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HO CHI MINH CITY UNIVERSITY OF TECHNOLOGY
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AI-Driven Optimization of Bus Scheduling in Ho Chi Minh City

Internship 1 Proposal

Major: Computer Science - IMP

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Abstract

Ho Chi Minh City's public bus system suffers from overcrowding during peak hours, underutilization in off-peak periods, and limited adaptability to real-time conditions. This project introduces an AI-driven framework that integrates Long Short-Term Memory (LSTM) networks for demand forecasting with Ant Colony Optimization (ACO) for dynamic schedule optimization. The system ingests data from ticketing, GPS, weather, and event sources to predict short-term passenger demand and allocate vehicles accordingly. By minimizing waiting times and balancing occupancy rates, the framework aims to improve service reliability, operational efficiency, and passenger satisfaction, supporting sustainable urban transportation.

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I. Problem statement

Ho Chi Minh City’s urban transportation system is facing persistent challenges in the operation of its public bus services. The current scheduling framework is largely based on fixed timetables, which fail to adequately capture temporal variations in passenger demand. Consequently, buses are frequently overcrowded during peak periods while operating inefficiently during off-peak hours.

A report by the Ho Chi Minh City People’s Committee (2024) indicates that the city currently operates 120 bus routes with approximately 2,052 vehicles, delivering around 13,000 trips per day and serving about 250,000 passenger trips daily [1]. However, another report shows that in 2023, the average bus trip carried only 18–19 passengers, a figure significantly below the minimum contractual threshold [2].

Furthermore, the allocation of buses across routes remains suboptimal: certain routes have surplus capacity while others experience shortages. The management system is largely reactive and lacks mechanisms to dynamically adjust operations based on real-time data, thereby diminishing service quality and reducing the overall attractiveness of public transportation. As a result, passengers often encounter extended waiting times, uncertainty regarding bus arrival, and overcrowded travel conditions.

II. Related Work

1. Demand Forecasting

Early approaches to bus passenger demand forecasting often relied on classical time-series models such as ARIMA and its seasonal variants, which were shown to capture short-term temporal fluctuations but failed to generalize under irregular events [3]. Machine learning methods such as Support Vector Regression (SVR) and Random Forests were subsequently introduced, improving prediction accuracy in heterogeneous urban settings [4]. More recently, deep learning approaches, particularly Long Short-Term Memory (LSTM) networks, have demonstrated superior performance in modeling non-linear temporal dependencies and handling exogenous features such as weather and special events. For instance, Cheng, Chen, Wang, and Chen (2022) applied LSTM models to smartcard data and achieved substantial improvements in RMSE and MAPE compared to ARIMA [5].

2. Schedule Optimization

Parallel to demand forecasting, research has explored optimization of bus dispatching and scheduling. Traditional integer programming models provide exact solutions but often become computationally intractable for large-scale networks. Consequently, heuristic and metaheuristic algorithms - such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) - have been widely adopted. For example, Barrera Hernandez, Reza, and Daza (2025) proposed a heuristic dispatching approach that integrates demand forecasting with bus allocation, demonstrating reduced waiting times in simulated case studies [6].

III. Solution Approach

To address the persistent imbalance between supply and demand in Ho Chi Minh City's bus system, this project proposes an AI-driven framework that integrates passenger demand forecasting with schedule optimization. The framework is designed around two tightly coupled components, each playing a critical role in enabling data-driven, adaptive operations.

The first component focuses on passenger demand forecasting using a Long Short-Term Memory (LSTM) neural network. This model predicts passenger volumes at the route, segment, and time-interval levels, leveraging a wide range of input features. These include historical boarding and alighting data obtained from electronic ticketing systems, temporal variables such as time-of-day, day-of-week, and holidays, as well as exogenous factors such as special events, traffic conditions, and weather patterns. Furthermore, the model incorporates real-time data streams including GPS-based bus locations and dynamic passenger counts where available. Previous studies have demonstrated the effectiveness of LSTM models in predicting passenger demand in public transport systems with high accuracy [7], [8]. The outcome of this component is a set of short-term demand forecasts with a target accuracy of over 85%, enabling proactive resource allocation rather than reactive responses.

