Green Route Planner: A Real-Time Air Quality-Aware Navigation System

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***Abstract*—Urban air pollution poses a growing threat to human health, particularly for individuals with respiratory conditions such as asthma or allergies. Despite increasing awareness of the Air Quality Index (AQI), most routing and navigation systems predominantly focus on time and distance optimization, neglecting critical air quality parameters. This study proposes the Green Route Planner (GRP), an intelligent routing system that integrates real-time AQI data to recommend cleaner, healthier commuting routes. Utilizing a novel algorithm enhanced with AQI metrics, the system offers personalized navigation options based on comprehensive user health profiles. The proposed model incorporates real-time data collection, dynamic re-routing capabilities, and AQI forecasting to enhance decision-making during daily travel. The experimental evaluation of the model demonstrates the efficacy of its forecasting components, revealing that simpler statistical models can perform comparably to complex deep learning architectures on the current dataset. The GRP aims to revolutionize urban commuting towards more sustainable and health-aware practices.**

Index Terms*—Air Quality Index, Pollution-Aware Navigation, Health-Centric Routing, Dynamic Re-routing, Smart Cities, Environmental Sustainability, Time Series Forecasting, ARIMA, LSTM, TCN.

I. INTRODUCTION

Urban environments globally are experiencing escalating levels of air pollution, primarily attributed to vehicular emissions, industrial activities, and dense population centers [10]. This pervasive environmental issue poses a significant and growing threat to human health, with prolonged exposure linked to a myriad of adverse health outcomes, particularly for individuals with pre-existing respiratory conditions such as asthma or cardiovascular diseases [11]. The World Health Organization (WHO) estimates that air pollution is responsible for over 7 million premature deaths annually [1], underscoring the critical need for effective mitigation strategies and personal protective measures. Despite the increasing public awareness of the Air Quality Index (AQI) and its implications, the vast majority of contemporary routing and navigation systems predominantly prioritize efficiency metrics, such as minimizing travel time and distance. This singular focus often leads to routes that traverse highly polluted urban corridors, inadvertently exposing commuters to unhealthy air.

Current popular navigation platforms, including Google Maps [6] and Waze [12], while excelling at optimizing for speed and proximity, largely neglect environmental quality parameters. Although some platforms, such as Google Maps, have introduced rudimentary AQI map overlays in select regions, these features typically serve as visual informational layers rather than integral components of intelligent route computation. They enable users to visualize pollution levels but do not offer actionable intelligence for route optimization based on real-time air quality.

The burgeoning availability of real-time AQI data from specialized services (e.g., BreezoMeter [2], Plume Labs [3]) presents a timely opportunity to revolutionize navigation intelligence. Concurrently, advancements in Artificial Intelligence (AI) and machine learning are enabling sophisticated forecasting of air pollution trends using time-series models [8], [13], which is crucial for proactive, health-conscious travel planning.

This study introduces the Green Route Planner (GRP), an innovative and intelligent routing system designed to address this critical gap. GRP transcends traditional navigation paradigms by integrating real-time and forecasted AQI data directly into its routing algorithms. It proposes a novel approach to route evaluation, recommending cleaner, healthier commuting paths that are optimized not only for time and distance but also for minimizing pollutant exposure. A key distinguishing feature of the GRP is its ability to offer personalized navigation options by incorporating individual user health profiles, dynamic re-routing capabilities in response to changing air quality conditions, and proactive AQI forecasting for planned journeys. This paper details the foundational methodology, a review of pertinent literature, and the experimental evaluation demonstrating the GRP's efficacy in advancing health-sensitive urban commuting towards more sustainable and health-aware practices.

II. RELATED WORKS

The integration of real-time Air Quality Index (AQI) data into route planning algorithms remains a relatively nascent field, with very few fully-realized systems [14]. Existing solutions in this domain can be broadly categorized into dedicated AQI data providers and conventional mapping services with tangential environmental overlays.

- AQI Data Provision and Personal Monitoring

Platforms such as BreezoMeter [2] offer comprehensive real-time air quality data, providing granular information on various pollutants and personalized exposure alerts. Similarly, Plume Labs' Flow [3] focuses on personal air quality tracking, enabling users to monitor their exposure over time via portable devices. While invaluable for awareness, these services primarily serve as data sources or monitoring tools; they notably lack integrated route planning functionality, live re-routing capabilities, or predictive features for future air quality.

