Operations Research - Assignment 1 Report

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1. Introduction

This report presents the implementation of a Linear Programming (LP) solver using the Simplex Method and its variations. The solver is designed to handle different types of LP problems efficiently and provides a stepby-step solution process.

2. Code Flow and Architecture Report

2.1. Main Application Flow (main.py)

The GUI application (main.py) serves as the entry point, built using PyQt5. It provides a user interface for defining LP problems and selecting solution methods.

Key components:

- **Tabs**: Problem Definition, Solution, Iteration Steps.
- Input Handling: Collects variables, constraints, objective type (max/min), and method selection.
- **Solver Dispatch**: Calls appropriate solver based on user selection (Simplex, Big-M, Two-Phase, Goal Programming).

Data Structures:

2.2 Solver Methods

The solver was implemented using **Python**.

2.2.1 Standard Simplex Method (Simplex.py)

Purpose: Solve LP problems with <= constraints and non-negative variables.

Key Functions:

- simplex method(c, A, b, isMax):
 - ^o Initializes a tableau with slack variables.
 - ^o Iteratively selects entering/leaving variables using pivot operations.
 - ^o Returns the optimal solution and iteration steps.

Steps:

- 1. Convert inequalities to equations using slack variables.
- 2. Iterate via pivoting to maximize/minimize the objective.

2.2.2 Big-M Method (Big_M.py)

Purpose: Handle problems with >= or = constraints using artificial variables and a penalty term (M). **Key Functions**:

- big_m_method(c, A, b, constraint_types, isMax, variable_types):
 - O Splits unrestricted variables into x+ and x-.
 - ^o Adds artificial variables with large penalty coefficients (M).
 - O Uses simplex iterations to drive artificial variables out of the basis.

Steps:

- 1. Add artificial variables with penalty coefficient M.
- 2. Solve using simplex, penalizing solutions where artificial variables are non-zero.

2.2.3 Two-Phase Method (Two_phase.py)

Purpose: Another way to Handle problems with >= or = constraints using two phases.

phase 1: To minimize the effect of artificial variables and find a feasible solution.

phase 2: Use the feasible basis to optimize the original objective. **Key Functions**:

- Phase 1: __execute_phase1() minimizes the sum of artificial variables.
- Phase 2: __execute_phase2() optimizes the original objective after removing artificial variables.
- make_vars_zeros_Linearly(): Adjusts the objective row to eliminate basic variables coefficients from it.

2.2.4 Goal Programming (Goal_Programming.py)

Purpose: Achieve multiple prioritized goals by minimizing deviations.

Key Functions:

- goal_method():
 - O Adds deviation variables (d+, d-) for each goal.
 - O Modifies the tableau to prioritize goals.

0

Checks goal satisfaction via isDone list.

Steps:

- 1. Convert goals into constraints with deviation variables.
- construct the objective function by summation of multiplyed priorities by deviation variables responsible for its Goal
- 3. Optimize goals sequentially based on priority using lexicographic simplex.

3. Key Data Structures

- **Numpy Arrays**: For constraint matrices (A), objective coefficients (c), RHS values (b) and 2D numpy array representing coefficients, slack/artificial variables, and RHS (tableau).
- **Lists**: Track variable types (unrestricted/non-negative), constraint types (<=, =, >=), main_row: Column headers (e.g., x1, s1, a1), basic_var: Current basic variables in the solution and goal priorities.
- **Dictionaries**: Store solutions and iterations for display.

4. Function Interactions

- 1. **GUI Inputs** → Converted to matrices (A, b, c) and constraint lists.
- 2. **Solver Selection** → Dispatches to simplex_method(), big_m_method(), etc.
- 3. **Tableau Initialization** → Built based on variable types and constraints.
- 4. **Pivoting** → __execute_simplex() performs iterations across all methods.
- 5. **Solution Extraction** \rightarrow Post-processing (e.g., merging $\times +/\times -$ for unrestricted variables).

