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Operations Research in Public Transit and Urban Mobility: A Comparative Review of Eighteen Studies

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ABSTRACT

Public transit is a vast, interconnected systems design problem: coordinating numerous routes, frequencies, vehicles, operators, signals and passengers with uncertain demand and travel times. Operations Research (OR) brings a rich and mature arsenal of tools to tackle these issues. This report brings together 18 published and preprint papers which we have reviewed individually in six student-focussed sections that all bring OR to design of bus routes, timing of signals, quality of service, scheduling of vehicles and crews, demand-responsive transit, gig transportation, bike sharing, and electric vehicle fleet management. We cluster the papers into five categories and compare the OR techniques, which include calculus-based optimisation, mixed-integer, and set-partitioning programming, column-generation, and decomposition, genetic, and large-neighbourhood-search heuristics, robust optimisation, queueing, and stochastic-process models, Markov decision processes, and simulation. Three broad insights stand out. The first is the near-exclusive use of large-scale heuristics for bigger problems versus exact algorithms for smaller problems. The second is the treatment of demand and supply uncertainties as part of the decision making rather than as a post-hoc model refinement. The third is the real improvements, which are measured relative to different baselines on different case studies. We conclude by addressing limitations in the literature as well as in our review.

Keywords: Operations Research, Public Transportation, Bus Scheduling, Demand-Responsive Transportation, Integer Programming Heuristics Robust Optimisation, Queueing Theory.

1. INTRODUCTION

Every single morning before a bus takes off it needs to answer so many basic questions. Namely, What are the streets that the bus should follow? What is the time difference between the same bus routes? Which designated driver takes up which route and trip? What happens to the waiting passengers when a bus unexpectedly breaks down? Each question's solution is a decision with a cost, a set of constraints and usually, some uncertainty. That is exactly the scenario of the problem Operations Research was built to tackle.

This report is about how OR (operations Research) is applied to public transportation in an urban space along with mobility. We found this specific topic the most important for three major particular reasons.

A. Transit is a public good in which a small percentage of the improvements translate into very large total savings, since even a meagre 1-2% reduction in an agency's annual cost will end up resulting as a large sum.

B. Transit problems are also a natural bridge between textbook Operations Research (assignment, transportation, linear and integer programming, network models) and real life practice and utilisation of them, where those simple models become large, uncertain and messy.

C. Finally, the given field is a moving one, thus making the ride-sharing, demand-responsive services, bike-sharing and electric buses creating new problems that old and timetable-centred models were not designed for.

In this project, each of the six members of our group read three papers and analysed them along the same unified lines. The Operations Research tools that are used, how it formulates and solves the problems that are faced by it. The benefits and limitations associated with it, its connection to topics covered in class and other possible applications in real life. This report merges all of those eighteen analyses into one concise comparative study. Section 2 splits and reviews the papers by theme. Section 3 analyses the Operation Research techniques across them and Section 4 presents the inferred conclusions that we have come up with (the gaps we found, and what we could have done better).

2. LITERATURE REVIEW

2.1 Route, frequency and vehicle-type design

Chien, Dimitrijevic and Spasovic (2003) designed a single bus route from a suburb to the city center. During this, the major problems encountered were which street the bus should drive on (operator cost) and how often it should come to the street (user cost). The route, headway, and fleet size are treated as decision variables, and the objective is the total system cost. Shorter headways raise the operator cost but lower the passenger waiting cost, so the optimal headway is calculated by finding the first and second (to prove minima) derivatives of headways (H). Since the streets are not in a grid pattern, the diagonal streets are converted into horizontal and vertical links, and infeasible links are given infinite length, similar to the big-M penalty. The choice of which street to drive on is discrete, and hence it is solved by exhaustive search. The benefit of this was that the closed-form headway formula is sensitive to demand, bus size, and value of time and hence is transparent and easy to interpret.

Bie, Tang and Wang (2020) tried to solve the problem that is faced by real cities: bus routes often overlap; hence, the passenger can board either bus (whichever comes first); however, on the non-overlapping part of the route the passenger can only choose one option. This causes uneven crowding, and overlapping routes get more frequency than non-overlapping routes. Passenger costs are determined based on passenger waiting time, passenger coincident waiting time, and passenger ride time. With the help of passenger origin-destination data, heuristic jointly determines the departure time of the bus and the vehicle size of the trip. It sends large buses where demand is heavy and smaller ones where demand is less. On three real routes in Harbin, China, it cut total passenger travel time by 5.2% and total cost by 8.8% compared to the baseline model that ignored the overlapping routes. The study is extremely helpful for measuring profit on real peak-hour data.

