Optimization using Meta-heuristics University Timetabling

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Overview

Introduction

Every semester universities face the problem of creating good feasible timetable due to many complex constraints that have to be taken into consideration.

- Limited room capacity
- A lecturer can teach more than one courses to be scheduled in different time slots
- A curriculum has more than one courses to be scheduled in different time slots
- Also lecturers and students have preferences

Motivation

- Better utilization of resources
- Atomized planning
- TODO: continue motivation

Problem Description

Meta-heuristics

A high level procedure to find a solution for given optimization problem.

- Efficient and practical
- Do not guaranty the optimal solution

Different types of meta-heuristics:

- Hill Climber
- Simulated Annealing
- TABU

Hill Climber

Incremental local search algorithm.

- Easy to implement
- Traps in local optimum

select inital solution s_0
$s^* = s_0$
repeat
  select $s \in N(s^*)$
  if $f(s) > f(s^*)$ **then**
    $s^* = s$
  end if
until *time limit reached*
return s^*

Algorithm : Hill Climber

Hill Climber - Implementation Details

Stochastic Hill Climber

- Fast average number of **??** iteration per seconds
- Traps local optimum
- Different results for every run
- Traps in local optimum

For each iteration selects the best state from two candidate Neighbours

- candidate state by removing a course in given time slot
- candidate state by adding given course in given time slot

Simulated Annealing

Probabilistic optimization methods that uses the idea of the annealing process in thermodynamic.

- In high temperatures algorithm generally select the proposed action even it worse than the current solution.
- Decreases the temperature for each iteration with given parameter

select inital solution s_0
$T = T_{start}$
$s^* = s_0$
repeat
  select $s \in N(s^*)$
  $\delta = f(s) - f(s^*)$
  if $\delta < 0 orwithprobablityp(\delta, t_i$ **then**
    $s^* = s$
  end if
  $t_{i+1} = t_i * \alpha$
until *time limit reached*
return s^*

Algorithm : Simulated Annealing

Simulated Annealing - Implementation Details

Each iteration algorithm calculates the delta value with remove, assign and swap actions and chooses the best one.

Search(s_0, T_{start}, α)
$T = T_{start}$
$s^* = s_0$
repeat
  repeat
    select day period room randomly
    calculate; new solutions by assign remove abd swap operations
  until *no hard constraint violations*
  selectbestaction $m \in \{Remove, Assign, Swap\}$ *has lowest* $f(s_i \oplus m)$
  $\delta = f(s) - f(s_i \oplus m)$
  if $\delta < 0 orwithprobablityp(\delta, t_i$ **then**
    $s^* = s_i \oplus m$
  end if
  $t_{i+1} = t_i * \alpha$
until *time limit reached*
return s^*

Algorithm : Simulated Annealing - Pseudo Code

TABU

Uses local search paradigm and memory for optimization.

- Generally finds better solution than the other optimization problems
- Contraction of the Tabu list is problem specific

TABU - Neighbourhood Function

The neighbours are the set of the different "*next to*" solutions To generate neighbour program uses three different action:

- Remove: Program goes through all time slots if the current time slots is not empty than it uses the Remove method to generate new solution
- Swap: If current time slot is not empty then program goes through all the time slots and choose another non empty time slot and generate new solution by swapping
- Assign: If the current time slot is empty then program goes through the course list and assign current course in current time slot

TABU - Neighbourhood Function Cont.

Therefore for each iteration program generates;

- $d * p * r$ (max) number of neighbours by removing
- $d * (d - 1) * p * (p - 1)r * (r * 1)$ (max) number of neighbours by swapping
- $d * p * r * c$ (max) number of neighbours by by assigning
- total max $d * (d - 1) * p * (p - 1)r * (r * 1) + d * p * r$ and min $d * p * r * c$ neighbours are generated in each iteration
- d = number of days
- p = number of periods per day
- r = number of rooms
- c = number of courses

TABU - Implementation Details I

Search$(s_0, \mathit{taboLength})$
$s^* = s_0$
repeat
    for each *slot* $t_1 \in \mathit{set}\{\mathit{day}, \mathit{period}, \mathit{room}\}$ **do**
        if t_1 *is not empty* **then**
            $s_n = \mathit{RemoveAt}(t_1$
            if $f(s_n) < f(s^{'})$ *and* $\mathit{RemoveAt}(t)$ *is not tabu* **then**
                $s^{'} = s_n$
            end if
            for each *slot* $t_2 \in \mathit{set}\{\mathit{day}, \mathit{period}, \mathit{room}\}$ **do**
                if t_2 *is not empty* **then**
                    $s_n = \mathit{Swap}(t_1, t_2)$

