

A SIMPLE NUMERICAL METHOD FOR PRICING AMERICAN POWER PUT OPTIONS

Kartikeya Kumar Gupta (180123020)

Naman Goyal (180123029)

Rathod Vijay Mahendra (180123037)



Indian Institute of Technology, Guwahati

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American power put options

- **American option**

- An American option is a style of options contract that allows holders to exercise their rights at any time before and including the expiration date.

- **Put option**

- A put option is a contract giving the option buyer the right, but not the obligation, to sell specified amount of an underlying security at a predetermined price within a specified time frame.
- This predetermined price at which the buyer of the put option can sell the underlying security is called the strike price.

- **Power option**

- An option whose payoff is based on the price of an underlying asset raised to a power.

- **Payoff of power put option**

- Payoff of power put option is given as

$$(K - S^n(T))^+ = \max \{K - S^n(T), 0\}.$$

- **Definition**

- Optimal exercise boundary separates the area where one should continue to hold the option and the area where one should exercise it.

- **Importance**

- The price problem requires complex analytical calculations. Due to the fact that the option holder has an early exercise right, the problem becomes a free boundary problem. As a result, determining the best exercise border is a major task when it comes to valuing American options.

● Definition

- In numerical analysis, finite-difference methods (FDM) are a class of numerical techniques for solving differential equations by approximating derivatives with finite differences.
- Both the spatial domain and time interval (if applicable) are discretized, or broken into a finite number of steps, and the value of the solution at these discrete points is approximated by solving algebraic equations containing finite differences and values from nearby points.

● Importance

- After determining the optimal exercise boundary, the American power put option values are calculated by applying the finite difference method (FDM).
- The proposed method provides fast and accurate results with respect to the calculation of the optimal exercise boundary and pricing of the American power put options.

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- PDE
 - Black-Scholes pde
 - Boundary Condition
 - Initial Condition
- Optimal exercise boundary (Beta)

- The Black–Scholes PDE for the price of an American power put option with a non-dividend yield can be given as

$$\frac{\partial P}{\partial \tau} - n \left\{ \frac{1}{2} \sigma^2 (n-1) + r \right\} S^n \frac{\partial P}{\partial S^n} - \frac{1}{2} (\sigma n S^n)^2 \frac{\partial^2 P}{\partial (S^n)^2} + rP = 0 \quad (1)$$

- Then (1) is subjected to the following boundary conditions.

$$\lim_{S^n \rightarrow \infty} P(\tau, S^n) = 0 \quad (2)$$

$$P(\tau, \beta(\tau)) = K - \beta(\tau) \quad (3)$$

$$P_{S^n}(\tau, \beta(\tau)) = -1 \quad (4)$$

and the initial condition

$$P(0, S^n) = \max \{K - S^n, 0\} \quad (5)$$

Optimal Exercise Boundary

- The best time to exercise an American option and its price are determined by the optimal exercise boundary denoted as $\beta = \{\beta(\tau) : \tau \in [0, T]\}$.
- Here, we suppose that the optimal exercise boundary $\beta(\tau)$ is continuously nonincreasing with $\beta(0) = K$. For each time $\tau \in [0, T]$, there exists an optimal exercise boundary $\beta(\tau)$, below which the American power put option should be exercised early, i.e., if

$$S^n(\tau) \leq \beta(\tau), \text{ then } P(\tau, S^n) = \max\{K - S^n(\tau), 0\} \quad (6)$$

and if

$$S^n(\tau) > \beta(\tau), \text{ then } P(\tau, S^n) > \max\{K - S^n(\tau), 0\} \quad (7)$$

Optimal Exercise Boundary - ctd.

- The time and asset price space are divided into two regions. A continuation region is the one in which it is optimal to hold, commonly known as $\Omega_C = [0, T] \times (\beta(\tau), \infty)$, and the region in which it is optimal to exercise, generally called the exercise (or stopping) region, is defined as $\Omega_E = [0, T] \times [0, \beta(\tau)]$.
- Following are the asymptotically optimal exercise boundaries for perpetual American power puts $\beta(\infty)$:

$$\beta(\infty) = \frac{\gamma}{\gamma + 1} K \quad (8)$$

where

$$\gamma = \frac{2r}{n^2 \sigma^2}$$

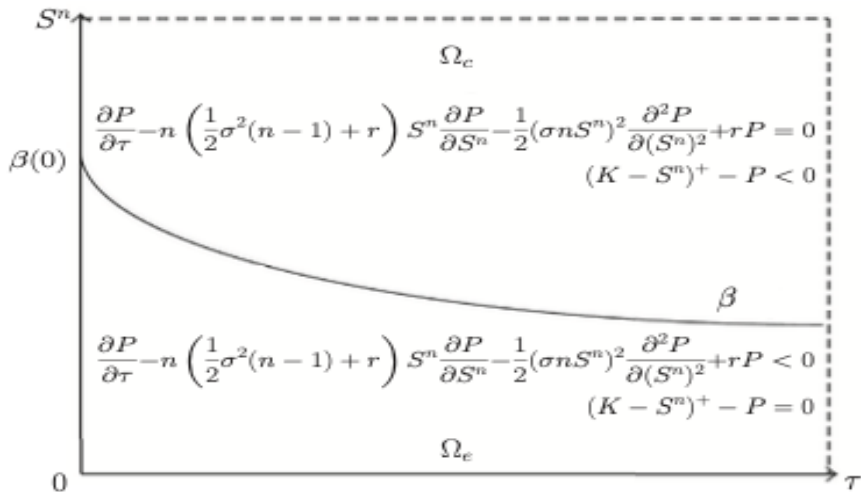


Figure: Optimal exercise boundary of an American power put option

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Transformed Function

- Before computing the PDE solution, we shall determine the ideal exercise border ($\beta(\tau)$) in this step. We give the following transformed function

$$Q(\tau, S^n) = \sqrt{P(\tau, S^n) - (K - S^n)} \quad (9)$$

- Since the solution is a horizontal line in the exercise zone and an inclined line in the continuation region, the aforementioned function is employed. As a result, $Q(\tau, S_n)$ equals 0 in the workout region and $Q(\tau, S_n) > 0$ in the continuation region. The boundary may be clearly detected since the transformed function create a sufficiently large angle with the horizontal line.

