# OPTIMIZATION AND SCHEDULING OF EXAM DATES

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## INTRODUCTION

The project is in the area of predicting and scheduling the most optimal exam plan with seating arrangement for the students of faculty Computer Science & Business Information Systems, THWS. Currently, the exam schedule is created manually which can be cumbersome as the constraint satisfaction is difficult to comply to.

## CONSTRAINTS

**Hard Constraints**:
- Room conflict
- Student conflict
- Room capacity conflict
- Multiple exams per day

**Soft Constraints**:
- Pause between exams
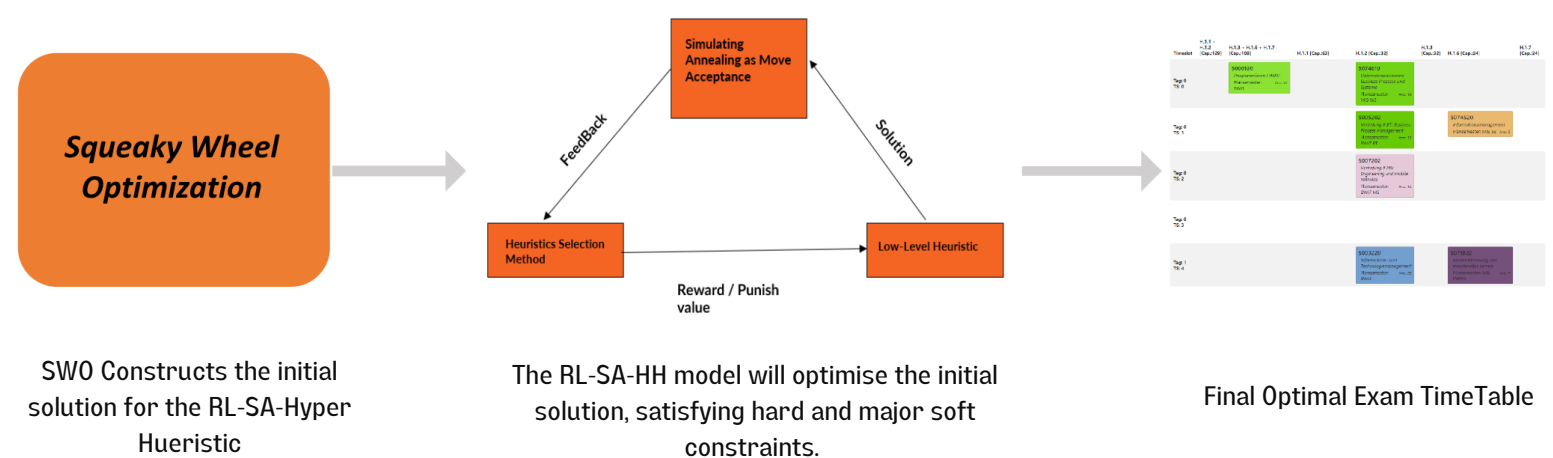- Lecturer availability
- Room availability

## OBJECTIVE

We aim to mitigate this gap with existing research by using combination of algorithms namely Reinforcement Learning(RL) to schedule the exam plan and Simulated Annealing(SA) to optimize it.

## DATASET

ITC 2007 Dataset provides a standardized evaluation framework for solving examination timetabling problems.
Our dataset comprises of lists of student-exam registrations, seating capacity, course-lecturer for each semester.

## METHODOLOGY

- Initial exam schedule is constructed with SWO algorithm.
- The low level heuristics are the actions, move acceptance is the SA optimization non-deterministic method.
- The learning policy guides the selection of the next action.
- The selection method decides the low-level heuristic to be used in the next iteration.
- ε-decay-greedy policy in heuristic selection method controls the Exploration -Exploitation tradeoff.



*Squeaky Wheel Optimization*

SWO Constructs the initial solution for the RL-SA-Hyper Hueristic

Feedback — Simulating Annealing as Move Acceptance — Solution

Heuristics Selection Method — Reward / Punish value — Low-Level Heuristic

The RL-SA-HH model will optimise the initial solution, satisfying hard and major soft constraints.

Final Optimal Exam TimeTable

## RESULTS

With RL approach, reward-penalty is awarded based on constraint satisfaction and violations.
Monte Carlo method is implemented by calculating the average utility value of each low-level heuristic as a score.

## CONCLUSION

The main take-away would be the time that would be effectively conserved on implementing this model.
The plan is to implement this model initially for our department and later upscale it to cater to all departments of our University.

**Related literature:**
Using Reinforcement Learning in Solving Exam Timetabling Problems.
Han, Kehan, 2018

**Contact for more details:**