- Conventional Navigation with Environmental Overlays

Mainstream navigation applications like Google Maps [6] have recently begun to acknowledge air quality by introducing AQI map overlays in certain geographical areas. Users can visualize pollution levels superimposed on their maps. However, this implementation is primarily informational. The system does not possess the inherent intelligence to actively recalculate or suggest alternative routes based on air quality metrics. It functions merely as a passive visual layer, without actionable routing intelligence to guide users away from high-pollution zones.

- Academic Contributions to Pollution-Aware Routing

Academic research has started to explore the conceptual frameworks for pollution-aware navigation. Liu et al. [7] proposed methods for integrating diverse environmental datasets into smart urban routing systems. Their work demonstrates the potential of such systems to contribute significantly to both urban sustainability and public health. Similarly, Wang et al. [4] developed an AQI-informed routing tool specifically for urban cyclists, utilizing dynamic shortest path algorithms. While a valuable step, their system's applicability is limited to a specific mode of transport and does not typically include broader dynamic re-routing or comprehensive personalization based on health profiles.

- Advancements in Air Quality Forecasting

The ability to predict future air quality is a critical component for proactive route planning. Research in time-series forecasting has seen significant advancements, with models like AutoRegressive Integrated Moving Average (ARIMA) [17] and Long Short-Term Memory (LSTM) [18] being widely applied. Sharma et al. [8] demonstrated the strong performance of LSTM networks in predicting pollutant trends, highlighting their utility for systems that require forward-looking environmental assessments, such as the Green Route Planner. Other studies have also explored these and other models for environmental forecasting [15], [16].

- Distinguishing the Green Route Planner

The current landscape reveals a significant gap: the absence of a fully integrated, real-time AQI-aware navigation system that not only adapts routes based on current air quality but also considers individual user health profiles, incorporates future AQI forecasts, and enables dynamic re-routing during a journey. The Green Route Planner (GRP) is designed to comprehensively address this multifaceted challenge, distinguishing itself by offering personalized, health-centric route optimization and seamlessly integrating live and predicted AQI data for a truly proactive and health-conscious commuting experience.

III. Proposed Method

The Green Route Planner (GRP) is built upon a robust, modular architecture designed to integrate real-time environmental data with personalized user preferences. The system operates through a sequential and iterative process flow, ensuring that route calculations are always based on the most current and relevant data. Its core components are outlined below:

A. Overall System Architecture

The GRP system operates through a sequential and iterative process flow, ensuring that route calculations are always based on the most current and relevant data. The core components are:

- Data Collection Layer: Responsible for fetching raw AQI and potentially other environmental data.
- Data Preparation and Integration Module: Processes raw data, generates synthetic data, and unifies all information into a structured format.
- AQI Forecasting Module: Utilizes machine learning models to predict future AQI values for different geographical segments.
- Health Profile Customization Module: Manages user-specific health sensitivities and preferences.
- Smart Routing Algorithm: The core logic for computing optimal paths considering AQI and user preferences.
- Dynamic Re-Routing Engine: Monitors in-journey conditions and triggers re-computation if necessary.
- Visualization and User Interface: Presents routes and AQI information clearly to the user.

Figure 1. Green Route Planner System Process Flow

B. Data Preparation Techniques

Effective air quality forecasting relies heavily on high-quality, comprehensive datasets. Given the practical challenges of acquiring extensive, real-time historical AQI data for specific urban road segments, our methodology employed a combination of real-time data fetching and sophisticated synthetic data generation to create a robust and representative dataset [19].

Real-Time/Historical Data Fetching (Simulated):

- Source: Initial, limited real-time and historical AQI data was simulated by interacting with a public API (e.g., OpenWeatherMap API) for a single location, Dhaka.
- Parameters: This data included key pollutants (PM2.5, PM10, SO2, NO2, CO, Ozone) and the composite AQI value.

- Mapping: The fetched data was geographically mapped to a dummy road segment (RS_A001) with specific latitude and longitude coordinates, providing a foundational real-world anchor.

Generating Synthetic Data:

- Methodology: A simple statistical method was implemented to augment the limited real data. This involved generating 9,999 additional synthetic air quality records. The process sampled existing real records and introduced random noise to pollutant values, ensuring plausibility. Crucially, realistic timestamps were generated to simulate temporal patterns [20].
- Purpose: The synthetic data was vital for creating a sufficiently large dataset (totaling 10,100 rows) to adequately train and validate various machine learning forecasting models, compensating for initial data scarcity.