5. Sample Runs

Below are example cases solved using our program:

5.1 Example 1 - Simplex Method

```
Maximize Z = 5x1 - 4x2 + 6x3 - 8x4

Subject to:

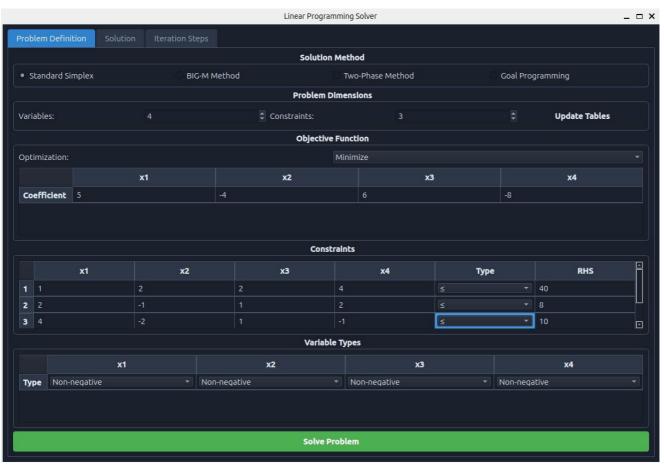
x1 + 2x2 + 2x3 + 4x4 \le 40

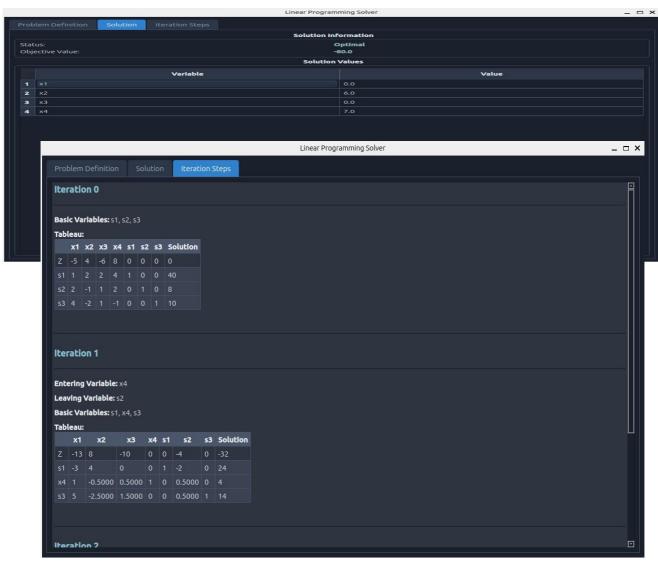
2x1 - x2 + x3 + 2x4 \le 8

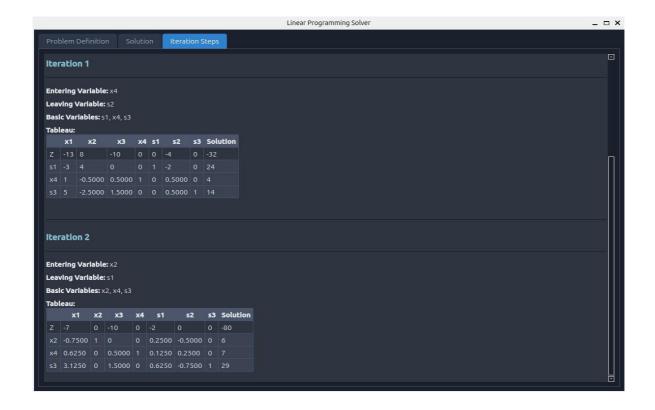
4x1 - 2x2 + x3 - x4 \le 10

x1, x2, x3, x4 \ge 0
```

Output:







- Optimal Solution: x1 = 0, x2 = 6, x3 = 0, x4 = 7
- • Optimal Objective Value: Z = -80