Angle b/w Q and Exercise region

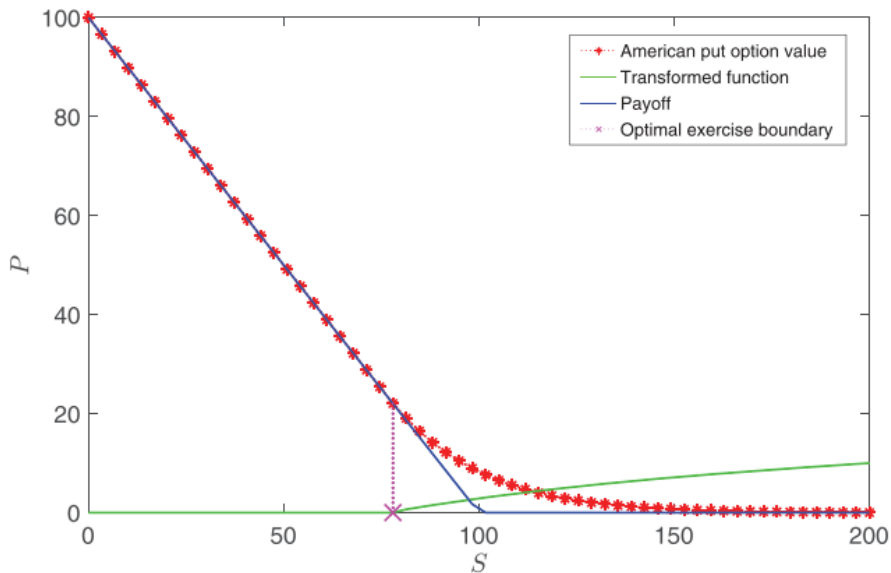


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- A numerical method developed based on the transformed function. The independent variables in the Black–Scholes PDE are time (τ) and the underlying stock price (S^n).
- To solve this problem using the FDM, we divide the time interval $[0, T]$ into L subintervals, that is
 $\tau_l = l\Delta\tau, l = 0, 1, 2, \dots, L-1, L$ where $\Delta\tau = \frac{T}{L}$ and the stock price interval $[0, S_M^n]$ into M subintervals, that is
 $S_i^n = i\Delta S^n, i = 0, 1, 2, \dots, M-1, M, \Delta S^n = \frac{S_M^n}{M}$.
- We intend to define a numerical method for computing the grid values $P_i^l \approx P(\tau_l, S_i^n)$ and the optimal exercise boundary values $\beta_l = \beta(\tau_l)$, for $i = 0, 1, 2, \dots, M-1, M$, and $l = 0, 1, 2, \dots, L-1, L$. Herein, i denotes the horizontal node index, l denotes the time step index, and τ_{l-1} represents the $(l-1)$ th previous time step and τ_l represents the l th current time step.
- For the proposed problem, $\beta(\tau_{l-1})$ and P_i^{l-1} are given and the objective is to compute $\beta(\tau_l)$ and P_i^l . We proceed step by step now:

Step 1

- We begin with the initial value at time T , which provides the value of the payoff function $(K - S_i^n)^+ = \max\{K - S_i^n, 0\}$ and the optimal exercise boundary $\beta(0) = K$.
- Because the optimal exercise boundary $\beta(\tau_{l-1})$ is dependent on the future boundary value $\beta(\tau_l)$, it must be determined by setting the initial boundary value to the strike price $\beta(\tau_0) = K$ and working backward through time from $T = \tau_0$ to $T = \tau_L$.

Step 2

- We obtain the current optimal exercise boundary $\beta(\tau_I)$ based on the previous optimal exercise boundary $\beta(\tau_{I-1})$. The current optimal exercise boundary can be obtained using a transformed function $Q(\tau_I, S^n) = \sqrt{P(\tau_I, S^n) - (K - S^n)}$.
- Herein, to obtain Q at the current time step, the option price $P(\tau_I, S^n)$ should be obtained. Further, to find $\beta(\tau_I)$, we derive the relation between $Q(\tau_I, S^n)$ and $\beta(\tau_I)$.
- Now We find $P(\tau_I, S^n)$ with respect to the current time step using a three-point FDM based on a uniform mesh.
- If the optimal exercise boundary does not depend on the grid point, then we cannot use the FDM based on a uniform mesh. Therefore, we use natural cubic spline interpolation. Based on the mesh point information, we can obtain value between the mesh points.

- Define:

$$S_1 = \beta(\tau_{l-1}) + \Delta S^n$$

$$S_2 = \beta(\tau_{l-1}) + 2\Delta S^n$$

then, we find $P(\tau_l, S_1)$.

- Because the previous optimal exercise boundary $\beta(\tau_{l-1})$ is dependent on the current optimal exercise boundary $\beta(\tau_l)$, we calculate the option price $P(\tau_l, S_1)$ on S_1 in the current time step using the explicit method.

- The Black Sholes equation can be approximated as:

$$P(\tau_l, S_1) = (1 - r\Delta\tau)P(\tau_{l-1}, S_1) + n \left\{ \frac{1}{2}\sigma^2(n-1) + r \right\} S_1 \Delta\tau \\ + \frac{\partial P(\tau_{l-1}, S_1)}{\partial S} + \frac{1}{2} (\sigma n S_1)^2 \frac{\partial^2 P(\tau_{l-1}, S_1)}{\partial S^2} \Delta\tau \quad (10)$$

- The derivatives in above equations could be formulated using:

$$\frac{\partial P(\tau_{l-1}, S_1)}{\partial S} \simeq \frac{P(\tau_{l-1}, S_2) - P(\tau_{l-1}, S_1)}{2(S_2 - S_1)} \quad (11)$$

$$\frac{\partial^2 P(\tau_{l-1}, S_1)}{\partial S^2} \simeq \frac{P(\tau_{l-1}, \beta(\tau_{l-1})) - 2P(\tau_{l-1}, S_1) + P(\tau_{l-1}, S_2)}{(S_2 - S_1)^2} \quad (12)$$

