Notebook 6.1 - Scheduling Mastery

Management Science - From Corporate Events to Rush Hours

Introduction

Welcome to your role as Bean Counter's Operations Manager! You've been tasked with solving two critical scheduling challenges that will determine the efficiency of your coffee empire:

Challenge 1: The Corporate Event (Sections 1-4)

A major tech company just ordered 20 specialty coffee drinks for their board meeting. All orders are known upfront with specific deadlines. This is a batch scheduling problem, you have complete information and need to sequence the orders optimally before starting work.

Challenge 2: The Friday Morning Rush (Sections 5-6)

Every Friday, your flagship store faces a continuous stream of orders arriving throughout the morning. You can't see future orders and thus you must make real-time decisions. This is an online scheduling problem where orders reveal themselves over time.

These two scenarios represent fundamentally different scheduling paradigms you'll master today!

> **i How to Use This Tutorial**
>
> Cells marked with "YOUR CODE BELOW" expect you to write code. Test your solutions with the provided assertions. Work through sections in order as each builds on previous concepts!

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
from datetime import datetime, timedelta

# Set random seed for reproducibility
np.random.seed(2025)

print("Libraries loaded! Ready to optimize Bean Counter's operations.")
```

```
Libraries loaded! Ready to optimize Bean Counter's operations.
```

Section 1 - The Corporate Event Problem

The Scenario

TechCorp's board meeting starts in 90 minutes. They've pre-ordered 20 specialty drinks with specific requirements. You have:

- Complete information: All 20 orders known upfront
- One machine: Must sequence orders optimally
- Varying complexity: From simple espressos (3 min) to complex mochas (12 min)
- Deadlines: Some executives need drinks early (rushed board members), others can wait (relaxed attendees)

This is static scheduling - you can plan the entire sequence before starting.

The Data Structure

Each order contains:

- Order ID: Customer identifier
- Processing Time: How long it takes to make
- Due Time: When the customer needs it (measured from start of your shift)

Note: No arrival times! All orders are available at time 0.

```
# TechCorp Corporate Event - 20 pre-orders
# All available at start (time 0)
np.random.seed(2025)

corporate_orders = []
for i in range(20):
    processing = np.random.choice([3, 5, 7, 10, 12], p=[0.25, 0.30, 0.25,
0.15, 0.05])

    # 30% tight (15-30 min), 40% medium (30-60 min), 30% relaxed (60-90
min)
    deadline_type = np.random.choice(['tight', 'medium', 'relaxed'],
p=[0.3, 0.4, 0.3])
    if deadline_type == 'tight':
        due = np.random.randint(15, 30)
    elif deadline_type == 'medium':
        due = np.random.randint(30, 60)
    else:
        due = np.random.randint(60, 90)

    corporate_orders.append({
        'id': f'C{i+1:02d}',
        'processing': processing,
        'due': due
    })

df_corporate = pd.DataFrame(corporate_orders)
```

```python
print("TechCorp Corporate Event Orders:")
print(f"Total orders: {len(corporate_orders)}")
print(f"Total processing time needed: {df_corporate['processing'].sum()}
minutes")
print(f"Event window: 90 minutes")
print(f"Tightest deadline: {df_corporate['due'].min()} minutes")
print(f"Latest deadline: {df_corporate['due'].max()} minutes")
print(f"\nFirst 10 orders:")
print(df_corporate.head(10)[['id', 'processing', 'due']])
```

```
TechCorp Corporate Event Orders:
Total orders: 20
Total processing time needed: 122 minutes
Event window: 90 minutes
Tightest deadline: 18 minutes
Latest deadline: 89 minutes

First 10 orders:
    id  processing  due
0  C01           3   72
1  C02           3   30
2  C03           5   44
3  C04           3   65
4  C05           5   81
5  C06           5   46
6  C07           5   58
7  C08           3   18
8  C09           7   64
9  C10          12   81
```

Key Performance Metrics

```python
def calculate_metrics(schedule_df):
    """
    Calculate key performance metrics for a schedule