Data Integration and Cleaning:

- Combination: Data from all simulated sources (road segments, limited real API data, and synthetic data) was meticulously combined into a single, unified Pandas DataFrame.
- Timestamp Handling: Robust timestamp parsing was implemented to handle mixed date formats across the integrated data, ensuring temporal consistency.
- Cleaning: Rows containing invalid or unparseable timestamps were systematically identified and removed to maintain data integrity. The dataset was then prepared for time-series analysis, ensuring proper indexing and format.

C. AQI Forecasting Module

Algorithms and Model Preparation The AQI Forecasting Module is critical for enabling proactive health-conscious route planning. It predicts future air quality patterns, allowing users to factor in expected changes along their planned routes. We evaluated three distinct time-series forecasting models: ARIMA [17], LSTM [18], and TCN [21]. Each model was chosen for its specific strengths in handling sequential data, ranging from traditional statistical methods to advanced deep learning architectures.

D. Smart Routing Algorithm The core of the Green Route Planner is its modified shortest path algorithm [22]. It adapts classic algorithms like Dijkstra's or A* search to consider air quality.

- Mechanism: Instead of solely minimizing distance or time, the algorithm minimizes a weighted sum that combines traditional travel cost (distance/time) with a "pollution exposure cost".
- Edge Weight Modification: Each segment (edge) in the city's transportation graph is assigned an AQI value. This AQI value is then used to calculate a cumulative pollution exposure score for that segment. The total weight of an edge (u,v) is calculated as:

$$\text{Weight}(u,v) = \alpha \cdot \text{Distance}(u,v) + \beta \cdot \text{TravelTime}(u,v) + \gamma \cdot \text{AQI\_Exposure}(u,v,\text{ForecastedAQI})$$

Where α, β, and γ are tunable weights influenced by the user's health profile and preferences. For instance, a user with severe respiratory conditions would have a higher γ value, prioritizing cleaner routes even if they are longer.

E. Health Profile-Based Customization

The Green Route Planner offers personalized navigation by allowing users to define a health profile. Parameters include specific respiratory conditions (e.g., asthma, allergies), sensitivity levels to various pollutants, and general travel preferences (e.g., a strong preference for cleaner routes even if they incur a longer travel time or distance). These user-defined inputs are translated into a weighting factor (e.g., respiratory_condition_factor in the pseudocode) that directly influences the γ parameter in the edge weight calculation. This ensures that the smart routing algorithm prioritizes air quality considerations more heavily for sensitive users. This concept aligns with personalized health applications in smart cities [23].

F. Dynamic Re-Routing

One of the advanced features of the GRP is its dynamic re-routing capability [24]. As users embark on their journey, the system actively monitors real-time AQI conditions along the planned route. If there is a significant deterioration in air quality on the current path, or if a newly computed cleaner and comparably efficient alternative becomes available, the route engine will automatically trigger a re-routing process. This is particularly beneficial in highly dynamic urban environments where air quality can fluctuate rapidly due to traffic congestion, industrial activity, or meteorological changes.

G. Visualization and User Interface

The Green Route Planner employs an intuitive and interactive map interface to present information to the user. Leveraging tools conceptually similar to Tableau [9] for visual clarity, the interface highlights pollution zones, color-codes route segments based on their current and forecasted AQI levels, and clearly displays alternate "green routes." Color-coded AQI indicators (e.g., green for good, yellow for moderate, red for unhealthy) provide immediate, intuitive feedback, empowering users to make informed decisions about their commute.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental phase aimed to evaluate the effectiveness of different machine learning models in forecasting Air Quality Index (AQI) values, a critical component for the Green Route Planner's proactive routing capabilities.

A. Dataset Description

For our experiments, a comprehensive dataset totaling 10,100 rows was constructed. This dataset primarily comprised synthetic air quality records, augmented with a small portion of limited real-time and historical AQI data fetched via the OpenWeatherMap API for Dhaka, Bangladesh. The inclusion of synthetic data was a necessity to create a sufficiently large and diverse dataset for robust model training and validation, given the initial scarcity of extensive real-world, segment-specific AQI data. Each record included AQI values, various pollutant concentrations, and precise timestamps. The dataset was split into training and testing sets to evaluate model generalization. Standard preprocessing steps were applied, including scaling and sequence generation, to prepare the data for the time-series forecasting models.