- We now apply the cubic spline interpolation in above 2 equations to find $P(\tau_{l-1}, S_1)$ and $P(\tau_{l-1}, S_2)$; thus, we obtain $P(\tau_{l-1}, S_1) \approx f(\tau_{l-1}, S_1)$, $P(\tau_{l-1}, S_2) \approx f(\tau_{l-1}, S_2)$, where f is the cubic spline function.
- Because $P(\tau, S^n) = Q^2(\tau, S^n) + K - S^n$, we obtain $P(\tau_{l-1}, \beta(\tau_{l-1})) = K - \beta(\tau_{l-1})$ near the optimal exercise boundary ($Q=0$). Thus, we obtain $P(\tau_l, S_1)$. As we can see that

$$Q(\tau_l, S_1) = \sqrt{P(\tau_l, S_1) - (K - S_1)} \quad (13)$$

- We find the relation between $\beta(\tau_{l-1})$ and $Q(\tau_l, S_1)$ using second-order Taylor expansion of Q :

$$\begin{aligned} Q(\tau, S^n) = & Q(\tau, \beta) + Q_{S^1}(\tau, \beta)(S^n - \beta) \\ & + \frac{1}{2} Q_{S^n S^1}(\tau, \beta)(S^n - \beta)^2 + \mathcal{O}(S^n - \beta)^3 \end{aligned} \quad (14)$$

- After some mathematical calculations we obtain:

$$6(\sigma n\beta)^2 Q_{S^n} Q = 6(\sigma n\beta Q_{S^n})^2 (S^n - \beta) - \{2Q_{S^n}^2 (\beta' + A\beta + \sigma^2 n^2 \beta) - (A - r)\} (S^n - \beta)^2 \quad (15)$$

where

$$\frac{\beta'}{\beta} \approx \frac{\ln\left(\frac{5^n}{\beta}\right) - \left(\frac{5^n}{\beta} - 1\right)}{\Delta\tau} \quad (16)$$

and

$$A = n \left\{ \frac{1}{2} \sigma^2 (n-1) + r \right\} \quad (17)$$

Combining the above 2 equations we can rewrite is as:

$$a\beta^5 + b\beta^4 + c\beta^3 + d\beta^2 + e\beta + f = 0 \quad (18)$$

where a, b, c, d, e, f are constants.

- This equation could be solved using Newton–Raphson method. Hence, the solution β could be found at the current optimal exercise boundary.

Step 3

- Now task is to obtain the option price using $\beta(\tau_l)$. let j be the smallest spatial grid index over $\beta(\tau_l)$. If $\beta(\tau_l)$ is too close to S_j^n , we select the index $j+1$ instead of j .

Using central difference for the spatial discretization, then:

$$\frac{\partial P_j^l}{\partial S_j^n} = \frac{P_{j+1}^l - P_{j-1}^l}{2\Delta S^n}, \quad \frac{\partial^2 P_j^l}{\partial (S_j^n)^2} = \frac{P_{j+1}^l - 2P_j^l + P_{j-1}^l}{(\Delta S^n)^2} \quad (19)$$

- Now using the implicit scheme for time discretization, equation (1.5) is discretized as follows:

$$(1 + r\Delta\tau)P_j^l - AS_j^n \frac{P_{j+1}^l - P_{j-1}^l}{2\Delta S^n} \Delta\tau - \frac{1}{2} \left(\sigma n S_j^n \right)^2 \frac{P_{j+1}^l - 2P_j^l + P_{j-1}^l}{(\Delta S^n)^2} \Delta\tau = P_j^{l-1}. \quad (20)$$

- Generally, the optimal exercise boundary may not be located at the grid points. Therefore, we cannot use FDM directly. Because we know the values of P at β , we consider using linear interpolation between adjacent data points.
- The value of P at β can be written as

$$P(\tau_l, \beta(\tau_l)) = \frac{(S_j^n - \beta(\tau_l)) P_{j-1}^l + (\Delta S - S_j^n + \beta(\tau_l)) P_j^l}{\Delta S^n} = K - \beta(\tau_l) \quad (21)$$

- Hence we obtain:

$$P_{j-1}^l = \frac{(K - \beta(\tau_l)) \Delta S^n - (\Delta S^n - S_j^n + \beta(\tau_l)) P_j^l}{S_j^n - \beta(\tau_l)} \quad (22)$$

