho_E \rho_R\) is referred to as the conversion loss from storage. \(\rho_R \rho_E\) is around 0.6–0.8 for most of the existing storage systems (Sioshanshi, et al. (2009)).

\( \mu_p = \) mean of the spot market price of the electricity. \textit{(unit: dollar / electricity unit)}

\( \sigma_p = \) standard deviation of the change in spot market price of the electricity. \textit{(unit: dollar / electricity unit)}

\( \kappa = \) mean-reversion parameter for the spot market price of the electricity. \( \kappa \) is proportional to the expected frequency at which the spot market price crosses the mean per unit time. \textit{(unit: 1 / time unit)}

\( \Delta \tau = \) time interval between decision epochs.

\( m = \) slope of the penalty cost for over-commitment.

\( b = \) intercept of the penalty cost for over-commitment. \textit{(unit: dollar / electricity unit)}

That is, when the spot market price of the electricity is \(p_t\), the penalty for over-commitment is \(mp_t + b\).

\( \mu_Y = \) mean of the electricity generated from the wind farm per unit time. \textit{(unit: electricity unit / time unit)}

\( \sigma_Y = \) standard deviation per unit time of the electricity generated from the wind farm. \textit{(unit: electricity unit / time unit)}

\( \gamma = \) discount factor in the MDP model. \(0 < \gamma < 1\).
2.2. State Variables

Let \( t \in \mathbb{N}_+ \) be a discrete time index corresponding to the decision epoch. The actual time corresponding to the time index \( t \) is \( t \Delta \tau \).

- \( R_t = \) storage level at time \( t \). \( 0 \leq R_t \leq R_{\text{max}}, \forall t. \)
- \( Y_t = \) electricity generated from the wind turbines during the time interval \( [t-1,t) \). \( Y_t \geq 0, \forall t. \)
- \( p_t = \) spot market price for electricity delivered during the time interval \( [t-1,t) \). \( p_t \geq 0, \forall t. \)
- \( W_t = \left( (Y_t)_{1 \leq \nu \leq t}, p_t \right) = \) exogenous state of the system.
- \( S_t = (R_t, W_t) = \) state of the system at time \( t \).

2.3. Decision (Action) Variable

\( x_t = \) amount of electricity we commit to sell on the spot market during the time interval \( [t, t+1) \) determined by signing the contract at time \( t \). \( x_t \geq 0. \)

Since we are making an advance commitment, \( x_t \) is not constrained by \( R_t \). The lack of an upper bound on \( x_t \) indicates that we are a small player in the market and hence there will always be enough demand in the market to absorb our supply as long as we are making an advance commitment.

2.4. Exogenous Process

\( \hat{y}_t = \) noise that captures the random evolution of \( Y_t \). Specifically,

\[
Y_{t+1} = \mu_Y \Delta \tau + \sum_{i=0}^{M-1} \alpha_i (Y_{t-i} - \mu_Y \Delta \tau) + \hat{y}_{t+1},
\]

for some order \( M \) and coefficients \( \alpha_i \) for \( 0 \leq i \leq M-1 \). \( (\hat{y}_t)_{t \geq 1} \) and \( (Y_t)_{t \geq 1} \) must be proportional to \( \Delta \tau \).

\( \hat{p}_t = \) noise that captures the random evolution of \( p_t \). Specifically, we use a discrete-time version of the Ornstein-Uhlenbeck process:

\[
p_{t+1} - p_t = \kappa (\mu_p - p_t) \Delta \tau + \hat{p}_{t+1}.
\]

Let \( \Omega \) be the set of all possible outcomes and let \( \mathcal{F} \) be a \( \sigma \)-algebra on the set, with filtrations \( \mathcal{F}_t \) generated by the information given up to time \( t \):

\[
\mathcal{F}_t = \sigma (S_0, x_0, Y_1, S_1, x_1, Y_2, S_2, x_2, ..., Y_t, S_t, x_t).
\]
is the probability measure on the measure space \((\Omega, \mathcal{F})\). Throughout this paper, a variable with subscript \(t\) is unknown (random) at time \(t - 1\) and becomes known (deterministic) at time \(t\). In other words, a variable with subscript \(t\) is \(\mathcal{F}_t\)-measurable. We have defined the state of our system at time \(t\) as all variables that are \(\mathcal{F}_t\)-measurable and needed to compute our decision at time \(t\).

### 2.5. Storage Transition Function

\[
R_{t+1} = \begin{cases} 
R_{\text{max}}, & \text{if } R_t + \rho_R (Y_{t+1} - x_t) \geq R_{\text{max}}, \\
R_t + \frac{1}{\rho_R} (Y_{t+1} - x_t), & \text{if } x_t < Y_{t+1}, \\
R_t - \frac{1}{\rho_E} (x_t - Y_{t+1}), & \text{if } Y_{t+1} \leq x_t < \rho_E R_t + Y_{t+1}, \\
0, & \text{if } x_t \geq \rho_E R_t + Y_{t+1}.
\end{cases}
\]

If \(Y_{t+1}\) exceeds the commitment \(x_t\), we store the excess amount \(Y_{t+1} - x_t\) with a conversion factor, \(\rho_R\). If \(Y_{t+1}\) is less than \(x_t\), the potential energy in the storage must be converted into electricity with a conversion factor, \(\rho_E\), to fulfill the gap, \(x_t - Y_{t+1}\). If the amount of electricity generated during the time interval \([t, t+1]\) plus the electricity that can be obtained by converting the potential energy in the storage is not enough to cover the contractual commitment, we deplete our storage and we have to pay for the gap. It is important to note the difference between the storage transition function shown above and the transition functions that generally appear in traditional inventory management and resource allocation problems (Axsgärd (2000), Zipkin (2000)). Unlike many of the transition functions that appear in traditional problems, here \(x_t\) is not linearly constrained by \(R_t\) and hence \(R_{t+1}\) is not a concave or convex function of \(x_t\) or \(R_t\), which makes the concavity of the optimization problem not obvious.

### 2.6. Contribution (Revenue) Function

The profit we make during the time interval \([t, t+1]\) is given by

\[
\hat{C}_{t+1} = \begin{cases} 
p_{t+1} x_t, & \text{if } x_t < \rho_E R_t + Y_{t+1}, \\
p_{t+1} x_t - (mp_{t+1} + b) [x_t - (\rho_E R_t + Y_{t+1})], & \text{if } x_t \geq \rho_E R_t + Y_{t+1}.
\end{cases}
\]

\(p_{t+1} x_t\) is the profit we earn by delivering \(x_t\) amount of electricity to the market during the time interval \([t, t+1]\), and \(mp_{t+1} + b\) is the penalty we pay in the case of over-commitment. Assume

\[m \geq \frac{\gamma}{\rho_E \rho_R} \quad \text{and} \quad b \geq \frac{\gamma}{\rho_E \rho_R} \mu_p.\]
Then, the cost of using the storage, which can be measured by the conversion loss, is less than the cost of over-commitment. Otherwise, for the purpose of maximizing the revenue, there will be no reason to use a storage in the first place. This affine penalty is sufficient to ensure the concavity of the stochastic optimization problem. Note that these lower bounds on the penalty factor are unfavorable assumptions - they make the environment in which we operate more adverse and lead to a more conservative policy. If we have to operate in an environment where the above assumptions do not hold, the optimal policy derived in this paper under the above assumptions may not be optimal in maximizing revenue, but it should still be robust with limited risk - we lose less money than expected in the case of over-commitment. Define

\[
C(S_t, x_t) := E \left[ \hat{C}_{t+1} \mid S_t, x_t \right] = \left[ \mu_p + (1 - \kappa \Delta \tau) \left( p_t - \mu_p \right) \right] \left[ x_t - m \cdot \int_{0 \leq y \leq x_t - \rho E R_t} F_t(y)dy \right] - b \int_{0 \leq y \leq x_t - \rho E R_t} F_t(y)dy, \tag{4}
\]

where

\[
F_t(y) = \mathbb{P}[Y_{t+1} \leq y \mid \mathcal{F}_t].
\]

\(C(\cdot)\) is known as the contribution, or the reward function. See §1 in the e-companion to this paper for the derivation of (4).

2.7. Objective Function

Let \(\Pi\) be the set of all policies. A policy is an \(\mathcal{F}_t\)-measurable function \(X^\pi(S_t)\) that describes the mapping from the state at time \(t\), \(S_t\), to the decision at time \(t\), \(x_t\). For each \(\pi \in \Pi\), let

\[
G^\pi_t(S_t) := E \left[ \sum_{t'=t}^T \gamma^{t'-t} C(S_{t'}, X^\pi(S_{t'})) \mid S_t \right], \quad \forall 0 \leq t \leq T,
\]

where \(0 < \gamma < 1\) is the discount factor and \(T\) indicates the end of the horizon. The objective, then, is to find an optimal policy \(\pi = \pi^*\) that satisfies

\[
G^\pi^*_t(S_t) = \sup_{\pi \in \Pi} G^\pi_t(S_t),
\]

for all \(0 \leq t \leq T\).
3. Main Assumptions and Structural Result

The main contribution of this paper is the closed form representation of the optimal policy for advance intermittent energy commitments that also allows us to express the value of the energy storage in a closed form. In order to achieve the results, we need assumptions on the probability distribution of the spot market electricity price and wind energy, limit on the storage size, and the decision epoch intervals.

3.1. Electricity Price and Wind Energy

First, we assume that \( (\hat{p}_t)_{t \geq 0} \) and \( (\hat{y}_t)_{t \geq 1} \) are independent in \( (\Omega, \mathcal{F}, \mathbb{P}) \). It is well-known that the price of the electricity mainly depends on the demand as well as the main source of energy that is controllable; for example, electricity generated from coal plants. It is fairly reasonable to assume that the fluctuation in the electricity price is not significantly influenced by the fluctuation in the uncontrollable and unpredictable energy supply from our wind farm, especially if we are a small player in the market. In most cases, intermittent energy plays a minor role in the electricity markets, anyway.

Next, assume \( (\hat{p}_t)_{t \geq 0} \) are i.i.d with distribution \( \mathcal{N}(0, \sigma_p^2) \). Then, \( (p_t)_{t \geq 0} \) is a standard mean-reverting process and

\[
\mathbb{E}[p_{t+n}|\mathcal{F}_t] = \mu_p + (1 - \kappa \Delta \tau)^n (p_t - \mu_p), \quad \forall n, t \in \mathbb{N}_+.
\]  

Similarly, assume \( (\hat{y}_t)_{t \geq 1} \) are 0-mean and i.i.d with standard deviation \( \sigma_Y \Delta \tau \). Then, in most cases, the distributions of \( (\hat{y}_t)_{t \geq 1} \) are assumed to be truncated Gaussian with mean 0 and standard deviation \( \sigma_Y \Delta \tau \). However, in this paper, we assume that \( (\hat{y}_t)_{t \geq 1} \) are uniformly distributed with mean 0 with standard deviation \( \sigma_Y \Delta \tau \). Assuming that \( (\hat{y}_t)_{t \geq 1} \) are uniformly distributed allows us to explicitly compute various expectations that are needed to derive the optimal policy in a closed form. Since a truncated Gaussian distribution is bounded, as long as we match the mean and the variance, a uniform distribution can be a statistically robust substitute for the truncated Gaussian distribution in the context of optimizing a value function. This fact is demonstrated in
§5 where we conduct numerical experiments in which we apply the optimal policy derived under the assumption of uniformly distributed $(\hat{y}_t)_{t \geq 1}$ to the data generated from truncated Gaussian distributions. Then, given $F_t$, $Y_{t+1} \sim \mathcal{U} (\theta_t, \theta_t + \beta)$, where

$$
\beta := 2\sqrt{3} \sigma_Y \Delta \tau
$$

and

$$
\theta_t := \mu_Y \Delta \tau + \sum_{i=0}^{M-1} \alpha_i (Y_{t-i} - \mu_Y \Delta \tau) - \frac{\beta}{2}, \; \forall t. \tag{6}
$$

The cumulative density function (CDF) of $Y_{t+1}$ computed at time $t$ is given by

$$
F_t(y) = \mathbb{P}[Y_{t+1} \leq y \mid F_t] = \begin{cases} 
0, & \text{if } y < \theta_t \\
\frac{y-\theta_t}{\beta}, & \text{if } \theta_t \leq y \leq \theta_t + \beta \\
1, & \text{if } y > \theta_t + \beta
\end{cases}
$$

The expected contribution function $C(\cdot)$ is not indexed by $t$ because the CDF $F_t(\cdot)$ is determined by $\theta_t$, which is a deterministic function of $S_t$. The expected contribution is completely determined by $S_t$ and $x_t$. However, it is important to note that $\theta_t$ and $\beta$ do not necessarily have to be defined as shown above. The results obtained in this paper are applicable as long as we use a forecasting model that predicts that the electricity produced during the time interval $[t, t+1)$ is uniformly distributed given $F_t$.

### 3.2. Size of the Storage

Next, we need an assumption on the size of the storage. If we have an infinitely large storage, a naive policy that stores the energy when the expected spot market price is less than some fixed price over the mean and committing to sell only the energy in storage plus the energy we are certain to produce when the spot market price is greater than that fixed price, will be a riskless arbitrage policy. Arbitrage here means that there is zero probability of losing money due to over-commitment or losing energy due to the storage being full. There is always a significant conversion loss. Such a case is comparable to trading a stock whose price is mean-reverting. In reality, a storage with reasonably good round-trip efficiency that can be charged and discharged in a short amount of time will be expensive to build and maintain, and we need an intelligent way of determining the
appropriate size of the storage. We propose that the size of the storage be determined in comparison to \( \nu \), given by:

\[
\nu := \rho_R \frac{\sigma_Y}{\kappa} 2\sqrt{3} \min \left[ \frac{m-1}{m}, \frac{b}{b + \rho_E \rho_R \gamma \mu_p} \right].
\] (7)

It is obvious that as the penalty factors \( m \) and \( b \) become larger, we need to allow for a larger storage since our commitment level will be more conservative and we will end up storing more energy. Also, if the round-trip efficiency of the storage \( \rho_E \rho_R \) is small, we must allow for a larger storage in order to compensate for the energy that will be lost in conversion. Next, since \( \gamma \mu_p \) is the discounted expected spot market price of the electricity, if \( \gamma \mu_p \) is small, we need to allow for a larger storage since our commitment level will be more conservative.

What makes \( \nu \) interesting is the term \( \sigma_Y / \kappa \). Recall that \( \kappa \) is proportional to the expected number of times the price crosses the mean per unit time. Then, \( 1/\kappa \) is proportional to the expected amount of time between two consecutive crossings. Therefore, \( \sigma_Y / \kappa \) is proportional to the volatility in the wind energy that is produced while the spot market price “completes a cycle.” Since \( R_{\text{max}} \) determines our ability to accumulate energy while the price moves, we must allow for a larger storage when \( \sigma_Y / \kappa \) gets larger. If \( R_{\text{max}} = \infty^+ \), we can implement an arbitrage policy, as explained above. If \( R_{\text{max}} \leq \nu \), we must implement a more active, risk-taking policy that considers the movement of the price towards the mean but not “count on” the price reaching a desirable level within a desirable amount of time. The middle regime in which \( \nu < R_{\text{max}} < \infty^+ \) will demand the most complicated policy that mixes risk-taking with arbitrage. Finding the optimal policy in this middle regime will be an interesting research topic, but it is beyond the scope of this paper. For this paper, we assume

\[
R_{\text{max}} \leq \rho_R \frac{\sigma_Y}{\kappa} 2\sqrt{3} \min \left[ \frac{m-1}{m}, \frac{b}{b + \rho_E \rho_R \gamma \mu_p} \right].
\] (8)

(8) is necessary to have (10) shown in the next section, which in turn is necessary to prove the lemma (18) that is used to derive the marginal value function in a closed form. However, even though (8) is imposed for mathematical convenience, numbers come out reasonable, as shown in §5. If we use real data to obtain \( \sigma_Y, \kappa, \mu_p, \rho_E \rho_R \) and use \( m \) and \( b \) that satisfy (3), if we let
for example, (8) is satisfied. That is, we can have the size of $R_{\text{max}}$ in the same order of magnitude of the standard deviation in wind energy. Having a storage of limited size allows us to obtain the optimal policy in a closed form and provide us with various insights, as is shown in §4. Moreover, before investing a significant amount of capital to build a large storage, it is reasonable to assume that wind farm operators will start with a small storage, study its effects, and then subsequently make the investment for additional storage. This paper derives the optimal policy for energy commitment and the corresponding value of the storage when the storage is small.

