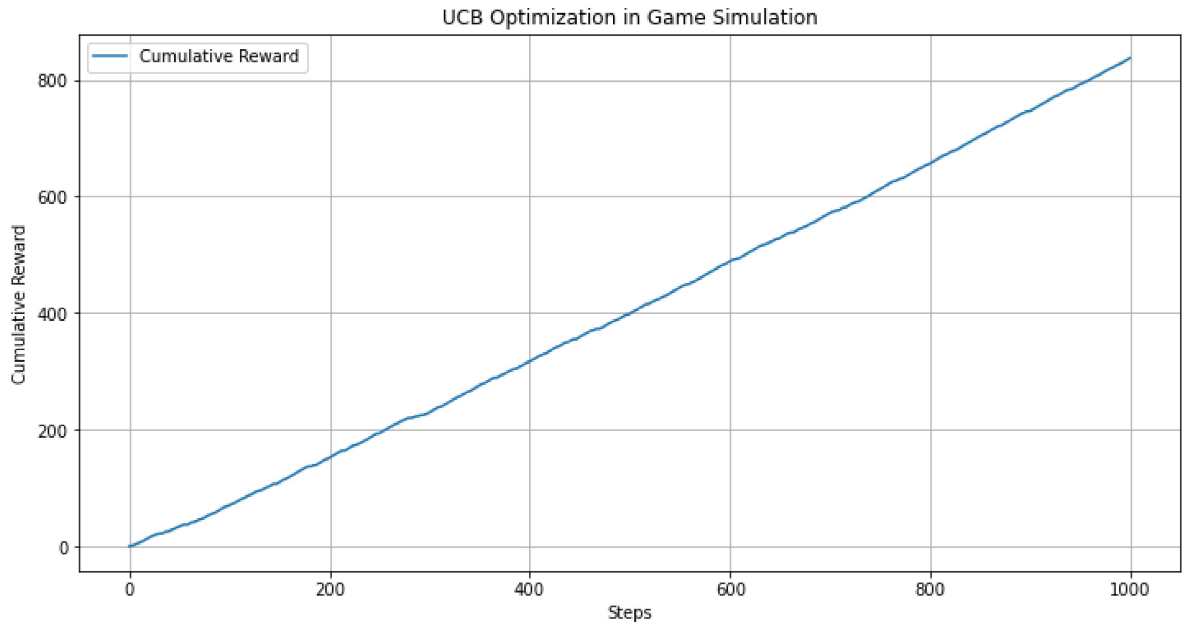
1.Implement Upper-Confidence bound algorithm (UCB) in Multi Arm Banding Problem to optimize player rewards in a basic game simulation with Python Program. The game scenario involves a player choosing between different "actions" (like doors, treasures, or paths), each with a hidden reward probability. The UCB algorithm must help the game adapt dynamically to maximize the player's experience

In [2]:
```
import numpy as np
import math
import matplotlib.pyplot as plt

# Define the UCB algorithm
class UCB:
    def __init__(self, n_actions):
        self.n_actions = n_actions
        self.action_counts = np.zeros(n_actions)  # Number of times each actio
        self.action_rewards = np.zeros(n_actions)  # Sum of rewards for each a

    def select_action(self, step):
        # Select action using UCB formula
        if step < self.n_actions:
            return step  # Choose each action once initially

        ucb_values = [
            (self.action_rewards[i] / (self.action_counts[i] + 1e-5)) +  # Avo
            math.sqrt(2 * math.log(step + 1) / (self.action_counts[i] + 1e-5))
            for i in range(self.n_actions)
        ]
        return np.argmax(ucb_values)

    def update(self, action, reward):
        # Update action counts and rewards
