

```
!pip install gym stable_baselines3
```

```
Requirement already satisfied: gym in /usr/local/lib/python3.10/dist-packages (0.25.2)
```

```
Collecting stable_baselines3
```

```
  Downloading stable_baselines3-2.2.1-py3-none-any.whl (181 kB)
```

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181.7/181.7 kB 4.2 MB/s eta
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Requirement already satisfied: numpy>=1.18.0 in
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```
/usr/local/lib/python3.10/dist-packages (from gym) (1.23.5)
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Requirement already satisfied: cloudpickle>=1.2.0 in
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/usr/local/lib/python3.10/dist-packages (from gym) (2.2.1)
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Requirement already satisfied: gym-notices>=0.0.4 in
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```
/usr/local/lib/python3.10/dist-packages (from gym) (0.0.8)
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Collecting gymnasium<0.30,>=0.28.1 (from stable_baselines3)
```

```
  Downloading gymnasium-0.29.1-py3-none-any.whl (953 kB)
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953.9/953.9 kB 16.2 MB/s eta
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Requirement already satisfied: torch>=1.13 in /usr/local/lib/python3.10/dist-packages (from stable_baselines3) (2.1.0+cu121)
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Requirement already satisfied: pandas in
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/usr/local/lib/python3.10/dist-packages (from stable_baselines3)
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(1.5.3)
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Requirement already satisfied: matplotlib in
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/usr/local/lib/python3.10/dist-packages (from stable_baselines3)
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(3.7.1)
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Requirement already satisfied: typing-extensions>=4.3.0 in
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```
/usr/local/lib/python3.10/dist-packages (from gymnasium<0.30,>=0.28.1->stable_baselines3) (4.5.0)
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```
Collecting farama-notifications>=0.0.1 (from gymnasium<0.30,>=0.28.1->stable_baselines3)
```

```
  Downloading Farama_Notifications-0.0.4-py3-none-any.whl (2.5 kB)
```

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Requirement already satisfied: filelock in
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```
/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable_baselines3) (3.13.1)
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Requirement already satisfied: sympy in
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/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable_baselines3) (1.12)
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Requirement already satisfied: networkx in
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/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable_baselines3) (3.2.1)
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Requirement already satisfied: jinja2 in
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/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable_baselines3) (3.1.2)
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Requirement already satisfied: fsspec in
```

```
/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable_baselines3) (2023.6.0)
```

```
Requirement already satisfied: triton==2.1.0 in
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```
/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable_baselines3) (2.1.0)
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Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib-
>stable_baselines3) (1.2.0)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib-
>stable_baselines3) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib-
>stable_baselines3) (4.47.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib-
>stable_baselines3) (1.4.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib-
>stable_baselines3) (23.2)
Requirement already satisfied: pillow>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib-
>stable_baselines3) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib-
>stable_baselines3) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib-
>stable_baselines3) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas-
>stable_baselines3) (2023.3.post1)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7-
>matplotlib->stable_baselines3) (1.16.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2->torch>=1.13-
>stable_baselines3) (2.1.3)
Requirement already satisfied: mpmath>=0.19 in
/usr/local/lib/python3.10/dist-packages (from sympy->torch>=1.13-
>stable_baselines3) (1.3.0)
Installing collected packages: farama-notifications, gymnasium,
stable_baselines3
Successfully installed farama-notifications-0.0.4 gymnasium-0.29.1
stable_baselines3-2.2.1

!pip install stable-baselines3[extra] gym

Requirement already satisfied: stable-baselines3[extra] in
/usr/local/lib/python3.10/dist-packages (2.2.1)
Requirement already satisfied: gym in /usr/local/lib/python3.10/dist-
packages (0.25.2)
Requirement already satisfied: gymnasium<0.30,>=0.28.1 in
/usr/local/lib/python3.10/dist-packages (from stable-
baselines3[extra]) (0.29.1)

Requirement already satisfied: numpy>=1.20 in
/usr/local/lib/python3.10/dist-packages (from stable-
baselines3[extra]) (1.23.5)

Requirement already satisfied: torch>=1.13 in
/usr/local/lib/python3.10/dist-packages (from stable-
baselines3[extra]) (2.1.0+cu121)

Requirement already satisfied: cloudpickle in
/usr/local/lib/python3.10/dist-packages (from stable-
baselines3[extra]) (2.2.1)

Requirement already satisfied: pandas in
/usr/local/lib/python3.10/dist-packages (from stable-
baselines3[extra]) (1.5.3)

Requirement already satisfied: matplotlib in
/usr/local/lib/python3.10/dist-packages (from stable-
baselines3[extra]) (3.7.1)

Requirement already satisfied: opencv-python in
/usr/local/lib/python3.10/dist-packages (from stable-
baselines3[extra]) (4.8.0.76)

Requirement already satisfied: pygame in
/usr/local/lib/python3.10/dist-packages (from stable-
baselines3[extra]) (2.5.2)

Requirement already satisfied: tensorboard>=2.9.1 in
/usr/local/lib/python3.10/dist-packages (from stable-
baselines3[extra]) (2.15.1)

Requirement already satisfied: psutil in
/usr/local/lib/python3.10/dist-packages (from stable-
baselines3[extra]) (5.9.5)

Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-
packages (from stable-baselines3[extra]) (4.66.1)

Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-
packages (from stable-baselines3[extra]) (13.7.0)

Collecting shimmy[atari]~=1.3.0 (from stable-baselines3[extra])
 Downloading Shimmy-1.3.0-py3-none-any.whl (37 kB)

Requirement already satisfied: pillow in
/usr/local/lib/python3.10/dist-packages (from stable-
baselines3[extra]) (9.4.0)

Collecting autorom[accept-rom-license]~=0.6.1 (from stable-
baselines3[extra])
 Downloading AutoROM-0.6.1-py3-none-any.whl (9.4 kB)

Requirement already satisfied: gym-notices>=0.0.4 in
/usr/local/lib/python3.10/dist-packages (from gym) (0.0.8)

Requirement already satisfied: click in
/usr/local/lib/python3.10/dist-packages (from autorom[accept-rom-
license]~=0.6.1->stable-baselines3[extra]) (8.1.7)

Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from autorom[accept-rom-
license]~=0.6.1->stable-baselines3[extra]) (2.31.0)

Collecting AutoROM.accept-rom-license (from autorom[accept-rom-
license]~=0.6.1->stable-baselines3[extra])

Downloading AutoROM.accept-rom-license-0.6.1.tar.gz (434 kB)
434.7/434.7 kB 6.7 MB/s eta

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ents to build wheel ... etadata (pyproject.toml) ... ent already
satisfied: typing-extensions>=4.3.0 in /usr/local/lib/python3.10/dist-
packages (from gymnasium<0.30,>=0.28.1->stable-baselines3[extra])
(4.5.0)

Requirement already satisfied: farama-notifications>=0.0.1 in
/usr/local/lib/python3.10/dist-packages (from gymnasium<0.30,>=0.28.1-
>stable-baselines3[extra]) (0.0.4)

Collecting ale-py~0.8.1 (from shimmy[atari]~=1.3.0->stable-
baselines3[extra])

Downloading ale_py-0.8.1-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (1.7 MB)
1.7/1.7 MB 13.8 MB/s eta

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ent already satisfied: absl-py>=0.4 in /usr/local/lib/python3.10/dist-
packages (from tensorboard>=2.9.1->stable-baselines3[extra]) (1.4.0)

Requirement already satisfied: grpcio>=1.48.2 in
/usr/local/lib/python3.10/dist-packages (from tensorboard>=2.9.1-
>stable-baselines3[extra]) (1.60.0)

Requirement already satisfied: google-auth<3,>=1.6.3 in
/usr/local/lib/python3.10/dist-packages (from tensorboard>=2.9.1-
>stable-baselines3[extra]) (2.17.3)

Requirement already satisfied: google-auth-oauthlib<2,>=0.5 in
/usr/local/lib/python3.10/dist-packages (from tensorboard>=2.9.1-
>stable-baselines3[extra]) (1.2.0)

Requirement already satisfied: markdown>=2.6.8 in
/usr/local/lib/python3.10/dist-packages (from tensorboard>=2.9.1-
>stable-baselines3[extra]) (3.5.1)

Requirement already satisfied: protobuf<4.24,>=3.19.6 in
/usr/local/lib/python3.10/dist-packages (from tensorboard>=2.9.1-
>stable-baselines3[extra]) (3.20.3)

Requirement already satisfied: setuptools>=41.0.0 in
/usr/local/lib/python3.10/dist-packages (from tensorboard>=2.9.1-
>stable-baselines3[extra]) (67.7.2)

Requirement already satisfied: six>1.9 in
/usr/local/lib/python3.10/dist-packages (from tensorboard>=2.9.1-
>stable-baselines3[extra]) (1.16.0)

Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0
in /usr/local/lib/python3.10/dist-packages (from tensorboard>=2.9.1-
>stable-baselines3[extra]) (0.7.2)

Requirement already satisfied: werkzeug>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from tensorboard>=2.9.1-
>stable-baselines3[extra]) (3.0.1)

Requirement already satisfied: filelock in
/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable-
baselines3[extra]) (3.13.1)

Requirement already satisfied: sympy in

/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable-baselines3[extra]) (1.12)
Requirement already satisfied: networkx in
/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable-baselines3[extra]) (3.2.1)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable-baselines3[extra]) (3.1.2)
Requirement already satisfied: fsspec in
/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable-baselines3[extra]) (2023.6.0)
Requirement already satisfied: triton==2.1.0 in
/usr/local/lib/python3.10/dist-packages (from torch>=1.13->stable-baselines3[extra]) (2.1.0)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->stable-baselines3[extra]) (1.2.0)
Requirement already satisfied: cyclor>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->stable-baselines3[extra]) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->stable-baselines3[extra]) (4.47.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->stable-baselines3[extra]) (1.4.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->stable-baselines3[extra]) (23.2)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->stable-baselines3[extra]) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->stable-baselines3[extra]) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas->stable-baselines3[extra]) (2023.3.post1)
Requirement already satisfied: markdown-it-py>=2.2.0 in
/usr/local/lib/python3.10/dist-packages (from rich->stable-baselines3[extra]) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
/usr/local/lib/python3.10/dist-packages (from rich->stable-baselines3[extra]) (2.16.1)
Requirement already satisfied: importlib-resources in
/usr/local/lib/python3.10/dist-packages (from ale-py~0.8.1->shimmy[atari]~1.3.0->stable-baselines3[extra]) (6.1.1)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3-

```

>tensorboard>=2.9.1->stable-baselines3[extra]) (5.3.2)
Requirement already satisfied: pyasn1-modules>=0.2.1 in
/usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3-
>tensorboard>=2.9.1->stable-baselines3[extra]) (0.3.0)
Requirement already satisfied: rsa<5,>=3.1.4 in
/usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3-
>tensorboard>=2.9.1->stable-baselines3[extra]) (4.9)
Requirement already satisfied: requests-oauthlib>=0.7.0 in
/usr/local/lib/python3.10/dist-packages (from google-auth-
oauthlib<2,>=0.5->tensorboard>=2.9.1->stable-baselines3[extra])
(1.3.1)
Requirement already satisfied: mdurl~=0.1 in
/usr/local/lib/python3.10/dist-packages (from markdown-it-py>=2.2.0-
>rich->stable-baselines3[extra]) (0.1.2)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests-
>autorom[accept-rom-license]~=0.6.1->stable-baselines3[extra]) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests-
>autorom[accept-rom-license]~=0.6.1->stable-baselines3[extra]) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests-
>autorom[accept-rom-license]~=0.6.1->stable-baselines3[extra]) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests-
>autorom[accept-rom-license]~=0.6.1->stable-baselines3[extra])
(2023.11.17)
Requirement already satisfied: MarkupSafe>=2.1.1 in
/usr/local/lib/python3.10/dist-packages (from werkzeug>=1.0.1-
>tensorboard>=2.9.1->stable-baselines3[extra]) (2.1.3)
Requirement already satisfied: mpmath>=0.19 in
/usr/local/lib/python3.10/dist-packages (from sympy->torch>=1.13-
>stable-baselines3[extra]) (1.3.0)
Requirement already satisfied: pyasn1<0.6.0,>=0.4.6 in
/usr/local/lib/python3.10/dist-packages (from pyasn1-modules>=0.2.1-
>google-auth<3,>=1.6.3->tensorboard>=2.9.1->stable-baselines3[extra])
(0.5.1)
Requirement already satisfied: oauthlib>=3.0.0 in
/usr/local/lib/python3.10/dist-packages (from requests-
oauthlib>=0.7.0->google-auth-oauthlib<2,>=0.5->tensorboard>=2.9.1-
>stable-baselines3[extra]) (3.2.2)
Building wheels for collected packages: AutoROM.accept-rom-license
  Building wheel for AutoROM.accept-rom-license (pyproject.toml) ... -
license: filename=AutoROM.accept_rom_license-0.6.1-py3-none-any.whl
size=446660
sha256=61ea886a6ab05a3e22ace0ce2eddeccbc7f6d8d55a662cac0215444018f195
3
  Stored in directory:
/root/.cache/pip/wheels/6b/1b/ef/a43ff1a2f1736d5711faalba4c1f61be1131b

```

8899e6a057811

Successfully built AutoROM.accept-rom-license

Installing collected packages: ale-py, shimmy, AutoROM.accept-rom-license, autorom

Successfully installed AutoROM.accept-rom-license-0.6.1 ale-py-0.8.1 autorom-0.6.1 shimmy-1.3.0