2.2 Signal coordination and service reliability

The authors raise the question of whether signal priority for buses can be used as a replacement of bus dwell time to provide service reliability after timetabling of the public transport system has been established. They analyze the problem of conditional bus signal priority where the request for priority is made by the bus only when it is late and evaluate it against the strategies of no priority and unconditional priority for various holding policies (none, schedule and headway). Bus lateness in their approach follows the pattern of Brownian motion with drift allowing them to obtain analytical formulas for the mean lateness, its variance, recovery distance and stability condition similarly to queueing systems that converge and diverge. Analytical expressions correspond well to the results of the microsimulator and conditional priority provides the same level of service reliability as the unconditional one with only half of the number of priority requests.

2.3 Vehicle, crew and staff scheduling

Mertens, Wolbeck, Rößler, Xie and Kliever, the authors discuss the various optimization techniques applied to vehicle scheduling, crew scheduling, and crew rostering, which have traditionally been solved separately but increasingly jointly, since this is cheaper through the use of integration. The authors organize their discussion around four dimensions of the existing literature, including network representation, optimization criteria, solution approaches and data used in testing, where the authors point out that these optimization problems are most often modeled using network flow or set partitioning formulations and solved using column generation. Then, in Ge et al., the authors test what is the maximum that can be achieved by running a standard commercial solver on an integrated vehicle and crew scheduling problem. Their model deals with instances of roughly 3,000 duties, vehicles and trips with 10 depots, many more than the 238-trip instances that the original heuristic addressed, while buffer times and delay propagation cost very little in terms of computation time. The robust version runs in the same amount of time but gives worse results, thus putting a cost on the safety margin.

2.4 Demand-responsive transit, ride-sharing and multimodal systems

Zhang, McDonald, Yang, Zhao and Cochran present a formulation for the non-emergency medical travel problem as a mixed integer program (Dial-a-Ride routing model) with binary arc variables and time window, capacity and pick-up before drop-off constraints. The Operator Model aims to minimise operating time of vehicles; while the User Model tries to minimise deviation from planned departure times. Using the User Model on a one day instance of 58 trips (out of 22,870 cleaned records) using Gurobi software, time deviation was reduced from 35.7 to 0.9 minutes (97.4%) per trip, but it required extra time for vehicles (5,090 minutes versus 4,124 minutes).

Carotenuto, Monacelli, Raponi and Turco incorporate the use of a web-based insertion heuristic applied to the dynamic Dial-a-Ride problem with an Arena-based discrete event simulation which includes aspects of congestion and customer behaviour, they measure the waiting time and the proportion of customers who fail to receive service. Their key contribution is the ability to perform "what-if" analyses without affecting the live system, but at the cost of using non-optimal heuristics for insertion.

Guan, Wu, Wang and Zhao developed a twostage framework for demand-responsive transit. Stage one is a static stage, where historical demand is utilized to determine high probability boarding stations, and a linear integer programming problem is solved via genetic algorithm and large neighborhood search; stage two entails live demand insertion into routes. In this case, where there are 11,909 demands, 48 stations, and 232 live demands, the high probability stations approach increases the average full load rate

from 17.6% to 27.6% and passenger response rate from 23.5% to 36.8%, and multiple runs using GA deviate from the optimal solution by 3.1%. They observe that small passenger flow hinders full load achievement, and data is not public.

Hou et al. (2018) consider the ride-sharing problem as one of deciding who should be matched to what vehicle and also of choosing the appropriate routing for the vehicle involved through integer programming and large neighborhood search heuristics. The importance of their research comes from demonstrating that an apparently easy problem of matching turns into a difficult one when capacity and pick-up and drop-off ordering considerations are introduced.

Li and Chung (2020) consider ride-sharing for travel times which may be uncertain. Routes which seem reasonable on average may not work during congestion, thus they consider robust optimization with insertion and tabu search among other heuristics for large problems. Sensitivity to uncertainty decreases but perhaps unnecessarily in this way, thus choosing the right level of uncertainty becomes a modelling decision.