        self.action_counts[action] += 1
        self.action_rewards[action] += reward

# Simulate the game
def simulate_game(n_steps, n_actions, true_reward_probs):
    ucb = UCB(n_actions)
    total_reward = 0
    rewards = []
    for step in range(n_steps):
        action = ucb.select_action(step)
        # Simulate reward based on the true probability of the chosen action
        reward = 1 if np.random.rand() < true_reward_probs[action] else 0
        ucb.update(action, reward)
        total_reward += reward
        rewards.append(total_reward)
    return rewards, ucb.action_counts

# Define parameters
n_steps = 1000  # Total number of steps in the game
n_actions = 5  # Number of actions (e.g., doors, treasures, paths)
true_reward_probs = [0.1, 0.3, 0.5, 0.7, 0.9]

# Run the simulation
rewards, action_counts = simulate_game(n_steps, n_actions, true_reward_probs)

# Plot results
plt.figure(figsize=(12, 6))
plt.plot(rewards, label="Cumulative Reward")
plt.xlabel("Steps")
plt.ylabel("Cumulative Reward")
plt.title("UCB Optimization in Game Simulation")
plt.legend()
```

```
plt.grid(True)
plt.show()

# Print action counts
print("Action counts:", action_counts)
print("True reward probabilities:", true_reward_probs)
```

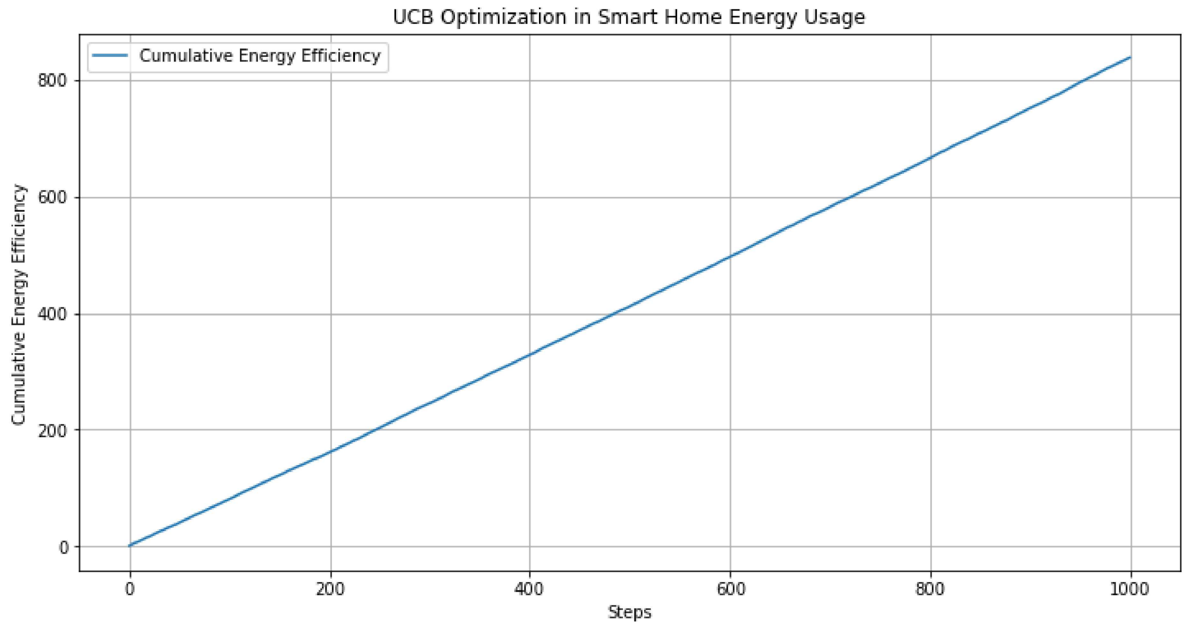



```
Action counts: [ 17.  22.  42.  83. 836.]