    - Makespan: Total time to complete all orders
    - Avg Flow Time: Average time from start until completion
    - Total Tardiness: Sum of delays beyond due times
    - Late Orders: Count of orders completed after deadline
    """
    metrics = {
        'makespan': schedule_df['completion'].max(),
        'avg_flow_time': schedule_df['completion'].mean(),
        'total_tardiness': np.maximum(0, schedule_df['completion'] -
schedule_df['due']).sum(),
        'late_orders': (schedule_df['completion'] >
schedule_df['due']).sum()
    }
    return metrics

print("Metrics function ready for comparing scheduling rules!")
```

```
Metrics function ready for comparing scheduling rules!
```

Exercise 1.1 - Calculate Order Slack

Slack tells you how much scheduling flexibility exists for each order. It's the time buffer before an order becomes late.

Formula: Slack = Due Time - Processing Time

Why? If an order takes 5 minutes and is due at 20 minutes, you have 15 minutes of slack (can start anytime from 0 to 15).

```
# YOUR CODE BELOW
# Calculate slack for each order
# Add a 'slack' column to df_corporate

df_corporate['slack'] = # Calculate: due - processing

# Find the most urgent order (minimum slack)
most_urgent = # Find the order ID with minimum slack
```

```
# Tests
assert 'slack' in df_corporate.columns, "Add a 'slack' column to
df_corporate"
assert len(df_corporate['slack']) == 20, "Should calculate slack for all 20
orders"
assert (df_corporate['slack'] == df_corporate['due'] -
df_corporate['processing']).all(), \
    "Slack formula: due - processing"
print(f"Perfect! Most urgent order: {most_urgent} with
{df_corporate['slack'].min()} minutes slack")
print("\nTop 5 most urgent orders:")
print(df_corporate.nsmallest(5, 'slack')[['id', 'processing', 'due',
'slack']])
```

Section 2 - Implementing Static Scheduling Rules

Now implement three fundamental scheduling rules. For static scheduling, we:

1. Sort all orders by the rule's criterion
2. Process them sequentially from time 0
3. Each order starts immediately after the previous one finishes

Rule 1: FIFO (First In, First Out)

Process orders in their original sequence (order ID order).

Tip

- `sorted()` function sorts a list based on a criterion
- `lambda x: x['id']` is a mini-function that is used in `sorted()` saying "sort by the 'id' field"

```python
def schedule_fifo_static(orders):
    """
    Schedule orders using First In, First Out (FIFO)
    Process in original order
    """
    # Sort by ID to maintain original order
    scheduled = sorted(orders, key=lambda x: x['id'])

    # Calculate completion times
    current_time = 0
    for order in scheduled:
        # In static scheduling, all orders are available at time 0
        # So we just start immediately after the previous order
        order['start'] = current_time
        order['completion'] = current_time + order['processing']
        current_time = order['completion']

    return scheduled

# Test FIFO
# Why .copy()? We don't want to modify the original 'orders' list
# Each scheduling function will modify the orders, so we give it a copy
fifo_schedule = schedule_fifo_static(corporate_orders.copy())
df_fifo = pd.DataFrame(fifo_schedule)

print("FIFO Schedule (first 10 orders):")
print(df_fifo.head(10)[['id', 'processing', 'start', 'completion', 'due']])
print(f"\nTotal makespan: {df_fifo['completion'].max()} minutes")
```

```
FIFO Schedule (first 10 orders):
    id  processing  start  completion  due
0  C01           3      0           3   72
1  C02           3      3           6   30
2  C03           5      6          11   44
3  C04           3     11          14   65
4  C05           5     14          19   81
5  C06           5     19          24   46
6  C07           5     24          29   58
7  C08           3     29          32   18
8  C09           7     32          39   64
9  C10          12     39          51   81

Total makespan: 122 minutes
```

Rule 2: SPT (Shortest Processing Time)

Now we implement SPT to always process the shortest job next and to process the quickest orders first to minimize average wait times.