Yu, Miao, Bayram, Yu and Chen (2021) study multimodal mobility with the integration of ride sharing with public transport as a mixed integer linear programming problem and propose an angle-based clustering heuristic that partitions a large problem into smaller sub-problems, as compared to the exact method. The benefits of this type of integration are a reduction in travel distance and time but at the cost of increased complexity and lack of optimality for the heuristic solution.

2.5 Shared mobility and electrified fleets

Zhou, Li, Yue, Nie and Guo (2022)

This paper is about bike-sharing systems in which bike stations are understocked and others have excess stock. Traditionally, most approaches to rebalance bikes make use of demand forecast ex-ante and plan routes based on the forecast. However, Zhou et al. consider the uncertain demand forecast in their approach. Specifically, they determine demand forecasts at each station by utilizing historic ride data in a data-driven distributionally robust optimization (DRO). This method ensures that the model does not make an assumption on one fitted demand distribution, but considers the worst-case demand distribution that is still compatible with the available data. Based on these probabilities of demand being either excess or shortage at the stations, they develop a routing problem for rebalancing operations.

Liang, Jena and Lodi (2024)

Ask a different question: how much does the way we write the model matter? They build a general mixed integer program for dynamic bike rebalancing and then change four things in it: how trips are represented, how time is discretised, how demand is reallocated, and the order in which events are processed. Each resulting plan is tested in a detailed simulator, so it is judged on something closer to real operation than the model's own assumptions. Two findings stand out. Dynamic rebalancing beat static plans, and assumptions that look minor changed the amount of lost demand noticeably. The paper is therefore less about a new algorithm and more about a way of checking which simplifications are safe. That is worth remembering when we read the other studies in this review, since a reported improvement can partly come from the model's own assumptions.

Najafi, Gao, Parishwad, Tsaousoglou, Jin and Yi (2025)

Shift focus from bicycles to electric buses. In this work, charging infrastructure, scheduling of buses, generation, storage and the distribution of electricity network are considered within an integrated optimization problem. It creates a complex non-linear formulation, which is made tractable by Bender's decomposition – an overarching master problem optimizes the entire scenario, whereas multiple sub-problems verify feasibility of constraints. In the authors' case study, the disregard of the electricity network led to violation of some constraints, implying that even though the scenario for the buses looks feasible, the grid cannot satisfy it. Besides, the model is based on several simplifying assumptions, such as dependence of energy consumption on distance only, costlessness of batteries degradation and impossibility of charging for long routes. Taking together with the complexity of computations, it is more suitable for infrastructure planning rather than for real-time management.

3. ANALYSIS AND METHODOLOGY

3.1 Approach

We analysed each paper using five metrics: the technique used, how it formulates the decision problem (variables, objective, constraints), its benefits and limitations, its link to course topics, and its potential for other applications. Then we compared papers across those objectives, grouped the techniques into families, and looked for patterns in what the authors chose to do, the problems they encountered, and the benefits they were able to achieve. For papers that reported numerical results, we recorded them as the authors stated and did not re-derive them.

3.2 Technique families

Table -1: Technique families

Technique family	Studies	Main strength	Main weakness
Calculus and exhaustive enumeration	Chien et al.	Gives clean, closed-form answers you can follow step by step, and is likely optimal on small cases	Doesn't scale, and assumes values stay fixed and demand is known
Mixed-integer and set-partitioning programming	Zhang et al.; Ge et al.; Ihara; Yu et al.; Hou et al.; Liang et al.	Finds exact or near-exact solutions, with constraints written out explicitly	Solve times balloon quickly as instances get bigger
Column generation, branch-and-price, Benders decomposition	Ihara; Zhou et al.; Najafi et al.	Splits very large problems into pieces that are easier to handle	Tricky to implement and computationally heavy
Heuristics and metaheuristics (GA, LNS, insertion, tabu, clustering)	Bie et al.; Yang et al.; Guan et al.; Carotenuto et al.; Hou et al.; Li and Chung; Yu et al.	Quick, scalable, and works well on real networks	Can't promise the solution is optimal
Robust optimisation	Ge et al.; Li and Chung; Zhou et al.	Solutions stay feasible even when inputs shift	Can end up overly cautious, and you have to define an uncertainty set up front
Queueing and stochastic processes	Mo et al.; Anderson and Daganzo	Quick formulas for expected performance and stability	Relies on fairly simple distributional assumptions
Markov decision processes and approximate dynamic programming	Song et al.	Copes well with a chain of decisions made under uncertainty	Hard to tell how far the approximation is from the true answer
Simulation (standalone or hybrid)	Carotenuto et al.; Liang et al.; Anderson and Daganzo (validation)	Shows how a plan holds up in realistic conditions and makes what-if testing easy	Only evaluates plans; it can't optimise them on its own

