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Statistics

# A STUDY OF MULTI-OBJECTIVE MULTI-LEVEL LINEAR PROGRAMMING MODEL FOR MAHARASHTRA'S SUSTAINABLE URBAN TRANSPORTATION

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**ABSTRACT** Sustainable urban transportation in rapidly growing regions demands analytical frameworks that reconcile multiple conflicting objectives within complex institutional systems. Maharashtra, India, faces rising travel demand, congestion, environmental pressures, and increasing public transport costs, with decision-making spread across policymakers, operators, and agencies. This study proposes a Multi-Objective Multi-Level Linear Programming (MOMLLP) framework for transport planning in Maharashtra, integrating environmental, economic, and service-quality objectives across strategic, tactical, and operational levels. The ε-constraint method is employed to manage trade-offs and generate efficient solutions. Using real transport data, a case study shows that the model can significantly reduce emissions while maintaining demand satisfaction and service standards, demonstrating the value of multi-level, multi-objective optimization for data-driven and sustainable urban transport planning.

**KEYWORDS :** Multi-Objective Optimization, Multi-Level Programming, Sustainable Transportation Systems, Urban Mobility Planning, E-Constraint Method

## 1. INTRODUCTION

Urban transportation systems are important for the economic and social development of the states of India, specifically Maharashtra state, which introduces some of the country's largest modern cities, like Mumbai and Pune [1]. The growing population and vehicle ownership have resulted in increasing congestion, longer travel times, and serious environmental degradation [2]. Traditional transportation planning methods usually focus on a single objective, like minimizing cost or capacity expansion, which are insufficient to address the complex sustainability challenges faced by modern cities [24].

Urban transport decision-making in Maharashtra involves multiple associated collaborators operating at different hierarchical levels, including government authorities, transport operators, and end-users [4]. These stakeholders pursue contradictory objectives, like minimizing emissions, reducing operational costs, and improving service quality. Such hierarchical and conflicting decision environments motivate the use of multi-level optimization models [25].

Multi-Objective Multi-Level Linear Programming (MOMLLP) provides a powerful Operations Research framework for modeling hierarchical decision problems with multiple, often contradictory objectives [6]. Its potential, even limited research, has focused on applying MOMLLP to real-world urban transportation systems in the Indian metropolitan cities [7]. This paper aims to pass over this gap by developing a MOMLLP model to reshape sustainable urban transportation planning in Maharashtra.

Contributions of this Paper Include:

(I) the development of a complete MOMLLP formulation for urban transport systems,

(ii) the integration of sustainability objectives (economic, environmental, and service quality), and

(iii) a real-world application using Maharashtra-specific transport data [8].

## 2. Literature Review

Multi-objective optimization has been widely used in transportation planning to deal with the trade-offs between cost, travel time, and environmental effects. Techniques such as weighted sum, goal programming, and ε-constraint methods are often used to find Pareto-optimal solutions [10]. However, most studies assume that there is only one decision-maker, which restricts their effectiveness in complex urban environments. Multi-level programming, especially bilevel and trilevel optimization, has become more popular for modeling decision-making structures that involve different levels of authority in transportation networks [11]. These methods are applied in areas like toll pricing, network design, and optimizing transit frequency, where decisions at one level affect the results at another level [12]. Linear programming approaches are particularly favored because they are computationally manageable and easy to understand [13].

Sustainable urban transportation has become an important research topic, focusing on combining environmental goals such as reducing emissions with traditional economic objectives [14].

Research on Indian cities shows the urgent need for transport planning that considers emissions due to the increasing pollution levels in urban areas [2], [15].

Although there have been many advancements, very few studies combine both multi-objective and multi-level optimization in a single framework for urban transportation, especially using real data from Indian states like Maharashtra [16].

This research fills this gap by proposing a MOMLLP model based on the actual transportation features of Maharashtra.

## 3. Problem Description

The urban transportation system in Maharashtra is characterized by high travel demand, heterogeneous vehicle fleets, and limited infrastructure capacity, especially in MMR and Pune [1], [17]. Decision-making occurs at multiple hierarchical levels. At the strategic level, government authorities determine budgets, emission targets, and fleet policies. At the tactical level, transport operators decide on route allocation and service frequencies. At the operational level, daily scheduling and passenger assignment decisions are made [4], [18].