```
def schedule_spt_static(orders):
    """
    Schedule orders using Shortest Processing Time (SPT)
    Process shortest jobs first
    """
    # Sort by processing time (shortest first)
    scheduled = sorted(orders, key=lambda x: x['processing'])

    # Calculate completion times
    current_time = 0
    for order in scheduled:
        order['start'] = current_time
        order['completion'] = current_time + order['processing']
        current_time = order['completion']

    return scheduled

# Test SPT
spt_schedule = schedule_spt_static(corporate_orders.copy())
df_spt = pd.DataFrame(spt_schedule)

print("SPT Schedule (first 10 orders - sorted by processing time):")
print(df_spt.head(10)[['id', 'processing', 'start', 'completion', 'due']])
print(f"\nTotal makespan: {df_spt['completion'].max()} minutes")
```

```
SPT Schedule (first 10 orders - sorted by processing time):
    id  processing  start  completion  due
0  C01           3      0           3   72
1  C02           3      3           6   30
2  C04           3      6           9   65
3  C08           3      9          12   18
4  C15           3     12          15   52
5  C17           3     15          18   89
6  C20           3     18          21   36
7  C03           5     21          26   44
8  C05           5     26          31   81
9  C06           5     31          36   46

Total makespan: 122 minutes
```

Exercise 2.1 - Implement EDD (Earliest Due Date)

Implement EDD to minimize tardiness by processing urgent orders first.

> **Tip**
>
> Structure is identical to SPT! Just change what you sort by.

```
# YOUR CODE BELOW
def schedule_edd_static(orders):
    """
    Schedule orders using Earliest Due Date (EDD)
    Process orders with earliest deadlines first
    """
    # Sort by due date (earliest first)
    scheduled = # YOUR CODE

    # Calculate completion times
    current_time = 0
    for order in scheduled:
        order['start'] = # YOUR CODE
        order['completion'] = # YOUR CODE
        current_time = # YOUR CODE

    return scheduled

# Test your EDD implementation
edd_schedule = schedule_edd_static(corporate_orders.copy())
df_edd = pd.DataFrame(edd_schedule)
```

```
# Tests
assert df_edd.iloc[0]['due'] <= df_edd.iloc[1]['due'], "First order should
have earliest due date"
assert df_edd['completion'].max() == df_fifo['completion'].max(), "All
schedules have same makespan"
total_tardiness = np.maximum(0, df_edd['completion'] - df_edd['due']).sum()
print(f"EDD implementation correct!")
print(f"\nEDD Schedule (first 10 orders - sorted by due date):")
print(df_edd.head(10)[['id', 'due', 'processing', 'start', 'completion']])
print(f"Total tardiness: {total_tardiness:.0f} minutes")
```

Section 3 - Visualizing Schedules

A picture is worth a thousand schedules! Let's create Gantt charts to visualize how each rule performs. Try to use generate AI to come up with the code to create a beautiful Gantt chart here based on the results of your schedule.

