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Abstract

Cities increasingly rely on public transportation to provide residents with equitable and sustainable access to key opportunities and services. Yet conventional fixed-route transit (FRT) systems often struggle to serve low-density or suburban areas efficiently, while purely on-demand services are costly to operate at scale. Hybrid transit systems, which combine the efficiency of scheduled fixed-route services with the flexibility of demand-responsive transit (DRT), have emerged as a promising way to reconcile these competing goals. Realizing this potential, however, requires planning methods that treat the design of both systems as interdependent rather than sequential, since decisions about the fixed-route network directly shape the demand and cost of the on-demand service it must complement, and, conversely, a significant share of the system's total operational cost stems from the demand-responsive component, meaning the quality of the fixed-route network cannot be properly assessed without accounting for the DRT operations it generates.

This thesis addresses that challenge through the central research question: *how can the strategic design of a fixed-route transit network and operational planning of a demand-responsive transit service be jointly optimized within a single, computationally tractable decision-support framework?*

To answer this question, the thesis first establishes a structured understanding of the field through a systematic review of the FRT–DRT integration literature, identifying a unified classification of existing approaches and showing that truly joint strategic optimization of both systems remains largely unexplored. Building on this gap, it introduces the Integrated Hybrid Transit Design Problem (IHTDP), a bi-level optimization problem that simultaneously designs the fixed-route network and the demand-responsive operations that support it, solved through a tailored metaheuristic algorithm. Numerical experiments show that this joint design approach substantially reduces total fleet requirements compared to conventional sequential planning, without compromising service coverage or passenger service quality. Finally, to make the framework practical for large-scale, real-world planning, machine learning surrogate models are integrated into the optimization process to approximate costly operational evaluations, cutting computational effort while preserving solution quality.

Together, these contributions demonstrate that combining mathematical optimization with machine learning within a unified framework has the potential to offer transit planners a

scalable and effective tool for designing integrated hybrid transit systems that are both efficient and responsive to real travel needs.