```
!pip install 'shimmy>=0.2.1'
```

Requirement already satisfied: shimmy>=0.2.1 in

/usr/local/lib/python3.10/dist-packages (1.3.0)

Requirement already satisfied: numpy>=1.18.0 in

/usr/local/lib/python3.10/dist-packages (from shimmy>=0.2.1) (1.23.5)

Requirement already satisfied: gymnasium>=0.27.0 in

/usr/local/lib/python3.10/dist-packages (from shimmy>=0.2.1) (0.29.1)

Requirement already satisfied: cloudpickle>=1.2.0 in

/usr/local/lib/python3.10/dist-packages (from gymnasium>=0.27.0->shimmy>=0.2.1) (2.2.1)

Requirement already satisfied: typing-extensions>=4.3.0 in

/usr/local/lib/python3.10/dist-packages (from gymnasium>=0.27.0->shimmy>=0.2.1) (4.5.0)

Requirement already satisfied: farama-notifications>=0.0.1 in

/usr/local/lib/python3.10/dist-packages (from gymnasium>=0.27.0->shimmy>=0.2.1) (0.0.4)

```
import gym
```

```
from gym import spaces
```

```
import numpy as np
```

```
from stable_baselines3 import PP0
```

```
class JobSchedulingEnv(gym.Env):
```

```
    def __init__(self):
```

```
        super(JobSchedulingEnv, self).__init__()
```

```
        self.num_jobs = 6
```

```
        self.job_durations = [2, 3, 5, 6, 2, 3]
```

```
        self.action_space = spaces.Discrete(self.num_jobs)
```

```
        self.observation_space = spaces.MultiBinary(self.num_jobs)
```

```
        self.max_steps = 100 # Maximum number of steps per episode
```

```
        self.reset()
```

```
    def step(self, action):
```

```
        # Toggle the machine assignment for the selected job
```

```
        self.state[action] = 1 - self.state[action]
```

```
        # Calculate the makespan for each machine
```

```
        makespan_m1 = sum([duration for i, duration in
```

```
enumerate(self.job_durations) if self.state[i] == 0])
```

```
        makespan_m2 = sum([duration for i, duration in
```

```
enumerate(self.job_durations) if self.state[i] == 1])
```

```
        new_makespan = max(makespan_m1, makespan_m2)
```

```

    # Calculate reward based on the change in makespan
    reward = self.current_makespan - new_makespan
    self.current_makespan = new_makespan

    # Increment the step count and check for termination
    self.current_step += 1
    done = self.current_step >= self.max_steps

    return self.state, reward, done, {}

def reset(self):
    self.state = np.zeros(self.num_jobs, dtype=int)
    self.current_makespan = sum(self.job_durations)
    self.current_step = 0
    return self.state

def render(self, mode='human', close=False):
    if close:
        return

    # Assign jobs to each machine based on the current state
    jobs_on_m1 = [f"J{i+1}" for i in range(self.num_jobs) if
self.state[i] == 0]
    jobs_on_m2 = [f"J{i+1}" for i in range(self.num_jobs) if
self.state[i] == 1]

    # Calculate makespan for each machine
    makespan_m1 = sum([duration for i, duration in
enumerate(self.job_durations) if self.state[i] == 0])
    makespan_m2 = sum([duration for i, duration in
enumerate(self.job_durations) if self.state[i] == 1])

    # Print the scheduling status
    print(f"Machine 1 (M1) - Jobs: {'', ' '.join(jobs_on_m1)} |
Makespan: {makespan_m1} minutes")
    print(f"Machine 2 (M2) - Jobs: {'', ' '.join(jobs_on_m2)} |
Makespan: {makespan_m2} minutes")
    print("-" * 50)

    # Method to set a specific initial state (optional)
    def set_initial_state(self, initial_state):
        if len(initial_state) == self.num_jobs:
            self.state = np.array(initial_state, dtype=int)

# Initialize the environment and the model
env = JobSchedulingEnv()
model = PP0("MlpPolicy", env, verbose=1)

# Train the model

```



```

model.learn(total_timesteps=10000)

# Optionally, set a specific problem before testing
# env.set_initial_state([0, 0, 1, 1, 0, 1]) # Example initial state

# Test the trained agent
obs = env.reset()
for i in range(1000):
    action, _states = model.predict(obs, deterministic=True)
    obs, rewards, dones, info = env.step(action)
    if dones:
        obs = env.reset()
    env.render()

# Save the model
model.save("job_scheduling_model")

from stable_baselines3 import PPO

# Load the trained model
model = PPO.load("job_scheduling_model")

# Update the job durations for the new problem
new_job_durations = [2.30, 4.12, 7, 6, 2, 3] # Replace with your job
durations

# Create a new environment with the updated job durations
class NewJobSchedulingEnv(JobSchedulingEnv):
    def __init__(self):
        super().__init__()
        self.job_durations = new_job_durations # Update the job
durations

# Initialize the new environment
new_env = NewJobSchedulingEnv()

# Initialize variables to track the optimal solution
optimal_makespan = float('inf')
optimal_state = None

# Test the trained agent on the new environment
obs = new_env.reset()
for i in range(1000):
    action, _states = model.predict(obs, deterministic=True)
    obs, rewards, dones, info = new_env.step(action)

    # Check if the current solution is better than the best found so
    far
    if new_env.current_makespan < optimal_makespan:

```

```

        optimal_makespan = new_env.current_makespan
        optimal_state = obs.copy()

    if done:
        obs = new_env.reset()

# Print the optimal solution
    jobs_on_m1 = [f"J{i+1}" for i in range(new_env.num_jobs) if
        optimal_state[i] == 0]
    jobs_on_m2 = [f"J{i+1}" for i in range(new_env.num_jobs) if
        optimal_state[i] == 1]

    print("Optimal Solution:")
    print(f"Machine 1 (M1) - Jobs: {', '.join(jobs_on_m1)} | Makespan:
        {sum(new_env.job_durations[i] for i in range(new_env.num_jobs) if
            optimal_state[i] == 0)} minutes")
    print(f"Machine 2 (M2) - Jobs: {', '.join(jobs_on_m2)} | Makespan:
        {sum(new_env.job_durations[i] for i in range(new_env.num_jobs) if
            optimal_state[i] == 1)} minutes")

import gym
from gym import spaces
import numpy as np
import random
from stable_baselines3.common.env_util import make_vec_env
from stable_baselines3 import PP0

class JobSchedulingEnv(gym.Env):
    def __init__(self, num_jobs=6, job_durations=[2, 3, 5, 6, 2, 3],
        num_machines=2):
        super(JobSchedulingEnv, self).__init__()
        self.num_jobs = num_jobs
        self.job_durations = job_durations
        self.num_machines = num_machines

        # Action space: Each element in the action array represents a
        job's assigned machine
        self.action_space = spaces.MultiDiscrete([num_machines] *
            num_jobs)

        # Observation space: Each job's current machine assignment
        self.observation_space = spaces.MultiDiscrete([num_machines] *
            num_jobs)

        self.max_steps = 2000
        self.reset()

    def step(self, action):
        # Save the previous maximum makespan before updating the state
        prev_max_makespan = max([sum(self.job_durations[j] for j in

```

```

range(self.num_jobs) if self.state[j] == m) for m in
range(self.num_machines)])

    # Update the state based on the action
    self.state = action

    # Calculate the new makespan for each machine
    makespans = [sum(self.job_durations[j] for j in
range(self.num_jobs) if self.state[j] == m) for m in
range(self.num_machines)]
    new_max_makespan = max(makespans)

    # Calculate reward based on the change in the maximum makespan
    reward = prev_max_makespan - new_max_makespan

    # Increment the step count and check if the episode is done
    self.current_step += 1
    done = self.current_step >= self.max_steps

    return self.state, reward, done, {}

def reset(self):
    self.state = np.zeros(self.num_jobs, dtype=int)
    self.current_makespan = sum(self.job_durations)
    self.current_step = 0
    return self.state

def render(self, mode='human', close=False):
    if close:
        return

    for m in range(self.num_machines):
        jobs_on_machine = [f"J{i+1}" for i in range(self.num_jobs)
if self.state[i] == m]
        makespan = sum(self.job_durations[i] for i in
range(self.num_jobs) if self.state[i] == m)
        print(f"Machine {m+1} - Jobs: {' '.join(jobs_on_machine)}
| Makespan: {makespan} minutes")
    print("-" * 50)

number_of_epochs = 10 # Define the number of epochs
timesteps_per_epoch = 2000 # Define the number of timesteps per epoch
num_jobs = 6
num_machines = 3

# Initialize the environment with initial job durations
initial_job_durations = [random.uniform(1, 12) for _ in

```

```

range(num_jobs)]
env = JobSchedulingEnv(num_jobs=num_jobs,
job_durations=initial_job_durations, num_machines=num_machines)
env = make_vec_env(lambda: env, n_envs=1)

# Initialize the model
model = PPO("MlpPolicy", env, learning_rate=0.00025, n_steps=2048,
batch_size=64,
            gamma=0.99, gae_lambda=0.95, clip_range=0.2,
ent_coef=0.01,
            verbose=1,
tensorboard_log="./ppo_job_scheduling_tensorboard/")

# Train the model over multiple epochs with different job durations
for epoch in range(number_of_epochs):
    # Generate new job durations for this epoch
    new_job_durations = [random.uniform(1, 12) for _ in
range(num_jobs)]

    # Update the environment with new job durations
    env.envs[0].env.job_durations = new_job_durations

    # Continue training the model
    model.learn(total_timesteps=timesteps_per_epoch)

    # Optional: Save the model after each epoch
model_filename =
f"job_scheduling_model_epoch_{num_machines}machines_{num_jobs}jobs"
model.save(model_filename)

import gym
from gym import spaces
import numpy as np
import random
from stable_baselines3.common.env_util import make_vec_env
from stable_baselines3 import PPO

from stable_baselines3.common.callbacks import EvalCallback,
CheckpointCallback

class JobSchedulingEnv(gym.Env):
    def __init__(self, num_jobs=6, job_durations=[2, 3, 5, 6, 2, 3],
num_machines=2):
        super(JobSchedulingEnv, self).__init__()
        self.num_jobs = num_jobs
        self.job_durations = job_durations
        self.num_machines = num_machines
        self.action_space = spaces.MultiDiscrete([num_machines] *
num_jobs)

```