3.3 Exact versus heuristic methods

The common trend across the literature is that the methodological choices correlate directly with the dimension of the problem. The authors of the reports applied formulation strategies such as complete enumeration (Chien et al.) or standard solver optimization (Zhang et al.) and then they explicitly restricted their test cases to small scales (e.g., 56 zones or 58 trips per day). However, in the case of modeling large-scale situations such as signalized arterials (Yang et al.), overlapping routes (Bie et al.), or demand-responsive transit fleets (Guan et al.), the authors mostly resorted to genetic algorithms or insertion heuristics and thus accepted near-optimal solutions.

However, recent findings challenge this dichotomy:

- Advances in algorithms for exact solvers: Ge and others have shown that modern solvers are now capable of dealing with larger problem instances than was previously thought, which means that the size of an instance on its own no longer has to lead to the use of heuristic approximations.
- In exact frameworks, there are performance gaps: Ihara demonstrates that in only about 3% of the test cases genuinely global optimality was achieved using standard column generation, which shows that conceptual optimality does not ensure empirical convergence.
- Bias in baseline selection: Heuristic evaluations often depend on inadequate benchmarks (for example, random signal offsets in the work of Yang et al. or overlap-ignoring models in that of Bie et al.). Although such comparisons do show

that the heuristic approaches are more effective than naive baselines, they do not measure how closely the heuristic solutions approximate the theoretical global optima.

3.4 Treatment of uncertainty

Uncertainty is handled in the reviewed studies in four different fashions. The deterministic approach uses demand and travel times as known parameters: Chien, Dimitrijevic and Spasovic (2003) consider static demand and fixed intersection delays, Yang et al. (2015) set travel times at section level, and Zhang et al. run their tests on one day based on 58 trips where the reliability of results is equal to the accuracy of assumption that planning and operational days are similar. Analytic approaches define randomness explicitly: Anderson and Daganzo model random walk with drift, Mo et al. build up combination of bulk service queuing system and Markov process of normal/disrupted state, and Song, Shalaby and Bodur develop Markov Decision Process; closed form solutions rely on simple distributional assumptions. The robust approach maximizes the worst case: Ge et al. prove that using the safety margin increases the value of the objective function, Li and Chung demonstrate that robust solutions to ride sharing problems are over conservative, and Zhou et al. propose distributionally robust optimization solution that is valid only under assumption that demand lies within the assumed uncertainty set. Simulation runs the scenario of the plan being applied in the conditions unseen by the optimizer (e.g., Carotenuto et al., Liang, Jena and Lodi). None of the treatments can be considered better than others, depending on the context – planning or online decision-making and costliness of the wrong assumption.

3.5 Realism versus tractability, and whose objective?

However, any model sacrifices some degree of realism in order to be solvable. For instance, Chien et al. assume exhaustive search, which applies to only a 56-zone grid, Bie, Tang and Wang (2020), Yang et al. (2015) and Hou et al. (2018) make heuristic assumption without the guarantee of optimality, Song et al. use multiple layers of approximations, and Najafi et al. oversimplify the energy consumption and obtain a model that is still inefficient. But the border is quite flexible – for example, Ge et al. demonstrate that a generic solver is able to accommodate buffers and delay propagation without great expense, Ihara manages to bring the share of optimal solutions by his column elimination procedure from 3% to 99%, and Liang et al. observe how small changes in the problem formulation, such as the choice of an ordering of events, may significantly influence the amount of lost demand. The second issue is whose interests the objective of the model represents. In case of Chien et al. and Bie et al., operator and user costs are combined into one sum, thus implicitly assuming a certain exchange rate of money and time, while Zhang et al. make two separate models demonstrating the trade-off explicitly: their User model decreased average schedule deviation from 35.7 to 0.9 minutes but increased vehicle-minutes from 4,124 to 5,090. Anderson and Daganzo prove that priority impacts negatively other road users, while Mo et al. establish that crowded stations are especially affected by disturbances; such an objective is hard to reflect using averages.