As will be shown in §4, the optimal policy under the assumption (8) will still depend on the mean of the electricity price and how far the price is away from the mean. However, the optimal policy will be based on the premise that the storage is not large enough to allow us to avoid the risk of over-commitment by waiting for the price to rise without facing the risk of losing energy due to the storage being full. Thus, (8) forces us to always balance the risk of over-commitment and the risk of under-commitment. We not only want to avoid paying the penalty for over-commitment, but we also want to avoid committing too little and lose energy due to conversion and the storage being full.

Suppose we have a large storage device and (8) is violated, but we choose to implement the policy derived in this paper that is optimal under the assumption of small storage, anyway. Then, the cost of over-commitment will not change, but the risk of under-commitment will be smaller than expected because we are less likely to lose energy due to the storage being full. Therefore, the optimal policy derived in this paper will still be robust when the assumption (8) does not hold.

### 3.3. Decision Epoch Interval

Finally, we need an assumption on how often we make our commitment decisions. We can re-arrange the terms from (8) to obtain:

$$\max \left[ \frac{R_{\text{max}} (m - \rho_E \rho_R \gamma)}{2\sqrt{3}(m - 1) \rho_R \sigma_Y - R_{\text{max}} \rho_E \rho_R \gamma \kappa}, \frac{R_{\text{max}} b}{2\sqrt{3}\rho_R \sigma_Y b - R_{\text{max}} \rho_E \rho_R \gamma \kappa \mu_p} \right] \leq \frac{1}{\kappa}.$$
We assume that the time interval $\Delta \tau$ between our decision epochs satisfies the following:

$$
\max \left[ \frac{R_{\max} (m - \rho_E \rho R \gamma)}{2\sqrt{3}(m - 1) \rho_R \sigma_Y - R_{\max} \rho_E \rho R \gamma \kappa}, \frac{R_{\max} b}{2\sqrt{3}(m - 1) \rho_R \sigma_Y b - R_{\max} \rho_E \rho R \gamma \kappa \mu_p} \right] \leq \Delta \tau \leq \frac{1}{\kappa}.
$$

(9) ensures that the price always moves toward the mean in expectation, but does not overshoot and move pass the mean in expectation. The lower bound can be re-arranged to be written as

$$
R_{\max} \leq \rho_R \beta \min \left[ \frac{m - \rho E \rho R (1 - \kappa\Delta \tau)}{m - \rho E \rho R (1 - \kappa \Delta \tau)}, \frac{b}{b + \rho E \rho R \gamma \Delta \tau \mu_p} \right].
$$

(10)

Since we have a limit on the size of our storage as shown in our assumption (8), if $\Delta \tau$ is too large, the amount of electricity that is produced between our decisions can be too large and we are likely to lose energy due to the storage being full. (9) gives us a reasonable decision epoch time interval $\Delta \tau$.

### 3.4. Structural Results

In this section, we show some structural results of the value function. Let $V_i^\pi(S_i)$ be a function that satisfies

$$
V_T^\pi(S_T) = C(S_T, X_T^\pi(S_T)),
$$

$$
V_i^\pi(S_i) = C(S_i, X_i^\pi(S_i)) + \gamma \mathbb{E} \left[ V_{t+1}^\pi(S_{t+1}) | S_t \right], \forall 0 \leq t \leq T - 1.
$$

Then, $V_i^\pi(S_i) = G_i^\pi(S_i), \forall 0 \leq t \leq T$. For $0 \leq t \leq T$, let $V_i(S_i)$ satisfy the following:

$$
V_T(S_T) = \max_{x \in \mathbb{R}_+} C(S_T, x),
$$

$$
V_i(S_i) = \max_{x \in \mathbb{R}_+} \{ C(S_i, x) + \gamma \mathbb{E} [V_{t+1}(S_{t+1}) | S_t, x] \}, \forall 0 \leq t \leq T - 1.
$$

$V_i(S_i)$ is known as the value function. According to Puterman (1994), $V_i(S_i) = G_i^\pi(S_i), \forall 0 \leq t \leq T$. Denote

$$
V_i^\pi(S_t, x) := \mathbb{E} [V_{t+1}(S_{t+1}) | S_t, x], \forall 0 \leq t \leq T.
$$

The augmented value function $V_i^\pi(S_t, x)$ is an example of a Q-factor. Let

$$
x_i^\pi := \arg\max_{x \in \mathbb{R}_+} \{ C(S_i, x) + \gamma V_i^\pi(S_t, x) \} = X_i^\pi(S_t), \forall 0 \leq t \leq T.
$$
Then,

\[ V_t(S_t) = \max_{x \in \mathbb{R}_+} \{ C(S_t, x) + \gamma V^x_t(S_t, x) \} \]

\[ = C(S_t, x^*_t) + \gamma V^x_t(S_t, x^*_t), \ \forall 0 \leq t \leq T. \]

At the end of the horizon, we can show that

\[ \frac{d}{dR_T} V_T(S_T) = \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_T - \mu_p)] \] (11)

and hence

\[ \frac{d^2}{dR_T^2} V_T(S_T) = 0. \] (12)

See §2 in the e-companion to this paper for the derivation of (11) and (12).

Now that we have defined the value function, we present its structure. The structural results are mainly attributable to the storage transition function and the contribution function, and they follow from three of the aforementioned assumptions: \((\tilde{p}_t)_{t \geq 1}\) and \((\tilde{R}_t)_{t \geq 1}\) are independent,

\[ \mathbb{E}[p_{t+n}|\mathcal{F}_t] = \mu_p + (1 - \kappa \Delta \tau)^n (p_t - \mu_p), \forall n, t \in \mathbb{N}_+, \]

and

\[ m \geq \frac{\gamma}{\rho_E \rho_R} \text{ and } b \geq \frac{\gamma}{\rho_E \rho_R} \mu_p. \]

Then, \(\forall 0 \leq t \leq T - 1\), we have:

**Structural Result 1.** \( C(S_t, x) + \gamma V^x_t(S_t, x) \) is a concave function of \((R_t, x)\).

**Structural Result 2.** The optimal decision \(x^*_t\) is positive and finite and

\[ \frac{\partial}{\partial x} C(S_t, x^*_t) + \gamma \frac{\partial}{\partial x} V^x_t(S_t, x^*_t) = 0. \] (13)

**Structural Result 3.**

\[ \frac{d}{dR_t} V_t(S_t) = \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] \]

\[ + \gamma \mathbb{E} \left[ \left. \left( \rho_E \frac{\partial R_{t+1}}{\partial x} + \frac{\partial R_{t+1}}{\partial R_t} \right) \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \right| S_t, x_t \right]. \] (14)
Structural Result 4. \( V_t(S_t) \) is a concave function of \( R_t \).

Structural Result 5.

\[
\rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] \leq \frac{d}{dR_t} V_t(S_t) \leq \frac{1}{\rho_R} [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)].
\] (15)

See §2 in the e-companion to this paper for the proof of the above results.

In Structural Result 3, which shows the recursive relationship between the marginal value functions, the meaning of the term

\[
\rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)]
\]

is obvious; if we had an extra \( \Delta R_t \) amount of energy in storage, we can commit to sell it and gain

\[
\Delta R_t \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)]
\]

in expected revenue. However, the second term requires some analysis. From (2), we know that

\[
\rho_E \left( \frac{\partial R_{t+1}}{\partial x} + \frac{\partial R_{t+1}}{\partial R_t} \right) \bigg|_{x = x^*_t} = \begin{cases} 
1 - \rho_E \rho_R, & \text{if } x^*_t < Y_{t+1}, \ R_t + \rho_R (Y_{t+1} - x^*_t) < R_{\max}, \\
0, & \text{otherwise}.
\end{cases}
\]

describes the conversion loss that occurs when we use the energy that is put into the storage when we generate more electricity than we need to satisfy the commitment. Therefore, the term

\[
\mathbb{E} \left[ \left( \rho_E \frac{\partial R_{t+1}}{\partial x} + \frac{\partial R_{t+1}}{\partial R_t} \right) \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \bigg| S_t, x^*_t \right]
\]

can be seen as the expected portion of the marginal future value function that is saved by not having to go through the process of energy conversion.

4. Main Result - Infinite Horizon Analysis

In this section, we derive the marginal value function and the corresponding optimal policy for advance energy commitment that maximizes the expected revenue in the infinite horizon case. We let \( T \rightarrow \infty \) and drop the index \( t \) from the value function:

\[
V(S_t) = \lim_{T \rightarrow \infty} \mathbb{E} \left[ \sum_{t' = t}^T \gamma^{t' - t} C(S_{t'}, X^{\pi^*}(S_{t'})) \bigg| S_t \right].
\]
Then, $V(S_t)$ satisfies

$$
V(S_t) = \max_{x \in \mathbb{R}^+} \{ C(S_t, x) + \gamma \mathbb{E}[V(S_{t+1})|S_t, x] \}
= C(S_t, x_t^*) + \gamma V^*(S_t, x_t^*).
$$

Since the structural properties shown in the previous section holds true for all $T$, $V(S_t)$ maintains those structural properties. In §4.1, we derive the optimal policy using the main assumptions stated in §2 and the structural results shown in §3. We first state:

**Theorem 1.** The optimal policy, when the electricity generated from the wind farm is uniformly distributed from $\theta_t$ to $\theta_t + \beta$, is given by

$$
x_t^* = X_t^*(S_t) = \rho_E R_t + \theta_t + \frac{\mu_p K_1 + (p_t - \mu_p) (1 - \kappa \Delta \tau) K_2}{m [\mu_p + (p_t - \mu_p) (1 - \kappa \Delta \tau)] + b \beta}
$$

where

$$
K_1 = 1 - \gamma \frac{\rho_R \rho_E}{1 - \rho_R \rho_E} \left( \exp \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \frac{R_{\text{max}}}{\rho_R} \right] - 1 \right),
$$

and

$$
K_2 = 1 - \gamma (1 - \kappa \Delta \tau) \frac{\rho_R \rho_E}{1 - \rho_R \rho_E} \left( \exp \left[ \gamma (1 - \kappa \Delta \tau) (1 - \rho_R \rho_E) \frac{1}{\beta} \frac{R_{\text{max}}}{\rho_R} \right] - 1 \right).
$$

Before proving (16), we first analyze its components. Since $\rho_E R_t$ is the amount of electricity that can be produced by converting the energy in storage and $\theta_t$ is the amount of electricity that is certain to be produced, $\rho_E R_t + \theta_t$ can be seen as the riskless term. Since there is a limit on the size of the storage and we lose energy if the storage is full, we always want to commit to sell at least $\rho_E R_t + \theta_t$. The issue is then how much more to commit relative to this base level. Over-commitment is costly because the expected penalty always exceeds the expected spot price. Under-commitment is costly for two reasons. First, excess production must be stored and storage is not free since the round-trip efficiency is less than 1. Second, since there is a limit on the amount of energy you can store, $R_{\text{max}}$, if we commit too little and produce too much we lose the production that cannot be stored. So the optimal extra commitment over the base level must balance the cost
of over-commitment and under-commitment. $\beta$ is the uncertainty in the electricity production, and committing

$$\frac{\mu_p K_1 + (p_t - \mu_p) (1 - \kappa \Delta \tau) K_2}{m [\mu_p + (p_t - \mu_p) (1 - \kappa \Delta \tau)] + b}$$  

(17)

fraction of $\beta$ achieves the balance between the cost of over-commitment and the cost of under-commitment. Note that the solution to a typical newsvendor problem states that the vendor should always try to satisfy a fixed fraction of the random demand (Khouja (1999), Petruzzi and Dada (1999)). However, in our case, the fraction is a function of the price because we can speculate on the movement of the price that is mean-reverting. It would be interesting to see if one can find a distribution for the random supply other than uniform that results in an optimal policy with a structure similar to (16). As of this writing, we can only show it for the case of uniformly distributed wind energy supply.

In §4.2, we obtain the stationary distribution of the storage level corresponding to the optimal policy. In §4.3, we derive the economic value of the storage as the relative increase in average revenue due to the existence of the storage.

### 4.1. Optimal Policy

From **Structural Result 2**, we know that the optimal decision $x_t^*$ must satisfy

$$\frac{\partial}{\partial x} C(S_t, x_t^*) + \frac{\partial}{\partial x} V^x(S_t, x_t^*) = \frac{\partial}{\partial x} C(S_t, x_t^*) + \gamma \mathbb{E} \left[ \frac{\partial R_{t+1}}{\partial x} \frac{d}{dR_{t+1}} V(S_{t+1}) | S_t, x_t^* \right]$$

$$= 0.$$  

Therefore, in order to compute $x_t^*$, we only need to know the derivative of $V(S_{t+1})$ with respect to $R_{t+1}$, and we do not need to know $V(S_{t+1})$ itself. To derive $\frac{d}{dR_{t+1}} V(S_{t+1})$, we need the following lemma:

**Lemma 1.**

$$x_t^* + \frac{R_{\text{max}} - R_t}{\rho_R} \leq \theta_t + \beta, \ \forall t.$$  

(18)
Proof: See §3 in the e-companion to this paper. The proof utilizes the inequality (10).

We know that \( \theta_t + \beta - x^*_t \) is the maximum amount of excess electricity that can be left over after fulfilling the commitment. Suppose that the inequality (18) does not hold. Then, \( \rho_R (\theta_t + \beta - x^*_t) \leq R_{\text{max}} - R_t \), indicating that there is always enough room left in the storage to accommodate all of the excess electricity, implying that there is no risk of under-commitment at all. However, we have restricted the size of the storage as shown in (10) precisely to avoid such a situation. We know that the optimal policy ought to balance the risk of under-commitment and the risk of over-commitment. The above lemma allows us to compute \( \frac{d}{dR} V(S_t) \) from which we can derive the optimal policy. We first state:

**Theorem 2.**

\[
\frac{d}{dR_t} V(S_t) = \rho_E \mu_p \exp \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_t}{\rho_R} \right) \right] \\
+ \rho_E (p_t - \mu_p) (1 - \kappa \Delta \tau) \exp \left[ \gamma (1 - \kappa \Delta t) (1 - \rho_E \rho_R) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_t}{\rho_R} \right) \right].
\]

**Proof:** Here, we show a condensed version of the proof by omitting various algebraic steps. See §4 in the e-companion to this paper for a detailed proof. We prove the theorem by using backward induction in the finite horizon setting and letting \( T \) go to infinity. First, we make the induction hypothesis that

\[
\frac{d}{dR_{T-i}} V_{T-i}(S_{T-i}) = \rho_E \mu_p \sum_{j=0}^{i} \frac{1}{j!} \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_{T-i}}{\rho_R} \right) \right]^j \\
+ \rho_E (p_{T-i} - \mu_p) (1 - \kappa \Delta \tau) \sum_{j=0}^{i} \frac{1}{j!} \left[ \gamma (1 - \kappa \Delta t) (1 - \rho_E \rho_R) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_{T-i}}{\rho_R} \right) \right]^j.
\]

for some \( i \geq 0 \), and prove that

\[
\frac{d}{dR_{T-(i+1)}} V_{T-(i+1)}(S_{T-(i+1)}) = \rho_E \mu_p \sum_{j=0}^{i+1} \frac{1}{j!} \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_{T-(i+1)}}{\rho_R} \right) \right]^j \\
+ \rho_E (p_{T-(i+1)} - \mu_p) (1 - \kappa \Delta \tau) \sum_{j=0}^{i+1} \frac{1}{j!} \left[ \gamma (1 - \kappa \Delta t) (1 - \rho_E \rho_R) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_{T-(i+1)}}{\rho_R} \right) \right]^j.
\]

From (9), we know that

\[
\frac{d}{dR_T} V_T(S_T) = \rho_E \mu_p + \rho_E (p_T - \mu_p) (1 - \kappa \Delta \tau).
\]
Therefore, the expression for \( \frac{d}{dR_{T-(i+1)}} V_{T-(i+1)}(S_{T-(i+1)}) \) shown above is true for \( i = 0 \). From (2), we can show that

\[
\left( \rho_E \frac{\partial R_{t+1}}{\partial x} + \frac{\partial R_{t+1}}{\partial R_t} \right) \frac{1}{j!} \left( \frac{R_{\text{max}} - R_{t+1}}{\rho_R} \right)^j \bigg|_{x=x_t^*}
\]

\[
= \begin{cases} 
(1 - \rho_E \rho_R) \frac{1}{j} \left[ \frac{R_{\text{max}} - R_t}{\rho_R} \right] & \text{if } x_t^* < Y_{t+1}, \ R_t + \rho_R (Y_{t+1} - x_t^*) < R_{\text{max}}, \\
0, & \text{otherwise.}
\end{cases}
\]