TABU - Implementation Details II

if $f(s_n) < f(s^{'})$ *and* $Swap(t_1, t_2)$ *is not tabu* **then**
$s^{'} = s_n$
end if
end if
end for
end if
if t_1 *is empty* **then**
for each *courses* $c \in CourseList$ **do**
$s_n = Assign(t_1, c)$
if $f(s_n) < f(s^{'})$ *and* $Assign(t_1, c)$ *is not tabu* **then**
$s^{'} = s_n$
end if
end for

TABU - Implementation Details III

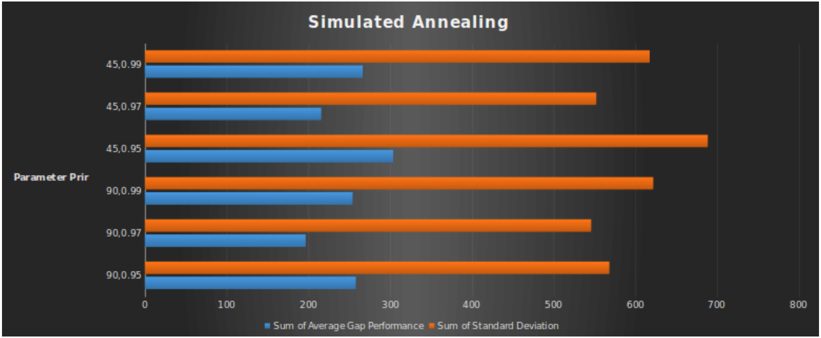
        end if
    end for
    $s = s^{'}$
    $AddTaboList(action)$
    if $f(s') < f(s^*)$ **then**
        $s^* = s^{'}$
    end if
until *time limit reached*
return s^*

Algorithm : TABU - Pseudo Code

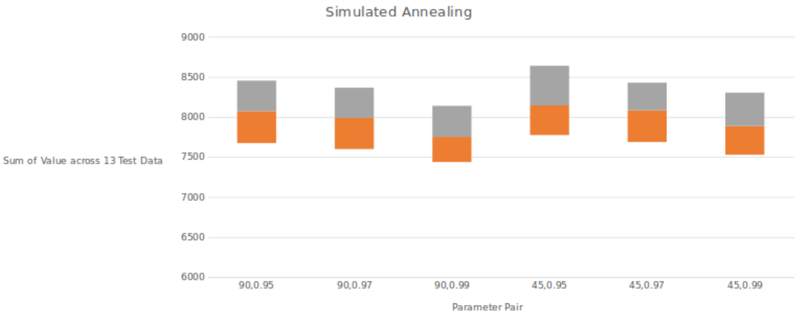
Parameter Tuning

- 13 different test data, 15 runs for each test data
- Simulated Annealing
  - 2 initial temperatures : 90 and 45
  - 3 cooling rate : 0.95, 0.97,0.99
- TABU:
  - 3 taboo length: 5, 10 and 20

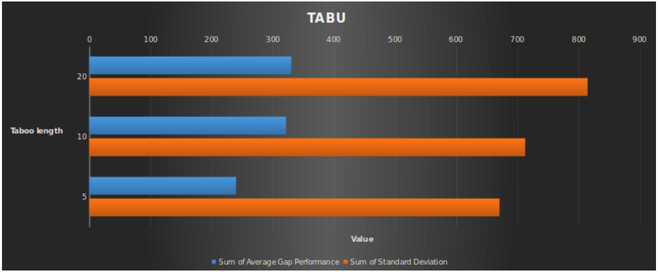
Simulated Annealing



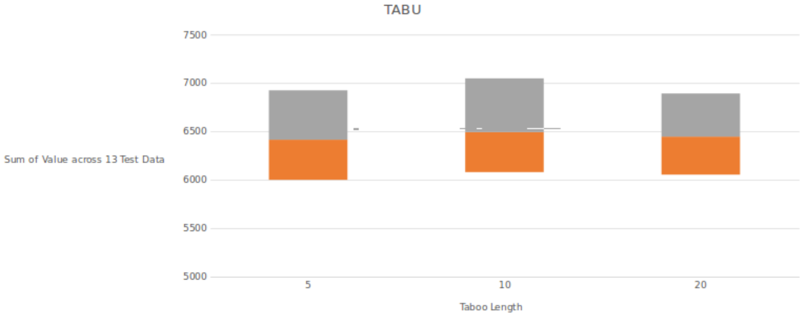
Simulated Annealing



TABU


TABU
0
100
200
300
400
500
600
700
800
900
20
10
5
Taboo length
Value
Sum of Average Gap Performance
Sum of Standard Deviation

TABU


TABU
7500
7000
6500
6000
5500
5000
Sum of Value across 13 Test Data
5
10
20
Taboo Length

Conclusion

Questions