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Optimising Transfer Coordination in Hanoi's Multimodal Public Transport Network

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ABSTRACT : *Poorly coordinated transfers can offset the accessibility gains created by multimodal public transport, particularly when feeder services are exposed to road congestion while connecting metro and bus services operate at different frequencies. This study develops a mixed-integer nonlinear programming (MINLP) model that jointly selects integer timetable shifts and continuous headways for a Hanoi network comprising metro, bus rapid transit (BRT), and conventional bus services. The model minimises a demand-weighted, convex generalised transfer cost, which incorporates observed waiting, the probability and penalty of a missed connection, schedule intervention, vehicle capacity, and a system-wide service-resource limit. A hybrid solution procedure combines differential evolution for 54 route-period headways with exact enumeration of feasible integer shifts across 236 transfer-demand groups. The operationally realistic, simulation-calibrated dataset contains 12,414 automatic vehicle location records, 20,946 smart-card events, and 5,236 raw transfer links; after rule-based quality screening, 4,372 transfers remain. Under a 5% service-resource allowance, the best feasible solution reduces demand-weighted mean waiting from 7.09 to 5.64 min (20.49%), the modelled missed-connection rate from 18.60% to 13.87% (25.42%), and generalised transfer cost by 26.60%. With no additional service resource, retiming alone still produces a 15.53% waiting-time reduction. These findings demonstrate the value of combining data-driven transfer identification with nonlinear, capacity-constrained coordination; however, because the dataset is simulated and the metaheuristic does not certify global optimality, field calibration and controlled operational trials are required before implementation.*

KEYWORDS - *automatic vehicle location; differential evolution; Hanoi; mixed-integer nonlinear programming; public transport; smart card; timetable synchronisation; transfer waiting time.*

I. INTRODUCTION

An urban public transport journey is experienced as a chain rather than as a set of independent routes. Even when each line performs acceptably in isolation, a passenger who arrives shortly after a connecting departure may face an additional headway, uncertainty about vehicle arrival, and crowding at the interchange. These penalties are operationally important because waiting and transfer inconvenience are salient components of perceived journey quality. Empirical evidence shows that passengers commonly report waiting times that exceed their observed duration, while the surrounding environment and information provision alter that perception [1], [2]. Schedule coordination therefore has a behavioural as well as a technical purpose. Transfer quality affects the attractiveness of the whole network.

The issue is relevant to Hanoi, where the public transport system increasingly combines rail and road-based modes. Line 2A runs for 13.1 km between Cát Linh and Yên Nghĩa and contains 12 stations [3], whereas Line 3 links Nhổn with the central corridor through Cầu Giấy [4]. The BRT01 service connects Yên Nghĩa and Kim Mã and was introduced as Hanoi's first BRT line [5]. These services create transfer opportunities, but their operating environments differ: metro running times are comparatively controlled, while buses and BRT remain exposed, to varying degrees, to road congestion and intersection delay. Hanoi Metro's February 2026 timetable, which specifies 6-min peak and 10-min weekend frequencies for both operating metro corridors, also illustrates that service plans are actively adjusted as demand evolves [6].

Research has long treated timetable construction, frequency setting, vehicle scheduling, and transfer coordination as interdependent tactical decisions [7], [8]. Early synchronisation models maximised simultaneous arrivals or minimised transfer waiting through mixed-integer linear formulations [9], [10]. Although these models are transparent, linearisation can suppress three features that matter in practice: the discrete consequences of catching or missing a connection, the nonlinear growth of passenger disutility as waiting lengthens, and the reciprocal relationship between headway and service resource. MINLP can represent these relationships directly, albeit at the cost of a more difficult non-convex search [11].

This paper addresses that methodological and applied gap. It constructs a simulation-calibrated Hanoi case from smart-card-like transactions and automatic vehicle location (AVL) records, applies explicit data-quality rules before optimisation, and develops a MINLP in which integer timetable shifts interact with continuous route-period headways. The contribution is threefold. First, the model anchors missed-connection risk to each group's observed baseline rather than imposing a single network-wide probability. Second, it combines a convex perceived-wait penalty with capacity and service-resource controls, so improvements cannot be obtained merely by adding unrestricted frequency. Third, it reports sensitivity to both the resource allowance and the behavioural response parameter, while clearly distinguishing the best feasible metaheuristic solution from a globally certified optimum. This distinction supports reproducible interpretation.

