Large-scale production in complex equipment manufacturing

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Backgorund

This project focuses on a provider of rail transit maintenance equipment, The company produces 38 kinds of large-scale rail transit operation and maintenance vehicles, each model involves more than 10,000 structural parts, and the materials, priorities, processes and other requirements of different parts are different. In the long-term implementation process of manual production scheduling in its structural branch plant, problems such as low efficiency and poor accuracy are gradually exposed

- **importance of efficient scheduling**
  - reduce production times,
  - minimize costs,
  - increase overall factory efficiency
- **Limitation of current solutions**
  - traditional heuristic algorithms alostuggle to handle complex multi-objective optimization
  - only partly optimal solutions can be found in some situation

Aim

Design a scheduling algorithm and build up its mathematic model to efficiently solve large scale parallel machine scheduling problems. To tackle the challenges of large-scale parallel machine scheduling, particularly in high-end equipment manufacturing industries, this project proposes the design of an scheduling algorithm. The mathematical model underpinning this algorithm is aimed at optimizing several critical aspects of production processes: priority handling, material type management, and the processing numbers of parts. The objective is to minimize the total completion time of scheduled jobs while optimizing the allocation and utilization of resources.

Assuptions

- Homogeneous parallel machine problem
- Single Operation Per Machine
- Consistent Machine Operation
- Negligible Transport Time
- Exclusion of Assembly Time

Mathmatic model

Stage1 model: to minimise the total completion time using simulated annealing

Parameters and variables	Descriptions
N	Set of machines
J	Set of parts
R	Set of operations
s_{ijk}	The start time of operation i for part j on machine k
t_{ijk}	The process time of operation i for part j on machine k
a_{ijk}	Binary variable (0 or 1). $a_{ijk} = 1$ if operation i for part j on machine k is valid
x_{ijk}	Binary variable (0 or 1). x_{ij}=1 if part J_i is processed before part J_j
c_i	The completion processing time of part J_i
P_k	The largest work hour of machine k
M	Very large number
C_{max}	Maximum completion time

$$C_{max} > c_i \qquad \forall j \in J \qquad (1)$$

$$\sum_{j \in J} a_{ijk} = 1 \qquad \forall i \in R, \forall k \in N \qquad (2)$$

$$(s_{i_1 j_1 k_1}, s_{i_1 j_1 k_1} + t_{i_1 j_1 k_1}) \cap \left((s_{i_2 j_2 k_2}, s_{i_2 j_2 k_2} + t_{i_2 j_2 k_2}\right) = \phi \quad (3)$$

$$\sum_{j \in J} \sum_{i \in R} \sum_{k \in N} t_{ijk}\, a_{ijk} \leq P_k \qquad (4)$$

Mathmatic model

Stage 2 model: 3 objectives

1. Minimize the number of material changes during the processing of parts.
2. Prioritize the processing of parts with a higher priority
3. Prioritize the processing of parts with higher priority within the same project

Parameters and variables	Descriptions
J	Set of parts
p_i	Processing time of part J_i
s_{ij}	Binary variable (0 or 1). s_{ij}=1 if material of part J_i is different from priority of part J_j
y_i	Priority of part J_i
u_{ij}	Binary variable (0 or 1). u_{ij}=1 if priority of part J_i is lower than priority of part J_j
q_{ij}	Binary variable (0 or 1). q_{ij}=1 if process number of part J_i is lower than process number of part J_j
x_{ij}	Binary variable (0 or 1). x_{ij}=1 if part J_i is processed before part J_j
c_{ij}	The completion processing time of part J_i
Z	The optimize object
M	Very large number
ω	Weight of each term in object function

$$minZ = \omega_1 \sum_{i\in J}\sum_{j\in J} x_{ij}\, s_{ij} + \omega_2 \sum_{i\in J}\sum_{j\in J} x_{ij}\, u_{ij} + \omega_3 \sum_{i\in J}\sum_{j\in J} x_{ij}\, q_{ij} \quad (5)$$

