Multi Objective Optimization Model for Air Pollution Control in a Urea Plant

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Abstract
Air pollution control is a critical challenge for industrial planners and environmental policymakers, especially in developing regions where cost and compliance often conflict.This project proposes a Multi-Objective Mixed-Integer Linear Programming (MO-MILP) model to support decision-making in selecting optimal pollution control strategies across multiple industrial sources. Extending the foundational work by Shaban et al. (1997), the proposed model simultaneously minimizes total cost—comprising both capital investment and operational expenses—and maximizes pollutant reduction across multiple emissions types.

1 Introduction

Industrial processes in fertilizer production, especially in urea plants, emit air pollutants such as PM and NH3. Regulatory agencies require these emissions to be reduced within limits. The goal is to identify which control technologies to install, where, and for how long, while staying within budget and meeting pollution reduction targets.

1.1 Background And Motivation

Industrialization, while central to economic growth, remains a major contributor to ambient air pollution. Urban regions and industrial belts in countries like India, China, and many parts of the Global South face critical challenges in managing air quality while maintaining industrial productivity. With increasing pressure from environmental regulations and public health imperatives, there is a growing need for systematic frameworks to aid pollution control decisions that are both economically viable and environmentally effective.

One of the foundational models addressing this need is the linear programming-based framework developed by Shaban et al. (1997), which provided a cost-minimization approach to technology selection for air pollution control. However, modern environmental governance demands a more comprehensive view—where cost and pollution reduction are treated not as competing goals, but as co-objectives in a multi-criteria decision-making process.

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2.1 Problem Statement

This project extends the original Shaban et al. model into a Multi-Objective Mixed-Integer Linear Programming (MO-MILP) formulation. The updated model introduces the ability to:

- Simultaneously optimize for both cost and pollution reduction
- Handle multiple pollutants and industrial sources
- Incorporate real-world budgetary

2.2 Objectives

- To develop a MO-MILP model that helps select appropriate pollution control technologies for each industrial unit.
- To minimize total cost, defined as the sum of investment and operational costs.
- To maximize overall pollutant reduction, considering multiple pollutants.
- To explore trade-offs between cost and environmental benefit using scalarization and Pareto analysis.

2.3 Methodology

The model is built using Pyomo, a Python-based optimization modeling language, and solved using standard MILP solvers such as GLPK or Gurobi. The decision variables represent the adoption of technologies across plants, while constraints enforce cost limits, feasibility, and pollution caps. The objective functions are weighted and normalized for multi-objective optimization. The model can be visualized using Pareto fronts and implementation schedules.

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3 Model Formulation

3.1 Formulation

This section outlines the mathematical formulation of the Multi-Objective Mixed-Integer Linear Programming (MO-MILP) model designed for optimal selection of air pollution control technologies.

3.2 Sets and Indices

- I: Set of industrial sources (e.g., factories, power plants)
- J: Set of pollution control technologies
- P: Set of pollutants

3.3 Decision Variables

- xij : Binary variable indicating whether technology j is installed at source i. Binary, 1 if control j is selected for source i
- Tij : Time in years that control j is used on source i
- Tj : Duration control j is implemented.

3.4 Parameters

- C_{ij}: Annual operating cost for applying control j on source i
- R_{ijk} : Pollution reduction (per year) by control j on source i for pollutant k
- a_j, b_j : Investment cost coefficients for each control j
- T_{max} : Maximum time horizon (18 years)
- $\epsilon_{PM}, \epsilon_{NH3}$:Required minimum total reductions
- Buggetlimit : Total budget available

3.5 Objective Function

Minimize total cost:

$$TotalCost = \sum(c_{ij} * T_{ij}) + \sum(a_j * T_j + b_j * x_{ij})$$

3.6 Constraints

- One Control per Source : Each source can have at most one control assigned.
- Time Binding : $TijTmax * xij$
- Pollution Reduction : Total PM and NH reduction must meet `epsilon_pm`,

epsilon_nh3

- Budget Constraint : Total cost must be less than or equal to budget_limit

3.7 Execution and Solver

- Solver: glpk via Pyomo
- Method: ε-constraint method (epsilon for PM and NH).
- Result: Optimal control assignments for each source under constraints

3.8 Concepts Used

- Mixed Integer Linear Programming (MILP)
- Epsilon-constraint method for multi-objective optimization
- Feasible region, design vector, constraint surfaces
- Objective function surface is cost-based and minimized

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4 Conclusions

4.1 Results

The solver found optimal control assignments with minimal cost and acceptable pollution reduction.

- Example Output:
- - Source 2 → Control 6 for 0.92 years
- - Source 3 → Control 7 for 2.68 years
- - Total Cost: 2.60 units

5 References:

"An Optimization Model for Air Pollution Control Decision Making" by Shaban et al., 1997