```
# YOUR CODE BELOW
```

Section 4 - Performance Comparison

Exercise 4.1 - Compare Scheduling Rules

Calculate metrics for all three rules to see which performs best.

Coding Hints

- The `calculate_metrics()` function is already defined - you just call it!
- It returns a dictionary with metrics like `{'makespan': 29, 'avg_flow_time': 15.2, ...}`
- To create a DataFrame from dictionaries, use: `pd.DataFrame([DICTIONARY])`

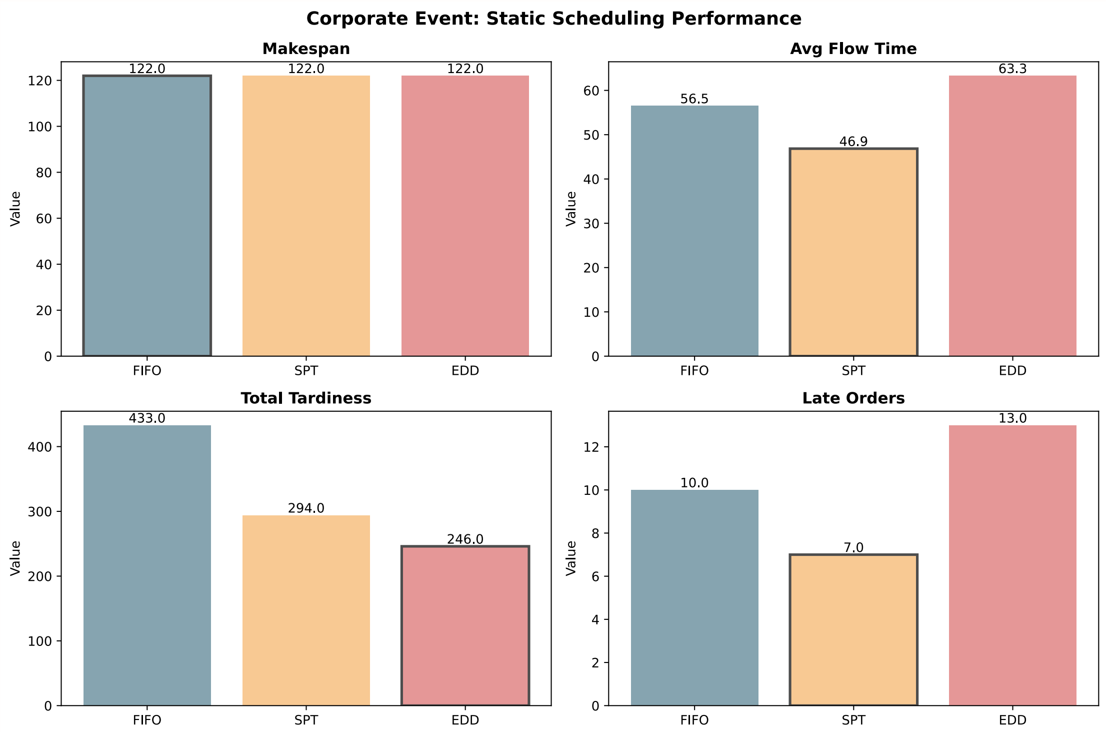
```
# YOUR CODE BELOW
# Calculate metrics for each schedule

metrics_fifo = # YOUR CODE
metrics_spt = # YOUR CODE
metrics_edd = # YOUR CODE

# Create comparison DataFrame
comparison = pd.DataFrame({
    'FIFO': metrics_fifo,
    'SPT': metrics_spt,
    'EDD': metrics_edd
}).T

print("Performance Comparison - Corporate Event:")
print(comparison.round(2))
```

```
# Tests
assert comparison.loc['SPT', 'avg_flow_time'] <= comparison.loc['FIFO',
'avg_flow_time'], \
    "SPT should have best average flow time"
assert comparison.loc['EDD', 'total_tardiness'] <= comparison.loc['FIFO',
'total_tardiness'], \
    "EDD should minimize tardiness"
assert comparison.loc['EDD', 'total_tardiness'] <= comparison.loc['SPT',
'total_tardiness'], \
    "EDD should beat SPT on tardiness"
print("✓ Excellent analysis!")
print(f"\nKey Insights:")
print(f" SPT reduces avg flow time by {(1 - comparison.loc['SPT',
'avg_flow_time']/comparison.loc['FIFO', 'avg_flow_time'])*100:.1f}% vs
FIFO")
print(f" EDD reduces tardiness by {comparison.loc['FIFO',
'total_tardiness'] - comparison.loc['EDD', 'total_tardiness']:.0f} minutes
vs FIFO")
print(f" EDD reduces late orders from {comparison.loc['FIFO',
'late_orders']:.0f} to {comparison.loc['EDD', 'late_orders']:.0f}")
print(f" All methods have same makespan:
```

```
{comparison['makespan'].iloc[0]:.0f} minutes (sum of all processing
times)")
```

Visualizing the Trade-offs

```
# Create visual comparison
fig, axes = plt.subplots(2, 2, figsize=(12, 8))

metrics_to_plot = ['makespan', 'avg_flow_time', 'total_tardiness',
'late_orders']
colors = ['#537E8F', '#F6B265', '#DB6B6B']

for ax, metric in zip(axes.flat, metrics_to_plot):
    values = [comparison.loc[rule, metric] for rule in ['FIFO', 'SPT',
'EDD']]
    bars = ax.bar(['FIFO', 'SPT', 'EDD'], values, color=colors, alpha=0.7)

    # Highlight the best performer
    best_idx = np.argmin(values)
    bars[best_idx].set_edgecolor('black')
    bars[best_idx].set_linewidth(2)

    ax.set_title(metric.replace('_', ' ').title(), fontweight='bold')
    ax.set_ylabel('Value')