3.6 Connection to course concepts

As we went through the eighteen studies, we constantly came across things that we had already covered in class, but on a much larger scale. The matching of vehicle types with drivers to jobs is an example of the Assignment Problem in practical terms. Ride-sharing and multimodal routing are once again instances of the Transportation and Assignment Problems, with the exception that the variables must be whole numbers since you can't send 0.4 of a car. The headway studies, which examine how far apart buses or trains should be, involve setting a derivative to zero and then checking the second-order condition to make sure it's a minimum. The "infinite-length" dummy links which some of the papers include in a network are equivalent to big-M penalties: a very large cost that prevents the model from ever selecting that route. Crew scheduling is an example of integer programming with coverage constraints, meaning that every trip must be covered by someone. Signal-offset timing brought back memories of project networks, in which you add up the cumulative times along a path to determine when each event can take place.

What we've learned from this is that simplex is the starting point, but it doesn't take you all the way there; when decisions have to be integers, the future is uncertain, or the network is large, then you need the additional tools that are provided in these papers.

3.7 Transferability

The authors as well as our reviewers each mentioned separately that these ideas are not restricted to the field of transport. The method of set partitioning, which is used for grouping flights into crew pairings, can just as easily be applied to the preparation of hospital rosters. Conditional-intervention control, which only acts when certain conditions are met, could be used to operate elevator dispatch or to make room for emergency vehicles. Robust optimisation, a technique that takes account of the possibility of things going wrong, is suitable for inventory and workforce planning. The approach known as predict-then-optimize—which involves making a forecast first and then making a decision—applies to parcel delivery and to warehouse replenishment. Finally, bulk-service queues, in which people are served in groups, also apply to call centres and system outages.

4. CONCLUSION

4.1 Conclusions

Operations Research performs effectively in all eighteen cases of transit choices, although its use must be determined by answering three important questions, namely the size of the instance, the level of uncertainty of the input and the intended objective. In case of small instances, it is beneficial to adopt a more precise approach to solving the problem, whereas in the case of large instances, a decomposition heuristic approach is better suited. It is important to mention that the best papers adopt several approaches at once, for example heuristics with simulation (Carotenuto), prediction with exact routing (Zhou), or optimization with decomposition (Najafi).

4.2 Benefits

There is substantial literature on quantified improvements made by various optimization strategies, such as 5.2% reduced passenger travel time and 8.8% reduced cost (Bie), 31.9% reduced red-light duration (Yang), reduced schedule deviation from 35.7 minutes to 0.9 minutes (Zhang), increase in optimization from roughly 3% to 99% (Ihara), and similar reliability with half the number of

requests for priority at signalized intersections (Anderson and Daganzo). Also, many algorithms do not require significant costs to implement since there are ready-made solutions.

4.3 Drawbacks and gaps in the research

- **Narrow Case Studies:** A lot of the findings are based on one particular route, one particular artery, one particular day, or even one particular bike sharing system.
- **Simple assumptions used in all papers:** Travel time, uniform vehicles, fixed delay at intersections, simplified distributions and neglected battery aging.
- **Single-route focus.** Several models ignore interactions between routes, which limits network-level contingency planning (Mo and Chien).
- **No guarantee of optimality:** The heuristic approaches and the approximations give gains over the baseline, but seldom quantify the distance from the optimal solution.
- **Lack of a comparable baseline and restricted access to data:** Papers benchmark their models with different baselines, and one of the datasets used for benchmarking is unavailable (Guan).
- **Geographical coverage:** Out of those case studies which specify their geographical location, not one comes from India because some of the assumptions made (for example, constant travel time, homogeneous transport vehicles) do not hold true there.

4.4 What we could have done better

There are some limitations to our literature review. First, the eighteen papers were selected individually by the group members, without the help of any search protocol. Consequently, there is unequal representation. While some topics are represented by six papers, there are only two that cover other topics. We have provided numerical results given in the papers as they are but comparison of them was impossible since the research used different baseline, different measurements and data. We did not attempt to recreate any of the models mentioned above. To improve our analysis in the future, we will need to formulate clear selection criteria, to take into account papers that deal with issues from developing-country cities, to recreate at least one or two of the models, for example, headway formula and dial-a-ride formulation, on the same dataset, and to examine how sensitive they are to assumptions mentioned above. Reading each paper in full, including its supplementary material, would also let us judge the quality of its experimental design more rigorously.

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