True reward probabilities: [0.1, 0.3, 0.5, 0.7, 0.9]
```

2. Imagine an IoT-based smart home system that dynamically optimizes energy usage across multiple devices (e.g., air conditioner, heater, and lights). Each device has a varying energy consumption efficiency based on real-time environmental factors like temperature or occupancy. Design an UCB algorithm is used to determine which device settings (e.g., energy modes) should be prioritized to maximize energy efficiency and implement the algorithm in Python

In [3]:
```python
import numpy as np
import math
import matplotlib.pyplot as plt

# Define UCB algorithm for device modes
class UCB:
    def __init__(self, n_modes):
        self.n_modes = n_modes
        self.mode_counts = np.zeros(n_modes)  # Number of times each mode was
        self.mode_rewards = np.zeros(n_modes)  # Sum of rewards for each mode

    def select_mode(self, step):
        # Use UCB to select the mode
        if step < self.n_modes:
            return step  # Choose each mode once initially
        ucb_values = [
            (self.mode_rewards[i] / (self.mode_counts[i] + 1e-5)) +
            math.sqrt(2 * math.log(step + 1) / (self.mode_counts[i] + 1e-5))
            for i in range(self.n_modes)
        ]
        return np.argmax(ucb_values)

    def update(self, mode, reward):
        # Update mode counts and rewards
        self.mode_counts[mode] += 1
        self.mode_rewards[mode] += reward

# Simulate the smart home energy optimization
def simulate_smart_home(n_steps, n_modes, true_efficiency):
    ucb = UCB(n_modes)
    total_efficiency = 0
    efficiencies = []
    for step in range(n_steps):
        mode = ucb.select_mode(step)
        # Simulate energy efficiency based on the true efficiency of the chose
        efficiency = np.random.normal(loc=true_efficiency[mode], scale=0.1)
        ucb.update(mode, efficiency)
        total_efficiency += efficiency
        efficiencies.append(total_efficiency)
    return efficiencies, ucb.mode_counts

# Define parameters
n_steps = 1000  # Number of steps in the simulation
n_modes = 4  # Number of energy modes (e.g., "low", "medium", "high", "eco")
true_efficiency = [0.6, 0.7, 0.8, 0.9]  # True average efficiency for each mod

# Run the simulation
efficiencies, mode_counts = simulate_smart_home(n_steps, n_modes, true_efficie

# Plot results
plt.figure(figsize=(12, 6))
plt.plot(efficiencies, label="Cumulative Energy Efficiency")
plt.xlabel("Steps")
plt.ylabel("Cumulative Energy Efficiency")
plt.title("UCB Optimization in Smart Home Energy Usage")
plt.legend()
plt.grid(True)
```

```
plt.show()

# Print mode counts and true efficiencies
print("Mode counts:", mode_counts)
print("True mode efficiencies:", true_efficiency)
```




```
Mode counts: [ 65. 109. 208. 618.]
True mode efficiencies: [0.6, 0.7, 0.8, 0.9]
```

3. Develop a Chess-like game using PAC (Probably approximately correct) algorithm where the problem set-up is as follows Problem Setup i) Game Environment: Simplify chess to a smaller grid with basic pieces (like pawns and a king). ii) PAC Learning: Train a model to approximate a move policy that is "probably approximately correct" (i.e., likely correct within some error bounds). iii) Implementation Goals: Use supervised learning to train a model with a dataset of board states and corresponding optimal moves.