B. Performance Metrics

The primary metric used to evaluate the forecasting accuracy of the models was Root Mean Squared Error (RMSE). RMSE is a widely used metric in regression problems that measures the average magnitude of the errors [25]. It is calculated as the square root of the average of the squared differences between predicted values and actual values. The formula for RMSE is given by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

Where:

- N is the number of observations
- yi is the actual AQI value
- y^i is the predicted AQI value

C. Experimental Results

After extensive model training and hyperparameter tuning for each algorithm (ARIMA, LSTM, TCN) on the prepared dataset, the following RMSE scores were achieved for AQI forecasting:

Table I. AQI Forecasting Model Performance (RMSE)

Model	RMSE Score (Lower is Better)
Optimized ARIMA	0.249
Optimized LSTM	0.249
TCN	0.257

D. Analysis of Results

The experimental results revealed a particularly intriguing and significant insight: the Optimized ARIMA model performed identically to the Optimized LSTM model, both achieving an RMSE of 0.249. This outcome challenges the common assumption that more complex deep learning models, such as LSTMs, will inherently outperform traditional statistical methods in all time-series forecasting tasks, especially given their ability to capture non-linear relationships.

Several factors could contribute to this observed parity:

1. **Dataset Characteristics:** The synthetic nature of the majority of our dataset, even with added noise, might have introduced a level of linearity or simplicity that ARIMA, a linear model, could effectively capture. Highly complex, real-world time series with strong non-linear dynamics often highlight LSTM's superiority. In our case, the underlying patterns, while plausible, might not have been sufficiently complex to necessitate the deep learning capabilities of LSTM.
2. **Feature Set:** The models primarily relied on historical AQI values. The absence of diverse exogenous features (e.g., weather data, traffic density, industrial activity) meant that the models might not have had enough rich, external context to leverage the full non-linear modeling power of LSTMs. With a richer feature set, the performance gap between ARIMA and LSTM might widen, favoring LSTM.
3. **Hyperparameter Tuning:** While both models were optimized, it's possible that the "optimal" configuration for LSTM on this specific synthetic dataset converged to a performance level achievable by a well-tuned ARIMA model.
4. **TCN Performance:** The Temporal Convolutional Network (TCN) showed a slightly higher RMSE of 0.257, indicating marginally lower accuracy compared to ARIMA and LSTM. While TCNs offer advantages in efficiency and parallelization for very long sequences, their performance on this dataset did not surpass the other two models. This suggests that for the observed data characteristics, the architectural benefits of TCNs didn't translate into superior predictive accuracy.
5. **Implications:** This finding underscores that data quality and characteristics are often more crucial than model complexity in achieving forecasting accuracy, particularly in the initial research phases with synthesized data [26]. For future real-world deployments, the choice of the model might lean towards simpler, more interpretable options like ARIMA if their performance is comparable to complex deep learning models, thereby reducing computational overhead and simplifying deployment.

V. CONCLUSION

Urban air pollution presents a profound public health challenge, yet current navigation systems largely overlook environmental quality, routing users through potentially harmful zones. This study successfully addresses this critical gap by proposing and developing the Green Route Planner (GRP), an intelligent navigation system that integrates real-time and forecasted Air Quality Index (AQI) data to suggest cleaner, healthier commuting routes. Our proposed methodology encompasses a robust system architecture, including modules for real-time AQI data collection, sophisticated data preparation (combining real and synthetically generated data), health-profile-based customization, an novel smart routing algorithm that modifies edge weights based on pollution exposure, an advanced AQI forecasting module, and dynamic re-routing capabilities. This comprehensive approach ensures personalized and adaptive navigation for health-conscious individuals.

A key contribution of this research lies in the experimental evaluation of various time-series forecasting models for AQI prediction: ARIMA, LSTM, and TCN. Our empirical results, based on a 10,100-row dataset, revealed that the Optimized ARIMA model achieved an RMSE of 0.249, performing identically to the more complex Optimized LSTM model. The TCN model showed a slightly higher RMSE of 0.257. This surprising parity highlights that, for the current dataset, a simpler, more interpretable model like ARIMA can be as effective as deep learning counterparts, underscoring the paramount importance of data quality and characteristics over sheer model complexity. The Green Route Planner represents a significant step towards revolutionizing urban commuting, shifting the paradigm from mere efficiency to environmental health and personal well-being. By empowering users with information and actionable healthier routes, GRP contributes to more sustainable urban practices and improved public health outcomes.

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