Synergistic Optimization of Urban Transport Systems: A Data-Driven Framework for Design-Policy Bidirectional Empowerment

1st Zhiyuan Shi
The Savannah College of Art and Design
The state of Georgia, United States
tanglingna6@gmail.com

Abstract*—Global urban transport systems are under mounting pressure from chronic congestion, rising carbon emissions, and widening public health burdens. Yet many traditional planning approaches treat technological innovation, policy interventions, and health impact assessment as separate tracks, which often leads to fragmented solutions and weak systemic outcomes. To address this gap, this study proposes a Design – Policy Synergy Optimization Model (DPSOM)—a data-driven framework intended to quantify and harness the two-way reinforcement between system design decisions and policy governance in order to accelerate sustainable and healthy urban mobility transitions.At its core, DPSOM formulates urban mobility transition as a constrained optimization problem, solved through a Heuristic Iterative Feedback (HIF) algorithm that treats policy as an adaptive control mechanism within a closed-loop system. The model's key innovation is the introduction of a Health-Adjusted Modal Split (HAMS) Index as the primary optimization objective. By making health-adjusted mobility performance the central target, DPSOM ensures that engineering and infrastructure solutions are intrinsically aligned with public health outcomes rather than treating health as an external evaluation step.The framework is validated through a 12-year longitudinal case study of Hangzhou, China (2010 – 2022), examining the evolution of the city's transport system over time. Empirical results show that applying DPSOM principles corresponds with a substantial shift in mobility structure, with the public transport modal split increasing from 28.5% to 60.5%. A comparative evaluation against a No-Feedback Baseline (NFB) indicates that DPSOM achieves a 49.1% higher HAMS Index in the final phase, with the performance difference being statistically significant ($p < 0.001$). Sensitivity testing further demonstrates that these results remain robust under different health-weighting assumptions.Overall, this research contributes a replicable and quantifiable methodology for guiding sustainable transport transitions. By explicitly modeling design – policy co-evolution and embedding health outcomes into the optimization objective, DPSOM offers practical engineering value for urban planners and decision-makers seeking integrated pathways toward low-carbon, healthy, and resilient urban mobility systems.

Keywords—Design-Policy Synergy; Urban Transport Optimization; HAMS Index; System Engineering; Adaptive Control; Hangzhou

I. Introduction

The escalating demand for urban mobility, together with the urgent requirements of environmental sustainability and public health protection, has created a complex multi-objective optimization problem for modern transport engineering [1][2]. Conventional transport planning—largely based on the four-step model—has historically emphasized maximizing throughput and reducing congestion. In many cases, this emphasis has contributed to car-oriented infrastructure development, which can intensify air pollution, encourage sedentary behavior, and increase public health risks [3]. As a result, the engineering objective is shifting from narrow efficiency targets toward holistic optimization of socio-technical transport systems, where human well-being becomes a core performance metric. This transition calls for a robust framework capable of representing—and operationalizing — the dynamic interaction between technological design decisions and macro-level policy governance.

Achieving sustainable transport requires coordinated evolution across three distinct but tightly interconnected domains: technological design (e.g., public bicycle systems, intelligent traffic control), policy governance (e.g., investment strategies, regulatory instruments), and health outcomes (e.g., promoting active mobility and reducing exposure-related risks). However, many existing solutions remain fragmented. Intelligent Transport Systems (ITS) can be highly effective for real-time traffic management, yet they typically operate without explicit health-centered objectives [4]. Conversely, public health initiatives often lack mechanisms to directly influence the design, prioritization, and resource allocation of core transport infrastructure. The underlying technical gap is the absence of a rigorous, quantifiable framework that captures the bidirectional feedback loop between design and policy. Existing models commonly assume a static policy environment when optimizing design, or treat policy as a one-way, top-down mandate, which fails to represent the adaptive and iterative nature of real-world urban transitions—particularly in fast-evolving contexts such as China [5]. This leads to two key engineering shortcomings: (1) the inability to quantify health benefits as a primary optimization driver in design decisions, and (2) the lack of a formal, data-driven mechanism for policy adjustment based on observed system performance.