Building upon these forecasts, the second component applies Ant Colony Optimization (ACO) to dynamically allocate buses and adjust headways. The algorithm considers multiple constraints, including fleet size, vehicle capacity, driver shifts, and operational regulations. Its primary objective is to construct an optimal dispatch plan that minimizes average passenger waiting time while simultaneously improving vehicle occupancy rates. Prior research has shown that ACO is well-suited for solving complex public transport planning and line scheduling problems, effectively balancing service quality with operational efficiency [9], [10]. By leveraging these insights, this component ensures that the system not only enhances passenger experience but also reduces operating costs for transit authorities.

The proposed framework is designed to operate in near real-time through a closed-loop feedback system. The process begins with data ingestion from various sources, such as GPS tracking, ticketing records, weather APIs, and event databases. The LSTM module then generates short-term demand forecasts, which serve as inputs to the ACO-based optimization module for producing revised scheduling plans. These plans are subsequently communicated to the central control system and, where applicable, integrated into passenger-facing applications such as BusMap. Finally, actual operational data are continuously compared against the forecasts, allowing the system to self-adjust and improve prediction accuracy through iterative retraining. Similar real-time spatio-temporal prediction frameworks have been successfully implemented in on-demand transport systems, demonstrating the feasibility of integrating deep learning with adaptive optimization for urban mobility [11], [12].

The implementation of this framework is expected to yield several key outcomes. Specifically, passenger demand forecasts are projected to achieve an accuracy exceeding 85%, average passenger waiting times are anticipated to decrease by at least 20%, and bus occupancy rates during off-peak periods are expected to improve to between 70% and 80%. In addition, more efficient vehicle allocation will contribute to cost savings, thereby enhancing the long-term sustainability of Ho Chi Minh City's public transportation system.

IV. Problem - Solution Mapping

Problem	Proposed Solution
Bus schedules are currently fixed and fail to reflect temporal variations in passenger demand across different hours, days, weather conditions, or special events.	Apply an LSTM-based model to forecast passenger demand at the level of route, segment, and time interval. Input features include historical boarding and alighting data, GPS traces, weather conditions, and holiday calendars.
Long passenger waiting times occur due to capacity mismatches, with severe overcrowding during peak hours and underutilization of vehicles during off-peak periods, leading to inefficiencies.	Employ Ant Colony Optimization (ACO) to optimize service frequency, headways, and vehicle allocation dynamically based on demand forecasts.
Vehicle allocation is suboptimal: some routes operate with excess capacity while others face shortages.	Use ACO to reallocate buses across routes, or introduce shuttle services to high-demand segments without increasing frequency across the entire route.
The system is reactive and lacks mechanisms to adapt quickly to real-time operational data.	Design a real-time operational framework that continuously ingests streaming data (ticketing, GPS, weather) and integrates LSTM forecasts with heuristic ACO updates to provide immediate scheduling recommendations.
Passenger experience is poor, characterized by unreliable information, long waiting times, and frequent overcrowding.	Provide a passenger-facing application that displays estimated arrival times and available capacity, enabling users to plan trips more effectively.

V. Data Types and Sources

In developing an AI-driven framework for bus demand forecasting and schedule optimization, the availability and quality of data play a decisive role. To structure data requirements, they are categorized into three tiers: must have, should have, and nice to have. Must have data are essential inputs without which the system cannot function reliably. Should have data that are highly desirable and significantly improve the accuracy and robustness of predictions. Nice to have data are supplementary inputs that enhance adaptability and user-centric design but are not strictly necessary for baseline system performance.

1. Must have

Data Type: Passenger Data
Key Fields: Boarding/alighting counts, route, timestamp
Potential Sources: Electronic ticketing system, Synthetic Data
Intended Use: Training LSTM, estimating occupancy rates

Data Type: GPS & Operational Data
Key Fields: Latitude/longitude, timestamp, travel time, dwell time
Potential Sources: xebuyt.net, google map
Intended Use: Estimating travel times for ACO optimization

Data Type: Current Timetable
Key Fields: Departure times, headways, driver shifts
Potential Sources: xebuyt.net
Intended Use: Baseline benchmark for comparison

Data Type: Operational Constraints
Key Fields: Fleet size, vehicle capacity, driver shifts
Potential Sources: xebuyt.net
Intended Use: Constraints for ACO scheduling optimization

2. Should have

Data Type: Weather Data
Key Fields: Temperature, rainfall, humidity
Potential Sources: OpenWeatherMap API
Intended Use: Exogenous feature for LSTM forecasting