II. LITERATURE REVIEW

Transit network planning spans strategic route design, tactical frequency and timetable decisions, and operational control. Guihaire and Hao [7] show that these layers are strongly connected, while Ibarra-Rojas et al. [8] demonstrate that bus planning and control problems frequently share demand, fleet, reliability, and passenger-cost variables. Within this wider domain, transfer coordination seeks to align departures at interchange nodes without making the timetable infeasible or excessively expensive.

Ceder, Golany, and Tal [9] formulated maximal timetable synchronisation as a mixed-integer linear problem and developed a heuristic for larger networks. Ibarra-Rojas and Rios-Solis [10] subsequently provided a structured bus timetabling formulation whose synchronisation decisions balance feasible departures and connection opportunities. Genetic algorithms have also been used system-wide: Cevallos and Zhao [12], for example, minimised transfer time by encoding timetable decisions within an evolutionary search. Later studies integrated passenger and operator objectives. Fonseca et al. [13] combined transfer synchronisation with vehicle scheduling through a matheuristic, while Abdolmaleki, Masoud, and Yin [14] minimised transfer time in a network-wide timetable model. The 2021 review by Liu, Cats, and Gkiotsalitis [15] concludes that demand heterogeneity, uncertainty, operational cost, and computational scalability remain central challenges.

Reliability complicates deterministic coordination. A connection with almost no scheduled slack may appear efficient but fail when a feeder arrives late. Wu, Liu, and Jin [16] incorporated safety control margins into a robust coordination scheme, showing why timetable planning should retain a buffer for disruption. Headway control research reaches a similar conclusion from another direction: unstable intervals can generate bunching and irregular waits, so frequency adjustments must preserve operational regularity [17]. Consequently, a useful objective should reward well-timed connections while discouraging brittle synchronisation and unbounded increases in service intensity. Reliable coordination needs operational slack.

Data availability has changed the empirical basis of these models. Smart-card systems generate detailed transaction streams that support ridership measurement, origin–destination inference, and service evaluation [18]. AVL feeds add realised vehicle times. Munizaga and Palma [19] demonstrated that passive card records can be used to estimate a disaggregate multimodal origin–destination matrix, and Nassir, Hickman, and Ma [20] developed procedures for identifying activities and transfers from fare-card observations. When card events are linked to AVL data, planned and realised times can be compared at the trip level. Nevertheless, raw operational data are rarely analysis-ready. Duplicate identifiers, absent trip references, clock errors, implausible waits, and uncertain matches can bias the objective function; Robinson et al. [21] therefore emphasise preprocessing methods that improve smart-card data quality before modelling.

Two gaps motivate the present formulation. First, much transfer-synchronisation research remains linear or uses piecewise linear approximations even though waiting disutility and connection failure interact nonlinearly. Second, empirical and optimisation stages are often separated, so uncertainty created during card–AVL linkage is not reflected in the analytical sample. MINLP provides a coherent representation of integer schedule decisions, continuous headways, nonlinear passenger cost, and capacity constraints [11]. Because large non-convex MINLPs are computationally demanding, evolutionary methods such as differential evolution are suitable for producing high-quality feasible solutions, provided that global optimality is not overstated [22].

III. METHODOLOGY

3.1. Network representation and data collection

The research network contains nine simplified routes: two metro services, one BRT service, and six conventional bus routes. Seven monitored hubs represent Cát Linh, Thái Hà, Yên Nghĩa, Cầu Giấy, Nhổn, Kim Mã, and La Khê. Only six hubs generate linked transfers because Thái Hà has no qualifying inter-route connection in the analytical extract. The observation window covers 6–12 July 2026 and samples 06:00–10:00, 11:00–13:00, and 16:00–20:00. The principal unit is a linked passenger transfer reconstructed from a feeder alighting event, a walking interval, and a connecting boarding event.