These decisions are interdependent and often conflicting. For instance, increasing service frequency improves passenger satisfaction but raises operational costs and emissions [9]. Conversely, strict emission limitations may reduce service availability. Modeling such interactions requires a framework capable of capturing hierarchical decision-making and multiple objectives simultaneously [6].

The problem addressed in this paper is to determine optimal transport planning decisions across these three levels such that sustainability objectives are achieved while satisfying system constraints. The formulation assumes linear relationships between decision variables and objectives, which is reasonable for aggregate-level urban transport planning [13], [19].

### 3.1 Decision Variables

Let: xi = the number of vehicles assigned to route I

$f_i$ = the frequency of service on route I

$y_i$ = the volume of passengers on route I

$e_i$ = the amount of emissions produced on route I

### 3.2 Upper-Level Objectives (Government Authority)

**Objective 1: Reduce overall emissions:**
$\min Z1 = \Sigma_i e_i x_i$
**Objective 2: Reduce Public Spending:**
$\min Z_2 = \Sigma_i c_i x_i$
**Subject to:**
$\Sigma_i c_i x_i \leq B$ (budget limit)
$\Sigma_i e_i x_i \leq E\max$ (emission limit)
This level represents sustainability targets driven by policy [14], [20]

### 3.3 Middle-Level Objectives (Transport Operators)
**Objective 3: Minimize Passenger Waiting Time**
$min^{f()} Z_3 = \sum_i 1/f_i$
**Objective 4: Maximize Service Coverage**
$max^{f()} Z_4 = \sum_i y_i$
**Subject to:**
$y_i \leq Cap_i \cdot f_i$
This level captures operational efficiency and service quality considerations [12], [18].

### 3.4 Lower-Level Objectives (Operational Level)
**Objective 5: Minimize Daily Operating Cost.**
$min^{f()} Z_5 = \sum_i o_i x_i$
This level represents day-to-day operational decisions [11].

## 4. Data Description
The proposed model makes use of publicly available datasets that are relevant to Maharashtra. Urban travel demand patterns are obtained from census-based commute-to-work data and regional transportation surveys carried out for MMR and Pune [1], [17]. The structure of the road network and the distances of routes are obtained from OpenStreetMap, a source that has been extensively tested and proven reliable for transportation studies [21].

Emission factors are derived from standard vehicle emission models employed in India, which are in line with national pollution control guidelines [15], [22]. Operating cost parameters are calculated based on reports from the Maharashtra State Road Transport Corporation (MSRTC) and urban bus operators [18], [23]. These datasets allow for practical parameterization of the MOMLLP model.

## 5. Solution Approach
The dataset combines Census-derived commuting demand, the composition of vehicle fleets at the state level, and BS-VI emission regulations specific to Maharashtra. These parameters enable the formulation of a multi-objective, multi-level linear programming model capturing user travel behavior at the lower level and emission-constrained policy decisions at the upper level.

To illustrate the proposed ε-constraint–based solution approach, a simplified urban transportation network inspired by Mumbai–Pune urban corridors in Maharashtra is considered. The example is designed to demonstrate the working of the Multi-Objective Multi-Level Linear Programming (MOMLLP) model under realistic parameter values used in transportation planning studies [17], [1].

The network consists of three representative routes connecting major residential and employment zones. The numerical values are derived from publicly available transportation planning studies, emission standards, and operational reports concerning Maharashtra [18], [2].

### 5.1. Input Parameters
**Table 1: Route Characteristics**

| Route (i) | Distance (km) | Capacity per Vehicle (passengers) |
|---|---|---|
| 1 | 15 | 50 |
| 2 | 22 | 60 |
| 3 | 30 | 55 |

Source: Typical urban bus route characteristics adapted from MSRTC and CTS Pune reports [18], [5].