```

        self.observation_space = spaces.MultiDiscrete([num_machines] *
num_jobs)
        self.max_steps = 2000
        self.reset()

    def step(self, action):
        prev_max_makespan = max([sum(self.job_durations[j] for j in
range(self.num_jobs) if self.state[j] == m) for m in
range(self.num_machines)])
        self.state = action
        makespans = [sum(self.job_durations[j] for j in
range(self.num_jobs) if self.state[j] == m) for m in
range(self.num_machines)]
        new_max_makespan = max(makespans)
        reward = prev_max_makespan - new_max_makespan
        self.current_step += 1
        done = self.current_step >= self.max_steps
        return self.state, reward, done, {}

    def reset(self):
        self.state = np.zeros(self.num_jobs, dtype=int)
        self.current_makespan = sum(self.job_durations)
        self.current_step = 0
        return self.state

    def render(self, mode='human', close=False):
        if close:
            return
        for m in range(self.num_machines):
            jobs_on_machine = [f"J{i+1}" for i in range(self.num_jobs)
if self.state[i] == m]
            makespan = sum(self.job_durations[i] for i in
range(self.num_jobs) if self.state[i] == m)
            print(f"Machine {m+1} - Jobs: {' '.join(jobs_on_machine)}
| Makespan: {makespan} minutes")
            print("-" * 50)

number_of_epochs = 50
timesteps_per_epoch = 2000
num_jobs = 5
num_machines = 3

training_scenarios = [
    [random.uniform(1, 12) for _ in range(num_jobs)] for _ in
range(number_of_epochs)
]

initial_job_durations = training_scenarios[0]

```

```

env = JobSchedulingEnv(num_jobs=num_jobs,
job_durations=initial_job_durations, num_machines=num_machines)
env = make_vec_env(lambda: env, n_envs=1)

model = PPO("MlpPolicy", env, learning_rate=0.00025, n_steps=2048,
batch_size=64,
            gamma=0.99, gae_lambda=0.95, clip_range=0.2,
ent_coef=0.01,
            verbose=1,
tensorboard_log="./ppo_job_scheduling_tensorboard/")
# Evaluation callback for logging performance and progress
eval_env = make_vec_env(lambda: JobSchedulingEnv(num_jobs=num_jobs,
job_durations=initial_job_durations, num_machines=num_machines),
n_envs=1)
eval_callback = EvalCallback(eval_env, best_model_save_path='./logs/',
log_path='./logs/', eval_freq=500,
deterministic=True, render=False)

# Checkpoint callback for saving the model
checkpoint_callback = CheckpointCallback(save_freq=1000,
save_path='./logs/',
name_prefix='rl_model')

for epoch, new_job_durations in enumerate(training_scenarios):
    env.envs[0].env.job_durations = new_job_durations
    model.learn(total_timesteps=timesteps_per_epoch)

model_filename =
f"job_scheduling_model_epoch_{num_machines}machines_{num_jobs}jobs"
model.save(model_filename)

```

Using cuda device

Logging to ./ppo_job_scheduling_tensorboard/PP0_2

/usr/local/lib/python3.10/dist-packages/stable_baselines3/common/vec_env/patch_gym.py:49: UserWarning: You provided an OpenAI Gym environment. We strongly recommend transitioning to Gymnasium environments. Stable-Baselines3 is automatically wrapping your environments in a compatibility layer, which could potentially cause issues.

warnings.warn(

rollout/		
ep_len_mean	2e+03	
ep_rew_mean	20.6	
time/		
fps	230	
iterations	1	

	time_elapsed		8	
	total_timesteps		2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_3

	rollout/			
	ep_len_mean		2e+03	
	ep_rew_mean		20.6	
	time/			
	fps		230	
	iterations		1	
	time_elapsed		8	
	total_timesteps		2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_4

	rollout/			
	ep_len_mean		2e+03	
	ep_rew_mean		21.5	
	time/			
	fps		228	
	iterations		1	
	time_elapsed		8	
	total_timesteps		2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_5

	rollout/			
	ep_len_mean		2e+03	
	ep_rew_mean		8.89	
	time/			
	fps		226	
	iterations		1	
	time_elapsed		9	
	total_timesteps		2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_6

	rollout/			
	ep_len_mean		2e+03	
	ep_rew_mean		21.5	
	time/			
	fps		227	
	iterations		1	
	time_elapsed		8	
	total_timesteps		2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_7

rollout/	
ep_len_mean	2e+03
ep_rew_mean	21.4
time/	
fps	228
iterations	1
time_elapsed	8
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_8

rollout/	
ep_len_mean	2e+03
ep_rew_mean	14.2
time/	
fps	229
iterations	1
time_elapsed	8
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_9

rollout/	
ep_len_mean	2e+03
ep_rew_mean	13.3
time/	
fps	224
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_10

rollout/	
ep_len_mean	2e+03
ep_rew_mean	21.4
time/	
fps	225
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_11

rollout/	
ep_len_mean	2e+03
ep_rew_mean	14
time/	
fps	224

iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_12

rollout/	
ep_len_mean	2e+03
ep_rew_mean	14.8
time/	
fps	226
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_13

rollout/	
ep_len_mean	2e+03
ep_rew_mean	21.4
time/	
fps	228
iterations	1
time_elapsed	8
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_14

rollout/	
ep_len_mean	2e+03
ep_rew_mean	19.8
time/	
fps	227
iterations	1
time_elapsed	8
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_15

rollout/	
ep_len_mean	2e+03
ep_rew_mean	14.7
time/	
fps	230
iterations	1
time_elapsed	8
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_16

rollout/		
ep_len_mean	2e+03	
ep_rew_mean	20	
time/		
fps	236	
iterations	1	
time_elapsed	8	
total_timesteps	2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_17

rollout/		
ep_len_mean	2e+03	
ep_rew_mean	14	
time/		
fps	238	
iterations	1	
time_elapsed	8	
total_timesteps	2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_18

rollout/		
ep_len_mean	2e+03	
ep_rew_mean	19.8	
time/		
fps	237	
iterations	1	
time_elapsed	8	
total_timesteps	2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_19

rollout/		
ep_len_mean	2e+03	
ep_rew_mean	5.81	
time/		
fps	239	
iterations	1	
time_elapsed	8	
total_timesteps	2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_20

rollout/		
ep_len_mean	2e+03	
ep_rew_mean	19.8	
time/		

fps	239
iterations	1
time_elapsed	8
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_21

rollout/	
ep_len_mean	2e+03
ep_rew_mean	19.8
time/	
fps	238
iterations	1
time_elapsed	8
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_22

rollout/	
ep_len_mean	2e+03
ep_rew_mean	16.2
time/	
fps	240
iterations	1
time_elapsed	8
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_23

rollout/	
ep_len_mean	2e+03
ep_rew_mean	22.2
time/	
fps	237
iterations	1
time_elapsed	8
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_24

rollout/	
ep_len_mean	2e+03
ep_rew_mean	20.6
time/	
fps	232
iterations	1
time_elapsed	8
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_25

rollout/	
ep_len_mean	2e+03
ep_rew_mean	22.2
time/	
fps	229
iterations	1
time_elapsed	8
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_26

rollout/	
ep_len_mean	2e+03
ep_rew_mean	14
time/	
fps	227
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_27

rollout/	
ep_len_mean	2e+03
ep_rew_mean	7.47
time/	
fps	225
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_28

rollout/	
ep_len_mean	2e+03
ep_rew_mean	15.6
time/	
fps	223
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_29

rollout/	
ep_len_mean	2e+03
ep_rew_mean	14

time/	
fps	226
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_30

rollout/	
ep_len_mean	2e+03
ep_rew_mean	20
time/	
fps	224
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_31

rollout/	
ep_len_mean	2e+03
ep_rew_mean	15.6
time/	
fps	224
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_32

rollout/	
ep_len_mean	2e+03
ep_rew_mean	13.3
time/	
fps	224
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_33

rollout/	
ep_len_mean	2e+03
ep_rew_mean	7.47
time/	
fps	226
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_34

rollout/	
ep_len_mean	2e+03
ep_rew_mean	20
time/	
fps	227
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_35

rollout/	
ep_len_mean	2e+03
ep_rew_mean	20
time/	
fps	225
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_36

rollout/	
ep_len_mean	2e+03
ep_rew_mean	14.7
time/	
fps	224
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_37

rollout/	
ep_len_mean	2e+03
ep_rew_mean	14.7
time/	
fps	225
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_38

rollout/	
ep_len_mean	2e+03

ep_rew_mean	13.3
time/	
fps	224
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_39

rollout/	
ep_len_mean	2e+03
ep_rew_mean	13.1
time/	
fps	225
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_40

rollout/	
ep_len_mean	2e+03
ep_rew_mean	16.4
time/	
fps	225
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_41

rollout/	
ep_len_mean	2e+03
ep_rew_mean	16.4
time/	
fps	223
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_42

rollout/	
ep_len_mean	2e+03
ep_rew_mean	14.7
time/	
fps	223
iterations	1
time_elapsed	9

	total_timesteps		2048	
--	-----------------	--	------	--

Logging to ./ppo_job_scheduling_tensorboard/PP0_43

	rollout/			
	ep_len_mean		2e+03	
	ep_rew_mean		13.1	
	time/			
	fps		227	
	iterations		1	
	time_elapsed		8	
	total_timesteps		2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_44

	rollout/			
	ep_len_mean		2e+03	
	ep_rew_mean		21.5	
	time/			
	fps		226	
	iterations		1	
	time_elapsed		9	
	total_timesteps		2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_45

	rollout/			
	ep_len_mean		2e+03	
	ep_rew_mean		15.6	
	time/			
	fps		227	
	iterations		1	
	time_elapsed		8	
	total_timesteps		2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_46

	rollout/			
	ep_len_mean		2e+03	
	ep_rew_mean		22.2	
	time/			
	fps		226	
	iterations		1	
	time_elapsed		9	
	total_timesteps		2048	

Logging to ./ppo_job_scheduling_tensorboard/PP0_47

	rollout/			
	ep_len_mean		2e+03	

ep_rew_mean	21.4
time/	
fps	224
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_48

rollout/	
ep_len_mean	2e+03
ep_rew_mean	8.89
time/	
fps	226
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_49

rollout/	
ep_len_mean	2e+03
ep_rew_mean	20
time/	
fps	225
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_50

rollout/	
ep_len_mean	2e+03
ep_rew_mean	22.2
time/	
fps	226
iterations	1
time_elapsed	9
total_timesteps	2048

Logging to ./ppo_job_scheduling_tensorboard/PP0_51

rollout/	
ep_len_mean	2e+03
ep_rew_mean	15.6
time/	
fps	224
iterations	1
time_elapsed	9

```
| total_timesteps | 2048 |  
-----
```

```
# Load the model- working testing model  
loaded_model = PPO.load("job_scheduling_model_epoch_3machines_5jobs")  
  
# Create an instance of the environment for testing  
num_jobs = 5  
job_durations = [10, 3, 20, 8, 1] # These should match the training setup  
num_machines = 3  
test_env = JobSchedulingEnv(num_jobs=num_jobs,  
job_durations=job_durations, num_machines=num_machines)  
  
# Initialize variables to track the optimal solution  
optimal_makespan = float('inf')  
optimal_state = None  
  
# Run the model to find the optimal solution  
obs = test_env.reset()  
for _ in range(20000):  
    # Introduce a small probability of random action to allow exploration  
    if random.random() < 0.05: # 5% chance of random action  
        action = test_env.action_space.sample()  
    else:  
        action, _states = loaded_model.predict(obs,  
deterministic=False)  
  
    obs, _, done, _ = test_env.step(action)  
  
    # Track the best solution  
    if test_env.current_makespan < optimal_makespan:  
        optimal_makespan = test_env.current_makespan  
        optimal_state = obs.copy()  
  
    if done:  
        obs = test_env.reset()  
  
# Print the optimal solution  
print("Optimal Schedule:")  
for m in range(num_machines):  
    jobs_on_machine = [f"J{i+1}" for i in range(num_jobs) if  
optimal_state[i] == m]  
    makespan = sum(test_env.job_durations[i] for i in range(num_jobs)  
if optimal_state[i] == m)  
    print(f"Machine {m+1} - Jobs: {'', '.join(jobs_on_machine)} |  
Makespan: {makespan} minutes")
```

Optimal Schedule:

Machine 1 - Jobs: J2, J4, J5 | Makespan: 12 minutes

Machine 2 - Jobs: J1 | Makespan: 10 minutes

Machine 3 - Jobs: J3 | Makespan: 20 minutes

