Pareto-Based Multi-Objective Optimization Framework for Public Transport Scheduling

1. Problem Statement

Efficient public transport management is one of the key challenges in modern smart cities. Authorities need to plan bus schedules that provide **good service to passengers** while also being **cost-effective**. However, these two goals often **conflict**:

1. Increasing the **number of buses** reduces passenger **waiting time** but **increases operational costs**.
2. Reducing the **number of buses** saves money but leads to **longer waiting times** and **lower satisfaction**.

Hence, the **main problem** is to **find the best trade-off** between:

1. **Operational Cost (minimize it)**
2. **Average Passenger Waiting Time (minimize it)**

This project focuses on solving this real-world issue using a **Pareto-based multi-objective optimization framework**, which helps find **balanced solutions** that are both economical and efficient.

2. Pareto-Based Multi-Objective Framework for Optimization in Application Domain of Public Transport Scheduling

The **Pareto-Based Multi-Objective Optimization Framework** is the core concept used in this project to design an intelligent scheduling system for **public bus transport**. In a real city network, it is difficult to achieve both **low operational cost** and **high service quality** at the same time. Increasing the number of buses improves passenger comfort but raises daily expenses, while reducing buses saves money but increases waiting time. This conflicting nature of objectives makes the problem ideal for **multi-objective optimization**, and that is why a **Pareto-based approach** was chosen.

Why This Framework Was Chosen

Traditional single-objective optimization methods can minimize either cost or waiting time but not both simultaneously.
Public transport planning requires a balance — one that considers both passenger convenience

and financial sustainability.
The **Pareto-based framework** is perfectly suited for this type of problem because:

1. **It optimizes multiple objectives together:**
   It minimizes both **operational cost** and **average waiting time** without ignoring either one.
2. **It produces a range of best solutions:**
   Instead of one rigid answer, it generates a **Pareto front** — a set of trade-off solutions showing different cost–quality balances.
3. **It supports flexible decision-making:**
   City planners can choose a solution depending on the current situation — for example, selecting a lower-cost schedule on low-demand days or a higher-frequency schedule during peak hours.
4. **It matches real-world transport behavior:**
   The same approach can handle uncertainties like variable passenger demand, changing route lengths, and fuel price fluctuations.

Practical Impact

By applying this Pareto-based framework, the project achieves:

- **Optimized transport schedules** that balance economy and efficiency
- **Reduced passenger waiting time** without overspending on resources
- **Multiple viable choices** for transport managers to adapt to real-time needs
- A **visual understanding of trade-offs** using Pareto front graphs

Thus, this framework provides a **data-driven and flexible solution** for improving public transport systems.
It directly addresses the core challenge of balancing **cost-effectiveness** with **quality of service**, making it the most suitable optimization approach for this application.

3. Relevant Literature Study

Many recent studies have applied **multi-objective and Pareto-based optimization techniques** such as **NSGA-II** to improve transportation systems, scheduling, and smart city management. These works show how such algorithms effectively balance **conflicting goals** like cost, waiting time, and service quality.

1. **Legault et al. (2025)** – Focused on **electric bus fleet planning** using multi-objective optimization to balance **operational cost and sustainability**. It proved that optimization methods can improve both cost efficiency and eco-friendly operations.

2. **Winschermann et al. (2025)** – Used a **Pareto-based model** for optimizing **carbon emissions, charging capacity, and cost** of electric buses, demonstrating how multiple objectives can be effectively balanced in transport systems.
3. **Hangzhou Case Study (2025)** – Developed a **multi-objective scheduling model** for **urban rail transit**, minimizing **energy use, carbon emissions, and passenger waiting time**, showing relevance to our bus scheduling problem.
4. **Mousavi et al. (2025)** – Proposed a **bi-objective model** for **bus timetabling and scheduling** using **NSGA-II**, proving its efficiency in producing high-quality, balanced solutions between service quality and cost.
5. **Multi-Modal Optimization (2024)** – Applied **NSGA-II** to optimize **transfer schedules** between buses and metro systems, minimizing **transfer waiting time** and **schedule changes**, improving multi-modal transport efficiency.
6. **Faroqi H. (2024)** – Implemented **NSGA-II** for **route optimization** in multimodal transport, minimizing **travel time, distance, and cost**, showing its suitability for real-world transport networks.
7. **Bandyopadhyay et al. (2023)** – Explained how **evolutionary algorithms** like **NSGA-II** solve **resource allocation and scheduling** problems efficiently by providing diverse Pareto-optimal solutions.

4. Algorithm, Experimental Setup, and Results

Algorithm Used: NSGA-II

Step-by-Step Explanation:

1. **Initialization:**
   Generate a random population of possible bus schedules. Each schedule contains the number of buses assigned to different routes.
2. **Evaluation:**
   For each schedule, calculate:
   a. **Operational cost** = (number of buses × route length × cost per km)
   b. **Average waiting time** = inversely proportional to the number of buses (more buses → less waiting time)
3. **Non-Dominated Sorting:**
   Classify the population into different fronts (Pareto levels).
   The first front represents the best trade-off solutions.
4. **Crowding Distance Calculation:**
   Maintain diversity among solutions by preferring those that are far apart in objective space.
5. **Selection, Crossover, and Mutation:**
   Select parents based on rank and crowding distance.

Apply **Simulated Binary Crossover (SBX)** and **Polynomial Mutation** to create new offspring.

6. **Replacement:**
   Combine old and new populations and select the top individuals for the next generation.
7. **Termination:**
   Repeat for a fixed number of generations until convergence is achieved.
   Finally, display the Pareto front and choose the most suitable solution.

