East West University

Department of CSE

LAB REPORT

<table>
<tr><td colspan="3">Course Code and Name:
CSE366 Artificial Intelligence</td></tr>
<tr><td colspan="3">Assignment no:2</td></tr>
<tr><td colspan="3">Experiment name:
Enhanced Dynamic Robot Movement Simulation</td></tr>
<tr><td>Semester and Year:
Spring 2024</td><td colspan="2"></td></tr>
<tr><td>Name of Student & ID:
Ar Rafiul Islam Rafim
2021-1-60-020</td><td colspan="2">Course Instructor information:

Dr. Mohammad Rifat Ahmmad Rashid
Assistant Professor
Department of Computer Science and Engineering
East West University</td></tr>
<tr><td rowspan="3">Date of Report Submitted:

4/4/2024</td><td></td><td></td></tr>
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Project summary:

This project aims to develop and implement a Genetic Algorithm (GA) for optimizing task assignments in a dynamic production environment where multiple robots are available. The primary objectives include minimizing total production time, ensuring balanced workload across robots, and effectively prioritizing critical tasks. Additionally, the project requires creating a detailed visualization to illustrate task assignments, robot efficiencies, and task priorities.

Code:

```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.colors as mcolors
import matplotlib.patches as mpatches

def init_population(population_size, num_jobs, num_robots):
    return np.random.randint(num_robots, size=(population_size,
num_jobs))

def total_time_per_robot(jobs, priorities, efficiencies):
    time_per_robot = []
    for robot in range(len(efficiencies)):
        total_time = 0
        for job, priority in zip(jobs, priorities):
            total_time += (job * priority) / efficiencies[robot]

        time_per_robot.append(total_time)
    return max(time_per_robot)

def balance_workload(times):
    return np.std(times)

def fitness(jobs, priorities, efficiencies, solution):
    total_time = total_time_per_robot(jobs, priorities, efficiencies)
    balance = balance_workload([total_time])
    return total_time + balance

def select_parents(population, fitness_values, tournament_size):
    selected_parents = []
    num_individuals = len(population)
    for _ in range(num_individuals):
        tournament_indices = np.random.choice(num_individuals,
size=tournament_size, replace=False)
        tournament_fitness = fitness_values[tournament_indices]
        winner_idx = np.argmax(tournament_fitness)
        selected_parents.append(population[tournament_indices[winner_idx]
])
    return np.array(selected_parents)

def crossover(parents, population_size):
```