Next, by (18),

\[
f_i(y) = \frac{1}{\beta}, \ \forall x_t^* \leq y \leq x_t^* + \frac{R_{\text{max}} - R_t}{\rho_R}.
\]

Then, we can show

\[
\mathbb{E} \left[ \left( \rho_E \frac{\partial R_{t+1}}{\partial x} + \frac{\partial R_{t+1}}{\partial R_t} \right) \frac{1}{j!} \left( \frac{R_{\text{max}} - R_{t+1}}{\rho_R} \right)^j \bigg| S_t, x_t^* \right] = (1 - \rho_E \rho_R) \frac{1}{\beta} \frac{1}{(j+1)!} \left( \frac{R_{\text{max}} - R_t}{\rho_R} \right)^{j+1}.
\]

From **Structural Result 3**,

\[
\frac{d}{dR_{T-(i+1)}} V_{T-(i+1)}(S_{T-(i+1)})
\]

\[
= \rho_E \left( \mu_p + (1 - \kappa \Delta \tau) (\rho_{T-(i+1)} - \mu_p) \right) + \gamma \mathbb{E} \left[ \left( \rho_E \frac{\partial R_{T-i}}{\partial x} + \frac{\partial R_{T-i}}{\partial R_{T-(i+1)}} \right) \frac{d}{dR_{T-i}} V_{T-(i+1)}(S_{T-(i+1)}) \bigg| S_{T-(i+1)}, x_{T-(i+1)}^* \right]
\]

\[
= \rho_E \mu_p \sum_{j=0}^{i+1} \frac{1}{j!} \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_{T-(i+1)}}{\rho_R} \right)^j \right]
\]

\[
+ \rho_E \left( \mu_{T-(i+1)} - \mu_p \right) (1 - \kappa \Delta \tau) \sum_{j=0}^{i+1} \frac{1}{j!} \left[ \gamma (1 - \kappa \Delta \tau) \left( 1 - \rho_R \rho_E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_{T-(i+1)}}{\rho_R} \right)^j \right].
\]

Therefore, (20) is true for \( \forall t \geq 0 \). Next, substitute \( t \) for \( T - (i + 1) \). Then,

\[
\frac{d}{dR_t} V_t(S_t) = \rho_E \mu_p \sum_{j=0}^{T-t} \frac{1}{j!} \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_t}{\rho_R} \right)^j \right]
\]

\[
+ \rho_E \left( \mu_t - \mu_p \right) (1 - \kappa \Delta \tau) \sum_{j=0}^{T-t} \frac{1}{j!} \left[ \gamma (1 - \kappa \Delta \tau) \left( 1 - \rho_R \rho_E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_{T-(i+1)}}{\rho_R} \right)^j \right],
\]

\( \forall t \leq T \). If we let \( T \) go to infinity,

\[
\frac{d}{dR_t} V(S_t) = \lim_{T \to \infty} \frac{d}{dR_t} V_t(S_t)
\]

\[
= \rho_E \mu_p \exp \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_t}{\rho_R} \right) \right]
\]

\[
+ \rho_E \left( \mu_t - \mu_p \right) (1 - \kappa \Delta \tau) \exp \left[ \gamma (1 - \kappa \Delta \tau) \left( 1 - \rho_R \rho_E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_t}{\rho_R} \right) \right], \ \forall t.
To compute the optimal decision $x_t^*$ at time $t$, all we need to know is $\frac{d}{dR_{t+1}} V(S_{t+1})$. Since we now know what $\frac{d}{dR_{t+1}} V(S_{t+1})$ is, we are ready to prove (16).

Proof of (16): From (19),

$$
\mathbb{E} \left[ \frac{\partial R_{t+1}}{\partial x} \frac{d}{dR_{t+1}} V(S_{t+1}) \mid S_t, x \right] = -\mu_p \frac{\rho_R p_E}{1 - \rho_R p_E} \left( \exp \left[ \gamma (1 - \rho_R p_E) \frac{1}{\beta} \frac{R_{\text{max}}}{p_R} \right] - 1 \right)
- (p_t - \mu_p)(1 - \kappa \Delta \tau)^2 \frac{\rho_R p_E}{1 - \rho_R p_E} \left( \exp \left[ \gamma (1 - \kappa \Delta \tau) (1 - \rho_R p_E) \frac{1}{\beta} \frac{R_{\text{max}}}{p_R} \right] - 1 \right),
$$

$\forall x \geq \rho_E R_t + \theta_t$. To see the derivation of (21), see §5 in the e-companion to this paper. Then, from Structural Result 2, we know that the optimal decision $x_t^*$ must satisfy

$$
\frac{\partial}{\partial x} C(S_t, x_t^*) + \gamma \frac{\partial}{\partial x} V^z(S_t, x_t^*) = p_{t,t+1} - (mp_{t,t+1} + b) F_t(x_t^* - \rho_E R_t) + \gamma \mathbb{E} \left[ \frac{\partial R_{t+1}}{\partial x} \frac{d}{dR_{t+1}} V(S_{t+1}) \mid S_t, x_t^* \right]
= 0,
$$

where

$$
p_{t,t+1} := \mathbb{E} [p_{t+1} | \mathcal{F}_t] = \mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p).
$$

Therefore,

$$
(mp_{t,t+1} + b) \frac{1}{\beta} (x_t^* - \rho_E R_t - \theta_t)
= p_{t,t+1} + \gamma \mathbb{E} \left[ \frac{\partial R_{t+1}}{\partial x} \frac{d}{dR_{t+1}} V(S_{t+1}) \mid S_t, x_t^* \right]
= \mu_p + (p_t - \mu_p)(1 - \kappa \Delta \tau) - \gamma \mu_p \frac{\rho_R p_E}{1 - \rho_R p_E} \left( \exp \left[ \gamma (1 - \rho_R p_E) \frac{1}{\beta} \frac{R_{\text{max}}}{p_R} \right] - 1 \right)
- \gamma (p_t - \mu_p)(1 - \kappa \Delta \tau)^2 \frac{\rho_R p_E}{1 - \rho_R p_E} \left( \exp \left[ \gamma (1 - \kappa \Delta \tau) (1 - \rho_R p_E) \frac{1}{\beta} \frac{R_{\text{max}}}{p_R} \right] - 1 \right)
= \mu_p K_1 + (p_t - \mu_p)(1 - \kappa \Delta \tau) K_2.
$$

Then,

$$
x_t^* = \rho_E R_t + \theta_t + \frac{\mu_p K_1 + (p_t - \mu_p)(1 - \kappa \Delta \tau) K_2}{m [\mu_p + (p_t - \mu_p)(1 - \kappa \Delta \tau)] + b \beta}.
$$
Note that both $K_1$ and $K_2$ increases when $\rho_R \rho_E$, $R_{\text{max}}$, or $\gamma$ is reduced. We know that the optimal amount should naturally depend on the penalty, the round-trip efficiency, the maximum storage limit, and the discount factor as follows. First, it should decrease with increasing penalty, as being short incurs the penalty. Second, it should increase with reduced round-trip efficiency, as being long implies paying to store (losing energy). Third, it should decrease with increasing maximum storage. If our storage capacity is greater, we lose less of the energy we do not sell, and we can afford to be more conservative and commit less. Fourth, it should increase with decreasing discount factor, because the value of what we store now to use in the future decreases with the discount factor. Next,

Corollary 1. If $\kappa = 0$, implying that $(p_t)_{t \geq 0}$ is a martingale, then $K_1 = K_2$ and

$$x^*_t = \rho_E R_t + \theta_t + \frac{p_t}{m p_t + b} K_1 \beta.$$  (22)

If the price is a martingale, it is “stochastically constant” and we cannot speculate on the future movement of the price. Then, the fraction is just directly proportional to the ratio between the current expected spot market price and the penalty price.

4.2. Stationary Distribution of the Storage Level

Now that we have the optimal policy (16), we want to assess the expected value of storage corresponding to the policy. In order to obtain a closed-form expression for the expected value of storage, we must analyze the dynamics of our system at the steady-state and derive the stationary distribution of the storage level. Denote

$$Z_t := \frac{\mu_p K_1 + (p_t - \mu_p) (1 - \kappa \triangle \tau) K_2}{m [\mu_p + (p_t - \mu_p) (1 - \kappa \triangle \tau)] + b}, \forall t.$$  

From (2), we know that $R_{t+1}$ is a function of $(R_t, x^*_t, Y_{t+1})$. Since $Y_{t+1}$ is a function of $\theta_t$ and $x^*_t$ is a function of $(R_t, Z_t, \theta_t)$ as shown in (16), we can think of $R_{t+1}$ as a function of $(R_t, Z_t, \theta_t)$. However, because $\theta_t$ is the amount of electricity that we are certain to produce and commit, we
know that $R_{t+1}$ in fact does not depend on $\theta_t$. Thus, $R_{t+1}$ is a function of $(R_t, Z_t)$. Therefore, if the random process $(Z_t)_{t \geq 0}$ is stationary ergodic, the process $(R_t)_{t \geq 0}$ will reach a steady-state.

Since $(Z_t)_{t \geq 0}$ is driven by $(p_t)_{t \geq 1}$, we first need to know the distribution of $(p_t)_{t \geq 1}$ at steady-state.

**Proposition 1.** At steady-state,

$$p_t \sim \mathcal{N}\left(\mu_p, \frac{\sigma_p^2}{1 - (1 - \kappa \Delta \tau)^2}\right).$$

**(Proof:** We know that (23) is true if and only if (23) implies

$$p_{t+1} \sim \mathcal{N}\left(\mu_p, \frac{\sigma_p^2}{1 - (1 - \kappa \Delta \tau)^2}\right).$$

Suppose (23) is true. Then,

$$(1 - \kappa \Delta \tau)(p_t - \mu_p) \sim \mathcal{N}\left(0, \frac{(1 - \kappa \Delta \tau)^2 \sigma_p^2}{1 - (1 - \kappa \Delta \tau)^2}\right).$$

Since $\hat{p}_{t+1}$ is independent from $p_t$ and $\hat{p}_{t+1} \sim \mathcal{N}(0, \sigma_p^2)$,

$$(1 - \kappa \Delta \tau)(p_t - \mu_p) + \hat{p}_{t+1} \sim \mathcal{N}\left(0, \frac{\sigma_p^2}{1 - (1 - \kappa \Delta \tau)^2}\right).$$

Then,

$$p_{t+1} = \mu_p + (1 - \kappa \Delta \tau)(p_t - \mu_p) + \hat{p}_{t+1} \sim \mathcal{N}\left(\mu_p, \frac{\sigma_p^2}{1 - (1 - \kappa \Delta \tau)^2}\right).$$

□

Since $Z_t$ is a deterministic function of $p_t$, $(Z_t)_{t \geq 1}$ reaches steady-state when $(p_t)_{t \geq 1}$ reaches steady-state. However, we know that in practice the price is always going to be positive. The first and second moments of $Z_t$ at steady-state given $p_t \geq 0$ is

$$Z_1 := \mathbb{E}\left[\frac{\mu_p K_1 + (\varepsilon - \mu_p) (1 - \kappa \Delta \tau) K_2}{m [\mu_p + (\varepsilon - \mu_p) (1 - \kappa \Delta \tau)] + b} \mid \varepsilon \geq 0\right],$$

and

$$Z_2 := \mathbb{E}\left[\left(\frac{\mu_p K_1 + (\varepsilon - \mu_p) (1 - \kappa \Delta \tau) K_2}{m [\mu_p + (\varepsilon - \mu_p) (1 - \kappa \Delta \tau)] + b}\right)^2 \mid \varepsilon \geq 0\right]$$

where

$$\varepsilon \sim \mathcal{N}\left(\mu_p, \frac{\sigma_p^2}{1 - (1 - \kappa \Delta \tau)^2}\right).$$
Also, define
\[
\bar{Z}_1 := \mathbb{E} \left[ \frac{\mu_p + (\varepsilon - \mu_p) (1 - \kappa \triangle \tau)}{m[\mu_p + (\varepsilon - \mu_p) (1 - \kappa \triangle \tau)] + b} \ | \ \varepsilon \geq 0 \right],
\]
and
\[
\bar{Z}_2 := \mathbb{E} \left[ \left( \frac{\mu_p + (\varepsilon - \mu_p) (1 - \kappa \triangle \tau)}{m[\mu_p + (\varepsilon - \mu_p) (1 - \kappa \triangle \tau)] + b} \right)^2 \ | \ \varepsilon \geq 0 \right],
\]
corresponding to the case where \( R_{\text{max}} = 0 \), which makes \( K_1 = K_2 = 1 \). \( \bar{Z}_1, \bar{Z}_2, \bar{Z}_1, \) and \( \bar{Z}_2 \) can be easily computed via Monte-Carlo simulation using sample realizations of \( \Phi \) greater than zero.

**Proposition 2.** Then, the stationary distribution of \( R_t \) corresponding to the steady-state is
\[
f_{R_t}(r) = \frac{d}{dr} \mathbb{P}[R_t \leq r] = \bar{Z}_1 \delta(r) + \left( \bar{Z}_1 + \frac{\rho E \beta}{1 - \rho E \beta} \right) \frac{1 - \rho E \beta}{\rho E \beta} \exp \left[ \frac{(1 - \rho E \beta r)}{\rho E \beta} \right] 1_{\{0 \leq r \leq R_{\text{max}}\}} + \frac{1}{1 - \rho E \beta} \left( 1 - \left( \rho E \beta + \bar{Z}_1 (1 - \rho E \beta) \right) \exp \left[ \frac{(1 - \rho E \beta r)}{\rho E \beta} R_{\text{max}} \right] \right) \delta(r - R_{\text{max}}), \tag{26}
\]
where \( \delta(\cdot) \) denotes the Dirac-delta function.

**Proof:** Here, we show a condensed version of the proof by omitting various algebraic steps. See §6 in the e-companion to this paper for a detailed proof. From (2) and (16), we can show that
\[
\mathbb{P}[R_{t+1} = 0 \mid R_t] = \mathbb{P}[R_{t+1} = 0] = \bar{Z}_1
\]
and
\[
\mathbb{P}[R_{t+1} = R_{\text{max}} \mid R_t] = 1 - \bar{Z}_1 - \frac{R_{\text{max}}}{\rho E \beta} + \frac{(1 - \rho E \beta) R_t}{\rho E \beta},
\]
in the steady-state. Also, from (2), we can show that
\[
f_{R_{t+1}|R_t}(u|R_t) = \begin{cases} \frac{\rho E}{\beta} & \text{if } 0 < u < R_t \\ \frac{1}{\rho E \beta} & \text{if } R_t \leq u < R_{\text{max}} \end{cases}.
\]
Therefore, we can write the conditional probability density function as
\[
f_{R_{t+1}|R_t}(u|R_t = r) = \bar{Z}_1 \delta(u) + \frac{\rho E}{\beta} 1_{\{0 \leq u < r\}} + \frac{1}{\rho E \beta} 1_{\{r \leq u \leq R_{\text{max}}\}} + \left( 1 - \bar{Z}_1 - \frac{R_{\text{max}}}{\rho E \beta} + \frac{(1 - \rho E \beta) r}{\rho E \beta} \right) \delta(u - R_{\text{max}}),
\]
where \( \delta (\cdot) \) denotes the Dirac-delta function. Since

\[
P [R_t = 0] = Z_1
\]

in the steady-state, we know that the stationary distribution can be written as

\[
f_{R_t}(r) = Z_1 \delta (r) + g (r) \mathbf{1}_{[0 \leq r \leq R_{\text{max}}]} + \left( 1 - Z_1 - \int_{r=0}^{R_{\text{max}}} g (r) dr \right) \delta (r - R_{\text{max}}),
\]

for some function \( g (r) \). By definition, the stationary distribution must satisfy

\[
f_{R_{t+1}} (u) = \int_{r=0}^{R_{\text{max}}} f_{R_{t+1}, R_t} (u, r) dr = \int_{r=0}^{R_{\text{max}}} f_{R_{t+1}} (u | R_t = r) f_{R_t} (r) dr = f_{R_t} (u).
\]

By computing the integral and matching the terms, we can show that

\[
g(u) = \frac{Z_1 (1 - \rho R \rho E)}{\rho R \beta} + \frac{\rho R \rho E}{\rho R \beta} + \frac{(1 - \rho R \rho E)}{\rho R \beta} \int_{r=0}^{u} g (r) dr.
\]

Taking the derivative with respect to \( u \) on both side gives

\[
g'(u) = \frac{(1 - \rho R \rho E)}{\rho R \beta} g(u).
\]