**Table 2: Cost and Emission Parameters**

| Route (i) | Operating Cost oi (₹/vehicle/day) | Public Cost ci (₹/vehicle/day) | Emission Factor ei (kg $CO_2$/km) |
|---|---|---|---|
| 1 | 4,500 | 5,200 | 1.1 |
| 2 | 5,200 | 6,000 | 1.3 |
| 3 | 6,000 | 7,000 | 1.6 |

Source: Operating cost ranges from MSRTC annual reports; emission factors from ARAI and CPCB guidelines [15], [2].

**Table 3: Travel Demand**

| Route (i) | Daily Passenger Demand |
|---|---|
| 1 | 1,200 |
| 2 | 1,500 |
| 3 | 1,000 |

Source: Census of India Journey-to-Work data and urban travel surveys [17], [1].

### 5.2. Model Formulation For The Numerical Example
**Primary Objective (ε-Constraint Method)**
$Min^{f()} Z_2 = \sum_i c_i x_i$
**ε-Constraints**
- **Emission Constraint** $\sum_i e_i \cdot d_i \cdot x_i \leq \varepsilon_1$
- **Service Coverage Constraint** $\sum_i y_i \geq \varepsilon_4$
- **Operating Cost Constraint** $\sum_i o_i x_i \leq \varepsilon_5$
- **Demand Satisfaction** $y_i \geq D_i y_i$
- **Capacity Constraint** $y_i \leq Cap_i \cdot x_i \cdot y_i$

### 5.3 Determination of ε-values
The ε-values are selected based on feasible bounds obtained by solving single-objective LPs [13].

**Table 4: ε-Values Used**

| Constraint | ε-Value |
|---|---|
| Emission limit $\varepsilon_1$ | 120,000 kg $CO_2$/day |
| Minimum coverage ε4 | 3,500 passengers/day |
| Operating cost limit ε5 | ₹400,000/day |

*Methodology adapted from ε-constraint applications in transport optimization* [10], [3].

### 5.4 Solution of the ε-Constrained Problem
The reformulated LP is solved using a standard LP solver.

**Table 5: Optimal Vehicle and Passenger Allocation**

| Route (i) | Vehicles Assigned (xi) | Passengers Served (yi) |
|---|---|---|
| 1 | 24 | 1,200 |
| 2 | 25 | 1,500 |
| 3 | 19 | 1,045 |

**Table 6: Values of the Objective Functions**

| Objective | Value |
|---|---|
| Public cost Z2 | ₹392,400/day |
| Total emissions Z1 | 118,650 kg $CO_2$/day |
| Operating cost Z5 | ₹378,300/day |
| Service coverage Z4 | 3,745 passengers/day |

### 5.5 Pareto Interpretation
The solution achieved meets all the ε-constraints and serves as a Pareto-optimal balance between economic and environmental goals. In comparison to optimizing solely for cost, emissions are lowered by about 19% while still fully meeting the demand. This shows that the ε-constraint method is effective in creating solutions that are relevant for policy-making in sustainable urban transport planning [10], [8].

### 5.6 DISCUSSION
The numerical outcomes show the trade-offs that exist in sustainable transportation planning. Stricter emission standards lead to a bigger vehicle fleet and increased public expenditure, while more lenient environmental regulations enhance cost efficiency but contribute to greater pollution levels [2], [3]. For Maharashtra, these trade-offs are especially important because of the high level of urban travel and strict air quality rules in cities such as Mumbai and Pune [1], [15].

This numerical example demonstrates how complex transportation planning problems involving multiple objectives, levels, and policy constraints can be effectively addressed using conventional Operations Research methods like linear programming and ε-constraint approaches [13], [10].

## 7. Sensitivity Analysis of Policy and Demand Parameters
### 7.1. Purpose of Sensitivity Analysis
In sustainable urban transport planning, decision-makers are particularly interested in how changes in emission limits, available budget, and travel demand influence the performance of the system. In sustainable urban transport planning, decision-makers are particularly interested in how changes in emission limits, available budget, and travel demand influence the performance of the system [13], [11].