The raw layers contain 12,414 AVL observations, 20,946 card events, and 5,236 candidate transfer links. Cleaning was rule-based and left the raw sheets unchanged. Each source layer was retained separately. A record was excluded when a required time or hub was missing, the inferred wait was negative or exceeded 60 min, match confidence was below 0.75, the two legs used the same route, an identifier was duplicated, or the event fell outside 05:00–23:00. The resulting analytical table contains 4,372 transfers, implying an exclusion rate of 16.50%. A separate quality log retains 2,356 issue entries because one record can trigger several flags. This architecture follows the principle that transformation should be auditable and that uncertain linkage should not silently enter model calibration [20], [21].

Transfers were aggregated by day type, time period, hub, feeder route, and connecting route, producing 236 demand groups. For each group, the inputs include passenger demand, current mean and 95th-percentile wait, baseline missed-connection rate, headway bounds, residual capacity, maximum schedule shift, a reliability buffer, and nonlinear penalty coefficients. Route-period combinations yield 54 headway blocks. This aggregation preserves the main transfer structure.

3.2. MINLP formulation

Let G denote the transfer groups and B the connecting route-period blocks. Each group g belongs to block $b(g)$. The primary decisions are the integer timetable shift δ_g, measured in minutes, and the continuous connecting headway h_b. A positive shift delays the connecting departure, whereas a negative value advances it. Parameters include demand q_g, current mean wait a_g, baseline missed-connection probability p_g^0, headway h_b^0, maximum shift Δg, residual capacity cg, passenger arrival rate λ_g, and cost coefficients α_g, β_g, P_g, and γ. The missed-connection response is anchored to the observed group probability and updated through a logistic function:

$$p_g(\delta_g) = \left\{1 + \exp\left[-\left(\mathrm{logit}(p_g^0) - \kappa\delta_g\right)\right]\right\}^{-1} \quad (1)$$

where $\kappa>0$ controls how strongly a one-minute shift changes connection risk. The main specification uses $\kappa=0.45$. Because delaying the departure increases feasible slack, positive δ_g lowers p_g; advancing it has the opposite effect.

The modelled wait is defined relative to the observed baseline:

$$w_g = \max\left\{\varepsilon,\ a_g + \delta_g + \tfrac{1}{2}\left(h_{b(g)} - h^0_{b(g)}\right) + p_g(\delta_g)h_{b(g)} - p^0_g h^0_{b(g)}\right\}$$

The half-headway term approximates the change in residual waiting created by a frequency adjustment, while the final two terms measure the incremental headway exposure associated with a missed connection. The lower bound $\varepsilon=0.10$ prevents an artificial zero or negative wait when a large timetable advance is evaluated.

The objective minimises demand-weighted generalised transfer cost:

$$\min_{\delta,h} Z=\sum_{g\in G} q_g\left[\alpha_g w_g + \beta_g w_g^2 + P_g p_g(\delta_g) + \gamma\delta_g^2\right] \quad ($$

The linear term represents ordinary waiting, the quadratic term makes prolonged waiting progressively more costly, $P_g p_g$ penalises connection failure, and $\gamma_{\delta g}^2$ discourages unnecessary timetable intervention.

Feasibility is enforced through:

$$\begin{aligned} &-\Delta_g \le \delta_g \le \Delta_g,\ \delta_g \in \mathbb{Z};\quad h_b^{\min} \le h_b \le h_b^{\max} \\ &\lambda_g h_{b(g)} \le c_g;\quad \sum_{b\in B} \frac{\omega_b H_b}{h_b} \le (1+\eta)\sum_{b\in B}\frac{\omega_b H_b}{h_b^0} \end{aligned} \qquad (4)$$

The first line sets integer shift and headway bounds. The second limits passengers allocated to a departure to its mean residual capacity. The third constrains total service intensity, where H_b is the sampled duration, ω_b weights weekdays and weekends, and η is the permitted resource increase. The principal assumptions uses $\eta=0.05$; sensitivity tests use 0 and 0.10. This reciprocal constraint is nonlinear because the approximate number of departures in a period is H_b/h_b.