5.2 Example 2 - Big-M Method

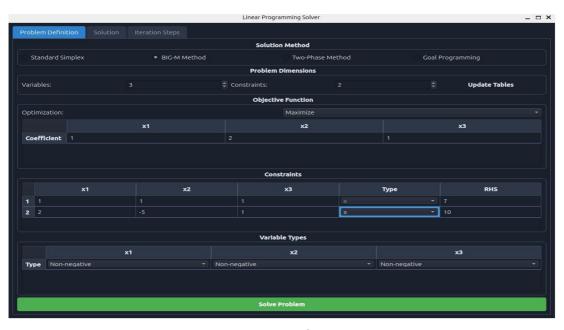
```
Maximize Z = x1 + 2x2 + x3

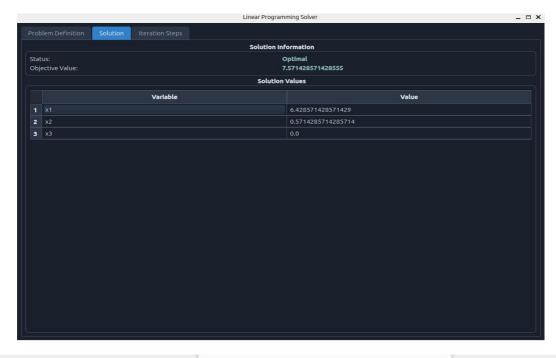
Subject to:

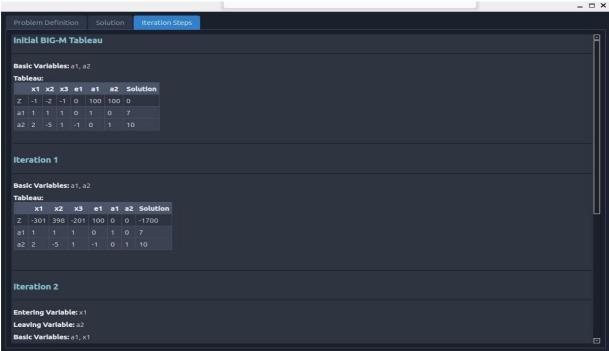
x1 + x2 + x3 = 7

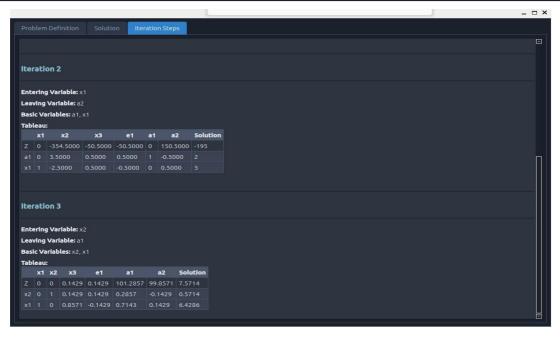
2x1 - 5x2 + x3 \ge 10

x1, x2, x3 \ge 0
```









Output:

- Optimal Solution: x1 = 45/7, x2 = 4/7
- Optimal Objective Value: Z = 53/7

Example 3 - Two-Phase Method

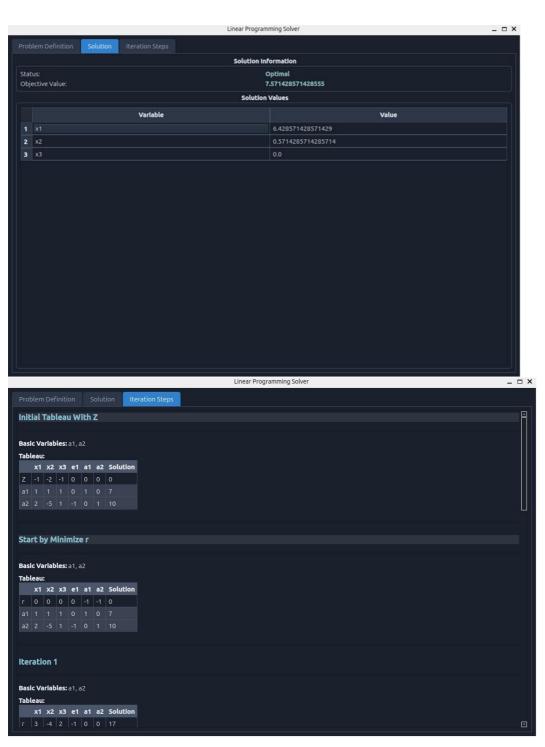
```
Maximize Z = x1 + 2x2 + x3

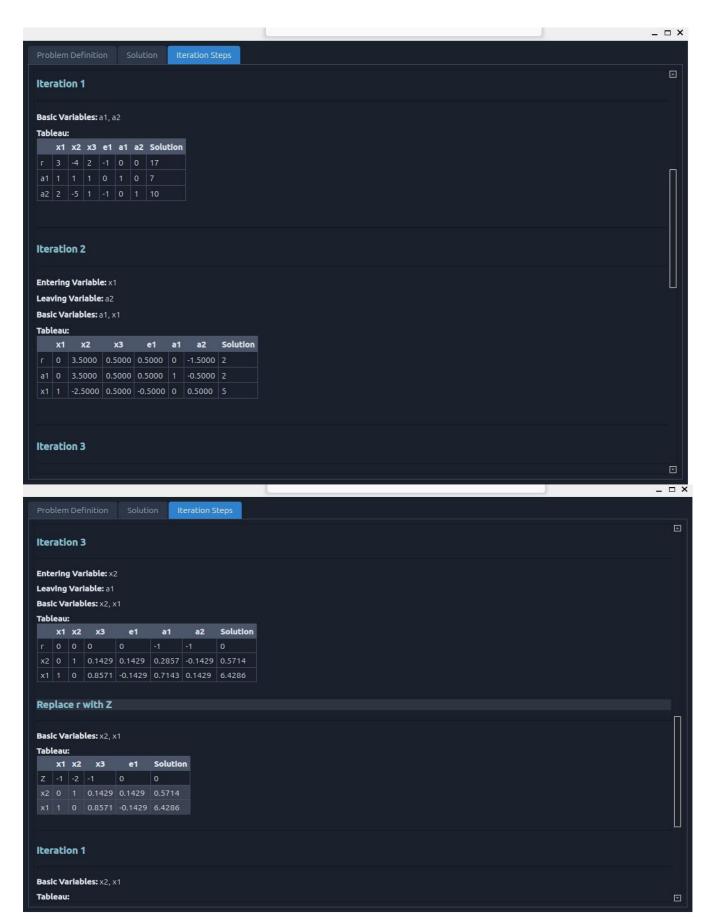
Subject to:

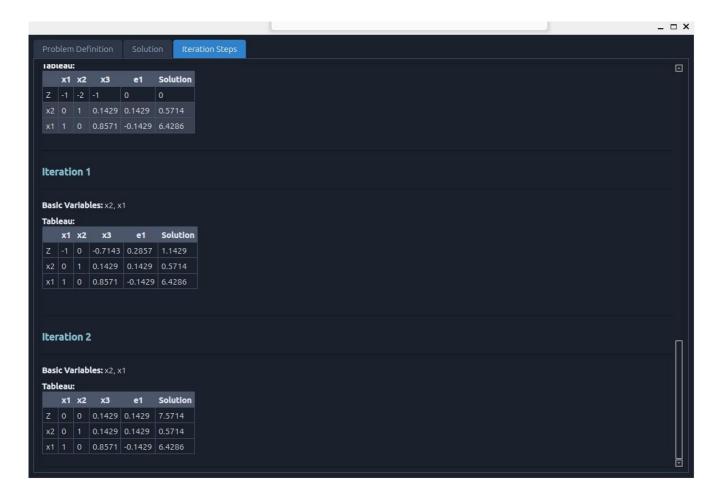
x1 + x2 + x3 = 7

2x1 - 5x2 + x3 \ge 10

x1, x2, x3 \ge 0
```