```
%load_ext tensorboard
```

```
%tensorboard --logdir ./ppo_job_scheduling_tensorboard/
```

```
# Load the model itioal development
```

```
loaded_model = PP0.load("job_scheduling_model", env=env)
```

```
# Create an instance of the original environment for rendering
```

```
render_env = JobSchedulingEnv(num_jobs=8, job_durations=[2, 1, 4, 3,  
5, 2, 6, 3], num_machines=3)
```

```
# Test the loaded model
```

```
obs = env.reset()
```

```
for i in range(200000):
```

```
    action, _states = loaded_model.predict(obs, deterministic=True)
```

```
    obs, rewards, dones, info = env.step(action)
```

```
# Synchronize the state of the rendering environment
```

```
render_env.state = env.get_attr("state")[0]
```

```
render_env.current_makespan = env.get_attr("current_makespan")[0]
```

```
# Use the render method of the original environment
```

```
render_env.render()
```

```
if dones:
```

```
    obs = env.reset()
```

```
import gym
```

```
from gym import spaces
```

```
import numpy as np
```

```
import random
```

```
from stable_baselines3 import PP0
```

```
from stable_baselines3.common.env_util import make_vec_env
```

```
class JobSchedulingEnv(gym.Env):
```

```
    def __init__(self, num_jobs=6, job_durations=[2, 3, 5, 6, 2, 3],  
num_machines=2):
```

```
        super(JobSchedulingEnv, self).__init__()
```

```
        self.num_jobs = num_jobs
```

```
        self.job_durations = job_durations
```

```
        self.num_machines = num_machines
```

```
        self.action_space = spaces.MultiDiscrete([num_machines] *  
num_jobs)
```

```
        self.observation_space = spaces.MultiDiscrete([num_machines] *  
num_jobs)
```

```
        self.max_steps = 2000
```

```
        self.reset()
```

```

def step(self, action):
    prev_max_makespan = max([sum(self.job_durations[j] for j in
range(self.num_jobs) if self.state[j] == m) for m in
range(self.num_machines)])
    self.state = action
    makespans = [sum(self.job_durations[j] for j in
range(self.num_jobs) if self.state[j] == m) for m in
range(self.num_machines)]
    new_max_makespan = max(makespans)
    reward = prev_max_makespan - new_max_makespan
    self.current_step += 1
    done = self.current_step >= self.max_steps
    return self.state, reward, done, {}

def reset(self):
    self.state = np.zeros(self.num_jobs, dtype=int)
    self.current_makespan = sum(self.job_durations)
    self.current_step = 0
    return self.state

def render(self, mode='human', close=False):
    if close:
        return
    for m in range(self.num_machines):
        jobs_on_machine = [f"J{i+1}" for i in range(self.num_jobs)
if self.state[i] == m]
        makespan = sum(self.job_durations[i] for i in
range(self.num_jobs) if self.state[i] == m)
        print(f"Machine {m+1} - Jobs: {' '.join(jobs_on_machine)}
| Makespan: {makespan} minutes")
    print("-" * 50)

# Initialize your environment parameters
number_of_epochs = 100
timesteps_per_epoch = 2000
num_jobs = 5
num_machines = 3

# Epsilon-Greedy Parameters
epsilon_start = 1.0
epsilon_end = 0.01
epsilon_decay = 0.995

def select_action(model, observation, epsilon, env):
    if random.random() < epsilon:
        # Generate a random action for each environment in the batch
        return [env.action_space.sample() for _ in
range(env.num_envs)]
    else:

```

```

        # Predict action using the model for each environment in the
        batch
        return model.predict(observation, deterministic=True)[0]

```

```

# Generating training scenarios

```

```

training_scenarios = [
    [random.uniform(1, 12) for _ in range(num_jobs)] for _ in
    range(number_of_epochs)
]

```

```

initial_job_durations = training_scenarios[0]
env = JobSchedulingEnv(num_jobs=num_jobs,
    job_durations=initial_job_durations, num_machines=num_machines)
env = make_vec_env(lambda: env, n_envs=1)

```

```

# Initialize the PPO model

```

```

model = PPO("MlpPolicy", env, learning_rate=0.0025, n_steps=2048,
    batch_size=64,
    gamma=0.99, gae_lambda=0.95, clip_range=0.2,
    ent_coef=0.01,
    verbose=1,
    tensorboard_log="./ppo_job_scheduling_tensorboard/")

```

```

# Training loop with epsilon-greedy exploration

```

```

epsilon = epsilon_start
for epoch in range(number_of_epochs):
    obs = env.reset()
    for step in range(timesteps_per_epoch):
        action = select_action(model, obs, epsilon, env)
        obs, rewards, dones, infos = env.step(action)
        # ... (additional code for your training step) ...

```

```

    # Decay epsilon

```

```

    epsilon = max(epsilon_end, epsilon_decay * epsilon)

```

```

# Saving the model

```

```

model_filename =
    f"job_scheduling_model_epoch_{num_machines}machines_{num_jobs}jobs"
model.save(model_filename)

```

```

# ... [Your existing code for loading the model and testing] ...

```

Using cuda device

```

# Load the model- working testing model

```

```

loaded_model = PPO.load("job_scheduling_model_epoch_3machines_5jobs")

```

```

# Create an instance of the environment for testing

```

```

num_jobs = 5

```

```

job_durations = [10, 3, 20, 8, 1] # These should match the training
setup
num_machines = 3
test_env = JobSchedulingEnv(num_jobs=num_jobs,
job_durations=job_durations, num_machines=num_machines)

# Initialize variables to track the optimal solution
optimal_makespan = float('inf')
optimal_state = None

# Run the model to find the optimal solution
obs = test_env.reset()
for _ in range(1000):
    # Introduce a small probability of random action to allow
    exploration
    if random.random() < 0.05: # 5% chance of random action
        action = test_env.action_space.sample()
    else:
        action, _states = loaded_model.predict(obs,
deterministic=False)

    obs, _, done, _ = test_env.step(action)

    # Track the best solution
    if test_env.current_makespan < optimal_makespan:
        optimal_makespan = test_env.current_makespan
        optimal_state = obs.copy()

    if done:
        obs = test_env.reset()

# Print the optimal solution
print("Optimal Schedule:")
for m in range(num_machines):
    jobs_on_machine = [f"J{i+1}" for i in range(num_jobs) if
optimal_state[i] == m]
    makespan = sum(test_env.job_durations[i] for i in range(num_jobs)
if optimal_state[i] == m)
    print(f"Machine {m+1} - Jobs: {' '.join(jobs_on_machine)} |
Makespan: {makespan} minutes")

```

```

-----
-----
NameError                                Traceback (most recent call
last)
<ipython-input-1-e5d3635149aa> in <cell line: 2>()
      1 # Load the model- working testing model
----> 2 loaded_model =
PP0.load("job_scheduling_model_epoch_3machines_5jobs")
      3

```

```
4 # Create an instance of the environment for testing
5 num_jobs = 5
```

NameError: name 'PP0' is not defined

```
!pip install pulp
```

Collecting pulp

Downloading PuLP-2.7.0-py3-none-any.whl (14.3 MB)

14.3/14.3 MB 38.8 MB/s eta

0:00:00

```
import random
```

```
# Parameters
```

```
num_jobs = 5
job_durations = [10, 3, 20, 8, 1]
num_machines = 3
population_size = 50
generations = 100
crossover_rate = 0.8
mutation_rate = 0.1
```

```
# Initialize population
```

```
def initialize_population(population_size, num_jobs, num_machines):
    return [[random.randint(0, num_machines - 1) for _ in
range(num_jobs)] for _ in range(population_size)]
```

```
# Calculate makespan
```

```
def calculate_makespan(chromosome, job_durations, num_machines):
    machine_times = [0] * num_machines
    for job, machine in enumerate(chromosome):
        machine_times[machine] += job_durations[job]
    return max(machine_times)
```

```
# Selection - Tournament selection
```

```
def tournament_selection(population, fitness, tournament_size=3):
    selected = []
    for _ in range(len(population)):
        tournament = [random.choice(range(len(population))) for _ in
range(tournament_size)]
        fittest_individual = min(tournament, key=lambda i: fitness[i])
        selected.append(population[fittest_individual])
    return selected
```

```
# Crossover - Single point crossover
```

```
def crossover(parent1, parent2):
    if random.random() < crossover_rate:
        point = random.randint(1, len(parent1) - 1)
```

```

        return parent1[:point] + parent2[point:], parent2[:point] +
parent1[point:]
    else:
        return parent1, parent2

# Mutation - Randomly change a job's machine assignment
def mutate(chromosome, num_machines, mutation_rate):
    for i in range(len(chromosome)):
        if random.random() < mutation_rate:
            chromosome[i] = random.randint(0, num_machines - 1)
    return chromosome

# Main Genetic Algorithm
population = initialize_population(population_size, num_jobs,
num_machines)

for generation in range(generations):
    # Calculate fitness for each individual
    fitness = [calculate_makespan(individual, job_durations,
num_machines) for individual in population]

    # Selection
    selected = tournament_selection(population, fitness)

    # Crossover
    offspring = []
    for i in range(0, len(selected), 2):
        parent1, parent2 = selected[i], selected[i + 1]
        child1, child2 = crossover(parent1, parent2)
        offspring.extend([child1, child2])

    # Mutation
    population = [mutate(individual, num_machines, mutation_rate) for
individual in offspring]

# Find the best solution
best_solution = min(population, key=lambda chrom:
calculate_makespan(chrom, job_durations, num_machines))
best_makespan = calculate_makespan(best_solution, job_durations,
num_machines)

print("Best Schedule:", best_solution)
print("Best Makespan:", best_makespan)

Best Schedule: [1, 2, 0, 2, 1]
Best Makespan: 20

import gym
from gym import spaces
import numpy as np

```



```

import random
from stable_baselines3 import PPO
from stable_baselines3.common.env_util import make_vec_env

import random

# Genetic Algorithm Functions
def initialize_population(population_size, num_jobs, num_machines):
    return [[random.randint(0, num_machines - 1) for _ in
range(num_jobs)] for _ in range(population_size)]

def calculate_makespan(chromosome, job_durations, num_machines):
    machine_times = [0] * num_machines
    for job, machine in enumerate(chromosome):
        machine_times[machine] += job_durations[job]
    return max(machine_times)

def tournament_selection(population, fitness, tournament_size=3):
    selected = []
    for _ in range(len(population)):
        tournament = [random.choice(range(len(population))) for _ in
range(tournament_size)]
        fittest_individual = min(tournament, key=lambda i: fitness[i])
        selected.append(population[fittest_individual])
    return selected

def crossover(parent1, parent2, crossover_rate):
    if random.random() < crossover_rate:
        point = random.randint(1, len(parent1) - 1)
        return parent1[:point] + parent2[point:], parent2[:point] +
parent1[point:]
    else:
        return parent1, parent2

def mutate(chromosome, num_machines, mutation_rate):
    for i in range(len(chromosome)):
        if random.random() < mutation_rate:
            chromosome[i] = random.randint(0, num_machines - 1)
    return chromosome

def run_genetic_algorithm(num_jobs, job_durations, num_machines,
population_size, generations, crossover_rate, mutation_rate):
    population = initialize_population(population_size, num_jobs,
num_machines)

    for generation in range(generations):
        fitness = [calculate_makespan(individual, job_durations,
num_machines) for individual in population]
        selected = tournament_selection(population, fitness)
        offspring = []

```

```

        for i in range(0, len(selected), 2):
            parent1, parent2 = selected[i], selected[i + 1]
            child1, child2 = crossover(parent1, parent2,
crossover_rate)
            offspring.extend([child1, child2])
            population = [mutate(individual, num_machines, mutation_rate)
for individual in offspring]

        best_solution = min(population, key=lambda chrom:
calculate_makespan(chrom, job_durations, num_machines))
        best_makespan = calculate_makespan(best_solution, job_durations,
num_machines)
        print(best_makespan)
        return best_makespan

```