- After mathematical calculations:

$$a_1(K - \beta(\tau_l)) + b_1 P_j^l + c_1 P_{j+1}^l = P_j^{l-1} \quad (23)$$

where

$$\begin{aligned}
 a_1 &= -\frac{1}{2} (\sigma n S_j^n)^2 \Delta \tau \frac{1}{(S_j^n - \beta(\tau_l)) \Delta S^n} + A S_j^n \Delta \tau \frac{1}{2 (S_j^n - \beta(\tau_l))} \\
 b_1 &= 1 + r \Delta \tau - A S_j^n \Delta \tau \frac{\Delta S^n - S_j^n + \beta(\tau_l)}{2 (S_j^n - \beta(\tau_l)) \Delta S^n} \\
 &\quad + \frac{1}{2} (\sigma n S_j^n)^2 \Delta \tau \left\{ \frac{S_j^n - \beta(\tau_l) + \Delta S^n}{(S_j^n - \beta(\tau_l)) (\Delta S^n)^2} \right\} \\
 c_1 &= -A S_j^n \Delta \tau \frac{1}{2 \Delta S^n} - \frac{1}{2} (\sigma n S_j^n)^2 \Delta \tau \frac{1}{(\Delta S^n)^2}
 \end{aligned} \tag{24}$$

- We can rewrite a recursive formula like:

$$a_i P_{j-1}^l + b_i P_j^l + c_i P_{j+1}^l = P_j^{l-1} \tag{25}$$

where

$$a_i = \mu_i - \lambda_i, b_i = (1 + r\Delta\tau) + 2\lambda_i, c_i = -(\mu_i + \lambda_i)$$

$$\mu_i = A \frac{\Delta\tau}{2\Delta S^n} S_{j+i-1}^n, \lambda_i = \frac{(\sigma n)^2}{2(\Delta S^n)^2} \Delta\tau \left(S_{j+i-1}^n \right)^2, 2 \leq i \leq M - j + 1$$
(26)

- The Dirichlet boundary condition at $\beta(\tau_l)$ gives $K - \beta(\tau_l)$. Therefore we can observe a set of simultaneous equations which could be solved using matrix of from $W\mathbf{x} = \mathbf{y}$.

$$\begin{pmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ a_1 & b_1 & c_1 & \cdots & 0 & 0 \\ 0 & a_2 & b_2 & c_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & a_{M-j} & b_{M-j} & c_{M-j} \\ 0 & 0 & \cdots & 0 & a_{M-j+1} & b_{M-j+1} \end{pmatrix} \begin{pmatrix} P_\beta^I \\ P_j^I \\ P_{j+1}^I \\ \vdots \\ P_{M-1}^I \\ P_M^I \end{pmatrix} = \begin{pmatrix} K - \beta(\tau_l) \\ P_j^{I-1} \\ P_{j+1}^{I-1} \\ \vdots \\ P_{M-1}^{I-1} \\ P_M^{I-1} \end{pmatrix}$$
(27)

where

$$a_{M-j+1} = 2\mu_{M-j+1}, b_{M-j+1} = 1 + r\Delta\tau - 2\mu_{M-j+1}$$
(28)

Solution for W

- To solve this system, we verify if the coefficient matrix W is invertible. By following Proposition given below, we verify the existence and uniqueness of the system of equations.
- **Definition:** An $n \times n$ matrix is said to be strictly diagonally dominant when

$$|a_{ss}| > \sum_{t=1, s \neq t}^n |a_{st}| \quad (29)$$

holds for $s = 1, 2, \dots, n$, where a_{st} denotes the entry in the s th row and t th column.

- **Proposition:** If

$$\frac{1}{\Delta\tau} + r > A\tilde{C}(M+1) \quad (30)$$

then W is strictly diagonally dominant, where \tilde{C} is a constant. Therefore, the linear system has a unique solution.

- By some complex mathematical formulations we can show that W in equation is strictly diagonally dominant and it can be shown that every strictly diagonally dominant matrix is invertible.
- **Lemma:** Following conditions are equivalent on the $n \times n$ square matrix W .
 - (1) *The matrix W is invertible.*
 - (2) *The linear system $W\mathbf{x} = \mathbf{y}$ is consistent for every \mathbf{y} .*
 - (3) *The linear system $W\mathbf{x} = \mathbf{y}$ has a unique solution for every \mathbf{y} .*
- Hence, by above lemma, we prove the existence and uniqueness of the solution to system of equations. The system can be solved by finding the inverse matrix W^{-1} . Therefore, we can obtain the option value for the next time level.