$$\sum_{i\in J} x_{ij} = 1 \qquad \forall j \in J \quad (6)$$

$$\sum_{j\in J} x_{ji} = 1 \qquad \forall i \in J \quad (7)$$

$$c_i \geq c_j + p_i + M(x_{ji} - 1) \qquad \forall i \neq j;\ i,j \in J \quad (8)$$

$$c_i > x_{0i} p_i \qquad \forall i \in J \quad (9)$$

$$c_j \geq c_i + M(x_{ji} - 1) \qquad \forall i \neq j;\ i,j \in J \quad (10)$$

$$c_i \geq 0 \qquad \forall i \in J \quad (11)$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in J, \forall j \in J \quad (12)$$

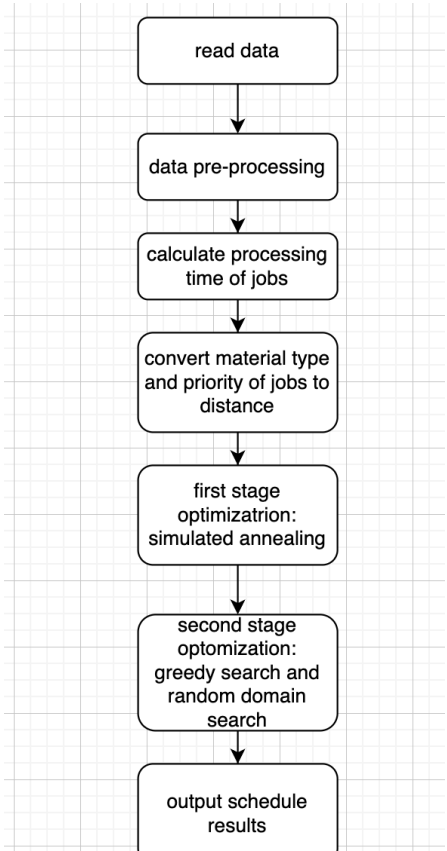
$$s_{ij} \in \{0,1\} \qquad \forall i \in J, \forall j \in J \quad (13)$$