```

class JobSchedulingEnv(gym.Env):
    def __init__(self, num_jobs=5, job_durations=[10, 3, 20, 8, 1],
num_machines=3, target_makespan=20, tolerance=1):
        super(JobSchedulingEnv, self).__init__()
        self.num_jobs = num_jobs
        self.job_durations = job_durations
        self.num_machines = num_machines
        self.target_makespan = target_makespan
        self.action_space = spaces.Discrete(num_jobs * num_machines)
# New action space
        self.observation_space = spaces.Box(low=0, high=num_machines,
shape=(num_jobs,), dtype=np.int32)
        self.max_steps = 2000
        self.tolerance = tolerance
        self.state = None
        self.reset()

    def reset(self):
        self.state = np.random.randint(low=0, high=self.num_machines,
size=self.num_jobs) # Random initial state
        self.current_step = 0
        return self.state

    def step(self, action):
        job_index = action // self.num_machines
        machine_index = action % self.num_machines
        self.state[job_index] = machine_index
        current_makespan = max([sum(self.job_durations[j] for j in
range(self.num_jobs) if self.state[j] == m) for m in
range(self.num_machines)])
        reward = -abs(current_makespan - self.target_makespan) #
Negative absolute difference as reward
        self.current_step += 1

```

```

        done = abs(current_makespan - self.target_makespan) <=
self.tolerance
        return self.state, reward, done, {}

    def render(self, mode='human', close=False):
        if close:
            return
        for m in range(self.num_machines):
            jobs_on_machine = [f"J{i+1}" for i in range(self.num_jobs)
if self.state[i] == m]
            makespan = sum(self.job_durations[i] for i in
range(self.num_jobs) if self.state[i] == m)
            print(f"Machine {m+1} - Jobs: {'', ' '.join(jobs_on_machine)}
| Makespan: {makespan} minutes")
        print("-" * 50)

# Training Parameters
number_of_epochs = 3
timesteps_per_epoch = 40000
num_jobs = 5
num_machines = 3
population_size = 50
generations = 100
crossover_rate = 0.8
mutation_rate = 0.1
tolerance = 5

# Initialize the PPO model
dummy_env = JobSchedulingEnv(num_jobs=num_jobs, job_durations=[1] *
num_jobs, num_machines=num_machines,
target_makespan=1,tolerance=tolerance)
model = PPO("MlpPolicy", dummy_env, learning_rate=0.00025,
n_steps=2000, batch_size=64, gamma=0.99, gae_lambda=0.95,
clip_range=0.2, ent_coef=0.01, verbose=1,
tensorboard_log="./ppo_job_scheduling_tensorboard/")

# Training loop
for epoch in range(number_of_epochs):
    # Generate random job durations for each epoch
    job_durations = [random.randint(1, 5) for _ in range(num_jobs)]

    # Run the Genetic Algorithm to find the target makespan
    target_makespan = run_genetic_algorithm(num_jobs, job_durations,
num_machines, population_size, generations, crossover_rate,
mutation_rate)

    # Create the real environment with new parameters
    real_env = JobSchedulingEnv(num_jobs=num_jobs,

```

```

job_durations=job_durations, num_machines=num_machines,
target_makespan=target_makespan,tolerance=tolerance)
    real_env = make_vec_env(lambda: real_env, n_envs=1)

```

```

# Update the model's environment
model.set_env(real_env)

```

```

# Train the model
model.learn(total_timesteps=timesteps_per_epoch)

```

```

# Saving the model
model.save("job_scheduling_model")

```

Using cuda device

Wrapping the env with a `Monitor` wrapper

Wrapping the env in a DummyVecEnv.

3

Logging to ./ppo_job_scheduling_tensorboard/PP0_290

/usr/local/lib/python3.10/dist-packages/stable_baselines3/ppo/ppo.py:155: UserWarning: You have specified a mini-batch size of 64, but because the `RolloutBuffer` is of size `n_steps * n_envs = 2000`, after every 31 untruncated mini-batches, there will be a truncated mini-batch of size 16

We recommend using a `batch_size` that is a factor of `n_steps * n_envs`.

Info: (n_steps=2000 and n_envs=1)
warnings.warn(

```

-----
| rollout/          |          |
|   ep_len_mean    | 1.04     |
|   ep_rew_mean    | -2.58    |
| time/           |          |
|   fps            | 684      |
|   iterations     | 1        |
|   time_elapsed   | 2        |
|   total_timesteps | 2000     |
|-----|

```