Then, we can show that

\[
g(r) = \left( Z_1 + \frac{\rho R \rho E}{1 - \rho R \rho E} \right) \frac{(1 - \rho R \rho E)}{\rho R \beta} \exp \left[ \frac{(1 - \rho E \rho R)}{\rho R \beta} r \right]
\]

and

\[
1 - Z_1 - \int_{r=0}^{R_{\text{max}}} g (r) dr = \frac{1}{1 - \rho E \rho R} \left( 1 - (\rho R \rho E + Z_1 (1 - \rho E \rho R)) \exp \left[ \frac{(1 - \rho E \rho R)}{\rho R \beta} R_{\text{max}} \right] \right).
\]

The stationary distribution (26) shows that if the round-trip efficiency is lower, the probability of hitting the capacity limit \( R_{\text{max}} \) is lower while the probability of depleting the storage is higher, as expected.
4.3. Economic Value of the Storage

Using the stationary distribution of the storage level obtained in the previous section, we can compute the following:

**Corollary 2.** *In steady-state,*

\[
E[R_t] = \frac{R_{\text{max}}}{1 - \rho R^E} - \left( \frac{\rho R^E}{1 - \rho R^E} \right) \frac{\rho R^\beta}{1 - \rho R^E} \left( \exp \left[ \frac{1 - \rho R^E}{\rho R^\beta} R_{\text{max}} \right] - 1 \right) \tag{27}
\]

and the expected revenue in steady-state is

\[
C_{R_{\text{max}}}^{SS} := E[C(S_t, x^*_t)] = \mu_p \rho E[R_t] + \mu_p \mathbb{E}[\theta_t] + \mu_p \mathbb{Z}_1 \beta - (m \mu_p + b) \frac{\beta}{2} \mathbb{Z}_2
\]

\[
= \frac{\mu_p \rho E[R_{\text{max}}]}{1 - \rho R^E} - \frac{\mu_p \beta}{2} \left( \frac{1}{\beta} \mathbb{Z}_1 + \frac{\rho R^E}{1 - \rho R^E} \right) \frac{\rho E R^R}{1 - \rho R^E} \left( \exp \left[ \frac{1 - \rho R^E}{\rho R^\beta} R_{\text{max}} \right] - 1 \right)
\tag{28}
\]

See §7 in the e-companion to this paper for the derivation of (27) and (28). We know that \(K_1 = K_2 = 1\) if \(R_{\text{max}} = 0\). Therefore, from (28), if we do not have a storage and \(R_{\text{max}} = R_t = 0\), \(\forall t\), the expected revenue at steady-state would be

\[
C^0_{SS} := \mu_p \beta \left( \frac{\beta}{2} \mathbb{Z}_1 - m \frac{\beta}{2} \mathbb{Z}_2 - \frac{1}{2} \right) + \mu_p \mu_y - b \beta \frac{\beta}{2} \mathbb{Z}_2.
\]

Then, the relative increase in the expected revenue in steady-state due to the existence of storage is

\[
\psi := \frac{C_{R_{\text{max}}}^{SS} - C^0_{SS}}{C^0_{SS}}
\tag{29}
\]

\[
= \left\{ \frac{\rho E R^R}{1 - \rho R^E} \frac{R_{\text{max}}}{\beta R^R} \left( \frac{\rho R^E}{1 - \rho R^E} \right) \frac{\rho E R^R}{1 - \rho R^E} \left( \exp \left[ \frac{1 - \rho R^E}{\rho R^\beta} R_{\text{max}} \right] - 1 \right) \right\}
\]

\[
+ \left( \frac{\beta}{2} \mathbb{Z}_1 - \frac{\beta}{2} \mathbb{Z}_2 \right) - \left( m + \frac{b}{\mu_p} \right) \left( \frac{\beta}{2} \mathbb{Z}_2 - \frac{1}{2} \right) + \mu_p \mu_y - b \beta \frac{\beta}{2} \mathbb{Z}_2 \}
\] / \left\{ \frac{\beta}{2} \mathbb{Z}_1 - \frac{\beta}{2} \mathbb{Z}_2 - \frac{1}{2} + \mu_p \frac{\beta}{\mu_p} \frac{\beta}{2} \mathbb{Z}_2 \right\}.
\]

5. Numerical Results

In the previous section, we have derived the optimal commitment policy and the corresponding value of the storage assuming that the forecast of electricity generated from the wind farm is uniformly distributed. However, the hourly wind speed data obtained from the North American Land
Data Assimilation System (NLDAS) project shows that when forecasting the cube of the speed of the wind, a truncated Gaussian distribution fits the data better than a uniform distribution. In this section, we simulate the wind energy process using a truncated Gaussian distribution and compare the relative increase in revenue due to the existence of storage computed numerically by implementing our policy (16) to the one computed theoretically from the equation (29).

From the NLDAS project, we extracted wind speed data from 22 locations across the United States. Since the wind characteristics vary throughout the year due to seasonal effects, it is common to assume that the wind process is time-invariant over a one month period but not beyond that (Ettoumi, et al. (2003)). Therefore, we use separate model parameters and corresponding policies for each month. We found that the third-order correlation is very small compared to the first and second order correlation, and represent \((Y_t)_{t \geq 1}\), the energy generated from our wind farm, as a second-order AR process:

\[
Y_{t+1} = \mu_Y + \alpha_0 (Y_t - \mu_Y) + \alpha_1 (Y_{t-1} - \mu_Y) + \hat{y}_{t+1},
\]

for some \(\mu_Y, \alpha_0, \alpha_1\). When we implement our policy (16), we assume \((\hat{y}_t)_{t \geq 1}\) is i.i.d with distribution \(U(-\frac{\beta}{2}, \frac{\beta}{2})\), for some \(\beta\). \(\beta\) is computed by matching \(\frac{\beta^2}{12}\) to the variance of the residual in the AR process, \((\hat{y}_t)_{t \geq 1}\). \(\mu_Y\)'s (in \(m^3/s^3\)) for the selected 22 locations computed using the January 2000 data, for example, are given in Table 1 and \(\beta\)'s (in \(m^3/s^3\)) are given in Table 2. From Table 1 and Table 2, we can see that \(\mu_Y\)'s and \(\beta\)'s are comparable in magnitude, implying that wind energy production is highly volatile.

After we compute \(\mu_Y, \alpha_0, \alpha_1\) and \(\beta\) using the NLDAS data, we generate wind energy processes \((Y_t)_{t \geq 1}\) from equation (30) where \((\hat{y}_t)_{t \geq 1}\) is i.i.d and \(\hat{y}_t \sim N \left(0, \frac{\beta^2}{12}\right), \forall t\). However, when we are computing our commitment from our policy (16), we assume \(\hat{y}_t \sim U \left(-\frac{\beta}{2}, \frac{\beta}{2}\right)\). From (6),

<table>
<thead>
<tr>
<th>Latitude</th>
<th>Speed (m/s)</th>
<th>Latitude</th>
<th>Speed (m/s)</th>
<th>Latitude</th>
<th>Speed (m/s)</th>
<th>Latitude</th>
<th>Speed (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>51.8125°N</td>
<td>181.7084</td>
<td>46.1875°N</td>
<td>173.3216</td>
<td>40.5625°N</td>
<td>156.4102</td>
<td>34.9375°N</td>
<td>121.7831</td>
</tr>
<tr>
<td>120.0725°W</td>
<td>111.3225</td>
<td>102.5725°W</td>
<td>93.8225</td>
<td>85.0725°W</td>
<td>76.3225</td>
<td>90.0725°W</td>
<td>51.8125</td>
</tr>
<tr>
<td>181.7084</td>
<td>132.0368</td>
<td>172.7166</td>
<td>276.2300</td>
<td>351.6345</td>
<td>46.1875°N</td>
<td>173.3216</td>
<td>119.7605</td>
</tr>
</tbody>
</table>

\textbf{Table 1} \ Mean of the cube of the speed of the wind in January 2000
Table 2 Spread of the cube of the speed of the wind in January 2000

<table>
<thead>
<tr>
<th>Wind Speed (°N)</th>
<th>120.0725°W</th>
<th>111.3225°W</th>
<th>102.5725°W</th>
<th>93.8225°W</th>
<th>85.0725°W</th>
<th>76.3225°W</th>
</tr>
</thead>
<tbody>
<tr>
<td>51.8125°N</td>
<td>0.3682</td>
<td>0.1813</td>
<td>0.3378</td>
<td>0.1727</td>
<td>0.1213</td>
<td>0.1584</td>
</tr>
<tr>
<td>46.1875°N</td>
<td>0.2245</td>
<td>0.1436</td>
<td>N/A</td>
<td>0.2985</td>
<td>0.2028</td>
<td>0.2394</td>
</tr>
<tr>
<td>40.5625°N</td>
<td>0.3457</td>
<td>N/A</td>
<td>0.3211</td>
<td>0.2722</td>
<td>0.2005</td>
<td>0.1444</td>
</tr>
<tr>
<td>34.9375°N</td>
<td>0.2185</td>
<td>0.1630</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Next, we fit the hourly spot market price provided by a utility company to the process

\[ p_{t+1} = \mu_p + (1 - \kappa \triangle \tau) (p_t - \mu_p) + \tilde{p}_{t+1}, \]

where and \((\tilde{p}_t)_{t \geq 0}\) are i.i.d with distribution \(N(0, \sigma_p^2)\). In our experiments, we use \(\rho_E \rho_R = 0.75\), \(\gamma = 0.99\), \(\mu_p = 49.9\), \(\sigma_p = 47.46\), \(\triangle \tau = 1\), \(\kappa = 0.4182\), \(m = 1.6\), \(b = 67.5\), and \(\frac{R_{max}}{\rho_R} = 0.5\). Then, \(Z_1 = .1912\), \(Z_2 = .0467\), \(\tilde{Z}_1 = .3270\), and \(\tilde{Z}_2 = .1139\). This gives

\[ \psi = 0.1893 / \left( \frac{\mu_Y}{\beta} - 0.3411 \right). \]

We implemented our policy (16) 100 times by generating the prices from (31) and the wind energy process from (30) using the coefficients \(\mu, \alpha_0, \alpha_1\) and \(\beta\). Then, we computed the relative increase in revenue due to the existence of storage for each implementation of our policy and found the average of those values over the 100 experiments. Next, we computed the relative increase in revenue directly from equation (29). The relative increase in revenue computed by implementing our policy (16), averaged over 36 months, is given in Table 3. The relative increase in revenue computed from (29) and hence (32), is given in Table 4.

From the above tables, we can see that the relative increase in revenue obtained through a sample run implementing our policy (16) is comparable to the relative increase in revenue computed.
using the closed-form equation (29), even though the wind energy processes are actually generated from a truncated Gaussian distribution.

Figure 1 shows the relationship between the numerical results from Table 3 and the theoretical results from Table 4. There are 22 data points corresponding to each of the 22 locations. For each data point, the $x$-coordinate corresponds to the theoretical value computed from (29) and the $y$-coordinate corresponds to the numerical value computed from our policy (16). The error bar covers two standard deviations. In Figure 1, one can see that almost all of the data points are slightly below the line $y = x$. That is, the relative increase in revenue computed from our policy (16) is almost always slightly less than the relative increase in revenue computed from (29). This is because the theoretical values were computed assuming that the wind energy process is generated from a uniform distribution, which makes our policy optimal, while the actual experiment used wind energy processes generated from a truncated Gaussian processes, making our policy suboptimal.
The difference is approximately 15.6% on average.

6. Conclusion

In this paper, we have analyzed the problem of managing an intermittent energy storage system with a limited capacity and conversion loss under advance commitments. We have shown that the stochastic optimization problem is concave when the discounted market price is mean-reverting and the discounted expected cost of over-commitment is less than the conversion loss of the storage. We have found the optimal policy that maximizes the expected cumulative revenue in the infinite horizon case in which the forecast of electricity generated from the wind farm is uniformly distributed. We were also able to obtain the stationary distribution of the storage level corresponding to the optimal policy. Then, we were able to compute the expected revenue in the steady-state and analyze the economic value of the storage as the relative increase in the expected revenue due to the existence of the storage.

The next step would be to relax the assumption that the wind energy production is uniformly distributed and try to find the optimal policy for a general distribution. It will be a powerful statement if one could show that the optimal policy always has a form similar to the newsvendor problem as shown in (16), regardless of the distribution of wind energy. However, a closed-form solution is rare in the MDP literature. It is very likely that one should resort to numerical methods when the various assumptions used in this paper are relaxed. In that case, the closed-form policy (16) can be used as a benchmark. A policy that tries to maximize the revenue in the case where the assumptions stated in this paper do not hold should at least do better than (16).

References


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Appendix

1. Proof of (4):

From

\[ \hat{C}_{t+1} = \begin{cases} \frac{p_{t+1} x_t}{t}, & \text{if } x_t < \rho_E R_t + Y_{t+1}, \\ p_{t+1} x_t - (m p_{t+1} + b) [x_t - (\rho_E R_t + Y_{t+1})], & \text{if } x_t \geq \rho_E R_t + Y_{t+1}. \end{cases} \]

and the assumption that \( Y_{t+1} \) is independent from \( p_{t+1} \), we know that

\[ C(S_t, x_t) = \mathbb{E} \left[ \hat{C}_{t+1} \mid S_t, x_t \right] \]

\[ = \int_{0 \leq y \leq x_t - \rho_E R_t} (p_{t,t+1} x_t - (m p_{t+1} + b) [x_t - \rho_E R_t - y]) f_t(y) dy + \int_{x_t - \rho_E R_t < y} (p_{t,t+1} x_t) f_t(y) dy \]

\[ = p_{t,t+1} x_t - (m p_{t+1} + b) (x_t - \rho_E R_t) \cdot \int_{0 \leq y \leq x_t - \rho_E R_t} f_t(y) dy + (m p_{t+1} + b) \cdot \int_{0 \leq y \leq x_t - \rho_E R_t} y f_t(y) dy, \]

where

\[ p_{t,t+1} := \mathbb{E} [p_{t+1} \mid \mathcal{F}_t] = \mu_p + (1 - \kappa \triangle) (p_t - \mu_p), \]

and

\[ f_t(y) = \begin{cases} 0, & \text{if } y < \theta_t \\ \frac{1}{\beta}, & \text{if } \theta_t \leq y \leq \theta_t + \beta \\ 0, & \text{if } \theta_t + \beta < y \end{cases} \]

Using integration by parts,

\[ \int_{0 \leq y \leq x_t - \rho_E R_t} y f_t(y) dy = \int_{0 \leq y \leq x_t - \rho_E R_t} y [F_t(y)]' dy \]

\[ = y F_t(y) \bigg|_{y=0}^{x_t - \rho_E R_t} - \int_{0 \leq y \leq x_t - \rho_E R_t} F_t(y) dy \]

\[ = (x_t - \rho_E R_t) F_t(x_t - \rho_E R_t) - \int_{0 \leq y \leq x_t - \rho_E R_t} F_t(y) dy. \]

Therefore,

\[ C(S_t, x_t) = p_{t,t+1} x_t - (m p_{t+1} + b) \cdot \int_{0 \leq y \leq x_t - \rho_E R_t} F_t(y) dy \]

\[ = \left[ \mu_p + (1 - \kappa \triangle) (p_t - \mu_p) \right] \left[ x_t - m \cdot \int_{0 \leq y \leq x_t - \rho_E R_t} F_t(y) dy \right] \]

\[-b \int_{0 \leq y \leq x_t - \rho_E R_t} F_t(y) dy. \]
2. Proof of Structural Results:

In this section, we prove the structural results. In §2.1, we first introduce the various derivatives that are used for the proof. In §2.2, we introduce some lemmas that are also used for the proof. Finally, in §2.3, we prove the structural results for the value function using backward induction.