    # Add value labels
    for bar, val in zip(bars, values):
        height = bar.get_height()
        ax.text(bar.get_x() + bar.get_width()/2., height,
                f'{val:.1f}', ha='center', va='bottom')

plt.suptitle('Corporate Event: Static Scheduling Performance', fontsize=14,
fontweight='bold')
plt.tight_layout()
plt.show()
```



Why these results?

- SPT minimizes avg flow time: Short jobs finish quickly, reducing overall wait
- EDD minimizes tardiness: Processing by deadline directly optimizes late penalties
- FIFO is neutral: No optimization, just processes in arbitrary order
- Same makespan: All schedules do the same work, just in different orders

Section 5 - The Friday Morning Rush Problem

Why Static Scheduling Isn't Enough

The corporate event was a batch problem, all orders known upfront. But most real operations face online problems where:

- Orders arrive over time
- You can't see future orders
- You must make decisions with partial information

Friday morning at Bean Counter is this type of problem!

The Friday Scenario

It's 6 AM Friday. Your flagship store faces:

- Orders arriving continuously over 2 hours
- No future visibility - can't see orders that haven't been placed yet
- Real-time decisions - when the machine is free, which available order should you process?

This requires dynamic dispatching: making decisions based only on orders that have already arrived.

```python
# Generate realistic Friday morning rush orders
# Generate realistic Friday morning rush orders
np.random.seed(2025)
n_orders = 30

friday_orders = []
current_arrival = 0

for i in range(n_orders):
    # Orders arrive with gaps (exponential inter-arrival times)
    if i > 0:
        current_arrival += np.random.exponential(2.0)

    processing = np.random.choice([1,2,3], p=[0.1,0.5, 0.4])

    # Due times are relative to arrival (customers want drinks soon after
ordering)
    order_urgency = np.random.choice(['rush', 'normal', 'relaxed'],
p=[0.10, 0.40, 0.50])
    if order_urgency == 'rush':
        due = current_arrival + processing + np.random.randint(1, 3)
    elif order_urgency == 'normal':
        due = current_arrival + processing + np.random.randint(4, 6)
    else:
        due = current_arrival + processing + np.random.randint(7, 12)

    friday_orders.append({
        'id': f'F{i+1:02d}',
        'arrival': round(current_arrival, 1),
        'processing': processing,
        'due': round(due, 1)
    })

df_friday = pd.DataFrame(friday_orders)

print("Friday Morning Rush - Flagship Store")
print(f"Total orders: {len(friday_orders)}")
print(f"Arrival span: {df_friday['arrival'].min():.1f} to
{df_friday['arrival'].max():.1f} minutes")
print(f"Total processing needed: {df_friday['processing'].sum()} minutes")
print(f"\nFirst 10 orders:")
print(df_friday.head(10)[['id', 'arrival', 'processing', 'due']])
```

```
Friday Morning Rush - Flagship Store
Total orders: 30
Arrival span: 0.0 to 61.6 minutes
Total processing needed: 67 minutes

First 10 orders:
    id  arrival  processing   due
```

```
0  F01      0.0          2  13.0
1  F02      0.2          3  10.2
2  F03      2.4          2  15.4
3  F04      5.6          1  14.6
4  F05      5.8          2  15.8
5  F06      6.5          2  17.5
6  F07      8.4          3  20.4
7  F08      9.1          2  16.1
8  F09      9.2          2  15.2
9  F10     13.4          1  19.4
```

What Happens If We Use Static Scheduling?

Let's see what goes wrong if we apply static SPT to this dynamic problem:

```
# Apply static SPT (sorts all orders, ignores arrivals)
friday_static_spt = schedule_spt_static(friday_orders.copy())
df_friday_static_spt = pd.DataFrame(friday_static_spt)

print("Static SPT on Friday Rush:")
print(df_friday_static_spt.head(10)[['id', 'arrival', 'processing',
'start', 'completion']])
print(f"\nNotice the problem: Order {df_friday_static_spt.iloc[0]['id']}
starts at time 0")
print(f"But it doesn't arrive until time {df_friday_static_spt.iloc[0]
['arrival']:.1f}!")
print(f"This creates {df_friday_static_spt.iloc[0]['arrival']:.1f} minutes
of idle time.")
```