In [4]:
```
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

# Define the board and pieces
class ChessBoard:
    def __init__(self):
        self.board = np.zeros((4, 4), dtype=int)  # 4x4 grid
        self.king_pos = (3, 0)  # King's initial position
        self.pawn_positions = [(0, 1), (1, 3), (2, 2)]  # Pawns' initial posit
        self.place_pieces()

    def place_pieces(self):
        self.board[self.king_pos] = 1  # King represented as 1
        for pos in self.pawn_positions:
            self.board[pos] = -1  # Pawns represented as -1

    def get_features(self):
        # Flatten board as feature vector
        return self.board.flatten()

    def move_king(self, new_pos):
        x, y = self.king_pos
        self.board[x, y] = 0  # Clear old king position
        self.king_pos = new_pos
        x, y = new_pos
        self.board[x, y] = 1  # Set new king position

    def is_valid_move(self, pos):
        x, y = pos
        return 0 <= x < 4 and 0 <= y < 4 and self.board[x, y] != 1  # Inside b

    def generate_king_moves(self):
        x, y = self.king_pos
        moves = [(x + i, y + j) for i in [-1, 0, 1] for j in [-1, 0, 1] if (i,
        return [move for move in moves if self.is_valid_move(move)]

# Reward function
def reward_function(board, move):
    x, y = move
    if board[x, y] == -1:  # Capture a pawn
        return 10
    else:  # Move to an empty space
        return 1

# Generate training data
def generate_training_data(n_samples):
    X = []
    y = []
    for _ in range(n_samples):
        board = ChessBoard()
        moves = board.generate_king_moves()
        optimal_move = None
        max_reward = -np.inf
        for move in moves:
            reward = reward_function(board.board, move)
            if reward > max_reward:
```

```python
                max_reward = reward
                optimal_move = move
        X.append(board.get_features())
        y.append(optimal_move)
    return np.array(X), np.array(y)

# Train a PAC model (decision tree classifier)
def train_pac_model(X, y):
    # Flatten move labels for multi-output classification
    y_flat = [x * 4 + y for x, y in y]
    model = DecisionTreeClassifier(max_depth=5)
    model.fit(X, y_flat)
    return model

# Predict a move
def predict_move(model, board):
    move_flat = model.predict([board.get_features()])[0]
    return divmod(move_flat, 4)

# Simulate a game
def simulate_game(model, n_steps=10):
    board = ChessBoard()
    for step in range(n_steps):
        print(f"Step {step + 1}:")
        print(board.board)
        move = predict_move(model, board)
        print(f"King moves to: {move}")
        board.move_king(move)

# Main function
if __name__ == "__main__":
    # Generate training data
    X, y = generate_training_data(500)
    # Train PAC model
    model = train_pac_model(X, y)
    # Evaluate model accuracy
    y_flat = [x * 4 + y for x, y in y]
    predictions = model.predict(X)
    print(f"Model Accuracy: {accuracy_score(y_flat, predictions) * 100:.2f}%")
    # Simulate a game
    simulate_game(model)
```

```
Model Accuracy: 100.00%
Step 1:
[[ 0 -1  0  0]
 [ 0  0  0 -1]
 [ 0  0 -1  0]
 [ 1  0  0  0]]
King moves to: (2, 0)
Step 2:
[[ 0 -1  0  0]
 [ 0  0  0 -1]
 [ 1  0 -1  0]
 [ 0  0  0  0]]
King moves to: (2, 0)
Step 3:
[[ 0 -1  0  0]
 [ 0  0  0 -1]
 [ 1  0 -1  0]
 [ 0  0  0  0]]
King moves to: (2, 0)
Step 4:
[[ 0 -1  0  0]
 [ 0  0  0 -1]
 [ 1  0 -1  0]
 [ 0  0  0  0]]
King moves to: (2, 0)
Step 5:
[[ 0 -1  0  0]
 [ 0  0  0 -1]
 [ 1  0 -1  0]
 [ 0  0  0  0]]
King moves to: (2, 0)
Step 6:
[[ 0 -1  0  0]
 [ 0  0  0 -1]
 [ 1  0 -1  0]
 [ 0  0  0  0]]
King moves to: (2, 0)
Step 7:
[[ 0 -1  0  0]
 [ 0  0  0 -1]
 [ 1  0 -1  0]
 [ 0  0  0  0]]
King moves to: (2, 0)
Step 8:
[[ 0 -1  0  0]
 [ 0  0  0 -1]
 [ 1  0 -1  0]
 [ 0  0  0  0]]
King moves to: (2, 0)
Step 9:
[[ 0 -1  0  0]
 [ 0  0  0 -1]
 [ 1  0 -1  0]
 [ 0  0  0  0]]
King moves to: (2, 0)
Step 10:
[[ 0 -1  0  0]
```

```
 [ 0  0  0 -1]
 [ 1  0 -1  0]
 [ 0  0  0  0]]
King moves to: (2, 0)
```