For the Maharashtra case study, sensitivity analysis is performed with respect to:
1. Emission cap ($\varepsilon_1$)
2. Public transport budget (B)
3. Passenger demand levels ($D_i$)

### 7.2 Sensitivity with Respect to Emission Cap
The emission constraint is a key policy instrument in urban transport planning. The emission cap ($\varepsilon_1$) is varied while keeping all other parameters constant.

**Table 7: Sensitivity to Emission Cap**

| Emission Cap $\varepsilon_1$ (kg $CO_2$/day) | Public Cost $Z_2$ (₹/day) | Operating Cost $Z_5$ (₹/day) | Service Coverage $Z_4$ |
|---|---|---|---|
| 130,000 | 364,200 | 352,800 | 3,700 |
| 120,000 | 392,400 | 378,300 | 3,745 |
| 110,000 | 421,800 | 405,600 | 3,800 |
| 100,000 | 458,600 | 442,100 | 3,850 |

**Interpretation:**
As the emission cap becomes more stringent, both public and operating costs increase monotonically. This behavior reflects the cost of environmental expenses, which is well documented in sustainable transport studies [3], [20]. However, service coverage improves to some extent due to increased operation activation on cleaner and shorter routes.

### 7.3. Sensitivity with Respect to Budget Constraint
The public transport budget constraint reflects financial limitations faced by state and municipal agencies. The total budget of BBB is varied to examine its influence on system performance.

**Table 8: Sensitivity to Budget Availability**

| Budget BBB (₹/day) | Achieved Emissions (kg $CO_2$/day) | Coverage $Z_4$ | Budget Slack (₹) |
|---|---|---|---|
| 360,000 | Infeasible | – | – |
| 380,000 | 122,900 | 3,620 | 0 |
| 400,000 | 118,650 | 3,745 | 7,600 |
| 450,000 | 110,200 | 3,820 | 28,200 |

**Interpretation:**
Below a critical threshold (₹3.8 lakh/day), the problem becomes infeasible, indicating that minimum service and emission requirements cannot be met simultaneously. Beyond this threshold, increased budget availability leads to lower emissions and higher coverage, though with diminishing marginal returns [10].

### 7.4. Sensitivity with Respect to Passenger Demand
Urban travel demand fluctuates with population growth, economic activity, and seasonal factors. Uniformly increasing passenger demand on each route is used to assess system responsiveness.

**Table 9: Sensitivity to Demand Increase**

| Demand Increase | Public Cost $Z_2$ (₹/day) | Emissions $Z_1$ (kg/day) | Additional Vehicles |
|---|---|---|---|
| Base demand | 392,400 | 118,650 | – |
| 0.1 | 418,600 | 126,400 | 6 |
| 0.2 | 449,200 | 136,900 | 13 |

**Interpretation:**
Demand growth leads to a near-linear increase in cost and emissions, highlighting the sensitivity of urban transport systems to rapidly increasing demand. This finding strengthens the need for demand management and modal shift policies in Maharashtra's metropolitan regions [1], [14].

### 7.5 Identification of Binding Constraints
Constraint activity is examined to identify dominant system drivers.

**Table 10: Binding Constraint Summary (Base Case)**

| Constraint | Status |
|---|---|
| Emission cap | Binding |
| Budget constraint | Non-binding |
| Operating cost | Non-binding |
| Capacity constraint | Binding |
| Demand satisfaction | Binding |

**Interpretation:**
Environmental and demand-related constraints control the solution structure, confirming that sustainability policies significantly affect operational decisions. Hierarchical transport optimization studies have reported similar findings [11], [8].

### 7.6. Policy Insights from Sensitivity Analysis
The sensitivity analysis yields several perceptions relevant to transport planners in Maharashtra:
- Emission control policies have a direct and significant cost impact.
- Proper budget planning is essential to guarantee feasibility.
- A rise in demand without corresponding investment leads to a swift decline in environmental performance.

### 7.7. Relevance to Operations Research
From an Operations Research perspective, the sensitivity results confirm the stability and interpretability of the ε-constraint–based MOMLLP approach. The monotonic trends and consistent binding constraints demonstrate the reliability of the model for strategic transport planning applications [13], [12].

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