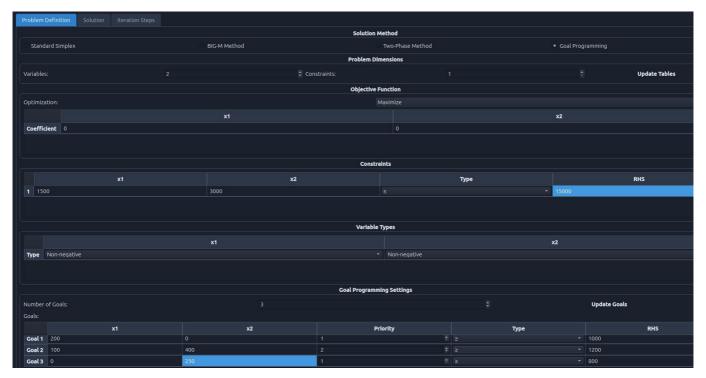
Output:

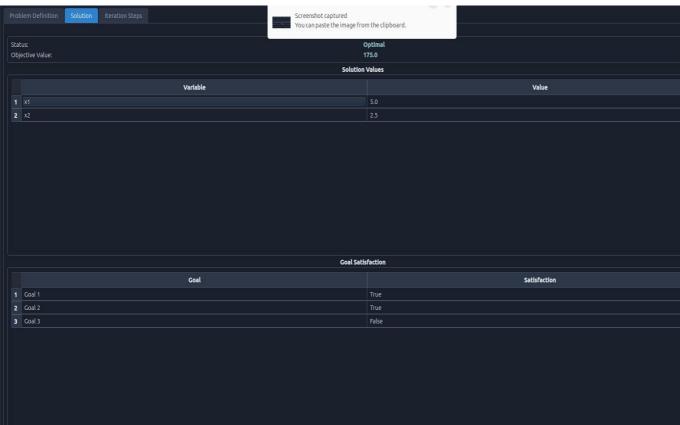
• Optimal Solution: x1 = 45/7, x2 = 4/7

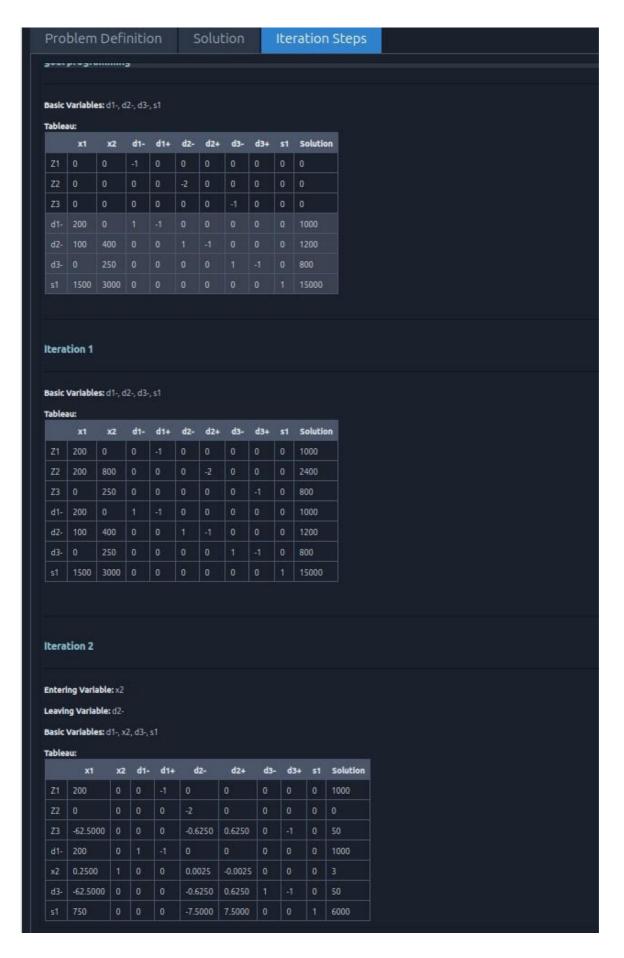
• Optimal Objective Value: Z = 53/7

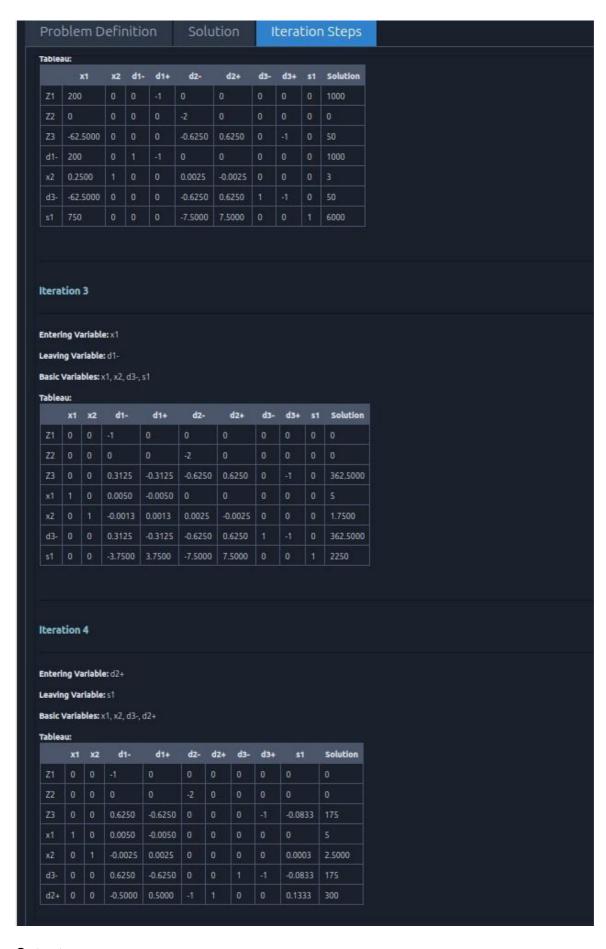