$$u_{ij} \in \{0,1\} \qquad \forall i \in J, \forall j \in J \quad (14)$$

$$q_{ij} \in \{0,1\} \qquad \forall i \in J, \forall j \in J \quad (15)$$

Implementation of optimization algorithm

Flow char of general algorithm

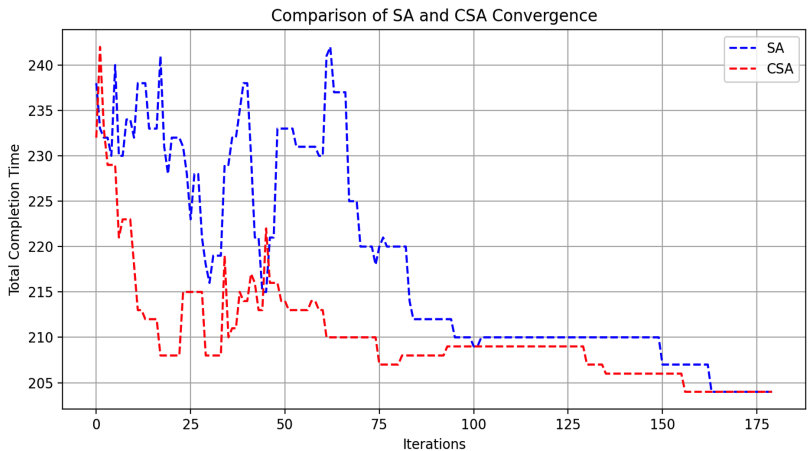


Implementation of optimization algorithm

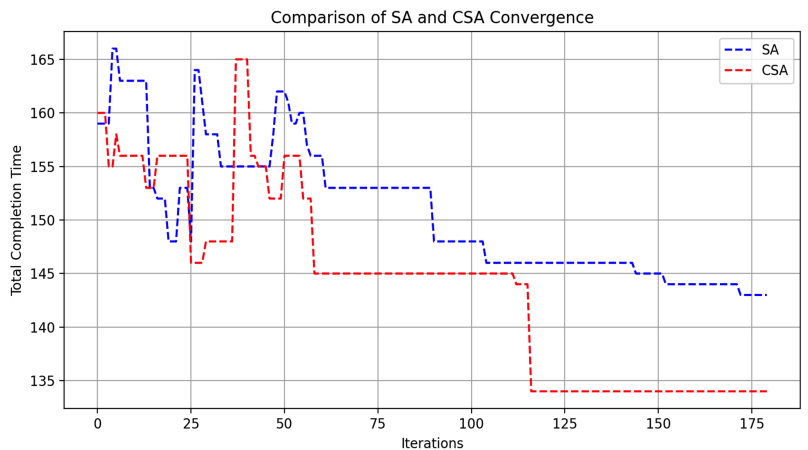
simulate annealing with chaotic operator