```
Static SPT on Friday Rush:
    id  arrival  processing  start  completion
0  F04      5.6           1      0           1
1  F10     13.4           1      1           2
2  F13     23.6           1      2           3
3  F23     46.9           1      3           4
4  F25     48.0           1      4           5
5  F01      0.0           2      5           7
6  F03      2.4           2      7           9
7  F05      5.8           2      9          11
8  F06      6.5           2     11          13
9  F08      9.1           2     13          15

Notice the problem: Order F04 starts at time 0
But it doesn't arrive until time 5.6!
This creates 5.6 minutes of idle time.
```

⚠ Warning

Static scheduling on online problems creates idle time!

Static SPT sorts all orders by processing time, then tries to do the shortest first. But if that order hasn't arrived yet, the machine sits idle waiting.

We need dynamic dispatching that only considers orders that have already arrived.

Section 6 - Dynamic Dispatching

The Dynamic Dispatching Algorithm

Instead of sorting everything upfront, we make decisions one at a time as the machine becomes free:

1. Start with `current_time = 0`
2. While there are unscheduled orders:
   - Find which orders have `arrival <= current_time` (the "available pool")
   - If no orders available, jump forward to the next arrival
   - Apply your rule (FIFO/SPT/EDD) to choose from the available pool
   - Schedule that order, update time, repeat

This simulates real-time decision-making!

Exercise 6.1 - Implement Dynamic SPT

Implement SPT with dynamic dispatching for Bean Counter.

Tip

- Use a `while remaining:` loop (not a for loop over pre-sorted list)
- Filter to `available = [orders where arrival <= current_time]`
- If no available orders, jump forward: `current_time = min(arrival of remaining)`
- Then apply SPT to the available pool

```
# YOUR CODE BELOW
def schedule_spt_dynamic(orders):
    """
    Schedule orders using DYNAMIC Shortest Processing Time
    At each decision point, choose shortest job among those that have
arrived
    """
    scheduled = []
    remaining = [o.copy() for o in orders]  # Make copies to avoid
modifying originals
    current_time = 0

    while remaining:
```

```
        # Find available orders (already arrived)
        available = # YOUR CODE: list of orders where arrival <=
current_time

        # If nothing available, jump to next arrival
        if not available:
            current_time = # YOUR CODE: min arrival time of remaining
orders
            available = # YOUR CODE: update available orders

        # Choose shortest processing time among available
        next_order = # YOUR CODE: min...

        # Schedule it
        next_order['start'] = current_time
        next_order['completion'] = current_time + next_order['processing']
        current_time = next_order['completion']

        # Move from remaining to scheduled
        scheduled.append(next_order)
        remaining.remove(next_order)

    return scheduled

# Test dynamic SPT
friday_dynamic_spt = schedule_spt_dynamic(friday_orders)
df_friday_dynamic_spt = pd.DataFrame(friday_dynamic_spt)
```

```
# Tests
assert all(df_friday_dynamic_spt['start'] >=
df_friday_dynamic_spt['arrival']), \
    "All orders should start at or after their arrival time"

# Calculate idle time for both approaches
static_idle = sum(max(0, row['arrival'] - (df_friday_static_spt.iloc[i-1]
['completion'] if i > 0 else 0))
                  for i, row in df_friday_static_spt.iterrows())
dynamic_idle = sum(max(0, row['start'] - (df_friday_dynamic_spt.iloc[i-1]
['completion'] if i > 0 else 0))
                   for i, row in df_friday_dynamic_spt.iterrows())

print("Excellent! Dynamic SPT implementation is correct!")
print(f"\nDynamic vs Static SPT on Friday Rush:")
print(f" • Static makespan (with arrival violations!):
{df_friday_static_spt['completion'].max():.1f} minutes")
print(f" • Dynamic makespan (no violations):
{df_friday_dynamic_spt['completion'].max():.1f} minutes")
print(f" • Change: {df_friday_static_spt['completion'].max() -
df_friday_dynamic_spt['completion'].max():.1f} minutes faster")
print(f" • Dynamic idle time: {dynamic_idle:.1f} minutes")
```

Exercise 6.2 - Implement Dynamic EDD

Now implement EDD with dynamic dispatching to minimize tardiness in the Friday rush.