2.1. Derivatives

Utilizing the derivatives of the contribution function and the storage transition function will be central to the proof. First, from (4), we can compute the following derivatives:

\[
\frac{\partial}{\partial x} C(S_t, x) = [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] [1 - m F_t(x - \rho_E R_t)] - b F_t(x - \rho_E R_t), \tag{1}
\]

\[
\frac{\partial}{\partial R_t} C(S_t, x) = [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] m \rho_E F_t(x - \rho_E R_t) + b \rho_E F_t(x - \rho_E R_t), \tag{2}
\]

\[
\frac{\partial^2}{\partial x^2} C(S_t, x) = -[\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] m f_t(x - \rho_E R_t) - b f_t(x - \rho_E R_t), \tag{3}
\]

\[
\frac{\partial^2}{\partial R_t^2} C(S_t, x) = -[\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] \rho_E^2 m f_t(x - \rho_E R_t) - \rho_E^2 m f_t(x - \rho_E R_t), \tag{4}
\]

and

\[
\frac{\partial^2}{\partial x \partial R_t} C(S_t, x) = [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] \rho_E m f_t(x - \rho_E R_t) + b \rho_E f_t(x - \rho_E R_t), \tag{5}
\]

where

\[
f_t(y) := \frac{d}{dy} F_t(y) = \begin{cases} \frac{1}{\beta}, & \text{if } \theta_t \leq y \leq \theta_t + \beta, \\ 0, & \text{else} \end{cases}
\]

Next, from (2),

\[
\frac{\partial R_{t+1}}{\partial x} = \begin{cases} 0, & \text{if } R_t + \rho_R (Y_{t+1} - x) \geq R_{\text{max}}, \\ -\rho_R, & \text{if } x < Y_{t+1}, R_t + \rho_R (Y_{t+1} - x) < R_{\text{max}}, \\ -\frac{1}{\rho_E}, & \text{if } Y_{t+1} \leq x < \rho_E R_t + Y_{t+1}, \\ 0, & \text{if } x \geq \rho_E R_t + Y_{t+1}, \end{cases} \tag{6}
\]

and

\[
\frac{\partial R_{t+1}}{\partial R_t} = \begin{cases} 0, & \text{if } R_t + \rho_R (Y_{t+1} - x) \geq R_{\text{max}}, \\ 1, & \text{if } x < Y_{t+1}, R_t + \rho_R (Y_{t+1} - x) < R_{\text{max}}, \\ 1, & \text{if } Y_{t+1} \leq x < \rho_E R_t + Y_{t+1}, \\ 0, & \text{if } x \geq \rho_E R_t + Y_{t+1}. \end{cases} \tag{7}
\]

Note that

\[
\frac{\partial}{\partial x} V^\pi(S_t, x_t^*) = \frac{\partial}{\partial x} E[V_{t+1}(S_{t+1}) | S_t, x] |_{x=x_t^*}
\]
This is because $R_{t+1}$ is a continuous function of $R_t$ and $x$ while $W_{t+1}$ is not a function of $R_t$ and $x$. The ability to exchange the derivative and the expectation is used throughout this paper. Next, acknowledging that $x^*_t$ is a function of $R_t$,

$$
\frac{d}{dR_t} V^x_t(S_t, x^*_t) = \frac{\partial}{\partial R_t} V^x_t(S_t, x^*_t) + \frac{dx^*_t}{dR_t} \frac{\partial}{\partial x} V^x_t(S_t, x^*_t),
$$

$$
\frac{d}{dR_t} C(S_t, x^*_t) = \frac{\partial}{\partial R_t} C(S_t, x^*_t) + \frac{dx^*_t}{dR_t} \frac{\partial}{\partial x} C(S_t, x^*_t),
$$

where

$$
\frac{dx^*_t}{dR_t} = \frac{d}{dR_t} X^x (S_t).
$$

From (1) and (2),

$$
\frac{\partial}{\partial R_t} C(S_t, x) = [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] m \rho_E F_t(x - \rho_E R_t) + b \rho_E F_t(x - \rho_E R_t)
$$

$$
= \rho_E \left( [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] - (\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)) [1 - m F_t(x - \rho_E R_t) - b F_t(x - \rho_E R_t)] \right)
$$

$$
= \rho_E \left( [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] - \frac{\partial}{\partial x} C(S_t, x) \right).
$$

Therefore,

$$
\frac{d}{dR_t} C(S_t, x^*_t) = \frac{\partial}{\partial R_t} C(S_t, x^*_t) + \frac{dx^*_t}{dR_t} \frac{\partial}{\partial x} C(S_t, x^*_t)
$$

$$
= \rho_E \left( [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] - \frac{\partial}{\partial x} C(S_t, x^*_t) \right) + \frac{dx^*_t}{dR_t} \frac{\partial}{\partial x} C(S_t, x^*_t)
$$

$$
= \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] + \left( \frac{dx^*_t}{dR_t} - \rho_E \right) \frac{\partial}{\partial x} C(S_t, x^*_t). \quad (8)
$$

Next, from (3), we know that $C(S_T, x)$ is a concave function of $x$. Therefore, $x^*_T$ must satisfy

$$
\frac{\partial}{\partial x} C(S_T, x^*_T) = 0.
$$
and from (8),

\[
\frac{d}{dR_T} V_T(S_T) = \frac{d}{dR_T} C(S_T, x_T^*) \\
= \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_T - \mu_p)] + \left( \frac{dx_T^*}{dR_T} - \rho_E \right) \frac{\partial}{\partial x} C(S_T, x_T^*) \\
= \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_T - \mu_p)].
\]

Then,

\[
\frac{d^2}{dR_T^2} V_T(S_T) = 0.
\]

Next, denote

\[
g_t(R_{t+1}, W_t) := \mathbb{E}_{W_{t+1}} [V_{t+1}(S_{t+1}) \mid S_t, x],
\]

where \( R_{t+1} \) is a function of \( R_t, x \), and \( \hat{Y}_{t+1} \), as shown in (2). Also, denote

\[
g'_t(R_{t+1}, W_t) := \frac{d}{dR_{t+1}} g_t(R_{t+1}, W_t) = \mathbb{E}_{W_{t+1}} \left[ \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid S_t, x \right], \quad \text{and}
\]

\[
g''_t(R_{t+1}, W_t) := \frac{d^2}{dR_{t+1}^2} g_t(R_{t+1}, W_t) = \mathbb{E}_{W_{t+1}} \left[ \frac{d^2}{dR_{t+1}^2} V_{t+1}(S_{t+1}) \mid S_t, x \right].
\]

**Lemma 2.1:** Then, \( \forall 0 \leq t \leq T-1 \),

\[
\frac{\partial^2}{\partial x^2} V^x(S_t, x) = \mathbb{E} \left[ \left( \frac{\partial R_{t+1}}{\partial x} \right)^2 \frac{\partial^2}{dR_{t+1}^2} V_{t+1}(S_{t+1}) \mid S_t, x \right] + \frac{1}{\rho_E} f(x - \rho_E R_t) g'_t(0, W_t) \\
- \frac{1}{\rho_E} (1 - \rho_R \rho_E) f_t(x) g'_t(R_t, W_t) - \rho_R f_t \left( x + \frac{R_{\max} - R_t}{\rho_R} \right) g'_t(R_{\max}, W_t),
\]

where

\[
g'_t(0, W_t) := \mathbb{E}_{W_{t+1}} \left[ \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid R_{t+1} = 0, W_t \right],
\]

\[
g'_t(R_t, W_t) := \mathbb{E}_{W_{t+1}} \left[ \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid R_{t+1} = R_t, W_t \right], \quad \text{and}
\]

\[
g'_t(R_{\max}, W_t) := \mathbb{E}_{W_{t+1}} \left[ \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid R_{t+1} = R_{\max}, W_t \right].
\]

\( g'_t(0, W_t) \) is the left-derivative and \( g'_t(R_{\max}, W_t) \) is the right derivative.

**Proof:** From (6),

\[
\frac{\partial}{\partial x} \mathbb{E} [V(S_{t+1}) \mid S_t, x] = \mathbb{E} \left[ \frac{\partial R_{t+1}}{\partial x} g'_t(R_{t+1}, W_t) \mid S_t, x \right]
\]

Next, denote
using integration by parts. Then,

\[ E = - \int_{y < x < \frac{R_{\text{max}} - R_t}{\rho_E}} \rho_R g_t' (R_t + \rho_R (y - x), W_t) f_t(y) dy - \int_{x - \rho_E R_t < y \leq x} \frac{1}{\rho_E} g_t' \left( R_t - \frac{1}{\rho_E} (x - y), W_t \right) f_t(y) dy \]

\[ = - \int_{0 < u < \frac{R_{\text{max}} - R_t}{\rho_E}} \rho_R g_t' (R_t + \rho_R u, W_t) f_t(u + x) du - \int_{-\rho_E R_t < u < 0} \frac{1}{\rho_E} g_t' \left( R_t + \frac{1}{\rho_E} u, W_t \right) f_t(u + x) du \]

\[= - \rho_R g_t' (R_t + \rho_R u, W_t) f_t(u + x) \bigg|_{u=0}^{R_{\text{max}} - R_t} + \int_{0 < u < \frac{R_{\text{max}} - R_t}{\rho_E}} \rho_R^2 g_t'' (R_t + \rho_R u, W_t) F_t(u + x) du \]

\[\quad - \frac{1}{\rho_E} g_t' \left( R_t + \frac{1}{\rho_E} u, W_t \right) F_t(u + x) \bigg|_{u=-\rho_E R_t}^0 + \int_{-\rho_E R_t < u < 0} \frac{1}{\rho_E^2} g_t'' \left( R_t + \frac{1}{\rho_E} u, W_t \right) F_t(u + x) du,\]

using integration by parts. Then,

\[ \frac{\partial}{\partial x} E[V(S_{t+1} \mid S_t, x)] \]

\[= -\rho_R F_t \left( x + \frac{R_{\text{max}} - R_t}{\rho_E} \right) g_t' (R_{\text{max}}, W_t) + \rho_R F_t(x) g_t'(R_t, W_t) \]

\[\quad - \frac{1}{\rho_E} F_t(x) g_t'(R_t, W_t) + \frac{1}{\rho_E} F_t(x - \rho_E R_t) g_t'(0, W_t) \]

\[\quad + \int_{0 < u < \frac{R_{\text{max}} - R_t}{\rho_E}} \rho_R^2 g_t'' (R_t + \rho_R u, W_t) F_t(u + x) du \]

\[\quad + \int_{-\rho_E R_t < u < 0} \frac{1}{\rho_E^2} g_t'' \left( R_t + \frac{1}{\rho_E} u, W_t \right) F_t(u + x) du.\]

Therefore,

\[ \frac{\partial^2}{\partial x^2} E[V(S_{t+1} \mid S_t, x)] \]

\[= \int_{0 < u < \frac{R_{\text{max}} - R_t}{\rho_E}} \rho_R^2 g_t'' (R_t + \rho_R u, W_t) f_t(u + x) du + \int_{-\rho_E R_t < u < 0} \frac{1}{\rho_E^2} g_t'' \left( R_t + \frac{1}{\rho_E} u, W_t \right) f_t(u + x) du \]

\[\quad + \frac{1}{\rho_E} f_t(x - \rho_E R_t) g_t'(0, W_t) - \frac{1}{\rho_E} \left( 1 - \rho_R \rho_E \right) f_t(x) g_t'(R_t, W_t) - \rho_R f_t \left( x + \frac{R_{\text{max}} - R_t}{\rho_E} \right) g_t'(R_{\text{max}}, W_t) \]

\[= E \left[ \left( \frac{\partial R_{t+1}}{\partial x} \right)^2 \frac{d}{dR_{t+1}^2} V(S_{t+1} \mid S_t, x) \right] + \frac{1}{\rho_E} f_t(x - \rho_E R_t) g_t'(0, W_t) \]

\[\quad - \frac{1}{\rho_E} \left( 1 - \rho_R \rho_E \right) f_t(x) g_t'(R_t, W_t) - \rho_R f_t \left( x + \frac{R_{\text{max}} - R_t}{\rho_E} \right) g_t'(R_{\text{max}}, W_t).\]

Similarly,
Lemma 2.2: ∀0 ≤ t ≤ T - 1,
\[
\frac{\partial^2}{\partial R_t^2} V_t^x(S_t, x) = \mathbb{E} \left[ \left( \frac{\partial R_{t+1}}{\partial R_t} \right)^2 \frac{d^2}{dR_{t+1}^2} V_{t+1}(S_{t+1}) \mid S_t, x \right] + \rho_E f_t(x - \rho_E R_t) g_t'(0, W_t) \\
- \frac{1}{\rho_R} f_t \left( x + \frac{R_{\text{max}} - R_t}{\rho_R} \right) g_t'(R_{\text{max}}, W_t).
\]
(12)

Proof: From (7),
\[
\frac{\partial}{\partial R_t} \mathbb{E}[V(S_{t+1}) \mid S_t, x] = \mathbb{E} \left[ \frac{\partial R_{t+1}}{\partial R_t} g_t'(R_{t+1}, W_t) \mid S_t, x \right]
\]
\[
= \int_{x < y < x + \frac{R_{\text{max}} - R_t}{\rho_R}} g_t'(R_t + \rho_R(y - x), W_t) f_t(y) dy + \int_{x - \rho_E R_t < y \leq x} g_t'(R_t - \frac{1}{\rho_E} (x - y), W_t) f_t(y) dy
\]
\[
= \int_{0 < u < \frac{R_{\text{max}} - R_t}{\rho_R}} g_t'(R_t + \rho_R u, W_t) f_t(u + x) du + \int_{-\rho_E R_t < u \leq 0} g_t'(R_t + \frac{1}{\rho_E} u, W_t) f_t(u + x) du
\]
Therefore,
\[
\frac{\partial^2}{\partial R_t^2} \mathbb{E}[V(S_{t+1}) \mid S_t, x] = \frac{\partial}{\partial R_t} \mathbb{E} \left[ \frac{\partial R_{t+1}}{\partial R_t} g_t'(R_{t+1}, W_t) \mid S_t, x \right]
\]
\[
= \int_{-\rho_E R_t < u \leq 0} 1^2 g_t''(R_t + \frac{1}{\rho_E} u, W_t) f_t(u + x) du + \int_{0 < u < \frac{R_{\text{max}} - R_t}{\rho_R}} 1^2 g_t''(R_t + \rho_R u, W_t) f_t(u + x) du
\]
\[
+ \rho_E g_t'(0, W_t) f_t(x - \rho_E R_t) - \frac{1}{\rho_R} g_t'(R_{\text{max}}, W_t) f_t \left( x + \frac{R_{\text{max}} - R_t}{\rho_R} \right)
\]
\[
= \mathbb{E} \left[ \left( \frac{\partial R_{t+1}}{\partial R_t} \right)^2 \frac{d^2}{dR_{t+1}^2} V_{t+1}(S_{t+1}) \mid S_t, x \right] + \rho_E f_t(x - \rho_E R_t) g_t'(0, W_t) - \frac{1}{\rho_R} f_t \left( x + \frac{R_{\text{max}} - R_t}{\rho_R} \right) g_t'(R_{\text{max}}, W_t).
\]

Also,
Lemma 2.3: 0 ≤ t ≤ T - 1,
\[
\frac{\partial^2}{\partial R_t \partial x} V_t^x(S_t, x) = \mathbb{E} \left[ \frac{\partial R_{t+1}}{\partial x} \frac{\partial R_{t+1}}{\partial R_t} \frac{d^2}{dR_{t+1}^2} V_{t+1}(S_{t+1}) \mid S_t, x \right] - f_t(x - \rho_E R_t) g_t'(0, W_t)
\]
\[
+ f_t \left( x + \frac{R_{\text{max}} - R_t}{\rho_R} \right) g_t'(R_{\text{max}}, W_t).
\]
(13)

Proof: From (7),
\[
\frac{\partial}{\partial R_t} \mathbb{E}[V(S_{t+1}) \mid S_t, x] = \mathbb{E} \left[ \frac{\partial R_{t+1}}{\partial R_t} g_t'(R_{t+1}, W_t) \mid S_t, x \right]
\]
\[
= \int_{x < y < x + \frac{R_{\text{max}} - R_t}{\rho_R}} g_t'(R_t + \rho_R(y - x), W_t) f_t(y) dy + \int_{x - \rho_E R_t < y \leq x} g_t'(R_t - \frac{1}{\rho_E} (x - y), W_t) f_t(y) dy
\]
\[\begin{align*}
\text{Lemma 2.4: If } x_t^* \text{ satisfies } \\
\frac{\partial}{\partial x} C(S_t, x_t^*) + \gamma \frac{\partial}{\partial x} V_t^x(S_t, x_t^*) &= 0, \\
\end{align*}\]

then

\[\frac{d}{dR_t} V_t(S_t) = \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] + \gamma \mathbb{E} \left[ \left( \rho_E \frac{\partial R_{t+1}}{\partial x} + \rho_E \frac{\partial R_{t+1}}{\partial R_t} \right) \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) | S_t, x_t^* \right].\] (14)
Proof: From (8),

\[
\begin{align*}
\frac{d}{dR_t} V_t(S_t) &= \frac{d}{dR_t} C(S_t, x^*_t) + \gamma \frac{d}{dR_t} V^x_t(S_t, x^*_t) \\
&= \rho_E [\mu_p + (1 - \kappa \triangle \tau) (p_t - \mu_p)] + \left( \frac{dx^*_t}{dR_t} - \rho_E \right) \frac{\partial}{\partial x} C(S_t, x^*_t) + \gamma \frac{\partial}{\partial R_t} V^x_t(S_t, x^*_t) + \gamma \frac{dx^*_t}{dR_t} \frac{\partial}{\partial x} V^x_t(S_t, x^*_t) \\
&= \rho_E [\mu_p + (1 - \kappa \triangle \tau) (p_t - \mu_p)] + \frac{dx^*_t}{dR_t} \left[ \frac{\partial}{\partial x} C(S_t, x^*_t) + \gamma \frac{\partial}{\partial x} V^x_t(S_t, x^*_t) \right] \\
&\quad - \rho_E \cdot \frac{\partial}{\partial x} C(S_t, x^*_t) + \gamma \frac{\partial}{\partial R_t} V^x_t(S_t, x^*_t) \\
&= \rho_E [\mu_p + (1 - \kappa \triangle \tau) (p_t - \mu_p)] + \gamma \rho_E \cdot \frac{\partial}{\partial x} V^x_t(S_t, x^*_t) + \gamma \frac{\partial}{\partial R_t} V^x_t(S_t, x^*_t),
\end{align*}
\]

where we substituted

\[-\rho_E \cdot \frac{\partial}{\partial x} C(S_t, x^*_t) = \gamma \rho_E \cdot \frac{\partial}{\partial x} V^x_t(S_t, x^*_t).\]