$$x_{n+1} = r \times x_n \times (1 - x_n)$$

20 job with random processing time between 1 and 100 on 5 machines

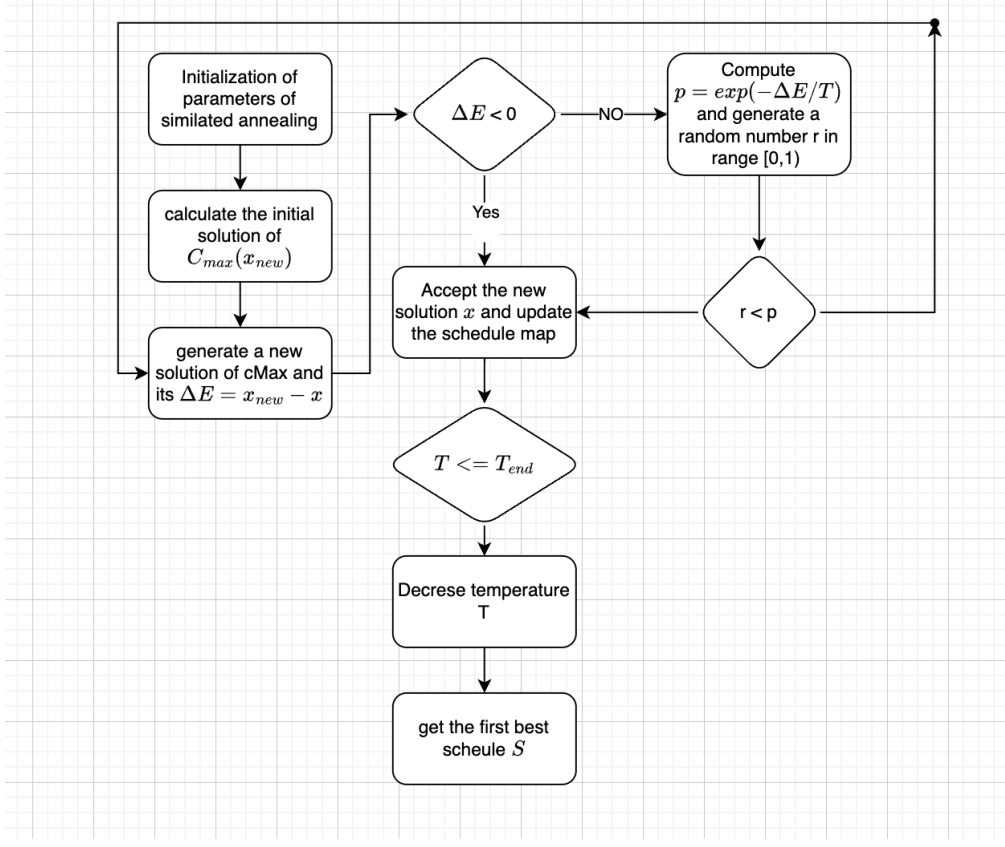


30 job with random processing time between 1 and 100 on 15 machines



Implementation of optimization algorithm

flow chart of simulate annealing



Implementation of optimization algorithm

Code of simulate annealing with chaotic operator

```
def simulated_annealing(initial_temp, cooling_rate, max_iterations):
    current_solution = np.random.randint(0, num_machines, size=num_tasks)
    current_cmax, _ = calculate_cmax_and_schedule(current_solution)
    best_solution = current_solution.copy()
    best_cmax = current_cmax
    chaotic_var = np.random.rand()
    for i in range(max_iterations):
        temp = initial_temp * (cooling_rate ** i)
        chaotic_var = logistic_map(chaotic_var)
        new_solution = generate_new_solution(current_solution, chaotic_var)
        new_cmax, _ = calculate_cmax_and_schedule(new_solution)
        energy_diff = new_cmax - current_cmax
        if energy_diff < 0 or np.exp(-energy_diff / temp) > np.random.rand():
            current_solution = new_solution.copy()
            current_cmax = new_cmax

            if new_cmax < best_cmax:
                best_solution = new_solution.copy()
                best_cmax = new_cmax
    best_cmax, best_schedule = calculate_cmax_and_schedule(best_solution)
    return best_solution, best_cmax, best_schedule
```