```

-----
| rollout/          |          |
|   ep_len_mean    | 1.02     |
|   ep_rew_mean    | -2.41    |
| time/           |          |
|   fps            | 553      |
|   iterations     | 2        |
|   time_elapsed   | 7        |
|   total_timesteps | 4000     |
| train/          |          |

```

approx_kl	0.018658869
clip_fraction	0.149
clip_range	0.2
entropy_loss	-2.7
explained_variance	-0.0262
learning_rate	0.00025
loss	0.536
n_updates	10
policy_gradient_loss	-0.0304
value_loss	4.86

rollout/	
ep_len_mean	1.02
ep_rew_mean	-2.4
time/	
fps	503
iterations	3
time_elapsed	11
total_timesteps	6000
train/	
approx_kl	0.021347404
clip_fraction	0.28
clip_range	0.2
entropy_loss	-2.64
explained_variance	-0.0314
learning_rate	0.00025
loss	0.853
n_updates	20
policy_gradient_loss	-0.0446
value_loss	2.46

rollout/	
ep_len_mean	1.03
ep_rew_mean	-2.29
time/	
fps	492
iterations	4
time_elapsed	16
total_timesteps	8000
train/	
approx_kl	0.021778788
clip_fraction	0.298
clip_range	0.2
entropy_loss	-2.56
explained_variance	0.0757
learning_rate	0.00025
loss	0.569

n_updates	30
policy_gradient_loss	-0.0519
value_loss	2.37

rollout/	
ep_len_mean	1.01
ep_rew_mean	-2.07
time/	
fps	486
iterations	5
time_elapsed	20
total_timesteps	10000
train/	
approx_kl	0.01946235
clip_fraction	0.365
clip_range	0.2
entropy_loss	-2.44
explained_variance	0.122
learning_rate	0.00025
loss	0.543
n_updates	40
policy_gradient_loss	-0.0646
value_loss	1.99

rollout/	
ep_len_mean	1
ep_rew_mean	-1.98
time/	
fps	474
iterations	6
time_elapsed	25
total_timesteps	12000
train/	
approx_kl	0.021550588
clip_fraction	0.39
clip_range	0.2
entropy_loss	-2.32
explained_variance	0.147
learning_rate	0.00025
loss	0.495
n_updates	50
policy_gradient_loss	-0.0745
value_loss	1.56

rollout/	
ep_len_mean	1.01

ep_rew_mean	-1.93
time/	
fps	473
iterations	7
time_elapsed	29
total_timesteps	14000
train/	
approx_kl	0.028465461
clip_fraction	0.401
clip_range	0.2
entropy_loss	-2.16
explained_variance	0.13
learning_rate	0.00025
loss	0.183
n_updates	60
policy_gradient_loss	-0.0762
value_loss	1.15

rollout/	
ep_len_mean	1
ep_rew_mean	-1.63
time/	
fps	468
iterations	8
time_elapsed	34
total_timesteps	16000
train/	
approx_kl	0.020976381
clip_fraction	0.261
clip_range	0.2
entropy_loss	-1.99
explained_variance	0.0626
learning_rate	0.00025
loss	0.327
n_updates	70
policy_gradient_loss	-0.0611
value_loss	0.928

rollout/	
ep_len_mean	1
ep_rew_mean	-1.5
time/	
fps	465
iterations	9
time_elapsed	38
total_timesteps	18000
train/	

approx_kl	0.018754754
clip_fraction	0.222
clip_range	0.2
entropy_loss	-1.85
explained_variance	0.0648
learning_rate	0.00025
loss	0.261
n_updates	80
policy_gradient_loss	-0.0523
value_loss	0.8

rollout/	
ep_len_mean	1
ep_rew_mean	-1.49
time/	
fps	465
iterations	10
time_elapsed	43
total_timesteps	20000
train/	
approx_kl	0.016115401
clip_fraction	0.213
clip_range	0.2
entropy_loss	-1.71
explained_variance	0.105
learning_rate	0.00025
loss	0.198
n_updates	90
policy_gradient_loss	-0.0449
value_loss	0.614

rollout/	
ep_len_mean	1
ep_rew_mean	-1.36
time/	
fps	461
iterations	11
time_elapsed	47
total_timesteps	22000
train/	
approx_kl	0.015000742
clip_fraction	0.145
clip_range	0.2
entropy_loss	-1.63
explained_variance	0.0638
learning_rate	0.00025
loss	0.138

n_updates	100
policy_gradient_loss	-0.0382
value_loss	0.688

rollout/	
ep_len_mean	1
ep_rew_mean	-1.43
time/	
fps	461
iterations	12
time_elapsed	52
total_timesteps	24000
train/	
approx_kl	0.013525712
clip_fraction	0.143
clip_range	0.2
entropy_loss	-1.54
explained_variance	0.101
learning_rate	0.00025
loss	0.206
n_updates	110
policy_gradient_loss	-0.0371
value_loss	0.566

rollout/	
ep_len_mean	1
ep_rew_mean	-1.43
time/	
fps	460
iterations	13
time_elapsed	56
total_timesteps	26000
train/	
approx_kl	0.015544775
clip_fraction	0.165
clip_range	0.2
entropy_loss	-1.43
explained_variance	0.0905
learning_rate	0.00025
loss	0.168
n_updates	120
policy_gradient_loss	-0.0383
value_loss	0.523

rollout/	
ep_len_mean	1

ep_rew_mean	-1.3
time/	
fps	457
iterations	14
time_elapsed	61
total_timesteps	28000
train/	
approx_kl	0.014967583
clip_fraction	0.155
clip_range	0.2
entropy_loss	-1.38
explained_variance	0.118
learning_rate	0.00025
loss	0.211
n_updates	130
policy_gradient_loss	-0.0362
value_loss	0.516

rollout/	
ep_len_mean	1
ep_rew_mean	-1.22
time/	
fps	457
iterations	15
time_elapsed	65
total_timesteps	30000
train/	
approx_kl	0.013354813
clip_fraction	0.112
clip_range	0.2
entropy_loss	-1.29
explained_variance	0.0782
learning_rate	0.00025
loss	0.228
n_updates	140
policy_gradient_loss	-0.0335
value_loss	0.499

rollout/	
ep_len_mean	1
ep_rew_mean	-1.45
time/	
fps	455
iterations	16
time_elapsed	70
total_timesteps	32000
train/	

approx_kl	0.010692762
clip_fraction	0.102
clip_range	0.2
entropy_loss	-1.22
explained_variance	0.0932
learning_rate	0.00025
loss	0.278
n_updates	150
policy_gradient_loss	-0.0306
value_loss	0.484

rollout/	
ep_len_mean	1
ep_rew_mean	-1.29
time/	
fps	455
iterations	17
time_elapsed	74
total_timesteps	34000
train/	
approx_kl	0.014578375
clip_fraction	0.0936
clip_range	0.2
entropy_loss	-1.17
explained_variance	0.11
learning_rate	0.00025
loss	0.431
n_updates	160
policy_gradient_loss	-0.0256
value_loss	0.441

rollout/	
ep_len_mean	1
ep_rew_mean	-1.38
time/	
fps	455
iterations	18
time_elapsed	78
total_timesteps	36000
train/	
approx_kl	0.011278259
clip_fraction	0.13
clip_range	0.2
entropy_loss	-1.13
explained_variance	0.129
learning_rate	0.00025
loss	0.131

n_updates	170
policy_gradient_loss	-0.0309
value_loss	0.463

rollout/	
ep_len_mean	1
ep_rew_mean	-1.19
time/	
fps	453
iterations	19
time_elapsed	83
total_timesteps	38000
train/	
approx_kl	0.009060815
clip_fraction	0.0945
clip_range	0.2
entropy_loss	-1.06
explained_variance	0.11
learning_rate	0.00025
loss	0.136
n_updates	180
policy_gradient_loss	-0.0258
value_loss	0.442

rollout/	
ep_len_mean	1
ep_rew_mean	-1.34
time/	
fps	453
iterations	20
time_elapsed	88
total_timesteps	40000
train/	
approx_kl	0.008264336
clip_fraction	0.0913
clip_range	0.2
entropy_loss	-1
explained_variance	0.178
learning_rate	0.00025
loss	0.158
n_updates	190
policy_gradient_loss	-0.0216
value_loss	0.399

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Logging to ./ppo_job_scheduling_tensorboard/PP0_291

rollout/	
ep_len_mean	1.03
ep_rew_mean	-2.31
time/	
fps	664
iterations	1
time_elapsed	3
total_timesteps	2000

rollout/	
ep_len_mean	1.08
ep_rew_mean	-2.75
time/	
fps	527
iterations	2
time_elapsed	7
total_timesteps	4000
train/	
approx_kl	0.010680847
clip_fraction	0.0947
clip_range	0.2
entropy_loss	-0.934
explained_variance	0.0364
learning_rate	0.00025
loss	1.87
n_updates	210
policy_gradient_loss	-0.019
value_loss	5.42

rollout/	
ep_len_mean	1.01
ep_rew_mean	-2.13
time/	
fps	507
iterations	3
time_elapsed	11
total_timesteps	6000
train/	
approx_kl	0.00815574
clip_fraction	0.0967
clip_range	0.2
entropy_loss	-0.921
explained_variance	0.121
learning_rate	0.00025
loss	0.665
n_updates	220
policy_gradient_loss	-0.0183

value_loss	4.63
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rollout/	
ep_len_mean	1.03
ep_rew_mean	-2.48
time/	
fps	485
iterations	4
time_elapsed	16
total_timesteps	8000
train/	
approx_kl	0.010172943
clip_fraction	0.102
clip_range	0.2
entropy_loss	-0.898
explained_variance	0.208
learning_rate	0.00025
loss	0.895
n_updates	230
policy_gradient_loss	-0.0221
value_loss	4.27

rollout/	
ep_len_mean	1.01
ep_rew_mean	-2.01
time/	
fps	482
iterations	5
time_elapsed	20
total_timesteps	10000
train/	
approx_kl	0.011878994
clip_fraction	0.138
clip_range	0.2
entropy_loss	-0.914
explained_variance	0.271
learning_rate	0.00025
loss	0.992
n_updates	240
policy_gradient_loss	-0.0256
value_loss	3.81

rollout/	
ep_len_mean	1
ep_rew_mean	-2.1
time/	
fps	478

iterations	6
time_elapsed	25
total_timesteps	12000
train/	
approx_kl	0.009134321
clip_fraction	0.104
clip_range	0.2
entropy_loss	-0.866
explained_variance	0.288
learning_rate	0.00025
loss	0.91
n_updates	250
policy_gradient_loss	-0.0221
value_loss	2.96

rollout/	
ep_len_mean	1
ep_rew_mean	-2.01
time/	
fps	469
iterations	7
time_elapsed	29
total_timesteps	14000
train/	
approx_kl	0.011752756
clip_fraction	0.122
clip_range	0.2
entropy_loss	-0.864
explained_variance	0.294
learning_rate	0.00025
loss	3.14
n_updates	260
policy_gradient_loss	-0.0243
value_loss	2.87

rollout/	
ep_len_mean	1.01
ep_rew_mean	-1.9
time/	
fps	469
iterations	8
time_elapsed	34
total_timesteps	16000
train/	
approx_kl	0.008926092
clip_fraction	0.0964
clip_range	0.2

entropy_loss	-0.852
explained_variance	0.357
learning_rate	0.00025
loss	0.354
n_updates	270
policy_gradient_loss	-0.0218
value_loss	2.35

rollout/	
ep_len_mean	1
ep_rew_mean	-1.97
time/	
fps	467
iterations	9
time_elapsed	38
total_timesteps	18000
train/	
approx_kl	0.009041598
clip_fraction	0.0971
clip_range	0.2
entropy_loss	-0.842
explained_variance	0.342
learning_rate	0.00025
loss	0.87
n_updates	280
policy_gradient_loss	-0.0203
value_loss	2.14

rollout/	
ep_len_mean	1
ep_rew_mean	-1.59
time/	
fps	464
iterations	10
time_elapsed	43
total_timesteps	20000
train/	
approx_kl	0.010144679
clip_fraction	0.118
clip_range	0.2
entropy_loss	-0.831
explained_variance	0.45
learning_rate	0.00025
loss	1.06
n_updates	290
policy_gradient_loss	-0.0216
value_loss	1.8

rollout/	
ep_len_mean	1.01
ep_rew_mean	-2.06
time/	
fps	464
iterations	11
time_elapsed	47
total_timesteps	22000
train/	
approx_kl	0.00745301
clip_fraction	0.104
clip_range	0.2
entropy_loss	-0.829
explained_variance	0.424
learning_rate	0.00025
loss	1.2
n_updates	300
policy_gradient_loss	-0.0233
value_loss	1.85

rollout/	
ep_len_mean	1.04
ep_rew_mean	-2.17
time/	
fps	459
iterations	12
time_elapsed	52
total_timesteps	24000
train/	
approx_kl	0.006748994
clip_fraction	0.09
clip_range	0.2
entropy_loss	-0.809
explained_variance	0.458
learning_rate	0.00025
loss	0.254
n_updates	310
policy_gradient_loss	-0.0245
value_loss	1.62

rollout/	
ep_len_mean	1.03
ep_rew_mean	-2.26
time/	
fps	460

iterations	13
time_elapsed	56
total_timesteps	26000
train/	
approx_kl	0.008977774
clip_fraction	0.135
clip_range	0.2
entropy_loss	-0.807
explained_variance	0.449
learning_rate	0.00025
loss	0.316
n_updates	320
policy_gradient_loss	-0.0283
value_loss	1.73

rollout/	
ep_len_mean	1.04
ep_rew_mean	-2.11
time/	
fps	460
iterations	14
time_elapsed	60
total_timesteps	28000
train/	
approx_kl	0.0083325375
clip_fraction	0.0859
clip_range	0.2
entropy_loss	-0.732
explained_variance	0.508
learning_rate	0.00025
loss	0.586
n_updates	330
policy_gradient_loss	-0.0241
value_loss	1.49

rollout/	
ep_len_mean	1
ep_rew_mean	-1.74
time/	
fps	458
iterations	15
time_elapsed	65
total_timesteps	30000
train/	
approx_kl	0.0094406605
clip_fraction	0.109
clip_range	0.2

entropy_loss	-0.726
explained_variance	0.536
learning_rate	0.00025
loss	1.17
n_updates	340
policy_gradient_loss	-0.0258
value_loss	1.25

rollout/	
ep_len_mean	1.01
ep_rew_mean	-1.87
time/	
fps	458
iterations	16
time_elapsed	69
total_timesteps	32000
train/	
approx_kl	0.008126431
clip_fraction	0.0842
clip_range	0.2
entropy_loss	-0.682
explained_variance	0.579
learning_rate	0.00025
loss	0.133
n_updates	350
policy_gradient_loss	-0.0227
value_loss	1.16

rollout/	
ep_len_mean	1.01
ep_rew_mean	-1.87
time/	
fps	457
iterations	17
time_elapsed	74
total_timesteps	34000
train/	
approx_kl	0.0076401755
clip_fraction	0.0826
clip_range	0.2
entropy_loss	-0.638
explained_variance	0.617
learning_rate	0.00025
loss	0.664
n_updates	360
policy_gradient_loss	-0.0202
value_loss	1.09

rollout/		
ep_len_mean		1.03
ep_rew_mean		-1.96
time/		
fps		457
iterations		18
time_elapsed		78
total_timesteps		36000
train/		
approx_kl		0.0066925795
clip_fraction		0.0892
clip_range		0.2
entropy_loss		-0.633
explained_variance		0.648
learning_rate		0.00025
loss		0.64
n_updates		370
policy_gradient_loss		-0.0218
value_loss		0.991

rollout/		
ep_len_mean		1.03
ep_rew_mean		-1.82
time/		
fps		457
iterations		19
time_elapsed		83
total_timesteps		38000
train/		
approx_kl		0.008884434
clip_fraction		0.0955
clip_range		0.2
entropy_loss		-0.609
explained_variance		0.646
learning_rate		0.00025
loss		0.415
n_updates		380
policy_gradient_loss		-0.0227
value_loss		0.936

rollout/		
ep_len_mean		1.01
ep_rew_mean		-1.7
time/		
fps		455

iterations	20
time_elapsed	87
total_timesteps	40000
train/	
approx_kl	0.014576204
clip_fraction	0.108
clip_range	0.2
entropy_loss	-0.596
explained_variance	0.648
learning_rate	0.00025
loss	0.0926
n_updates	390
policy_gradient_loss	-0.0234
value_loss	0.863

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Logging to ./ppo_job_scheduling_tensorboard/PP0_292

rollout/	
ep_len_mean	1.05
ep_rew_mean	-3.09
time/	
fps	692
iterations	1
time_elapsed	2
total_timesteps	2000

rollout/	
ep_len_mean	1.08
ep_rew_mean	-2.82
time/	
fps	558
iterations	2
time_elapsed	7
total_timesteps	4000
train/	
approx_kl	0.006262525
clip_fraction	0.062
clip_range	0.2
entropy_loss	-0.565
explained_variance	0.428
learning_rate	0.00025
loss	5.46
n_updates	410
policy_gradient_loss	-0.0182
value_loss	3.5

rollout/	
ep_len_mean	1.04
ep_rew_mean	-2.84
time/	
fps	506
iterations	3
time_elapsed	11
total_timesteps	6000
train/	
approx_kl	0.00887173
clip_fraction	0.092
clip_range	0.2
entropy_loss	-0.587
explained_variance	0.568
learning_rate	0.00025
loss	0.619
n_updates	420
policy_gradient_loss	-0.0193
value_loss	2.28

rollout/	
ep_len_mean	1.02
ep_rew_mean	-2.35
time/	
fps	495
iterations	4
time_elapsed	16
total_timesteps	8000
train/	
approx_kl	0.011628484
clip_fraction	0.0972
clip_range	0.2
entropy_loss	-0.57
explained_variance	0.656
learning_rate	0.00025
loss	0.444
n_updates	430
policy_gradient_loss	-0.0253
value_loss	2.36

rollout/	
ep_len_mean	1.01
ep_rew_mean	-2.45
time/	
fps	483
iterations	5
time_elapsed	20

total_timesteps	10000
train/	
approx_kl	0.009056151
clip_fraction	0.0908
clip_range	0.2
entropy_loss	-0.568
explained_variance	0.694
learning_rate	0.00025
loss	0.414
n_updates	440
policy_gradient_loss	-0.0251
value_loss	1.47

rollout/	
ep_len_mean	1.08
ep_rew_mean	-3.1
time/	
fps	479
iterations	6
time_elapsed	25
total_timesteps	12000
train/	
approx_kl	0.008488921
clip_fraction	0.0963
clip_range	0.2
entropy_loss	-0.599
explained_variance	0.698
learning_rate	0.00025
loss	0.41
n_updates	450
policy_gradient_loss	-0.0279
value_loss	1.7

rollout/	
ep_len_mean	1.03
ep_rew_mean	-2.56
time/	
fps	477
iterations	7
time_elapsed	29
total_timesteps	14000
train/	
approx_kl	0.0091473125
clip_fraction	0.0952
clip_range	0.2
entropy_loss	-0.599
explained_variance	0.659

learning_rate	0.00025
loss	0.93
n_updates	460
policy_gradient_loss	-0.0293
value_loss	1.83

rollout/	
ep_len_mean	1.06
ep_rew_mean	-2.79
time/	
fps	469
iterations	8
time_elapsed	34
total_timesteps	16000
train/	
approx_kl	0.012551058
clip_fraction	0.13
clip_range	0.2
entropy_loss	-0.59
explained_variance	0.708
learning_rate	0.00025
loss	0.932
n_updates	470
policy_gradient_loss	-0.0333
value_loss	1.51

rollout/	
ep_len_mean	1.04
ep_rew_mean	-2.74
time/	
fps	470
iterations	9
time_elapsed	38
total_timesteps	18000
train/	
approx_kl	0.010959093
clip_fraction	0.101
clip_range	0.2
entropy_loss	-0.585
explained_variance	0.707
learning_rate	0.00025
loss	0.745
n_updates	480
policy_gradient_loss	-0.0261
value_loss	1.52

rollout/	
ep_len_mean	1.02
ep_rew_mean	-2.46
time/	
fps	469
iterations	10
time_elapsed	42
total_timesteps	20000
train/	
approx_kl	0.013288228
clip_fraction	0.13
clip_range	0.2
entropy_loss	-0.608
explained_variance	0.718
learning_rate	0.00025
loss	0.24
n_updates	490
policy_gradient_loss	-0.033
value_loss	1.4

rollout/	
ep_len_mean	1.03
ep_rew_mean	-2.23
time/	
fps	465
iterations	11
time_elapsed	47
total_timesteps	22000
train/	
approx_kl	0.0113274045
clip_fraction	0.11
clip_range	0.2
entropy_loss	-0.607
explained_variance	0.756
learning_rate	0.00025
loss	0.658
n_updates	500
policy_gradient_loss	-0.03
value_loss	1.25

rollout/	
ep_len_mean	1.03
ep_rew_mean	-2.43
time/	
fps	465
iterations	12
time_elapsed	51
total_timesteps	24000

train/	
approx_kl	0.010241794
clip_fraction	0.128
clip_range	0.2
entropy_loss	-0.61
explained_variance	0.701
learning_rate	0.00025
loss	1.29
n_updates	510
policy_gradient_loss	-0.0337
value_loss	1.37

rollout/	
ep_len_mean	1.03
ep_rew_mean	-2.37
time/	
fps	461
iterations	13
time_elapsed	56
total_timesteps	26000
train/	
approx_kl	0.013626059
clip_fraction	0.127
clip_range	0.2
entropy_loss	-0.579
explained_variance	0.682
learning_rate	0.00025
loss	0.699
n_updates	520
policy_gradient_loss	-0.0339
value_loss	1.64

rollout/	
ep_len_mean	1
ep_rew_mean	-2.14
time/	
fps	460
iterations	14
time_elapsed	60
total_timesteps	28000
train/	
approx_kl	0.010502832
clip_fraction	0.108
clip_range	0.2
entropy_loss	-0.569
explained_variance	0.71
learning_rate	0.00025

loss	0.141
n_updates	530
policy_gradient_loss	-0.03
value_loss	1.52

rollout/	
ep_len_mean	1.04
ep_rew_mean	-2.54
time/	
fps	461
iterations	15
time_elapsed	65
total_timesteps	30000
train/	
approx_kl	0.009579731
clip_fraction	0.107
clip_range	0.2
entropy_loss	-0.583
explained_variance	0.744
learning_rate	0.00025
loss	0.125
n_updates	540
policy_gradient_loss	-0.0325
value_loss	1.13

rollout/	
ep_len_mean	1.01
ep_rew_mean	-2.15
time/	
fps	458
iterations	16
time_elapsed	69
total_timesteps	32000
train/	
approx_kl	0.007946995
clip_fraction	0.0918
clip_range	0.2
entropy_loss	-0.566
explained_variance	0.736
learning_rate	0.00025
loss	0.224
n_updates	550
policy_gradient_loss	-0.0323
value_loss	1.19

rollout/	
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ep_len_mean	1.01
ep_rew_mean	-1.79
time/	
fps	458
iterations	17
time_elapsed	74
total_timesteps	34000
train/	
approx_kl	0.008344554
clip_fraction	0.0919
clip_range	0.2
entropy_loss	-0.548
explained_variance	0.75
learning_rate	0.00025
loss	0.306
n_updates	560
policy_gradient_loss	-0.0283
value_loss	1.22

rollout/	
ep_len_mean	1
ep_rew_mean	-1.87
time/	
fps	459
iterations	18
time_elapsed	78
total_timesteps	36000
train/	
approx_kl	0.009061569
clip_fraction	0.0885
clip_range	0.2
entropy_loss	-0.536
explained_variance	0.726
learning_rate	0.00025
loss	1.03
n_updates	570
policy_gradient_loss	-0.0279
value_loss	1.3

rollout/	
ep_len_mean	1.02
ep_rew_mean	-1.9
time/	
fps	456
iterations	19
time_elapsed	83
total_timesteps	38000

train/	
approx_kl	0.007086073
clip_fraction	0.0761
clip_range	0.2
entropy_loss	-0.533
explained_variance	0.753
learning_rate	0.00025
loss	0.175
n_updates	580
policy_gradient_loss	-0.0283
value_loss	1.17

rollout/	
ep_len_mean	1.02
ep_rew_mean	-1.96
time/	
fps	457
iterations	20
time_elapsed	87
total_timesteps	40000
train/	
approx_kl	0.0077676857
clip_fraction	0.0776
clip_range	0.2
entropy_loss	-0.522
explained_variance	0.76
learning_rate	0.00025
loss	0.254
n_updates	590
policy_gradient_loss	-0.0268
value_loss	1.18