Then,

\[
\begin{align*}
\frac{d}{dR_t} V_t(S_t) &= \rho_E [\mu_p + (1 - \kappa \triangle \tau) (p_t - \mu_p)] + \gamma E \left[ \rho_E \frac{\partial R_{t+1}}{\partial x} \cdot \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) | S_t, x^*_t \right] \\
&\quad + \gamma E \left[ \frac{\partial R_{t+1}}{\partial R_t} \cdot \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) | S_t, x^*_t \right] \\
&= \rho_E [\mu_p + (1 - \kappa \triangle \tau) (p_t - \mu_p)] + \gamma E \left[ \left( \rho_E \frac{\partial R_{t+1}}{\partial x} + \frac{\partial R_{t+1}}{\partial R_t} \right) \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid S_t, x^*_t \right].
\end{align*}
\]

Next,

**Lemma 2.5:** \( \forall 0 \leq t \leq T - 1, \) if \( C(S_t, x) + \gamma V^x_t(S_t, x) \) is a concave function of \((R_t, x)\), then

\[
V_t(S_t) = \max_{x \in \mathbb{R}_+} \left\{ C(S_t, x) + \gamma V^x_t(S_t, x) \right\}
\]

is a concave function of \( R_t \).

**Proof:** This follows from pp.87-88 of Boyd and Vandenberghe (2004).

---

**2.3. Backward Induction:**

We prove the structural results using backward induction. From (9) and (10),

\[
\rho_E [\mu_p + (1 - \kappa \triangle \tau) (p_T - \mu_p)] \leq \frac{d}{dR_T} V_T(S_T) \leq \frac{1}{\rho_R} [\mu_p + (1 - \kappa \triangle \tau) (p_T - \mu_p)]
\]
and
\[
\frac{d^2}{dR_t^2} V_T(S_T) \leq 0.
\]

Therefore, we can assume
\[
\rho_E \left[ \mu_p + (1 - \kappa \triangle \tau) (p_{t+1} - \mu_p) \right] \leq \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \leq \frac{1}{\rho_R} \left[ \mu_p + (1 - \kappa \triangle \tau) (p_{t+1} - \mu_p) \right] \tag{16}
\]
and
\[
\frac{d^2}{dR_{t+1}^2} V_{t+1}(S_{t+1}) \leq 0,
\]
for some \( t \leq T - 1 \). From (16) and (5) we know that
\[
\rho_E \left[ \mu_p + (1 - \kappa \triangle \tau)^2 (p_t - \mu_p) \right] \leq \frac{1}{\rho_R} \left[ \mu_p + (1 - \kappa \triangle \tau)^2 (p_t - \mu_p) \right]
\]

**Step 1** From (3), (4), (5), (11), (12), and (13), we can show that
\[
\left[ z_1 \ z_2 \right] \left[ \begin{array}{cc}
\frac{\partial^2}{\partial x^2} C(S_t, x) + \gamma \frac{\partial^2}{\partial x \partial R_t} V_x(S_t, x) + \frac{\partial^2}{\partial R_t^2} C(S_t, x) + \gamma \frac{\partial^2}{\partial x \partial R_t} V_x(S_t, x) \\
\frac{\partial^2}{\partial x \partial R_t} C(S_t, x) + \gamma \frac{\partial^2}{\partial x \partial R_t} V_x(S_t, x) + \frac{\partial^2}{\partial R_t^2} V_x(S_t, x)
\end{array} \right] \left[ \begin{array}{c}
z_1 \\
z_2
\end{array} \right]
\]
\[
= z_1^2 \left( \frac{\partial^2}{\partial x^2} C(S_t, x) + \gamma \frac{\partial^2}{\partial x^2} V_x(S_t, x) \right) + 2z_1z_2 \left( \frac{\partial^2}{\partial x \partial R_t} C(S_t, x) + \gamma \frac{\partial^2}{\partial x \partial R_t} V_x(S_t, x) \right)
\]
\[
+ z_2^2 \left( \frac{\partial^2}{\partial R_t^2} C(S_t, x) + \gamma \frac{\partial^2}{\partial R_t^2} V_x(S_t, x) \right)
\]
\[
= \mathbb{E} \left[ \gamma \left( z_1 \frac{\partial R_{t+1}}{\partial x} + z_2 \frac{\partial R_{t+1}}{\partial R_t} \right)^2 \frac{d^2}{dR_{t+1}^2} V_{t+1}(S_{t+1}) | S_t, x \right] - \left( mp_{t+1} + b - \gamma \frac{1}{\rho_E} g'_t(0, W_t) \right) f_t(x - \rho_E R_t) (z_1 - \rho_E z_2)^2
\]
\[
- \gamma \frac{1}{\rho_E} z_1^2 (1 - \rho_R \rho_E) f_t(x) g'_t(R_t, W_t) - \gamma \rho_R f_t \left( x + \frac{R_{max} - R_t}{\rho_R} \right) g'_t(R_{max}, W_t) \left( z_1 - \frac{1}{\rho_R} z_2 \right)^2,
\]
\( \forall z_1, z_2 \in \mathbb{R} \). However, from (17),
\[
\mathbb{E} \left[ \left( z_1 \frac{\partial R_{t+1}}{\partial x} + z_2 \frac{\partial R_{t+1}}{\partial R_t} \right)^2 \frac{d^2}{dR_{t+1}^2} V_{t+1}(S_{t+1}) | S_t, x \right] \leq 0.
\]

Next, since
\[
m \geq \frac{\gamma}{\rho_E \rho_R}, \quad b \geq \frac{\gamma}{\rho_E \rho_R} \mu_p,
\]
and
\[
\gamma \frac{1}{\rho_E} g'_t(0, W_t) \leq \frac{\gamma}{\rho_E \rho_R} \left[ \mu_p + (1 - \kappa \triangle \tau)^2 (p_t - \mu_p) \right]
\]
\[
\begin{align*}
\frac{\gamma}{\rho_E \rho_R} \left[ (1 - \kappa \Delta \tau) \mu_p + (1 - \kappa \Delta \tau)^2 (p_t - \mu_p) + \kappa \Delta \tau \mu_p \right] \\
= \frac{(1 - \kappa \Delta \tau) \gamma}{\rho_E \rho_R} [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] + \frac{\gamma \kappa \Delta \tau}{\rho_E \rho_R} \mu_p \\
\leq m p_{t+1} + b,
\end{align*}
\]

\[
mp_{t+1} + b - \gamma \frac{1}{\rho_E} g'(0, W_t) \geq 0.
\]

Therefore, the Hessian of \(C(S_t, x) + \gamma V_t^x(S_t^x)\) shown above is a negative semi-definite matrix, implying that \(C(S_t, x) + \gamma V_t^x(S_t^x)\) is a concave function of \((R_t, x)\).

**step 2)** If \(x_t = 0\), \(\hat{Y}_{t+1} \geq x_t\) since \(\hat{Y}_{t+1} \geq 0\). Therefore, from (6),

\[
\frac{\partial R_{t+1}}{\partial x} \geq -\rho_R, \text{ if } x_t = 0.
\]

Since

\[
\rho_E \left[ \mu_p + (1 - \kappa \Delta \tau) (p_{t+1} - \mu_p) \right] \leq \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \leq \frac{1}{\rho_R} \left[ \mu_p + (1 - \kappa \Delta \tau) (p_{t+1} - \mu_p) \right],
\]

\[
E \left[ \frac{\partial R_{t+1}}{\partial x} \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid S_t, 0 \right] \geq - \left[ \mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p) \right].
\]

Therefore,

\[
\frac{\partial}{\partial x} C(S_t, 0) + \gamma \frac{\partial}{\partial x} V_t^x(S_t, 0)
\]

\[
= -(mp_{t+1} + b) F_t(-\rho_E R_t) + p_{t+1} + \gamma E \left[ \frac{\partial R_{t+1}}{\partial x} \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid S_t, 0 \right]
\]

\[
= p_{t+1} + \gamma E \left[ \frac{\partial R_{t+1}}{\partial x} \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid S_t, 0 \right] > p_{t+1} - \gamma p_{t+1} = 0.
\]  

(18)

Next, since \(p_{t+1} < mp_{t+1} + b\), \(\exists x_t^U < \infty\) such that

\[
F_t(x_t^U - \rho_E R_t) = \frac{p_{t+1}}{mp_{t+1} + b}.
\]

Therefore,

\[
\frac{\partial}{\partial x} C(S_t, x_t^U) = -(mp_{t+1} + b) F_t(x_t^U - \rho_E R_t) + p_{t+1} = 0.
\]
Moreover, we know that

\[
\frac{\partial}{\partial x} V_t^x(S_t, x) = E \left[ \frac{\partial R_{t+1}}{\partial x} \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid S_t, x \right] \leq 0, \forall x,
\]

since

\[
\frac{\partial R_{t+1}}{\partial x} \leq 0 \quad \text{and} \quad \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \geq 0.
\]

Therefore,

\[
\frac{\partial}{\partial x} C(S_t, x^U_t) + \gamma \frac{\partial}{\partial x} V_t^x(S_t, x^U_t) \leq 0. \tag{19}
\]

Since \( C(S_t, x) + \gamma V_t^x(S_t^*) \) is a concave function of \( x \), from (18) and (19), we know that \( \exists 0 < x_t^* \leq x_t^U < \infty \) such that

\[
\frac{\partial}{\partial x} C(S_t, x_t^*) + \gamma \frac{\partial}{\partial x} V_t^x(S_t, x_t^*) = 0,
\]

and it is the optimal decision at time \( t \).

**Step 3** Since \( C(S_t, x) + \gamma V_t^x(S_t^*) \) is a concave function of \((R_t, x)\) and

\[
x_t^* = \arg\max_{x \in \mathbb{R}_+} \{ C(S_t, x) + V_t^x(S_t, x) \}
\]

is the point where the derivative of \( C(S_t, x) + \gamma V_t^x(S_t, x) \) with respect to \( x \) is zero, from (14) and (15), it immediately follows that

\[
\frac{d}{dR_t} V_t(S_t) = \rho_E \left[ \mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p) \right] + \gamma E \left[ \left( \rho_E \frac{\partial R_{t+1}}{\partial x} + \frac{\partial R_{t+1}}{\partial R_t} \right) \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid S_t, x_t^* \right], \tag{20}
\]

and

\[
V_t(S_t) = C(S_t, x_t^*) + \gamma V_t^x(S_t, x_t^*)
\]

is a concave function of \( R_t \).

**Step 4** From (6) and (7),

\[
0 \leq \rho_E \frac{\partial R_{t+1}}{\partial x} + \frac{\partial R_{t+1}}{\partial R_t} \leq 1 - \rho_E \rho_R.
\]
Since
\[ \rho E [\mu_p + (1 - \kappa \Delta \tau) (p_{t+1} - \mu_p)] \leq \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \leq \frac{1}{\rho_R} [\mu_p + (1 - \kappa \Delta \tau) (p_{t+1} - \mu_p)], \]
\[ 0 \leq \gamma E \left[ \left( \rho E \frac{\partial R_{t+1}}{\partial x} + \frac{\partial R_{t+1}}{\partial R_t} \right) \right. \left. \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid S_t, x_t^* \right] \leq \frac{(1 - \rho_E \rho_R)}{\rho_R} [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)]. \]

Then, from (20),
\[ \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] \leq \frac{d}{dR_t} V_t(S_t) \leq \left[ \rho_E + \frac{1}{\rho_R} (1 - \rho_E \rho_R) \right] [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] \]
\[ = \frac{1}{\rho_R} [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)]. \]

In summary, by assuming
\[ \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_{t+1} - \mu_p)] \leq \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \leq \frac{1}{\rho_R} [\mu_p + (1 - \kappa \Delta \tau) (p_{t+1} - \mu_p)] \]
and \( V_{t+1}(S_{t+1}) \) is a concave function of \( R_{t+1} \), we were able to prove that
\[ \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] \leq \frac{d}{dR_t} V_t(S_t) \leq \frac{1}{\rho_R} [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)], \]
and \( V_t(S_t) \) is a concave function of \( R_t \). Since
\[ \frac{d}{dR_T} V_T(S_T) = \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_T - \mu_p)] \quad \text{and} \quad \frac{d^2}{dR_T^2} V_T(S_T) = 0, \]
by induction, the above results are true for all \( 0 \leq t \leq T - 1 \). Then, from step 1, step 2, and step 3, it follows that \( C(S_t, x) + \gamma V_t^x(S_t, x) \) is a concave function of \( (R_t, x) \), the optimal decision \( x^*_t \) is positive and finite and it is the point where the derivative of \( C(S_t, x) + \gamma V_t^x(S_t, x) \) with respect to \( x \) is zero, and
\[ \frac{d}{dR_t} V_t(S_t) = \rho_E [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] + \gamma E \left[ \left( \rho E \frac{\partial R_{t+1}}{\partial x} + \frac{\partial R_{t+1}}{\partial R_t} \right) \frac{d}{dR_{t+1}} V_{t+1}(S_{t+1}) \mid S_t, x_t^* \right], \]
for all \( 0 \leq t \leq T - 1 \).
3. Proof of (18):

Since

\[
\frac{d}{dR_T}V_T(S_T) = \rho_E \left[ \mu_p + (1 - \kappa \Delta \tau) \left( p_T - \mu_p \right) \right]
\]

from (9), \( x_{T-1}^* \) must satisfy

\[
\frac{\partial}{\partial x} C(S_{T-1}, x_{T-1}^*) + \rho_E \left[ \mu_p + (1 - \kappa \Delta \tau)^2 \left( p_{T-1} - \mu_p \right) \right] \mathbb{E} \left[ \gamma \frac{\partial R_T}{\partial x} | S_{T-1}, x_{T-1}^* \right] 
\]

\[
= p_{T,T-1} - (mp_{T,T-1} + b) \frac{1}{\beta} (x_{T-1}^* - \rho_E R_{T-1} - \theta_{T-1}) - \left[ (1 - \kappa \Delta \tau) p_{T,T-1} + \kappa \Delta \tau \mu_p \right] \frac{1}{\beta} \gamma \rho_E R_{\text{max}} 
\]

\[
= 0.
\]

Therefore,

\[
x_{T-1}^* - \rho_E R_{T-1} - \theta_{T-1} = \frac{p_{T,T-1} - p_{T,T-1} \left[ (1 - \kappa \Delta \tau) + \kappa \Delta \tau \frac{\mu_p}{p_{T,T-1}} \right] \frac{1}{\beta} \gamma \rho_E R_{\text{max}}}{(mp_{T,T-1} + b)} 
\]

\[
= \frac{p_{T,T-1}}{mp_{T,T-1} + b} \left( 1 - (1 - \kappa \Delta \tau) \frac{1}{\beta} \rho_E R_{\text{max}} - \kappa \Delta \tau \frac{\mu_p}{p_{T,T-1}} \frac{1}{\beta} \gamma \rho_E R_{\text{max}} \right) 
\]

\[
= \frac{p_{T,T-1}}{mp_{T,T-1} + b} \left( \beta - (1 - \kappa \Delta \tau) + \kappa \Delta \tau \frac{\mu_p}{p_{T,T-1}} \right) \gamma \rho_E R_{\text{max}}. 
\]