Implementation of optimization algorithm

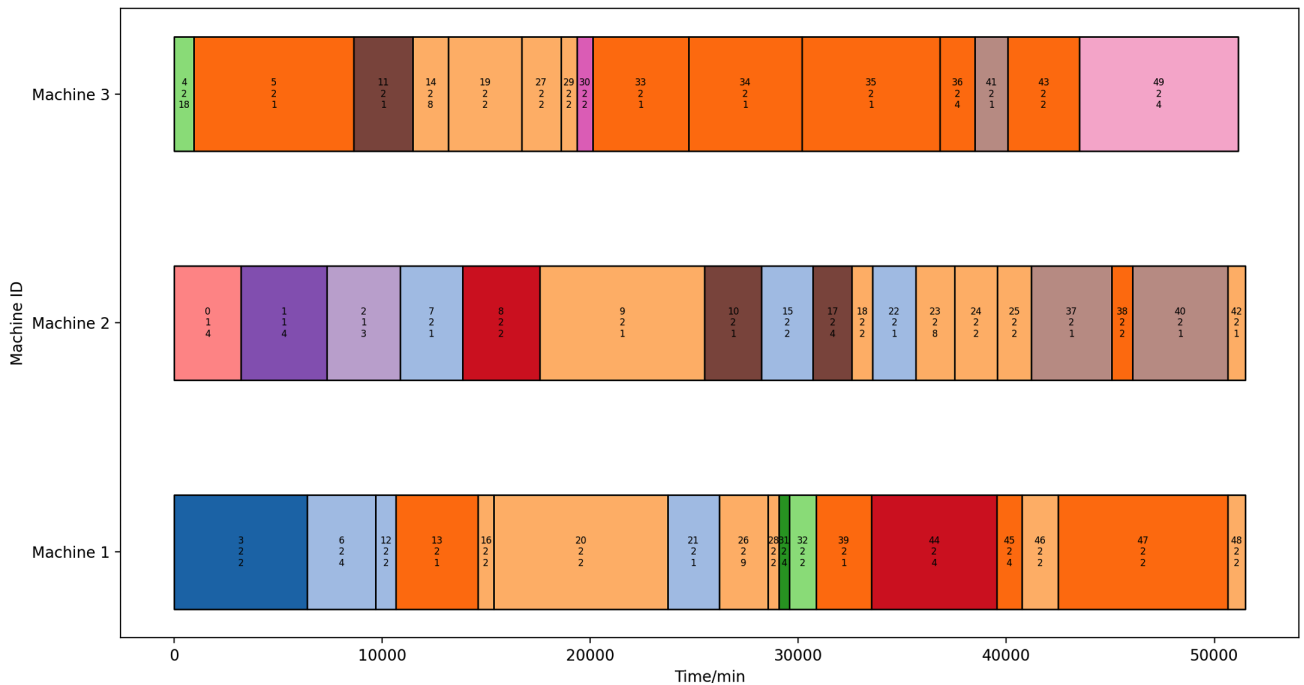
data used for test

Priority	Part code	Processing quantity	Part specification(thickness*length*width)	Material
1	20025203	4	45*455*80*	m15/Q235B
1	20024524	4	20*250*420*	m22/Q355B
1	20028407	3	38*218*218*	m28/Q355B
2	20005273	2	25*450*290*	m25/45
2	29001843	18	40*110*110*	mQ355B/20
2	23108228	1	40*280*350*	mQ355D/20
2	23108229	4	160*150*70*	mQ355D/16
2	23108230	1	16*475*200*	mQ355D/16
2	23108232	2	25*105*725*	mQ355D/25
2	23108235	1	54*272*275*	mQ355D/14
2	23108236	1	12*136*855*	mQ355D/12
2	23108237	1	12*136*885*	mQ355D/12
2	23108238	2	16*380*80*	mQ355D/16
2	23108239	1	20*265*380*	mQ355D/20
2	23108240	8	54*230*70*	mQ355D/14
2	23108241	2	16*110*717*	mQ355D/16
2	23108242	2	14*131*215*	mQ355D/14
2	23108243	4	12*110*717*	mQ355D/12
2	23108244	2	14*131*278*	mQ355D/14
2	23108245	2	54*131*254*	mQ355D/14
2	23108246	2	54*110*717*	mQ355D/14
2	23108247	1	16*110*717*	mQ355D/16
2	23108248	1	56*272*70*	mQ355D/16
2	23108249	8	64*210*70*	mQ355D/14
2	23108250	2	54*280*70*	mQ355D/14
2	23108251	2	54*217*70*	mQ355D/14
2	23108252	9	54*318*70*	mQ355D/14
2	23108253	2	54*256*70*	mQ355D/14
2	23114185	2	54*80*60*	mQ355D/14
2	23114186	2	54*120*60*	mQ355D/14
2	23114187	2	60*110*60*	mQ355D/10
2	23114201	4	72*60*60*	mQ355D/22

Implementation of optimization algorithm

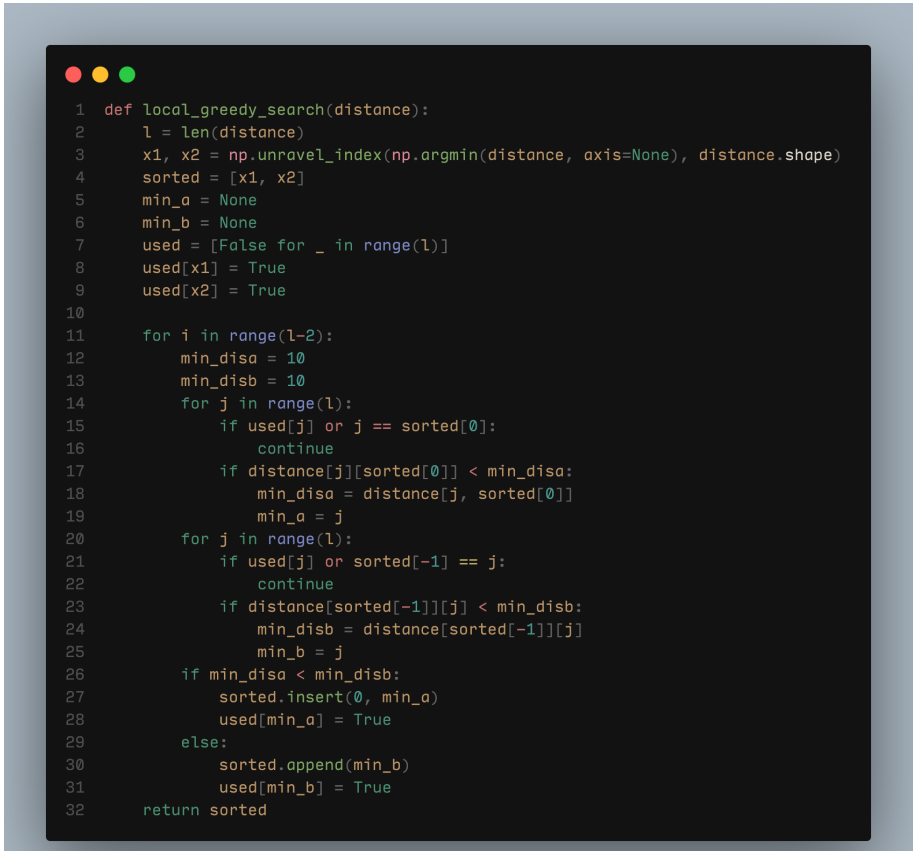
Gantt chart of schedule results of simulate annealing