```
# YOUR CODE BELOW
def schedule_edd_dynamic(orders):
    """
    Schedule orders using DYNAMIC Earliest Due Date
    At each decision point, choose order with earliest deadline among
available orders
    """
    scheduled = []
    remaining = [o.copy() for o in orders]
    current_time = 0

    while remaining:
        # YOUR CODE: Find available orders
        available = # [orders where arrival <= current_time]

        # YOUR CODE: Handle no available orders
        if not available:
            current_time = # min arrival of remaining
            available = # update available

        # YOUR CODE: Choose earliest due date
        next_order = # Hint: Just change the key from SPT

        # Schedule it (same as SPT)
        next_order['start'] = current_time
        next_order['completion'] = current_time + next_order['processing']
        current_time = next_order['completion']

        scheduled.append(next_order)
        remaining.remove(next_order)

    return scheduled

# Test dynamic EDD
friday_dynamic_edd = schedule_edd_dynamic(friday_orders)
df_friday_dynamic_edd = pd.DataFrame(friday_dynamic_edd)
```

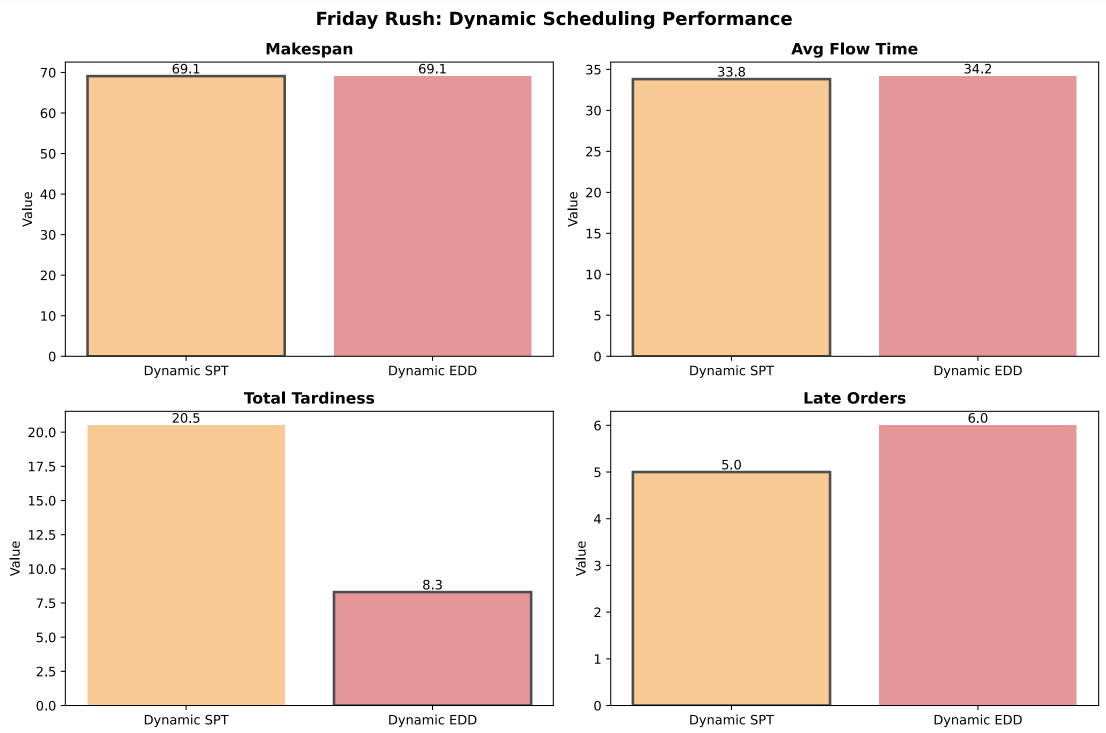
```
# Tests
assert all(df_friday_dynamic_edd['start'] >=
df_friday_dynamic_edd['arrival']), \
    "All orders should start at or after arrival"

metrics_dynamic_spt = calculate_metrics(df_friday_dynamic_spt)
metrics_dynamic_edd = calculate_metrics(df_friday_dynamic_edd)

assert metrics_dynamic_edd['total_tardiness'] <=
metrics_dynamic_spt['total_tardiness'], \
    "EDD should minimize tardiness better than SPT"
```