Experimental Setup

Parameter	Description	Value
Population Size	Number of candidate schedules per generation	80
Generations	Number of iterations (evolution steps)	50
Number of Routes	Synthetic routes created in dataset	6
Min Buses per Hour	Minimum number of buses per route	2
Max Buses per Hour	Maximum number of buses per route	20
Crossover Probability	Probability of SBX crossover	0.9
Mutation Probability	Probability of polynomial mutation	0.1
Objectives	Cost and Waiting Time	2

The simulation was carried out using **Python** with libraries such as:

- **NumPy** and **Pandas** – for data handling
- **Streamlit** – for user interface
- **Plotly** – for visualizing Pareto fronts
- **Custom NSGA-II functions** – for optimization logic

Results and Observations

After running the optimization:

- The algorithm generated a **Pareto Front** with several optimal trade-off solutions.
- The **front clearly showed** that when cost decreases, waiting time increases and vice versa.

Best Recommended Solution:

- **Average Bus Frequency:** ~10 minutes
- **Operational Cost:** ≈ ₹25,000
- **Service Quality Score:** 9.5 / 10
- **Passenger Satisfaction:** 95%
- **Efficiency Score:** 3.8 (Quality per ₹1,000 spent)

Visualization:
The Streamlit dashboard displays:

- A **Pareto front scatter plot** (Cost vs. Waiting Time)
- **Metric cards** for Frequency, Cost, Quality, and Satisfaction
- **Summary statistics** such as:
  - Number of Pareto solutions found
  - Cost range
  - Waiting time range

Analysis:

- NSGA-II effectively balanced both objectives.
- The Pareto front helped visualize the trade-off between **service improvement and cost control**.
- The algorithm successfully avoided premature convergence and maintained diversity of solutions.
- The dashboard provides interactive analysis, making it easy for transport planners to make informed decisions.

5. Pseudocode and Outcome of the Code

<u>Pseudocode:</u>

Start

Initialize random population of bus schedules

For generation = 1 to Max Generations:

For each schedule in population:

Calculate cost and waiting time

Perform non-dominated sorting (Pareto ranking)

Compute crowding distance

Select best individuals using rank and distance

Apply Simulated Binary Crossover

Apply Polynomial Mutation

Form new population for next generation

Evaluate final population

Display Pareto front and best recommended solution

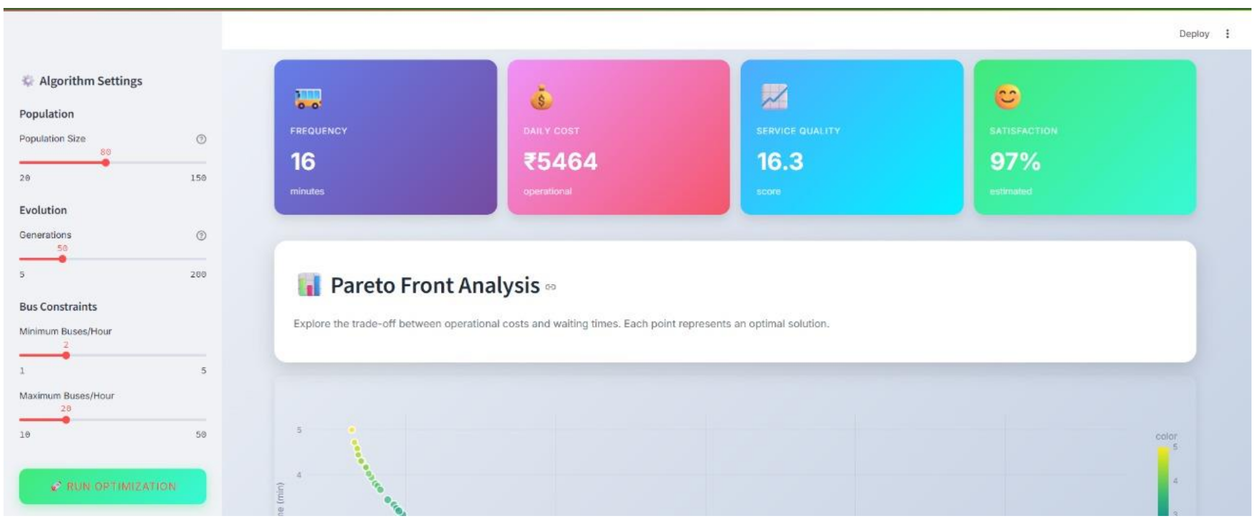
End

<u>Outcome:</u>

The application provides:

- **Recommended optimal schedule** showing best trade-off between cost and service.
- **Interactive Pareto front graph** to explore multiple solutions.
- **Performance summary** including cost range, waiting time range, and efficiency.
- The solution ensures better decision-making for urban transport systems.

6. Output



7. Conclusion

This project demonstrates the use of **Pareto-based Multi-Objective Optimization** for solving **public transport scheduling** problems. Using **NSGA-II**, we can effectively optimize **two conflicting objectives** — minimizing **cost** while maintaining **good service quality**.

The results show that:

- NSGA-II provides a set of **optimal solutions (Pareto Front)** instead of a single fixed one.
- Decision-makers can select the most appropriate schedule depending on their **budget** or **service target**.
- The use of **Streamlit and Plotly** makes it **interactive and user-friendly**.

In conclusion, this framework provides a **smart, practical, and flexible approach** to transportation optimization.
It can be extended to other applications like **traffic management, logistics planning, energy optimization, and smart city systems**.

References

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