5.4 Example 4 - Goal-programming Method

Constraints: Goals: $200x1+3000x2 \le 15000$ Goals: 200x1>=1000 priority:1 100x1+400x2>=1200 priority:2 250x2>=800 priority:1









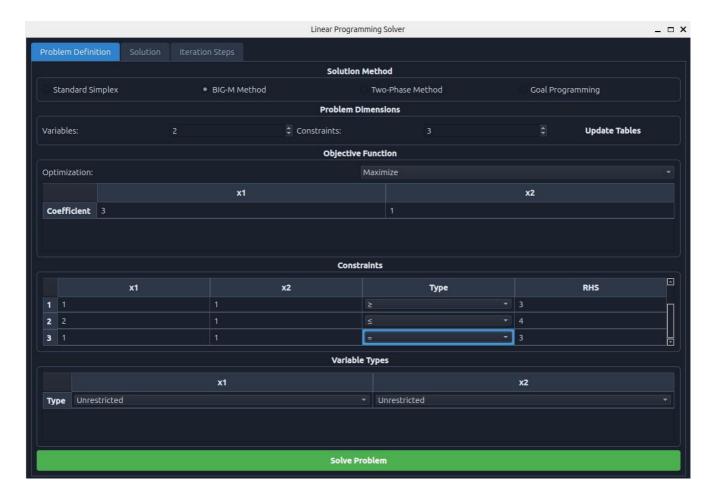
Output:

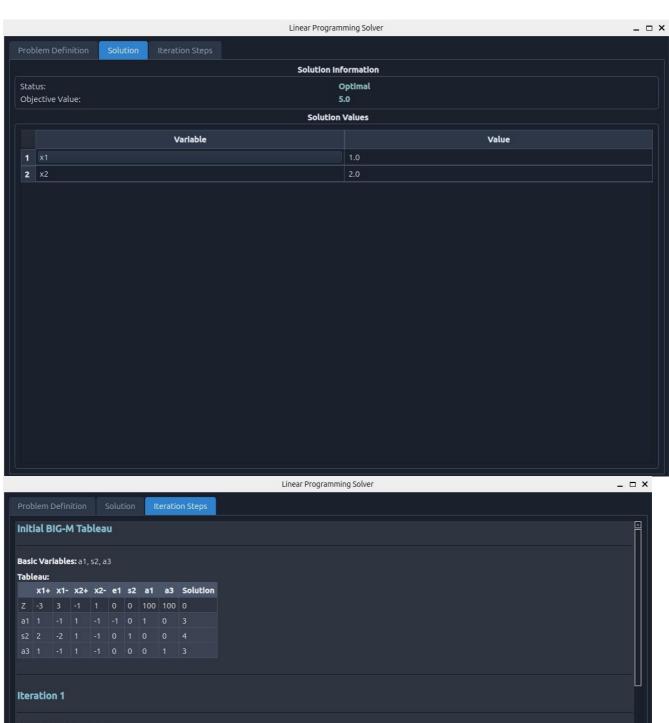
Optimal Solution: x1 = 5, x2 = 2.5

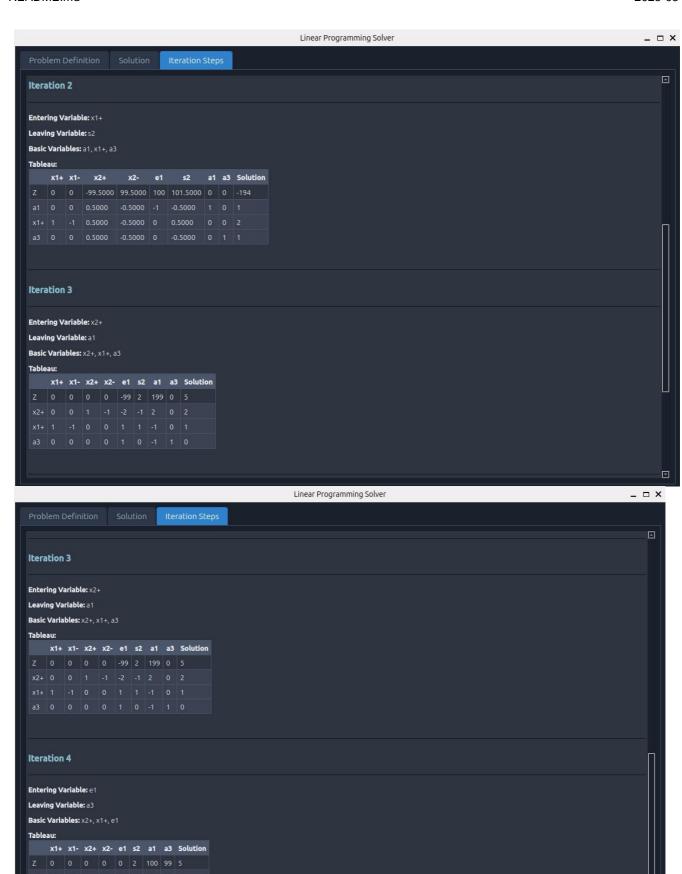
Satisfying Goals: G1 and G2

5.5 Example 5 – Unrestricted variables

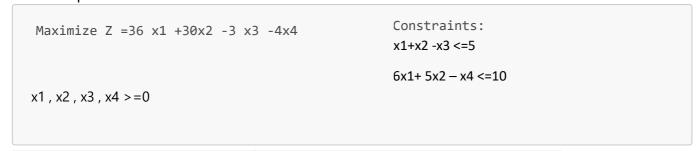
Maximize Z =3 x1 +x2 Constraints: x1+x2 >= 7 2x1+x2 <= 4 x1 & x2 are unrestricted variables. x1 + x2 = 800