```
print("✓ Dynamic EDD implementation correct!")
print(f"\nFriday Rush: Dynamic SPT vs Dynamic EDD")
print(f" • SPT avg flow time: {metrics_dynamic_spt['avg_flow_time']:.1f}
minutes")
print(f" • EDD avg flow time: {metrics_dynamic_edd['avg_flow_time']:.1f}
minutes")
print(f" • SPT total tardiness:
{metrics_dynamic_spt['total_tardiness']:.1f} minutes")
print(f" • EDD total tardiness:
{metrics_dynamic_edd['total_tardiness']:.1f} minutes")
print(f" • SPT late orders: {metrics_dynamic_spt['late_orders']:.0f}")
print(f" • EDD late orders: {metrics_dynamic_edd['late_orders']:.0f}")
```

Final Performance Comparison

```
# Calculate metrics for all Friday approaches
friday_comparison = pd.DataFrame({
    'Dynamic_SPT': calculate_metrics(df_friday_dynamic_spt),
    'Dynamic_EDD': calculate_metrics(df_friday_dynamic_edd)
}).T

print("Friday Morning Rush - Final Performance:")
print(friday_comparison.round(2))

# Visualization
fig, axes = plt.subplots(2, 2, figsize=(12, 8))
metrics_to_plot = ['makespan', 'avg_flow_time', 'total_tardiness',
'late_orders']
colors = ['#F6B265', '#DB6B6B']

for ax, metric in zip(axes.flat, metrics_to_plot):
    values = [friday_comparison.loc[rule, metric] for rule in
['Dynamic_SPT', 'Dynamic_EDD']]
    bars = ax.bar(['Dynamic SPT', 'Dynamic EDD'], values, color=colors,
alpha=0.7)

    best_idx = np.argmin(values)
    bars[best_idx].set_edgecolor('black')
    bars[best_idx].set_linewidth(2)

    ax.set_title(metric.replace('_', ' ').title(), fontweight='bold')
    ax.set_ylabel('Value')

    for bar, val in zip(bars, values):
        height = bar.get_height()
        ax.text(bar.get_x() + bar.get_width()/2., height,
                f'{val:.1f}', ha='center', va='bottom')

plt.suptitle('Friday Rush: Dynamic Scheduling Performance', fontsize=14,
fontweight='bold')
plt.tight_layout()
plt.show()
```

```
Friday Morning Rush - Final Performance:
              makespan  avg_flow_time  total_tardiness  late_orders
Dynamic_SPT       69.1          33.82             20.5          5.0
Dynamic_EDD       69.1          34.18              8.3          6.0
```



Conclusion

Congratulations! You've mastered both paradigms of scheduling:

Key Takeaways

1. Static Scheduling (Corporate Event):
   - All orders known upfront
   - Sort and sequence optimally
   - SPT minimizes flow time, EDD minimizes tardiness
   - Simple to implement and understand
2. Dynamic Scheduling (Friday Rush):
   - Orders arrive over time
   - Make real-time decisions with partial information
   - Only consider orders that have arrived
   - Better machine utilization, more realistic
3. Algorithm Performance:
   - FIFO: Simple, fair, but not optimized
   - SPT: Minimizes average wait time
   - EDD: Minimizes tardiness and late orders
   - Choice depends on business priorities!

4. When to Use Each:
    - Static: Batch processing, complete information, planning ahead
    - Dynamic: Real-time operations, orders arrive continuously, reactive scheduling

What's Next?

You've now mastered both static and dynamic scheduling approaches! In the next notebook, you'll tackle the Bike Factory Competition where you'll apply these scheduling techniques to a real two-stage manufacturing problem.

In the following lectures, you'll then learn advanced techniques like local search and metaheuristics that can improve even the best greedy solutions by intelligently exploring schedule variations.

Your Bean Counter operations are now optimized for both planning and real-time scenarios!

Bibliography