Why is every strict diagonally dominant matrix invertible

For an elementary proof, assume there exists a vector $x \neq 0$ such that $Ax = 0$. This implies $\sum_{j=1}^n a_{ij}x_j = 0, \forall i \in \{1, \dots, n\}$. Let $x_k = \|x\|_\infty \neq 0$, i.e. x_k is the largest entry of x by absolute value. We have:

$$0 = \sum_{j=1}^n a_{kj}x_j \implies a_{kk}x_k = -\sum_{j \neq k} a_{kj}x_j \implies a_{kk} = -\sum_{j \neq k} a_{kj} \frac{x_j}{x_k}$$

By taking the absolute value we get:

$$|a_{kk}| = \left| \sum_{j \neq k} a_{kj} \frac{x_j}{x_k} \right| \leq \sum_{j \neq k} |a_{kj}| \underbrace{\left| \frac{x_j}{x_k} \right|}_{\leq 1} \leq \sum_{j \neq k} |a_{kj}|$$

This is a contradiction since A is strictly diagonally dominant. This means that $0 \notin \sigma(A)$, hence A is invertible.

Step 4

- We repeat the previously mentioned process until τ_L and obtain the optimal exercise boundary in a time-recursive manner.

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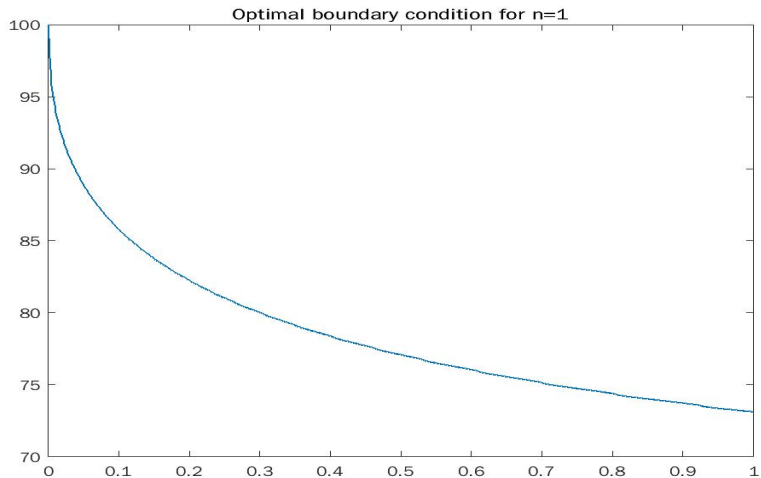
Numerical Experiments

- Optimal boundary condition for $n=1$
- American power put price vs asset price for $n = 1$
- Price of option vs asset price and Payoff vs asset price
- Beta for different values of n

Optimal boundary condition for $n=1$

- We consider the strike price $K = 100$, the interest rate $r = 0.1$, the volatility $\sigma = 0.3$, and the time to maturity $T = 1$ (year). Further, we construct the computational domain with 250 spatial steps and 1000 timesteps.
- At the maturity time, the optimal exercise boundary theoretically is $\beta(T) = 76.0964$, whereas it is $\beta(T) = 73.1258$ in the proposed method.
- The asymptotically optimal exercise boundary with respect to the perpetual American power put option is $\beta(\infty) = 68.9655$.

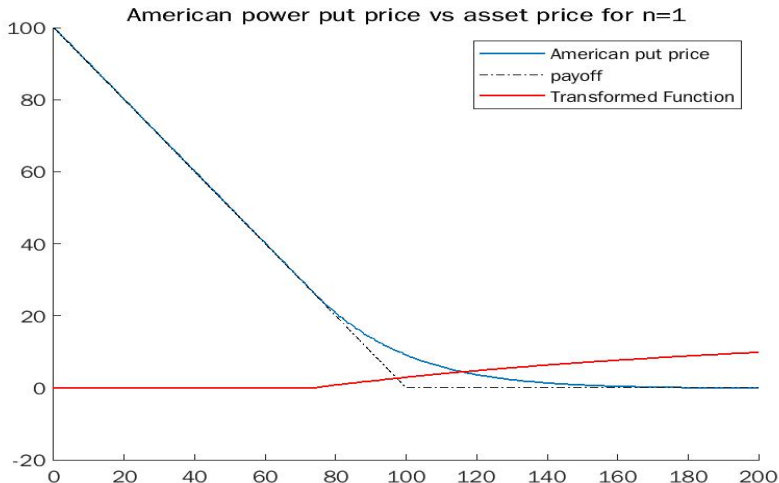
Optimal boundary condition for $n=1$ ctd.