```

from stable_baselines3 import PP0

# Load the trained model
model = PP0.load("job_scheduling_model")

# Test job durations and environment setup
test_job_durations = [1, 2, 3, 5, 1] # Example job durations
num_jobs = len(test_job_durations)
num_machines = 3
test_env = JobSchedulingEnv(num_jobs=num_jobs,
                             job_durations=test_job_durations, num_machines=num_machines,
                             target_makespan=20, tolerance=1)

# Run the model in the test environment
obs = test_env.reset()
done = False

```

```

max_iterations = 30000 # Prevent infinite loop
iteration = 0

while not done and iteration < max_iterations:
    action, _states = model.predict(obs, deterministic=True)
    obs, rewards, done, info = test_env.step(action)
    iteration += 1

# Check if loop exited due to reaching max iterations
if iteration >= max_iterations:
    print("Reached maximum iterations without fulfilling termination
conditions.")

# Print the schedule
def print_schedule(env):
    print("\nOptimal Schedule:")
    for m in range(env.num_machines):
        jobs_on_machine = [f"J{i+1}" for i in range(env.num_jobs) if
env.state[i] == m]
        makespan = sum(env.job_durations[i] for i in
range(env.num_jobs) if env.state[i] == m)
        print(f"Machine {m+1} - Jobs: {'', '.join(jobs_on_machine)} |
Makespan: {makespan} minutes")

print_schedule(test_env)

Reached maximum iterations without fulfilling termination conditions.

Optimal Schedule:
Machine 1 - Jobs: J5 | Makespan: 1 minutes
Machine 2 - Jobs: J1, J3 | Makespan: 4 minutes
Machine 3 - Jobs: J2, J4 | Makespan: 7 minutes

import random

# Parameters
num_jobs = 10
job_durations = [10, 3, 20, 8, 1, 10, 3, 20, 8, 1]
num_machines = 5
population_size = 50
generations = 100
crossover_rate = 0.8
mutation_rate = 0.1

# Initialize population
def initialize_population(population_size, num_jobs, num_machines):
    return [[random.randint(0, num_machines - 1) for _ in
range(num_jobs)] for _ in range(population_size)]

# Calculate makespan and balance

```

```

def calculate_makespan_and_balance(chromosome, job_durations,
num_machines):
    machine_times = [0] * num_machines
    for job, machine in enumerate(chromosome):
        machine_times[machine] += job_durations[job]
    max_makespan = max(machine_times)
    balance_penalty = sum([(max_makespan - time)**2 for time in
machine_times]) # Penalize unbalanced schedules
    return max_makespan + balance_penalty

# Tournament selection
def tournament_selection(population, fitness, tournament_size=3):
    selected = []
    for _ in range(len(population)):
        tournament = [random.choice(range(len(population))) for _ in
range(tournament_size)]
        fittest_individual = min(tournament, key=lambda i: fitness[i])
        selected.append(population[fittest_individual])
    return selected

# Crossover - Single point crossover
def crossover(parent1, parent2):
    if random.random() < crossover_rate:
        point = random.randint(1, len(parent1) - 1)
        return parent1[:point] + parent2[point:], parent2[:point] +
parent1[point:]
    else:
        return parent1, parent2

# Mutation - Randomly change a job's machine assignment
def mutate(chromosome, num_machines, mutation_rate):
    for i in range(len(chromosome)):
        if random.random() < mutation_rate:
            chromosome[i] = random.randint(0, num_machines - 1)
    return chromosome

# Function to create a readable schedule from the chromosome
def create_schedule(chromosome, job_durations):
    schedule = {machine: [] for machine in range(num_machines)}
    for job, machine in enumerate(chromosome):
        schedule[machine].append((f"J{job+1}", job_durations[job]))
    return schedule

# Main Genetic Algorithm
population = initialize_population(population_size, num_jobs,
num_machines)

for generation in range(generations):
    fitness = [calculate_makespan_and_balance(individual,
job_durations, num_machines) for individual in population]

```

```

    selected = tournament_selection(population, fitness)
    offspring = []
    for i in range(0, len(selected), 2):
        parent1, parent2 = selected[i], selected[i + 1]
        child1, child2 = crossover(parent1, parent2)
        offspring.extend([child1, child2])
    population = [mutate(individual, num_machines, mutation_rate) for
individual in offspring]

# Find the best solution and create schedule
best_solution = min(population, key=lambda chrom:
calculate_makespan_and_balance(chrom, job_durations, num_machines))
best_schedule = create_schedule(best_solution, job_durations)
print(best_schedule)
# Displaying the schedule
print("Optimal Schedule:")
for machine, jobs in best_schedule.items():
    job_list = ', '.join([job[0] for job in jobs])
    makespan = sum([job[1] for job in jobs])
    print(f"Machine {machine + 1} - Jobs: {job_list} | Makespan:
{makespan} minutes")

{0: [('J4', 8), ('J9', 8)], 1: [('J1', 10), ('J5', 1), ('J7', 3)], 2:
[('J2', 3), ('J6', 10), ('J10', 1)], 3: [('J8', 20)], 4: [('J3', 20)]}
Optimal Schedule:
Machine 1 - Jobs: J4, J9 | Makespan: 16 minutes
Machine 2 - Jobs: J1, J5, J7 | Makespan: 14 minutes
Machine 3 - Jobs: J2, J6, J10 | Makespan: 14 minutes
Machine 4 - Jobs: J8 | Makespan: 20 minutes
Machine 5 - Jobs: J3 | Makespan: 20 minutes

# Revised approach to include the robot cell information in the
schedule

# Original schedule
original_schedule = best_schedule

# User input for robot cells
user_input = {
    "R 1": [1, 3],
    "R 2": [2, 5],
    "R 3": [4]
}

# Function to find the robot cell for a given machine
def find_robot_cell(machine_number, user_input):
    for cell_name, machines in user_input.items():
        if machine_number in machines:
            return cell_name

```



```

    return None

# Adding robot cell information to each schedule
for machine, jobs in original_schedule.items():
    robot_cell = find_robot_cell(machine + 1, user_input) # +1
    because machine numbering starts from 1
    original_schedule[machine] = (robot_cell, jobs)

# Re-arranging the schedule by robot cell
rearranged_schedule = dict(sorted(original_schedule.items(),
key=lambda item: item[1][0]))

# Displaying the rearranged schedule
for machine, (cell, jobs) in rearranged_schedule.items():
    job_list = ', '.join([job[0] for job in jobs])
    makespan = sum([job[1] for job in jobs])
    print(f"Machine {machine} (in {cell}) - Jobs: {job_list} |
Makespan: {makespan} minutes")