top: id of the part, middle: priority, bottom: processing quantity



Implementation of optimization algorithm

code of local greedy search

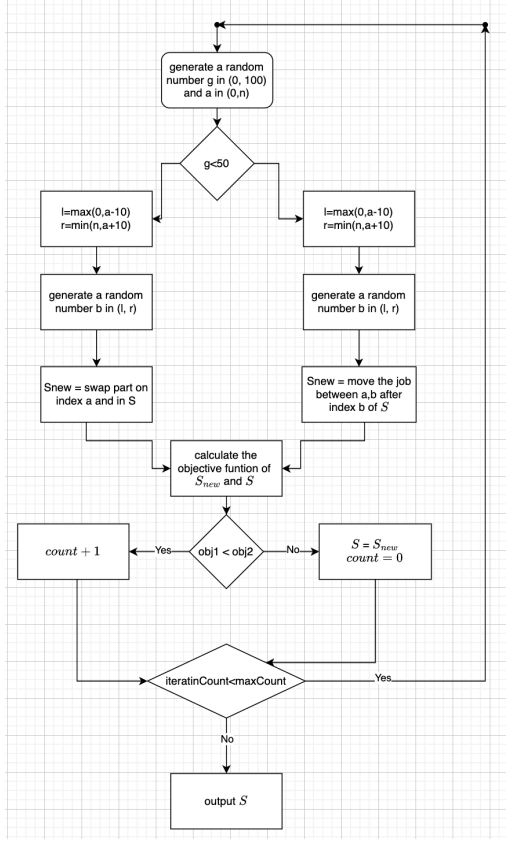


```python
def local_greedy_search(distance):
    l = len(distance)
    x1, x2 = np.unravel_index(np.argmin(distance, axis=None), distance.shape)
    sorted = [x1, x2]
    min_a = None
    min_b = None
    used = [False for _ in range(l)]
    used[x1] = True
    used[x2] = True

    for i in range(l-2):
        min_disa = 10
        min_disb = 10
        for j in range(l):
            if used[j] or j == sorted[0]:
                continue
            if distance[j][sorted[0]] < min_disa:
                min_disa = distance[j, sorted[0]]
                min_a = j
        for j in range(l):
            if used[j] or sorted[-1] == j:
                continue
            if distance[sorted[-1]][j] < min_disb:
                min_disb = distance[sorted[-1]][j]
                min_b = j
        if min_disa < min_disb:
            sorted.insert(0, min_a)
            used[min_a] = True
        else:
            sorted.append(min_b)
            used[min_b] = True
    return sorted
```