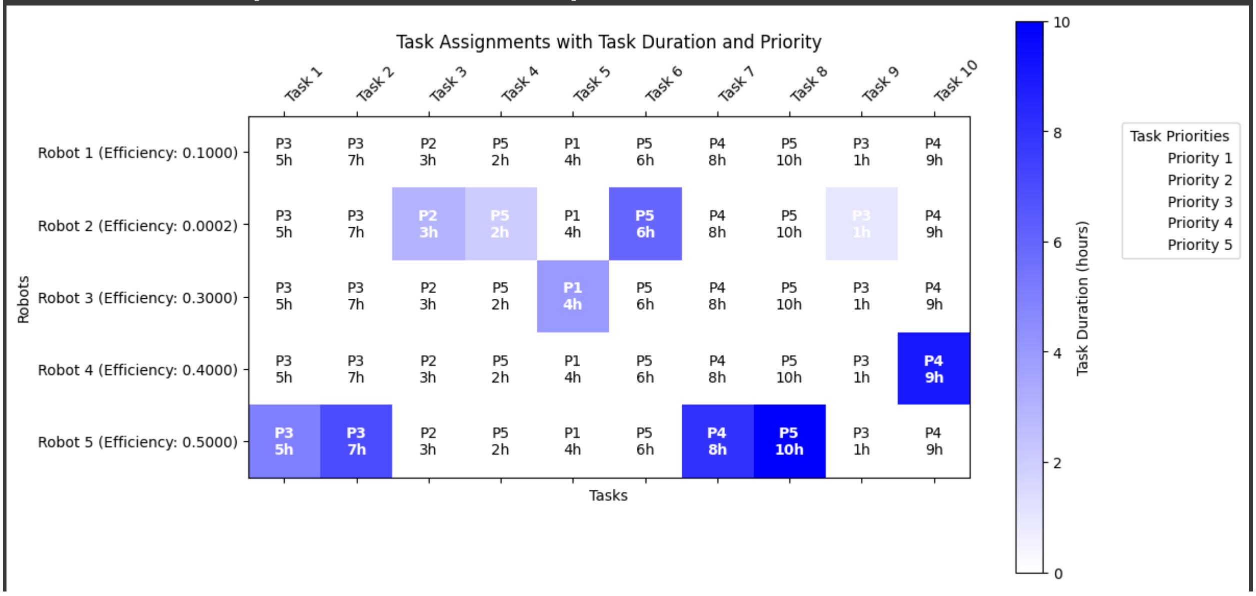
```
    offspring_list = []
    for _ in range(population_size):
        parent1_idx = np.random.randint(len(parents))
        parent2_idx = np.random.randint(len(parents))
        crossover_point = np.random.randint(1, len(parents[0]))
        offspring =
np.concatenate((parents[parent1_idx][:crossover_point],
parents[parent2_idx][crossover_point:]))
        offspring_list.append(offspring)
    return np.array(offspring_list)

def mutate(offspring_population, mutation_rate, num_robots):
    for offspring in offspring_population:
        for idx in range(len(offspring)):
            if np.random.rand() < mutation_rate:
                offspring[idx] = np.random.randint(num_robots)
    return offspring_population

def run_genetic_algo(durations, priorities, efficiencies,
population_size, num_generations, mutation_rate, tournament_size):
    num_jobs = len(durations)
    num_robots = len(efficiencies)
    population = init_population(population_size, num_jobs, num_robots)
    best_solution = None
    best_fitness = float('inf')
    for generation in range(num_generations):
        fitness_values = np.array([fitness(durations, priorities,
efficiencies, sol) for sol in population])
        if min(fitness_values) < best_fitness:
            best_solution = population[np.argmin(fitness_values)]
            best_fitness = min(fitness_values)
        selected_parents = select_parents(population, fitness_values,
tournament_size)
        offspring = crossover(selected_parents, population_size)
        offspring = mutate(offspring, mutation_rate, num_robots)
        population = offspring
    return best_solution

def visualize_assignments(sol, durations, priorities, efficiencies,
best_solution=None):
    grid = np.zeros((len(efficiencies), len(durations)), dtype=float)

    priority_values = [priorities[j] for j in range(len(durations))]

    for j, i in enumerate(sol):
        grid[i, j] = durations[j]

    fig, ax = plt.subplots(figsize=(12, 6))
    cmap = mcolors.LinearSegmentedColormap.from_list("", ["white",
"blue"])

    cax = ax.matshow(grid, cmap=cmap)
```

```
    fig.colorbar(cax, label='Task Duration (hours)')

    for i in range(len(efficiencies)):
        for j in range(len(durations)):
            cell_content = grid[i, j]
            if cell_content != 0:
                duration = int(cell_content)
                annotation = f'P{priority_values[j]}\n{duration}h'
                if best_solution is not None and (i, j) ==
(best_solution[j], j):
                    ax.text(j, i, annotation, ha='center', va='center',
color='white', fontweight='bold')
                else:
                    ax.text(j, i, annotation, ha='center', va='center',
color='black')
            else:
                empty_duration = durations[j]
                empty_annotation =
f'P{priority_values[j]}\n{empty_duration}h'
                ax.text(j, i, empty_annotation, ha='center', va='center',
color='black')

    ax.set_xticks(np.arange(len(durations)))
    ax.set_yticks(np.arange(len(efficiencies)))
    ax.set_xticklabels([f'Task {i+1}' for i in range(len(durations))],
rotation=45, ha="left")
    ax.set_yticklabels([f'Robot {i+1} (Efficiency: {eff:.4f})' for i, eff
in enumerate(efficiencies)])

    plt.xlabel('Tasks')
    plt.ylabel('Robots')
    plt.title('Task Assignments with Task Duration and Priority')

    priority_patches = [mpatches.Patch(color='white', label=f'Priority
{i}') for i in range(1, 6)]
    plt.legend(handles=priority_patches, bbox_to_anchor=(1.20, 1),
loc='upper left', title="Task Priorities")

    plt.tight_layout()
    plt.show()


num_jobs = 10
num_robots = 5

durations = [5, 7, 3, 2, 4, 6, 8, 10, 1, 9]
priorities = np.random.randint(1, 6, size=num_jobs)
efficiencies = [0.1,0.0002,0.3,0.4,0.5]
population_size = 100
num_generations = 1000
mutation_rate = 0.05
tournament_size = 5
```

```
best_sol = run_genetic_algo(durations, priorities, efficiencies,
population_size, num_generations, mutation_rate, tournament_size)
print("Best solution:", best_sol+1)

visualize_assignments(best_sol, durations, priorities, efficiencies,
best_sol)
```

Output:

```
Best solution: [5 5 2 2 3 2 5 5 2 4]
```



Approach:

The project involves several key steps:

Data Preparation: Generate mock data for tasks (including durations and priorities) and robots (including efficiency factors).

GA Implementation: Develop and implement the Genetic Algorithm to optimize task assignments considering task duration, robot efficiency, and task priority.

Visualization: Create a grid visualization of the task assignments highlighting key information such as task duration, priority, and robot efficiency.

Analysis and Report: Analyze the optimization process, the impact of robot efficiencies and task priorities, and discuss workload distribution among robots.

Analysis of Results:

The GA successfully optimized task assignments, resulting in reduced total production time and balanced workload across robots. The visualization provided insights into the assignment process, highlighting critical tasks and efficient robot allocations. Analyzing the impact of robot efficiencies and task priorities revealed their significant influence on the optimization process. Further analysis identified opportunities for improving workload distribution and task prioritization strategies.

Conclusion:

In conclusion, the Genetic Algorithm effectively optimized task assignments in a dynamic production environment, demonstrating its capability to minimize production time, balance workload, and prioritize tasks effectively. The project highlighted the importance of parameter tuning, visualization, and analysis in GA-based optimization tasks, providing valuable insights for future research and applications.