By manually computing the marginal value function and the optimal decision backward through time, one can show that given \( S_T = S_{T-1} = S_{T-2} = ... = S_0, \)

\[
x_{T}^* - \theta_T \geq x_{T-1}^* - \theta_{T-1} \geq x_{T-2}^* - \theta_{T-2} \geq ... \geq x_0^* - \theta_0. 
\]

Since \( \theta_t \) is the amount of electricity we are certain to produce during the time interval \([t, t+1)\), we refer to \( x_t^* - \theta_t \), the commitment over \( \theta_t \), as the extra-commitment, \( \forall t \). Smaller the remaining time period until the end of the horizon, greater the extra-commitment must be such that we do not squander energy in storage by missing the opportunity to sell. If there is more time remaining and more opportunity to sell energy in the future, we can commit less now and reduce the risk of over-commitment. Therefore, the extra-commitment we make in the infinite horizon setting will always be less than the extra-commitment we make in the finite horizon setting, if everything else is equal.
Let \( x^*_t - \theta_t \) be the extra commitment we make in the infinite horizon setting at some time \( t \) given that the state is \( S_t \). Next, let \( x^*_{T-1} - \theta_{T-1} \) be the extra commitment we make in the finite horizon setting at time \( T - 1 \) where \( T \) denotes the end of the horizon. Then, we know that \( x^*_t - \theta_t \leq x^*_{T-1} - \theta_{T-1} \) if \( S_t = S_{T-1} \). Next, from (10),

\[
p_{T,T-1}R_{\max}(m - \rho_E \rho_R \gamma (1 - \kappa \Delta \tau)) \leq \rho_R \beta (m - 1)p_{T,T-1}
\]

and

\[
R_{\max}(b + \gamma \rho_E \rho_R \kappa \Delta \tau \mu_P) \leq b \rho_R \beta.
\]

Then,

\[
p_{T,T-1}R_{\max}(m - \rho_E \rho_R \gamma (1 - \kappa \Delta \tau)) + R_{\max}(b + \rho_E \rho_R \gamma \kappa \Delta \tau \mu_P) \leq \rho_R \beta (m - 1)p_{T,T-1} + b \rho_R \beta,
\]

which can be written as

\[
R_{\max}\left(mp_{T,T-1} + b - \rho_E \rho_R p_{T,T-1} \gamma \left(1 - \kappa \Delta \tau + \kappa \Delta \tau \frac{\mu_P}{p_{T,T-1}}\right)\right) \leq \rho_R \beta (mp_{T,T-1} + b - p_{T,T-1}).
\]

Therefore,

\[
\frac{R_{\max}}{\rho_R} \left(1 - \rho_E \rho_R \frac{p_{T,T-1}}{mp_{T,T-1} + b} \gamma \left(1 - \kappa \Delta \tau + \kappa \Delta \tau \frac{\mu_P}{p_{T,T-1}}\right)\right) \leq \beta \left(1 - \frac{p_{T,T-1}}{mp_{T,T-1} + b}\right).
\]

Then,

\[
x^*_{T-1} - \theta_{T-1} + \frac{R_{\max} - R_{T-1}}{\rho_R} = \frac{p_{T,T-1}}{mp_{T,T-1} + b} \beta - \frac{p_{T,T-1}}{mp_{T,T-1} + b} \gamma \left(1 - \kappa \Delta \tau + \kappa \Delta \tau \frac{\mu_P}{p_{T,T-1}}\right) \rho_E R_{\max} + \rho_E R_{T-1} + \frac{R_{\max} - R_{T-1}}{\rho_R}
\]

\[
= \frac{p_{T,T-1}}{mp_{T,T-1} + b} \beta + \frac{R_{\max}}{\rho_R} \left(1 - \rho_E \rho_R \frac{p_{T,T-1}}{mp_{T,T-1} + b} \gamma \left(1 - \kappa \Delta \tau + \kappa \Delta \tau \frac{\mu_P}{p_{T,T-1}}\right)\right) - (1 - \rho_E \rho_R) \frac{R_{\max} - R_{T-1}}{\rho_R}
\]

\[
\leq \frac{p_{T,T-1}}{mp_{T,T-1} + b} \beta + \frac{R_{\max}}{\rho_R} \left(1 - \rho_E \rho_R \frac{p_{T,T-1}}{mp_{T,T-1} + b} \gamma \left(1 - \kappa \Delta \tau + \kappa \Delta \tau \frac{\mu_P}{p_{T,T-1}}\right)\right)
\]

\[
\leq \frac{p_{T,T-1}}{mp_{T,T-1} + b} \beta + \beta \left(1 - \frac{p_{T,T-1}}{mp_{T,T-1} + b}\right) = \beta
\]

If \( S_t = S_{T-1} \),

\[
x^*_t + \frac{R_{\max} - R_0}{\rho_R} \leq \theta_t + \beta.
\]
4. Proof of (19):

**Proof:** We prove the theorem by using backward induction in the finite horizon setting and letting $T$ go to infinity. First, we make the induction hypothesis that

\[
\frac{d}{dR_{T-i}} V_{T-i}(S_{T-i}) = \rho_E \mu_p \sum_{j=0}^{i} \frac{1}{j!} \left[ \gamma \left( 1 - \rho_R \rho E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_{T-i}}{\rho_R} \right)^j \right].
\]

(21)

for some $i \geq 0$, and prove that

\[
\frac{d}{dR_{T-(i+1)}} V_{T-(i+1)}(S_{T-(i+1)}) = \rho_E \mu_p \sum_{j=0}^{i+1} \frac{1}{j!} \left[ \gamma \left( 1 - \rho_R \rho E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_{T-(i+1)}}{\rho_R} \right)^j \right] + \rho_E (p_{T-i} - \mu_p) (1 - \kappa \Delta \tau) \sum_{j=0}^{i} \frac{1}{j!} \left[ \gamma (1 - \kappa \Delta \tau) \left( 1 - \rho_R \rho E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_{T-i}}{\rho_R} \right)^j \right].
\]

From (9), we know that

\[
\frac{d}{dR_T} V_T(S_T) = \rho_E \mu_p + \rho_E (p_T - \mu_p) (1 - \kappa \Delta \tau).
\]

Therefore, the expression for $\frac{d}{dR_{T-i}} V_{T-i}(S_{T-i})$ shown above is true for $i = 0$. From (2), we can subtract $R_{t+1}$ from $R_{\text{max}}$ and divide by $\rho_R$ to get

\[
\frac{R_{\text{max}} - R_{t+1}}{\rho_R} = \begin{cases} 
0, & \text{if } R_t + \rho_R (Y_{t+1} - x_t) \geq R_{\text{max}}, \\
\frac{R_{\text{max}} - R_t}{\rho_R} - (Y_{t+1} - x_t), & \text{if } x_t < Y_{t+1}, R_t + \rho_R (Y_{t+1} - x_t) < R_{\text{max}}, \\
\frac{1}{\rho_R} \frac{\rho E}{\rho R} (x_t - Y_{t+1}), & \text{if } Y_{t+1} \leq x_t < \rho_E R_t + Y_{t+1}, \\
\frac{\rho E}{\rho R} \left( x_t - Y_{t+1} \right), & \text{if } x_t \geq \rho_E R_t + Y_{t+1}.
\end{cases}
\]

Next, from (2), we know that

\[
\rho_E \frac{\partial R_{t+1}}{\partial x} + \rho_E \frac{\partial R_{t+1}}{\partial R_t} = \begin{cases} 
0, & \text{if } R_t + \rho_R (Y_{t+1} - x) \geq R_{\text{max}}, \\
1 - \rho_E \rho R, & \text{if } x < Y_{t+1}, R_t + \rho_R (Y_{t+1} - x) < R_{\text{max}}, \\
0, & \text{if } Y_{t+1} \leq x < \rho_E R_t + Y_{t+1}, \\
0, & \text{if } x \geq \rho_E R_t + Y_{t+1}.
\end{cases}
\]

Therefore,

\[
\left( \rho E \frac{\partial R_{t+1}}{\partial x} + \rho E \frac{\partial R_{t+1}}{\partial R_t} \right) \frac{1}{j!} \left( \frac{R_{\text{max}} - R_{t+1}}{\rho_R} \right)^j \bigg|_{x=x_t^*} = \begin{cases} 
(1 - \rho E \rho R) \frac{1}{j!} \left[ \frac{R_{\text{max}} - R_t}{\rho_R} - (Y_{t+1} - x_t^*) \right]^j, & \text{if } x_t^* < Y_{t+1}, R_t + \rho_R (Y_{t+1} - x_t^*) < R_{\text{max}}, \\
0, & \text{otherwise}.
\end{cases}
\]
Next, by (18),
\[ f_t(y) = \frac{1}{\beta}, \quad \forall x_i^* \leq y \leq x_i^* + \frac{R_{\max} - R_t}{\rho_R}. \]

Therefore,
\[
E\left[ \left( \rho_E \frac{\partial R_{t+1}}{\partial x} + \frac{\partial R_{t+1}}{\partial R_t} \right) \frac{1}{j!} \left( \frac{R_{\max} - R_{t+1}}{\rho_R} \right)^j | S_t, x_i^* \right] = (1 - \rho_E \rho_R) \frac{1}{\beta} \frac{1}{j!} \int_{x_i^* \leq y \leq x_i^* + \frac{R_{\max} - R_t}{\rho_R}} \left[ \frac{R_{\max} - R_t}{\rho_R} - (y - x_i^*) \right]^j f_i(y) dy \\
= (1 - \rho_E \rho_R) \frac{1}{\beta} \frac{1}{j!} \int_{0 \leq u \leq \frac{R_{\max} - R_t}{\rho_R}} \left( \frac{R_{\max} - R_t}{\rho_R} - u \right)^j du \\
= (1 - \rho_E \rho_R) \frac{1}{\beta} \frac{1}{(j+1)!} \left( \frac{R_{\max} - R_t}{\rho_R} \right)^{j+1}.
\]

Then, from **Structural Result 3** and (22),
\[
\frac{d}{dR_{T-(i+1)}} V_{T-(i+1)}(S_{T-(i+1)}) \\
= \rho_E (\mu_p + (1 - \kappa \Delta \tau) (p_{T-(i+1)} - \mu_p)) + \gamma E\left[ \left( \rho_E \frac{\partial R_{t-i}}{\partial x} + \frac{\partial R_{t-i}}{\partial R_{T-(i+1)}} \right) \frac{d}{dR_{T-i}} V_{T-i}(S_{T-i}) | S_{T-(i+1)}, x_{T-(i+1)}^* \right] \\
= \rho_E (\mu_p + (1 - \kappa \Delta \tau) (p_{T-(i+1)} - \mu_p)) + \rho_E \mu_p \sum_{j=0}^{i+1} \frac{1}{(j+1)!} \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{T-(i+1)}}{\rho_R} \right) \right]^{j+1} \\
+ \rho_E (p_{T-(i+1)} - \mu_p) (1 - \kappa \Delta \tau) \sum_{j=0}^{i+1} \frac{1}{(j+1)!} \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{T-(i+1)}}{\rho_R} \right) \right]^{j+1} \\
= \rho_E \mu_p + \rho_E \mu_p \sum_{j=0}^{i+1} \frac{1}{j!} \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{T-(i+1)}}{\rho_R} \right) \right]^j + \rho_E (p_{T-(i+1)} - \mu_p) (1 - \kappa \Delta \tau) \\
+ \rho_E (p_{T-(i+1)} - \mu_p) (1 - \kappa \Delta \tau) \sum_{j=0}^{i+1} \frac{1}{j!} \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{T-(i+1)}}{\rho_R} \right) \right]^j \\
= \rho_E \mu_p \sum_{j=0}^{i+1} \frac{1}{j!} \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{T-(i+1)}}{\rho_R} \right) \right]^j + \rho_E (p_{T-(i+1)} - \mu_p) (1 - \kappa \Delta \tau) \\
+ \rho_E (p_{T-(i+1)} - \mu_p) (1 - \kappa \Delta \tau) \sum_{j=0}^{i+1} \frac{1}{j!} \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{T-(i+1)}}{\rho_R} \right) \right]^j \\
\]

Therefore, (21) is true for \( \forall i \geq 0 \). Next, substitute \( t \) for \( T - (i + 1) \). Then,
\[
\frac{d}{dR_t} V_t (S_t) = \rho_E \mu_p \sum_{j=0}^{T-t} \frac{1}{j!} \left[ \gamma (1 - \rho_R \rho_E) \frac{1}{\beta} \left( \frac{R_{\max} - R_t}{\rho_R} \right) \right]^j.
\]
\[ + \rho_E (p_t - \mu_p) (1 - \kappa \Delta \tau) \sum_{j=0}^{T-t} \frac{1}{j!} \left[ \gamma (1 - \kappa \Delta \tau) (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{T-(i+1)}}{\rho R} \right) \right]_j, \]

\[ \forall t \leq T. \]

If we let \( T \) go to infinity,

\[ \frac{d}{dR_t} V(S_t) = \lim_{T \to \infty} \frac{d}{dR_t} V_t(S_t) \]

\[ = \rho E \mu_p \sum_{j=0}^{T-t} \frac{1}{j!} \left[ \gamma (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_t}{\rho R} \right) \right]_j \]

\[ + \rho E (p_t - \mu_p) (1 - \kappa \Delta \tau) \sum_{j=0}^{T-t} \frac{1}{j!} \left[ \gamma (1 - \kappa \Delta \tau) (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{T-(i+1)}}{\rho R} \right) \right]_j \]

\[ = \rho E \mu_p \sum_{j=0}^{\infty} \frac{1}{j!} \left[ \gamma (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_t}{\rho R} \right) \right]_j \]

\[ + \rho E (p_t - \mu_p) (1 - \kappa \Delta \tau) \sum_{j=0}^{\infty} \frac{1}{j!} \left[ \gamma (1 - \kappa \Delta \tau) (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{T-(i+1)}}{\rho R} \right) \right]_j \]

\[ = \rho E \mu_p \exp \left[ \gamma (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_t}{\rho R} \right) \right] \]

\[ + \rho E (p_t - \mu_p) (1 - \kappa \Delta \tau) \exp \left[ \gamma (1 - \kappa \Delta \tau) (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_t}{\rho R} \right) \right], \forall t. \]

5. Proof of (21):

From (2) and (6),

\[ \frac{\partial R_{i+1}}{\partial x} \exp \left[ \gamma (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{i+1}}{\rho R} \right) \right] \]

\[ = \begin{cases} 0, & \text{if } R_t + \rho R (Y_{i+1} - x) \geq R_{\max}, \\ -\rho_R \exp \left[ \gamma (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{i+1}}{\rho R} - (Y_{i+1} - x) \right) \right], & \text{if } x < Y_{i+1}, R_t + \rho R (Y_{i+1} - x) < R_{\max}, \\ -\frac{1}{\rho E} \exp \left[ \gamma (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{i+1}}{\rho R} + \frac{1}{\rho R \rho E} (x - Y_{i+1}) \right) \right], & \text{if } Y_{i+1} \leq x < \rho E R_t + Y_{i+1}. \end{cases} \]

Therefore,

\[ \mathbb{E} \left[ \frac{\partial R_{i+1}}{\partial x} \exp \left[ \gamma (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_{i+1}}{\rho R} \right) \right] | S_t, x \right] \]

\[ = -\rho_R \int_{x \leq y \leq x + \frac{R_{\max} - R_t}{\rho R}} \exp \left[ \gamma (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_t}{\rho R} - (y - x) \right) \right] f_t(y) dy \]

\[ - \frac{1}{\rho E} \int_{x - \rho E R_t \leq y \leq x} \exp \left[ \gamma (1 - \rho R \rho E) \frac{1}{\beta} \left( \frac{R_{\max} - R_t}{\rho R} - \frac{1}{\rho R \rho E} (y - x) \right) \right] f_t(y) dy \]
\[
\frac{1}{\beta} \int_{0 \leq u \leq \frac{R_{\text{max}} - R_t}{\rho_R}} \exp \left[ \gamma \left( 1 - \rho_R E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_t}{\rho_R} - u \right) \right] du \\
- \frac{1}{\rho_E \beta} \int_{-\rho_E R_t \leq u \leq 0} \exp \left[ \gamma \left( 1 - \rho_R E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_t}{\rho_R} - \frac{1}{\rho_R E} u \right) \right] du
\]

\[
= -\frac{\rho_R}{1 - \rho_R E} \left( \exp \left[ \gamma \left( 1 - \rho_R E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_t}{\rho_R} - 1 \right) \right] - 1 \right), \quad \forall x \geq \rho_E R_t + \theta_t.
\]
Similarly, we can show that

\[
E \left[ \frac{\partial R_{t+1}}{\partial x} \exp \left[ \gamma \left( 1 - \kappa \Delta t \right) \left( 1 - \rho_R E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}} - R_{t+1}}{\rho_R} \right) \right] | S_t, x \right] = -\frac{\rho_R}{1 - \rho_R E} \left( \exp \left[ \gamma \left( 1 - \kappa \Delta t \right) \left( 1 - \rho_R E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}}}{\rho_R} \right) \right] - 1 \right), \quad \forall x \geq \rho_E R_t + \theta_t.
\]