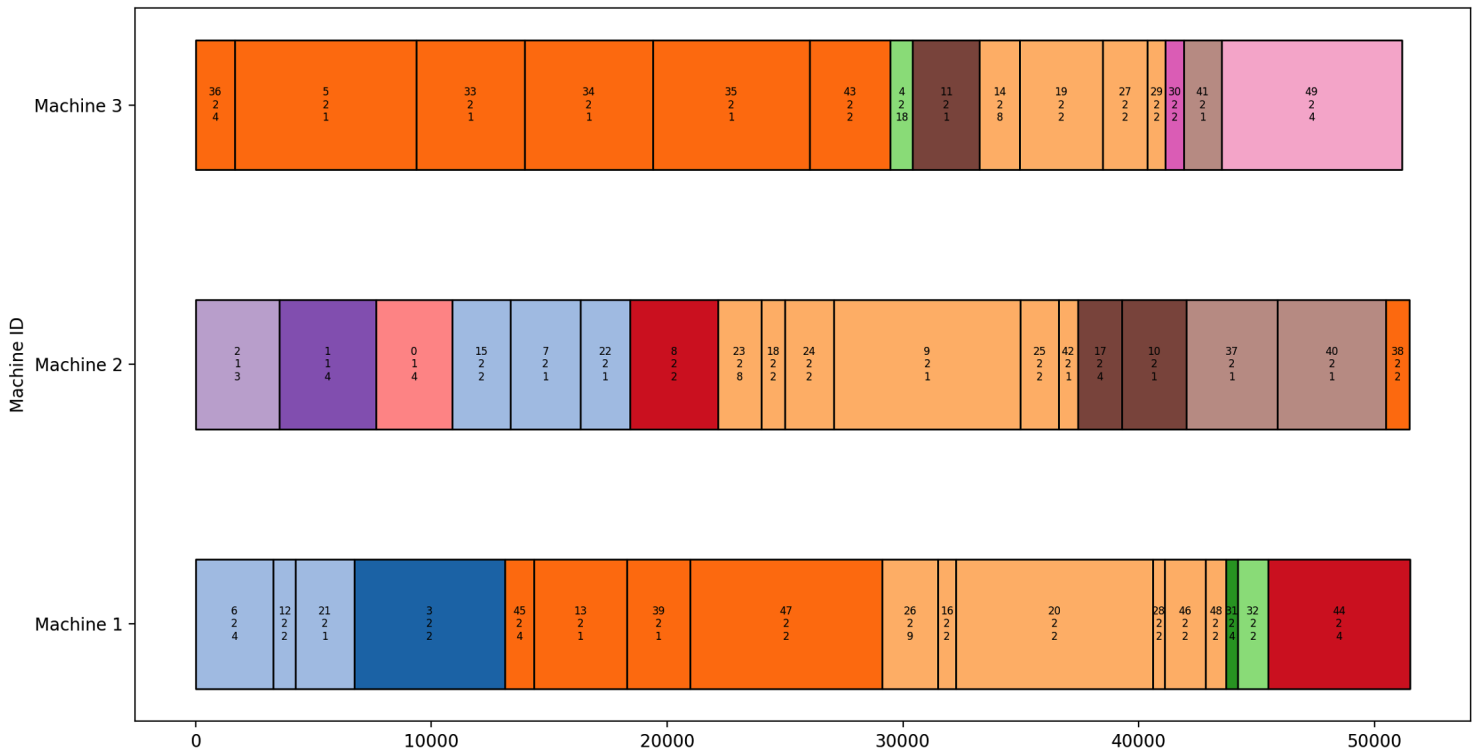
Implementation of optimization algorithm

flow chart of random neighborhood search



Implementation of optimization algorithm

results of second stage optimization



Summary

Key Achievements

- Development of a two-stage optimization algorithm and reach the optimization requirement
- Integration of chaotic simulated annealing for improved convergence
- Implementation of local greedy and random neighborhood searches
- Performance evaluation with Gantt charts

Future Work

- Incorporation of dynamic scheduling capabilities
- Development of a user-friendly software interface
- Make the algorithm more scaleable to suit different situations

END

thanks for listening