3.3. Solution procedure and evaluation

The MINLP was solved by exploiting its conditional structure. For a candidate vector of 54 continuous headways, every feasible integer shift in $[-\Delta_g,\Delta_g]$ was enumerated for each of the 236 groups; the shift with the lowest group cost was retained. Differential evolution then searched the continuous headway space [22]. The main run used a population multiplier of 10, a fixed seed of 20260725, a limit of 220 generations, and final local polishing. Constraint violations received large exterior penalties.

The algorithm evaluated 122,475 candidate vectors before reaching the iteration limit. The reported solution is consequently the best feasible solution found, not a proof of global optimality. All reported constraints were satisfied. Performance was assessed through demand-weighted mean wait, missed-connection probability, generalised cost, mean absolute shift, weighted headway, resource use, and maximum capacity violation. Sensitivity tests changed η and varied κ from 0.30 to 0.60.

IV. RESULTS

4.1. Sample Profile and Descriptive Statistics

The 4,372 usable transfers have a mean wait of 7.09 min, a median of 6.08 min, and a 95th percentile of 17.13 min. The observed missed-connection rate is 18.55%, while mean match confidence is 0.923. Weekdays account for 77.74% of transfers, and 87.51% occur in the two peak windows. Yên Nghĩa carries the largest analytical volume (1,043 transfers), followed by Cầu Giấy (948) and Cát Linh (837). La Khê has the longest mean wait at 8.13 min, whereas Kim Mã has the highest missed-connection rate at 22.62%.

Table 1. Reliability and descriptive statistics

Hub	Transfers	Mean wait (min)	P95 wait (min)	Missed connection
Yên Nghĩa	1,043	6.86	17.17	20.90%
Cầu Giấy	948	6.96	16.98	19.73%
Cát Linh	837	7.13	17.15	16.13%
Kim Mã	610	6.61	16.51	22.62%

Hub	Trans-fers	Mean wait (min)	P95 wait (min)	Missed connec-tion
Nhổn	560	7.51	16.72	14.82%
La Khê	374	8.13	17.78	13.37%

4.2. Optimisation outcomes

Under the 5% resource allowance, demand-weighted mean waiting falls from 7.09 to 5.64 min, a reduction of 20.49%. The modelled missed-connection rate decreases from 18.60% to 13.87%, or 25.42%, and generalised transfer cost falls from 13.25 to 9.73 equivalent minutes (26.60%). The weighted mean headway declines from 13.17 to 12.19 min. Timetable changes are distributed rather than concentrated: 93.05% of weighted demand is assigned a non-zero shift, although the mean absolute adjustment is only 2.42 min.

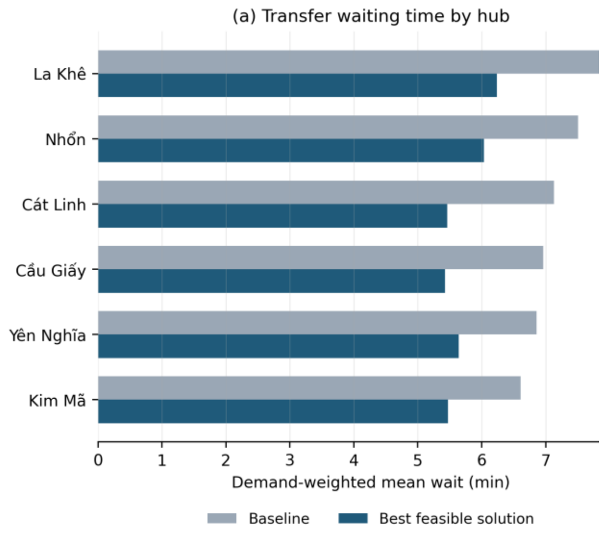

Figure 1. Transfer waiting time by hubs

The resource sensitivity is monotonic for waiting and generalised cost. Retiming supplies most of the initial gain. With no increase in total service intensity, schedule retiming and reallocation reduce mean waiting to 5.99 min (15.53%) and generalised cost by 22.24%. Allowing 10% more resource lowers waiting to 5.30 min (25.31%) and generalised cost by 30.70%. The behavioural sensitivity is less uniform. Across $\kappa=0.30–0.60$, generalised-cost reductions remain between 26.60% and 29.42%, but the balance between shorter waiting and connection protection changes, which confirms that the response parameter should be estimated empirically before deployment.