Data Type: Event Data
Key Fields: Date, time, location
Potential Sources: Websites, news outlets, web crawling
Intended Use: Adjusting for abnormal demand fluctuations

3. Nice to have

Data Type: Passenger Surveys (optional)
Key Fields: Feedback, satisfaction ratings, travel experience, service quality indicators
Potential Sources: Passenger surveys, mobile applications, post-trip feedback forms
Intended Use: Evaluating passenger satisfaction and service quality after deployment

VI. Methodology

1. Framework

The system is composed of two main modules: demand forecasting and schedule optimization. The forecasting module employs an LSTM network to estimate passenger volumes by route, stop, and time interval, using historical data combined with GPS, weather, and event information. The forecast then serves as input to the optimization module, where the Ant Colony Optimization (ACO) algorithm determines optimal headways, trip frequencies, and vehicle allocations. The overall workflow proceeds sequentially: data collection and preprocessing, LSTM forecasting, ACO optimization, generation of dynamic schedules for both the control center and passenger application.

2. Demand Forecasting Model (LSTM)

Inputs include passenger boarding/alighting time series and exogenous variables such as weather, holidays, events, and time-of-day indicators. Categorical features (routes, stops) are embedded into vector space representations. The model output is the forecasted passenger demand by route and stop across future time intervals. A stacked LSTM architecture is adopted, with performance evaluated by MAE and RMSE. A minimum prediction accuracy of 85% is required.

3. Schedule Optimization Model (ACO)

Inputs comprise forecasted demand, fleet capacity, and operational constraints. The output is a dynamic bus schedule specifying headways, trips per hour, and vehicle allocation. The objective function seeks to minimize average passenger waiting time while maximizing vehicle load factors (target 70–80%), subject to fleet and service constraints. In ACO, each “ant” represents a candidate schedule, evaluated by a cost function (waiting time + underutilization), with pheromone updates guiding the search toward optimal solutions.

4. Real-Time Operation

The system operates with streaming data from GPS, e-ticketing, and weather sources. The LSTM model produces short-term forecasts (15–30 minutes ahead), which are subsequently refined through ACO or lighter heuristics for rapid schedule updates. The resulting dynamic schedules are delivered to the control center to support operational decision-making and to passenger-facing applications providing updated waiting times and trip information.

VII. Expected Outcomes

The proposed AI-driven scheduling system is expected to generate several significant outcomes. First, the LSTM-based demand forecasting model is anticipated to achieve an accuracy level exceeding 85%, as measured by MAE and RMSE across different routes and time periods. Building upon these forecasts, the integration of ACO for dynamic headway and fleet allocation is expected to reduce average passenger waiting times by at least 20% compared to conventional fixed timetables. At the same time, bus occupancy rates are projected to improve, reaching 70–80% during both peak and off-peak periods, thereby mitigating issues of overcrowding and underutilization.

In addition, the system will demonstrate strong real-time adaptability by incorporating streaming data sources such as GPS, automated fare collection, weather, and event information, enabling schedule updates within 15–30 minutes. This adaptability enhances the responsiveness of operations to sudden demand fluctuations. From the operator's perspective, more efficient fleet distribution and reduced idle time are expected to yield cost savings in fuel consumption, labor, and vehicle maintenance, while maintaining service quality. Finally, passengers will benefit from shorter and more predictable waiting times, increased service reliability, and improved comfort, factors that are likely to encourage greater adoption of public transportation in Ho Chi Minh City.

VIII. Project Schedule

Phase	Duration	Activities
Phase 1: Data Collection & Preprocessing	2 weeks	- Gather passenger demand data - Collect GPS data from xebuyt.net - Retrieve weather & event data - Clean, normalize, and integrate datasets
Phase 2: Model Development (LSTM)	3 weeks	- Design and implement LSTM network - Train and validate model using historical data - Tune hyperparameters, incorporate exogenous features
Phase 3: Schedule Optimization (ACO)	3 weeks	- Design ACO algorithm for headway and fleet allocation - Integrate with forecast output - Test on simulated demand scenarios
Phase 4: Evaluation & Proposal of Deployment	2 weeks	- Evaluate forecast accuracy (MAE, RMSE) - Evaluate schedule performance (waiting time, occupancy) - Document outcomes and recommendations for real-world deployment

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