ARTIFICIAL INTELLIGENCE IN BUS ROUTE AND TIMETABLE OPTIMIZATION

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***Abstract.** The modern bus systems have become an integral part public transportation infrastructure, providing convenient and affordable transportation to large populations. However most of bus systems suffer from inefficient routes, irregular schedules and congestion related delays.*
***Keywords:** artificial intelligence, large datasets, dynamic time tables, optimization method.*

The traditional methods of bus routes and schedule planning rely on static schedules and historical averages, which limits their ability to adapt to dynamic changes in demand and traffic conditions. Artificial Intelligence (AI) offers advanced tools for optimizing bus routes and timetables through data-driven predictions and adaptive decision-making. The discoveries suggest that AI-based approaches can considerably reduce passenger waiting times, minimize operational costs, and enhance overall system performance.

Traditional bus planning involves fixed timetables and predetermined bus routes structures designed based on historical data. While these methods are straight forward, they lack flexibility and the ability to response. As modern populations grow and transportation systems become more complex, there is an increasing need for intelligent and efficient solutions that can adapt to changing conditions.

Bus route optimization involves designing paths that efficiently connect residential, commercial, and industrial areas while minimizing travel time and operational costs. In practice, route optimization must consider multiple constraints, including road capacity, stop locations, service coverage requirements, and vehicle limitations.

AI-based optimization techniques can process large datasets to identify high-demand corridors and underutilized segments. Machine learning models can detect spatial and temporal demand patterns, allowing planners to redesign routes to better serve passenger needs. Metaheuristic algorithms such as Genetic Algorithms and Ant Colony Optimization are commonly used to search for near-optimal route configurations within large and complex networks.

The optimization of time tables is inherently linked to bus routes; even if routes are well-designed, time tables may not necessarily run efficiently unless departures are well-scheduled. Bus bunching is one of the most common problems that occur within bus routes; it is defined by buses that are meant to run at regular headways arriving en masse instead of individually due to small delays that occur along the routes [1].

Artificial intelligence has the potential to mitigate this problem by using dynamic time tables to ensure that buses depart according to machine learning predictions of changes in passenger demand and time differences between routes [2]. By using this technology, transportation authorities would be able to adjust bus departures to run closer to actual passenger demand. In addition to this, reinforcement learning would allow buses to dynamically adjust their departures to run slightly earlier or later to maintain headways [1]. According to research results, using deep reinforcement learning would result in improved time tables and minimize passenger waiting time compared to static time tables [3].

Another optimization method is using hybrid optimization techniques to solve bus routes and time tables. Using this method would result in improved optimization of solutions to complex transportation systems [4].

Therefore, by using artificial intelligence to optimize bus routes and time tables, transportation systems would shift from static to dynamic decision-making systems, resulting in improved efficiency and sustainability of public transportation systems.

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