V. DISCUSSIONS AND CONCLUSIONS

The results support the central proposition that transfer performance can be improved without wholesale network redesign. In the zero-growth scenario, the model obtains a 15.53% waiting reduction by retiming connections and redistributing headways within the existing resource envelope. This finding is consistent with the synchronisation literature, where timetable structure, rather than frequency alone, creates substantial passenger benefits [9], [10], [13], [14]. The additional 5% resource produces a further five-percentage-point reduction in waiting, indicating diminishing but still meaningful returns.

The nonlinear specification matters because it changes which transfers receive priority. A purely linear objective values every saved minute equally, whereas the quadratic term assigns greater marginal cost to already long waits. The missed-connection function adds another distinction: delaying a departure may slightly increase the wait of passengers who are already ready, but it can protect a larger feeder cohort from incurring an entire extra headway. This is the operational rationale behind the best-found mean shift of only 2.42 min. It also explains why the solution reduces generalised cost more than mean waiting.

The model integrates demand evidence and feasibility more explicitly than a timetable-only exercise. Smart-card and AVL linkage identifies when and where transfers occur, while capacity and service-resource constraints prevent a nominal improvement that cannot be operated. Data-driven scheduling research similarly shows the value of time-dependent traffic and demand inputs [23]. Nevertheless, transfer identification is itself a modelled process. The 16.50% exclusion rate, dominated by low confidence, missing trip identifiers, absent times, and duplicates, demonstrates that linkage quality is part of the inferential chain rather than a preliminary clerical matter.

Several limitations directly affect the interpretation and practical implementation of the optimisation results. First, resource requirements are approximated through the number of departures within each sampled period. Although this indicator represents the nominal service supply, it does not fully capture operational cycles, including vehicle blocks, crew duties, depot entry and exit movements, mandatory breaks, layover requirements, and recovery time allocated to delay mitigation. Consequently, a solution may be feasible in terms of service frequency while remaining operationally infeasible under actual scheduling conditions. Second, the aggregate objective function minimises network-wide costs or passenger waiting times but may conceal local deterioration. Substantial benefits at high-demand interchange hubs may mathematically offset poorer service at less heavily used locations. A deployment-oriented model should therefore incorporate equity constraints, upper bounds on acceptable deterioration, or a minimax-regret criterion to prevent particular passenger groups or hubs from bearing disproportionate disadvantages. Third, travel time should not be treated as deterministic. Actual operations are affected by congestion, fluctuating passenger demand, traffic incidents, and recurrent or unexpected delays. Modelling travel time through probability distributions and introducing safety-control margins would produce more robust timetables. These extensions would improve solution reliability under uncertain conditions and strengthen the model's suitability for real-world public transport planning and operational decision-making.

VI. CONCLUSIONS

This study formulated multimodal timetable coordination in Hanoi as a data-driven MINLP with integer departure shifts, continuous route-period headways, nonlinear perceived waiting, missed-connection risk, capacity constraints, and a system-wide service-resource limit. After auditable screening, 4,372 simulated but operationally realistic transfers were aggregated into 236 demand groups and 54 headway blocks. A hybrid differential-evolution and exact-enumeration procedure produced a feasible solution that, under a 5% resource allowance, reduced demand-weighted waiting by 20.49%, missed connections by 25.42%, and generalised transfer cost by 26.60%. Retiming within the existing resource envelope still reduced waiting by 15.53%, showing that coordination quality is not synonymous with higher frequency. The practical implication is that Hanoi's expanding multimodal network could benefit from a common transfer-optimisation layer linking fare transactions, AVL feeds, and timetable management.

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