# Return rearranged_schedule for further analysis if needed
rearranged_schedule

```

```

Machine 0 (in R 1) - Jobs: J4, J9 | Makespan: 16 minutes
Machine 2 (in R 1) - Jobs: J2, J6, J10 | Makespan: 14 minutes
Machine 1 (in R 2) - Jobs: J1, J5, J7 | Makespan: 14 minutes
Machine 4 (in R 2) - Jobs: J3 | Makespan: 20 minutes
Machine 3 (in R 3) - Jobs: J8 | Makespan: 20 minutes

```

```

{0: ('R 1', [(('J4', 8), ('J9', 8))],
2: ('R 1', [(('J2', 3), ('J6', 10), ('J10', 1))],
1: ('R 2', [(('J1', 10), ('J5', 1), ('J7', 3))],
4: ('R 2', [(('J3', 20))],
3: ('R 3', [(('J8', 20))]}

```

```

# Original schedule with jobs
original_schedule = rearranged_schedule

```

```

# User input for subtasks of each job
job_subtasks = {
    'J1': [(('T1', 4), ('T2', 3), ('T3', 3))],
    'J2': [(('T1', 3))],
    'J3': [(('T1', 7), ('T2', 8), ('T3', 5))],
    'J4': [(('T1', 4), ('T2', 4))],
    'J5': [(('T1', 1))],
    'J6': [(('T1', 5), ('T2', 5))],
    'J7': [(('T1', 1), ('T2', 1), ('T3', 1))],
    'J8': [(('T1', 10), ('T2', 10))],
    'J9': [(('T1', 4), ('T2', 4))],

```

```

    'J10': [('T1', 1)]
}

# Replace jobs with their corresponding subtasks in the schedule
for machine, (cell, jobs) in original_schedule.items():
    new_jobs = []
    for job, _ in jobs:
        if job in job_subtasks:
            for subtask in job_subtasks[job]:
                new_subtask = (f"{subtask[0]}{job[1:]}", subtask[1])
# Format: T12 for Task 2 of Job 1
            new_jobs.append(new_subtask)
    original_schedule[machine] = (cell, new_jobs)

# Displaying the updated schedule
for machine, (cell, jobs) in original_schedule.items():
    job_list = ', '.join([f"{job[0]} ({job[1]})" for job in jobs])
    print(f"Machine {machine} (in {cell}) - Tasks: {job_list}")

# Return original_schedule for further analysis if needed
original_schedule

# Re-defining the original schedule and job subtasks due to code
execution state reset

# User input for subtasks of each job
job_subtasks = {
    'J1': [('T1', 4), ('T2', 3), ('T3', 3)],
    'J2': [('T1', 3)],
    'J3': [('T1', 7), ('T2', 8), ('T3', 5)],
    'J4': [('T1', 4), ('T2', 4)],
    'J5': [('T1', 1)],
    'J6': [('T1', 5), ('T2', 5)],
    'J7': [('T1', 1), ('T2', 1), ('T3', 1)],
    'J8': [('T1', 10), ('T2', 10)],
    'J9': [('T1', 4), ('T2', 4)],
    'J10': [('T1', 1)]
}

# Replace jobs with their corresponding subtasks in the schedule
for machine, (cell, jobs) in original_schedule.items():
    new_jobs = []
    for job, _ in jobs:
        if job in job_subtasks:
            for subtask in job_subtasks[job]:
                subtask_label = f"T{job[1]} if len(job) > 2 else
job[1]}{subtask[0][1]}" # Correct format: TXY

```

```

        new_jobs.append((subtask_label, subtask[1]))
    original_schedule[machine] = (cell, new_jobs)

# Displaying the updated schedule
for machine, (cell, jobs) in original_schedule.items():
    job_list = ', '.join([f"{job[0]} ({job[1]})" for job in jobs])
    print(f"Machine {machine} (in {cell}) - Tasks: {job_list}")

# Return original_schedule for further analysis if needed
original_schedule

Machine 0 (in R 1) - Tasks: T81 (10), T82 (10)
Machine 1 (in R 2) - Tasks: T51 (1), T61 (5), T62 (5), T71 (1), T72 (1), T73 (1)
Machine 2 (in R 1) - Tasks: T11 (4), T12 (3), T13 (3), T21 (3), T101 (1)
Machine 3 (in R 3) - Tasks: T31 (7), T32 (8), T33 (5)
Machine 4 (in R 2) - Tasks: T41 (4), T42 (4), T91 (4), T92 (4)

{0: ('R 1', [(('T81', 10), ('T82', 10))]),
 1: ('R 2', [(('T51', 1), ('T61', 5), ('T62', 5), ('T71', 1), ('T72', 1), ('T73', 1))]),
 2: ('R 1', [(('T11', 4), ('T12', 3), ('T13', 3), ('T21', 3), ('T101', 1))]),
 3: ('R 3', [(('T31', 7), ('T32', 8), ('T33', 5))]),
 4: ('R 2', [(('T41', 4), ('T42', 4), ('T91', 4), ('T92', 4))])}

# Re-defining the original schedule and job subtasks due to code execution state reset

# User input for subtasks of each job
job_subtasks = {
    'J1': [('T1', 4, 'S1'), ('T2', 3, 'S3'), ('T3', 3, 'S4')],
    'J2': [('T1', 3, 'S1')],
    'J3': [('T1', 7, 'S3'), ('T2', 8, 'S4'), ('T3', 5, 'S6')],
    'J4': [('T1', 4, 'S1'), ('T2', 4, 'S3')],
    'J5': [('T1', 1, 'S1')],
    'J6': [('T1', 5, 'S2'), ('T2', 5, 'S3')],
    'J7': [('T1', 1, 'S2'), ('T2', 1, 'S2'), ('T3', 1, 'S1')],
    'J8': [('T1', 10, 'S4'), ('T2', 10, 'S2')],
    'J9': [('T1', 4, 'S1'), ('T2', 4, 'S4')],
    'J10': [('T1', 1, 'S4')]
}

# Replace jobs with their corresponding subtasks and tools in the schedule
for machine, (cell, jobs) in original_schedule.items():
    new_jobs = []
    for job_info in jobs:

```

```

        job, duration = job_info[0], job_info[1] # Unpack job ID and
duration
        if job in job_subtasks:
            for subtask in job_subtasks[job]:
                # Extract task number and job number more safely
                task_number = subtask[0][1:] # Assuming task format
is 'T<number>'
                job_number = job[1:] # Extracting job number from job
ID
                subtask_label = f"T{job_number}{task_number}" #
Correct format: TXY

                tool = subtask[2] if len(subtask) > 2 else 'None' #
Handling missing tool info
                new_jobs.append((subtask_label, subtask[1], tool))
                original_schedule[machine] = (cell, new_jobs)

# Displaying the updated schedule with tools
for machine, (cell, jobs) in original_schedule.items():
    job_list = ', '.join([f"{job[0]} ({job[1]} units, Tool: {job[2]})"
for job in jobs])
    print(f"Machine {machine} (in {cell}) - Tasks: {job_list}")

# Return original_schedule for further analysis if needed
original_schedule

Machine 0 (in R 1) - Tasks: T41 (4 units, Tool: S1), T42 (4 units,
Tool: S3), T91 (4 units, Tool: S1), T92 (4 units, Tool: S4)
Machine 1 (in R 2) - Tasks: T11 (4 units, Tool: S1), T12 (3 units,
Tool: S3), T13 (3 units, Tool: None), T1 (4 units, Tool: None), T51 (1
units, Tool: S1), T71 (1 units, Tool: S2), T72 (1 units, Tool: S2),
T73 (1 units, Tool: S1)
Machine 2 (in R 1) - Tasks: T21 (3 units, Tool: S1), T61 (5 units,
Tool: S2), T62 (5 units, Tool: S3), T101 (1 units, Tool: S4)
Machine 3 (in R 3) - Tasks: T81 (10 units, Tool: S4), T82 (10 units,
Tool: S2)
Machine 4 (in R 2) - Tasks: T31 (7 units, Tool: S3), T32 (8 units,
Tool: S4), T33 (5 units, Tool: S6)

{0: ('R 1',
[('T41', 4, 'S1'), ('T42', 4, 'S3'), ('T91', 4, 'S1'), ('T92', 4,
'S4')]),
1: ('R 2',
[('T11', 4, 'S1'),
('T12', 3, 'S3'),
('T13', 3, 'None'),
('T1', 4, 'None'),
('T51', 1, 'S1'),
('T71', 1, 'S2'),
('T72', 1, 'S2'),

```

```

    ('T73', 1, 'S1'))],
2: ('R 1',
    [('T21', 3, 'S1'), ('T61', 5, 'S2'), ('T62', 5, 'S3'), ('T101', 1,
'S4')]),
3: ('R 3', [('T81', 10, 'S4'), ('T82', 10, 'S2')]),
4: ('R 2', [('T31', 7, 'S3'), ('T32', 8, 'S4'), ('T33', 5, 'S6')]))}

```

Original schedule with robotic cells and tasks

Filter function for a specific robotic cell

```

def filter_schedule_by_robot_cell(schedule, cell_name):
    return {machine: (cell, tasks) for machine, (cell, tasks) in
schedule.items() if cell == cell_name}

```

Example: Filtering for Robotic Cell R1

```

filtered_schedule_R1 =
filter_schedule_by_robot_cell(original_schedule, 'R 1')

```

Displaying the filtered schedule for R1

```

for machine, (cell, tasks) in filtered_schedule_R1.items():
    task_list = ', '.join([f"{task[0]} ({task[1]})" for task in
tasks])
    print(f"Machine {machine} (in {cell}) - Tasks: {task_list}")

```

Return filtered_schedule_R1 for further analysis if needed

```

filtered_schedule_R1

```

Machine 0 (in R 1) - Tasks: T41 (4), T42 (4), T91 (4), T92 (4)

Machine 2 (in R 1) - Tasks: T21 (3), T61 (5), T62 (5), T101 (1)

```

{0: ('R 1',
    [('T41', 4, 'S1'), ('T42', 4, 'S3'), ('T91', 4, 'S1'), ('T92', 4,
'S4')]),
2: ('R 1',
    [('T21', 3, 'S1'), ('T61', 5, 'S2'), ('T62', 5, 'S3'), ('T101', 1,
'S4')])}

```

```

def calculate_makespan_and_tool_change(schedule):

```

```

    machines = {}

```

```

    makespan = 0

```

```

    tool_changeover_time = 0

```

```

    for _, (job, tasks) in schedule.items():

```

```

        current_tool = None

```

```

        current_machine = None

```

```

        machine_time = 0

```

```

        for task in tasks:

```

```

            task_id, processing_time, tool = task

```

```

        if current_tool is None:
            current_tool = tool
            current_machine = job + current_tool
            machines[current_machine] = 0

        if current_tool != tool:
            tool_changeover_time += 5
            current_tool = tool

        if current_machine != job + current_tool:
            machine_time = machines.get(current_machine, 0)
            current_machine = job + current_tool

        machine_time += processing_time
        machines[current_machine] = machine_time
        makespan = max(makespan, machine_time)

    return makespan, tool_changeover_time

schedule = filtered_schedule_R1

makespan, tool_changeover_time =
calculate_makespan_and_tool_change(schedule)

print("Makespan:", makespan)
print("Tool Changeover Time:", tool_changeover_time)

# Remove 'R 1' from each schedule entry
new_schedule = {key: value[1] for key, value in schedule.items()}

print(new_schedule)

Makespan: 16
Tool Changeover Time: 30
{0: [('T41', 4, 'S1'), ('T42', 4, 'S3'), ('T91', 4, 'S1'), ('T92', 4, 'S4')], 2: [('T21', 3, 'S1'), ('T61', 5, 'S2'), ('T62', 5, 'S3'), ('T101', 1, 'S4')]}

schedule = {
    0: ('R 1', [('T41', 4, 'S1'), ('T42', 4, 'S3'), ('T91', 4, 'S1'), ('T92', 4, 'S4')]),
    2: ('R 1', [('T21', 3, 'S1'), ('T61', 5, 'S2'), ('T62', 5, 'S3'), ('T101', 1, 'S4')])
}

# Remove 'R 1' from each schedule entry
new_schedule = {key: value[1] for key, value in schedule.items()}

print(new_schedule)

```