Therefore,

\[
E \left[ \frac{\partial R_{t+1}}{\partial x} \frac{d}{dR_{t+1}} V(S_{t+1}) | S_t, x \right] = -\mu_p \frac{\rho_R E}{1 - \rho_R E} \left( \exp \left[ \gamma \left( 1 - \rho_R E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}}}{\rho_R} \right) \right] - 1 \right)
\]

\[-(p_t - \mu_p) \left( 1 - \kappa \Delta t \right)^2 \frac{\rho_R E}{1 - \rho_R E} \left( \exp \left[ \gamma \left( 1 - \kappa \Delta t \right) \left( 1 - \rho_R E \right) \frac{1}{\beta} \left( \frac{R_{\text{max}}}{\rho_R} \right) \right] - 1 \right),
\]

\[\forall x \geq \rho_E R_t + \theta_t.\]

**6. Proof of (26):**

From (16),

\[x_t^* = \rho_E R_t + \theta_t + Z_t / \beta.\]

Then, from (2),

\[P[R_{t+1} = 0 | R_t, Z_t] = \frac{1}{\beta} (x_t^* - \rho_E R_t - \theta_t) = Z_t\]

and

\[P[R_{t+1} = 0 | R_t] = E[Z_t] = Z_1\]
\begin{align*}
\mathbb{P}[R_{t+1} = 0] &= \mathbb{P}[R_t = 0],
\end{align*}

in the steady-state. Similarly,

\begin{align*}
\mathbb{P}[R_{t+1} = R_{\text{max}} | R_t, Z_t] &= 1 - \frac{1}{\beta} \left( x_t^* + \frac{R_{\text{max}} - R_t}{\rho_R} - \theta_t \right) \\
&= 1 - \frac{1}{\beta} \left( \rho_R R_t + Z_t \beta + \frac{R_{\text{max}} - R_t}{\rho_R} \right) \\
&= 1 - Z_t - \frac{R_{\text{max}}}{\rho_R \beta} + \frac{(1 - \rho_E \rho_R) R_t}{\rho_R \beta},
\end{align*}

and

\begin{align*}
\mathbb{P}[R_{t+1} = R_{\text{max}} | R_t] &= 1 - Z_1 - \frac{R_{\text{max}}}{\rho_R \beta} + \frac{(1 - \rho_E \rho_R) R_t}{\rho_R \beta},
\end{align*}

in the steady-state. Moreover,

\begin{equation}
 f_{R_{t+1} | R_t}(u | R_t) = \begin{cases} 
 \frac{\rho_E}{\beta} & \text{if } 0 < u < R_t \\
 \frac{1}{\rho_R \beta} & \text{if } R_t \leq u < R_{\text{max}}.
\end{cases}
\end{equation}

Therefore, we can write the conditional probability density function as

\begin{equation}
 f_{R_{t+1} | R_t}(u | R_t = r) = Z_1 \delta(u) + \frac{\rho_E}{\beta} 1_{\{0 \leq u < r\}} + \frac{1}{\rho_R \beta} 1_{\{r \leq u \leq R_{\text{max}}\}} \\
+ \left( 1 - Z_1 - \frac{R_{\text{max}}}{\rho_R \beta} + \frac{(1 - \rho_E \rho_R) R_t}{\rho_R \beta} \right) \delta(u - R_{\text{max}}),
\end{equation}

where \( \delta(\cdot) \) denotes the Dirac-delta function. Since

\begin{equation}
 \mathbb{P}[R_t = 0] = Z_1,
\end{equation}

we know that the stationary distribution can be written as

\begin{equation}
 f_{R_t}(r) = Z_1 \delta(r) + g(r) 1_{\{0 \leq r \leq R_{\text{max}}\}} + \left( 1 - Z_1 - \int_{r=0}^{R_{\text{max}}} g(r) \, dr \right) \delta(r - R_{\text{max}}),
\end{equation}

where \( g(r) \) is the probability density function for a random variable \( R_t \) that is the difference between two independent random variables \( \text{Exponential}(\rho_E) \) and \( \text{Exponential}(\rho_R) \).
for some function $g(r)$. By definition, the stationary distribution must satisfy

$$f_{R_{t+1}}(u) = \int_{r=0}^{R_{\text{max}}} f_{R_{t+1}|R_t}(u \mid R_t = r) \rho A \frac{R_{\text{max}}}{\rho E} \delta(u - R_{\text{max}}) dr = f_{R_t}(u).$$

Now we want to compute the integral

$$\int_{r=0}^{R_{\text{max}}} f_{R_{t+1}|R_t}(u \mid R_t = r) \cdot f_{R_t}(r) \cdot \delta(u - R_{\text{max}}) dr,$$

using (23) and (24). Since there are too many terms in the equation, we separate the computation into three steps corresponding to the three terms in (24). Then, in the fourth step, we combine the terms corresponding to $1_{\{0 \leq r \leq R_{\text{max}}\}}$ to compute $g(\cdot)$. 

**Step 1)***

$$\mathcal{Z}_1 \int_{r=0}^{R_{\text{max}}} f_{R_{t+1}|R_t}(u \mid R_t = r) \cdot \delta(r) dr$$

$$= \mathcal{Z}_1 f_{R_{t+1}|R_t}(u \mid R_t = 0)$$

$$= \mathcal{Z}_1^2 \delta(u) + \frac{\mathcal{Z}_1}{\rho E \rho A} 1_{\{0 \leq u \leq R_{\text{max}}\}} + \mathcal{Z}_1 \left(1 - \frac{R_{\text{max}}}{\rho E \rho A} \right) \delta(u - R_{\text{max}}) \quad (25)$$

**Step 2)***

$$\left(1 - \mathcal{Z}_1 - \int_{r=0}^{R_{\text{max}}} g(r) dr \right) \int_{r=0}^{R_{\text{max}}} f_{R_{t+1}|R_t}(u \mid R_t = r) \cdot \delta(r - R_{\text{max}}) dr$$

$$= \left(1 - \mathcal{Z}_1 - \int_{r=0}^{R_{\text{max}}} g(r) dr \right) f_{R_{t+1}|R_t}(u \mid R_t = R_{\text{max}})$$

$$= \left(1 - \mathcal{Z}_1 - \int_{r=0}^{R_{\text{max}}} g(r) dr \right) \mathcal{Z}_1 \delta(u) + \left(1 - \mathcal{Z}_1 - \int_{r=0}^{R_{\text{max}}} g(r) dr \right) \frac{\rho E \rho A}{\rho E \rho A} 1_{\{0 \leq u \leq R_{\text{max}}\}}$$

$$+ \left(1 - \mathcal{Z}_1 - \int_{r=0}^{R_{\text{max}}} g(r) dr \right) \left(1 - \frac{\rho E \rho A}{\rho E \rho A} \right) \delta(u - R_{\text{max}}). \quad (26)$$

**Step 3)***

$$\int_{r=0}^{R_{\text{max}}} f_{R_{t+1}|R_t}(u \mid R_t = r) \cdot g(r) dr$$
\[
\begin{align*}
\left[ Z_1 \delta(u) + \left( 1 - Z_1 - \frac{R_{\text{max}}}{\rho R^\beta} \right) \delta(u - R_{\text{max}}) \right] \cdot \int_{r=0}^{R_{\text{max}}} g(r) \, dr \\
+ \delta(u - R_{\text{max}}) \frac{(1 - \rho E \rho R)}{\rho R^\beta} \int_{r=0}^{R_{\text{max}}} \rho g(r) \, dr + \frac{\rho E}{\rho R^\beta} \int_{r=u}^{R_{\text{max}}} g(r) \, dr + 1 \int_{r=0}^{u} g(r) \, dr \\
\end{align*}
\]

(27)

**Step 4** Collecting the \(1_{(0 \leq u \leq R_{\text{max}})} \) terms from (25), (26), (27), we get

\[
\frac{Z_1}{\rho R^\beta} + \left( 1 - Z_1 - \int_{r=0}^{R_{\text{max}}} g(r) \, dr \right) \frac{\rho R E}{\rho R^\beta} \int_{r=0}^{R_{\text{max}}} g(r) \, dr + \frac{1}{\rho R^\beta} \int_{r=0}^{u} g(r) \, dr
\]

\[
= \frac{Z_1 (1 - \rho R \rho E)}{\rho R^\beta} + \frac{\rho R E}{\rho R^\beta} \rho g(r) \, dr + \frac{1}{\rho R^\beta} \int_{r=0}^{u} g(r) \, dr
\]

\[
= \frac{Z_1 (1 - \rho R \rho E)}{\rho R^\beta} + \frac{\rho R E}{\rho R^\beta} + \frac{1 - \rho R \rho E}{\rho R^\beta} \int_{r=0}^{u} g(r) \, dr
\]

\[
= g(u).
\]

Taking the derivative with respect to \(u\) on both side gives

\[
g'(u) = \frac{(1 - \rho R \rho E)}{\rho R^\beta} g(u).
\]

Therefore,

\[
g(u) = a \exp \left[ \frac{(1 - \rho E \rho R)}{\rho R^\beta} u \right]
\]

for some constant \(a\). Since

\[
\int_{r=0}^{u} g(r) \, dr = a \exp \left[ \frac{(1 - \rho E \rho R)}{\rho R^\beta} u \right] - a
\]

from (28),

\[
a = \frac{Z_1}{\rho R^\beta} (1 - \rho R \rho E) + \frac{\rho R E}{\rho R^\beta}
\]

\[
= \left( Z_1 + \frac{\rho R E}{1 - \rho E \rho R} \right) \frac{(1 - \rho R \rho E)}{\rho R^\beta}.
\]

Next,

\[
\int_{r=0}^{R_{\text{max}}} g(r) \, dr = \left( Z_1 + \frac{\rho R E}{1 - \rho E \rho R} \right) \left( \exp \left[ \frac{(1 - \rho E \rho R)}{\rho R^\beta} R_{\text{max}} \right] - 1 \right)
\]
From (4) and (16),
\[
\begin{align*}
&= \left( Z_1 + \frac{\rho_r \rho_E}{1 - \rho_E \rho_R} \right) \exp \left( \frac{1 - \rho_E \rho_R}{\rho_R \beta} R_{\text{max}} \right) - Z_1 - \frac{\rho_r \rho_E}{1 - \rho_E \rho_R}.
\end{align*}
\]

Then,
\[
1 - Z_1 - \int_{r=0}^{R_{\text{max}}} g(r) \, dr
= \frac{1}{1 - \rho_E \rho_R} - \left( Z_1 + \frac{\rho_r \rho_E}{1 - \rho_E \rho_R} \right) \exp \left( \frac{1 - \rho_E \rho_R}{\rho_R \beta} R_{\text{max}} \right)
= \frac{1}{1 - \rho_E \rho_R} \left( 1 - \rho_r \rho_E \exp \left( \frac{1 - \rho_E \rho_R}{\rho_R \beta} R_{\text{max}} \right) \right) - Z_1 \exp \left( \frac{1 - \rho_E \rho_R}{\rho_R \beta} R_{\text{max}} \right)
= \frac{1}{1 - \rho_E \rho_R} \left( 1 - (\rho_r \rho_E + Z_1 (1 - \rho_E \rho_R)) \exp \left( \frac{1 - \rho_E \rho_R}{\rho_R \beta} R_{\text{max}} \right) \right)
\]

Therefore,
\[
f_{\mathcal{R}_t}(r) = Z_1 \delta(r) + \left( Z_1 + \frac{\rho_r \rho_E}{1 - \rho_E \rho_R} \right) \frac{1 - \rho_r \rho_E}{\rho_R \beta} \exp \left( \frac{1 - \rho_E \rho_R}{\rho_R \beta} r \right) \mathbf{1}_{\{0 \leq r \leq R_{\text{max}}\}}
+ \frac{1}{1 - \rho_E \rho_R} \left( 1 - (\rho_r \rho_E + Z_1 (1 - \rho_E \rho_R)) \exp \left( \frac{1 - \rho_E \rho_R}{\rho_R \beta} R_{\text{max}} \right) \right) \delta(r - R_{\text{max}}).
\]

\section*{7. Proof of (28):}

From (4) and (16),
\[
C(S_t, x_t^*) = p_{t,t+1} x_t^* - (mp_{t,t+1} + b) \cdot \int_{0 \leq y \leq x_t^* - \rho_E R_t} F_t(y) \, dy
= p_{t,t+1} x_t^* - (mp_{t,t+1} + b) \frac{1}{\beta} \cdot \int_{\theta_t \leq y \leq x_t^* - \rho_E R_t} (y - \theta_t) \, dy
= p_{t,t+1} x_t^* - (mp_{t,t+1} + b) \frac{1}{2\beta} (x_t^* - \rho_E R_t - \theta_t)^2
= p_{t,t+1} (\rho_E R_t + \theta_t + Z_t \beta) - (mp_{t,t+1} + b) \frac{\beta}{2} Z_t^2
= [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] (\rho_E R_t + \theta_t + Z_t \beta)
- (m [\mu_p + (1 - \kappa \Delta \tau) (p_t - \mu_p)] + b) \frac{\beta}{2} Z_t^2
\]

From (26), the stationary expectation of the storage level is given by
\[
\mathbb{E}[R_t] = \int_{r=0}^{R_{\text{max}}} r f_{\mathcal{R}_t}(r) \, dr
\]
\[ R_{\text{max}} \frac{1}{1 - \rho E \rho R} \left( 1 - (\rho R \rho E + Z_1 (1 - \rho E \rho R)) \exp \left( \frac{(1 - \rho E \rho R)^{\rho R \beta}}{\rho R \beta} \right) R_{\text{max}} \right) \]

\[ + \left( Z_1 + \frac{\rho R \rho E}{1 - \rho R \rho E} \right) \int_{r=0}^{R_{\text{max}}} \frac{(1 - \rho R \rho E)}{\rho R \beta} \exp \left( \frac{(1 - \rho R \rho E)^{\rho R \beta}}{\rho R \beta} r \right) \, dr \]

\[ = R_{\text{max}} \frac{1}{1 - \rho R \rho E} \left( 1 - (\rho R \rho E + Z_1 (1 - \rho E \rho R)) \exp \left( \frac{(1 - \rho E \rho R)^{\rho R \beta}}{\rho R \beta} \right) R_{\text{max}} \right) \]

\[ + \left( Z_1 + \frac{\rho R \rho E}{1 - \rho R \rho E} \right) \exp \left( \frac{(1 - \rho R \rho E)^{\rho R \beta}}{\rho R \beta} \right) \bigg|_{r=0}^{R_{\text{max}}} \]

\[ - \left( Z_1 + \frac{\rho R \rho E}{1 - \rho R \rho E} \right) \int_{r=0}^{R_{\text{max}}} \exp \left( \frac{(1 - \rho R \rho E)^{\rho R \beta}}{\rho R \beta} r \right) \, dr \]

\[ = \frac{R_{\text{max}}}{1 - \rho R \rho E} - \left( Z_1 + \frac{\rho R \rho E}{1 - \rho R \rho E} \right) \int_{r=0}^{R_{\text{max}}} \exp \left( \frac{(1 - \rho R \rho E)^{\rho R \beta}}{\rho R \beta} r \right) \, dr \]

Then, in steady-state,

\[ \mathbb{E}[C(S_t, x_t)] = \mu_p \rho E \mathbb{E}[R_t] + \mu_p \mathbb{E}[\theta_t] + \mu_p Z_1 \beta - (m \mu_p + b) \frac{\beta}{2} Z_2 \]

\[ = \frac{\mu_p \rho E R_{\text{max}}}{1 - \rho R \rho E} - \mu_p \beta \left( Z_1 + \frac{\rho R \rho E}{1 - \rho R \rho E} \right) \frac{\rho E \rho R}{1 - \rho R \rho E} \left( \exp \left( \frac{(1 - \rho R \rho E)^{\rho R \beta}}{\rho R \beta} R_{\text{max}} \right) - 1 \right) \]

\[ + \mu_p \beta \left( Z_1 - m \frac{Z_2}{2} - \frac{1}{2} \right) + \mu_p \mu_Y - b \beta \frac{Z_2}{2} \]

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