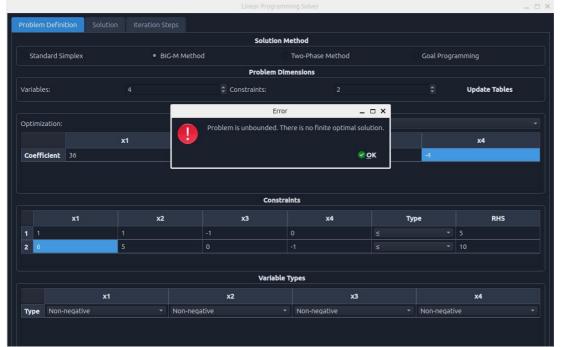


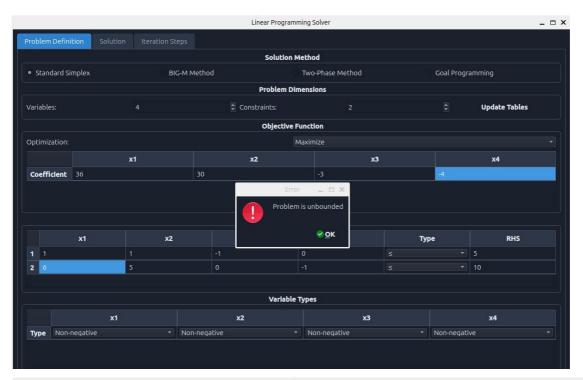


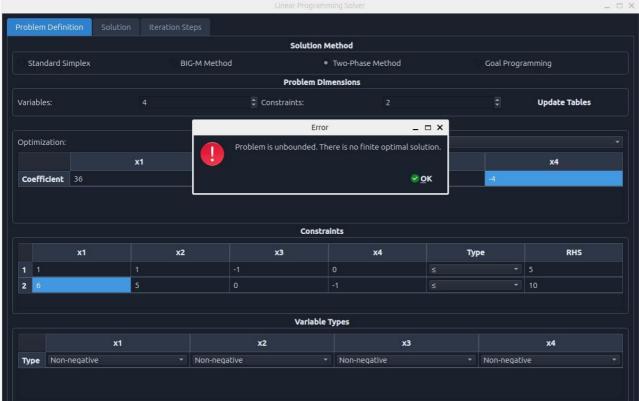


5.6 Example 6 – Unbounded solution



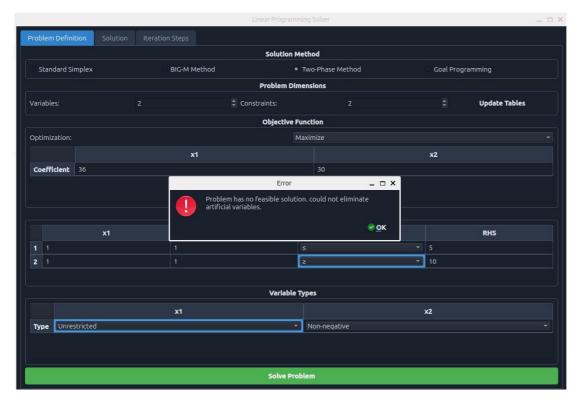






5.7 Example 7 – infeasible solution

Maximize Z = 36 x1 + 30x2 Constraints: x1+x2 >= 5 x1+x2 >= 5



6. Bonus Feature

We developed a **user-friendly interface** by pyQt5 in python that allows users to input LP problems easily and view the solution process interactively.

7. Conclusion

This project provided hands-on experience in solving LP problems using different methods. The solver successfully handles various constraints and outputs detailed step-by-step solutions. Future improvements include extending support for additional optimization techniques and graphical visualization of results.