American power put price vs asset price for $n = 1$

- The parameter values used to calculate the optimal exercise boundary and values of the American put options are $r = 0.1$, $\sigma = 0.3$, $K = 100$, $T = 1$ and $n = 1$ and the computational domain can be constructed with 250 spatial steps and 1000 time steps.

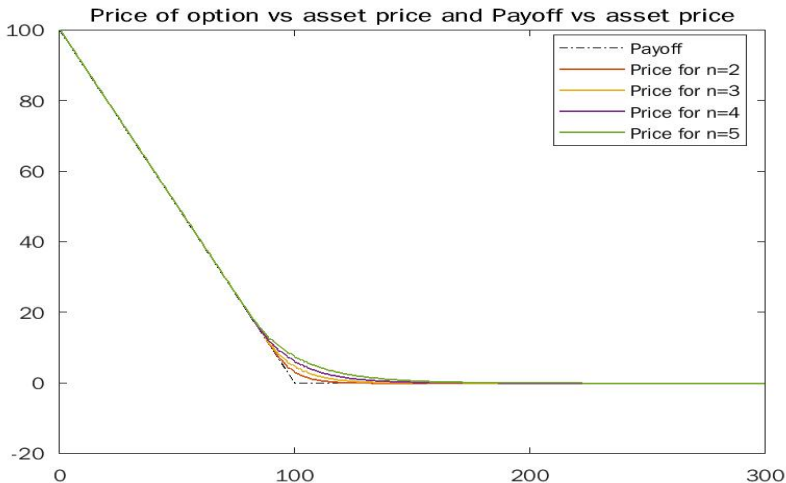
American power put price vs asset price for $n = 1$ ctd.



Price of option vs asset price and Payoff vs asset price

- The below figure shows that the American power put option values obtained when power $n = 2, 3, 4, 5$. The American power put option values increase with the increasing value of power n .
- The feature of nonlinear payoffs of power options provides the buyer with a potential to receive a considerably higher payoff than that received from a vanilla option.

Price of option vs asset price and Payoff vs asset price ctd.



Beta for different values of n

- We use $\sigma = 0.1$, $r = 0.08$, $K = 100$, $T = 0.5$, and $L \times M = 2000 \times 300$. The below figure optimal exercise boundary for different values of power $n = 2, 3, 4, 5$.
- Further, the optimal exercise boundaries are plotted as a function of time τ . The optimal exercise boundaries decrease with the increasing power.

Beta for different values of n ctd.

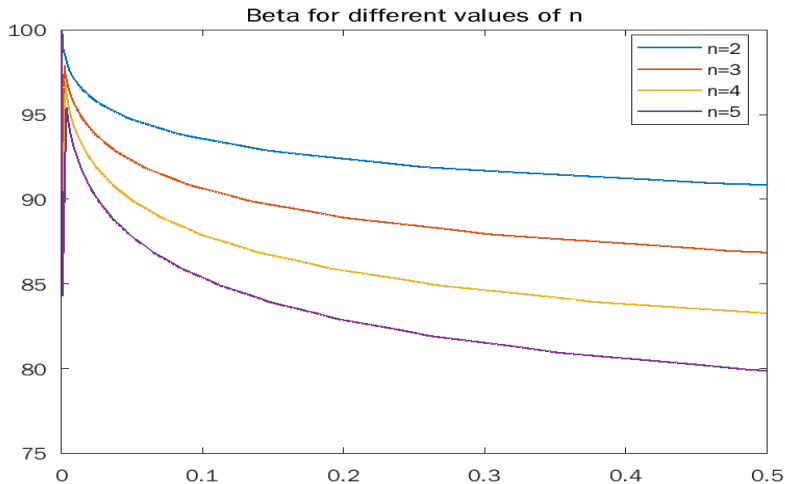


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Conclusions

- We provided a numerical method and examples for pricing the American power put option for non-dividend yields.
- we determined the optimal exercise boundary using the transformed function.
- We have compared the other results with the results obtained using the proposed method for the valuation of the American power put option when $n = 1$ to provide sufficient numerical analysis.
- We provided the optimal exercise boundary and American power put option values for different values of power n .
- The numerical experiment denotes that the proposed method is accurate, flexible, and efficient and provides accurate prices with respect to the critical stock price for various parameter combinations.