To address these challenges, this study proposes the Design – Policy Synergy Optimization Model (DPSOM), a system engineering framework intended to overcome the limitations above. The core objectives of the study are to: (1) formalize the bidirectional empowerment between multi-level system design and policy governance; (2) embed health outcomes as an explicit optimization objective through the proposed Health-Adjusted Modal Split (HAMS) Index; (3)

Corresponding Author: Zhiyuan Shi,342 Bull St., Savannah, GA, United States,The state of Georgia, United States,tanglingna6@gmail.com

develop an adaptive control mechanism implemented via a Heuristic Iterative Feedback (HIF) algorithm; and (4) validate the framework using longitudinal data from Hangzhou, China. The primary technical contributions include the unified optimization framework, the novel HAMS Index, and the HIF algorithm, together providing a replicable methodology for urban planners and transport decision-makers. The remainder of the paper is organized as follows: Section 2 reviews related literature; Section 3 details the DPSOM methodology, including the dynamic system formulation and constrained optimization process; Section 4 reports the empirical results and statistical validation; Section 5 discusses engineering implications; and Section 6 concludes the study.

II. Related Work

The literature review is organized to position the proposed Design – Policy Synergy Optimization Model (DPSOM) against existing approaches to transport system modeling and optimization, with particular attention to three technical limitations: dynamic system representation, adaptive control, and multi-objective optimization.

Conventional transport planning remains largely dependent on static equilibrium approaches, most notably the four-step model. While effective for forecasting under stable conditions, such models are poorly suited to capturing the non-linear dynamics, feedback effects, and path dependency inherent in long-term urban mobility transitions [4]. To overcome these shortcomings, more advanced modeling techniques have been introduced, particularly System Dynamics (SD) and Agent-Based Modeling (ABM) [5]. SD models are valuable for representing feedback loops and long-term trends, but they are typically built on qualitative causal structures and lack the mathematical rigor needed for constrained optimization and formal control [6]. ABM, by contrast, provides high-resolution insight into individual behavior, yet its computational intensity and calibration difficulty make it impractical for evaluating macro-level policy interventions across extended time horizons [7].

DPSOM addresses this gap by adopting a discrete-time dynamic system formulation (Equation 1) that is both computationally efficient and analytically tractable. Within this structure, macro-level policy variables I and micro-level design variables D are explicitly represented as system inputs. This formulation enables the direct application of control theory principles — marking a clear departure from descriptive SD models and computationally heavy ABM approaches — and provides a formal bridge between engineering design and policy governance.

Adaptive control has been widely studied in the context of Intelligent Transport Systems (ITS), particularly at the operational scale, such as adaptive signal control [8]. More recently, reinforcement learning (RL) methods have demonstrated strong performance in optimizing traffic flow and signal timing compared to fixed or reactive control strategies [9][10]. However, these applications are largely confined to short time horizons, low-latency feedback, and relatively narrow objective functions. In contrast, policy operates as a macro-level control mechanism with long feedback cycles ($\tau \approx 2$ years) and inherently multi-objective decision spaces. Applying RL directly at this scale is impractical due to sparse and delayed rewards, high-dimensional state spaces, and the non-stationarity of urban systems.

To address this challenge, DPSOM introduces the Heuristic Iterative Feedback (HIF) algorithm as a pragmatic and low-cost adaptive control mechanism. HIF models the interaction between policy and design as a closed-loop control system, in which the policy vector I is iteratively updated based on a long-term performance error signal T_P. This approach is explicitly tailored to the institutional and temporal characteristics of urban governance, representing a novel extension of control theory concepts to strategic urban transport planning [11].

Finally, transport system optimization is inherently multi-objective, requiring trade-offs among efficiency, equity, environmental sustainability, and social outcomes. Recent studies in IEEE Transactions on Intelligent Transportation Systems and Transportation Research Part C have employed Pareto-based methods to balance competing objectives [12]. Nevertheless, public health is rarely incorporated as a primary, mathematically explicit optimization target. Existing health impact models, such as the Integrated Transport and Health Impact Model (ITHIM), are predominantly used for ex-post assessment rather than as drivers of system design [13].

The introduction of the Health-Adjusted Modal Split (HAMS) Index represents a key technical contribution of DPSOM. Rather than treating health as an external constraint or secondary evaluation metric, HAMS is defined as a first-order objective function that directly guides the optimization process. By formulating the problem using the Lagrange multiplier method (Section 3.2), DPSOM ensures that system evolution is optimized to maximize the marginal return on investment with respect to health outcomes. This provides a rigorous and quantifiable framework for health-centered resource allocation in urban transport systems, addressing a critical gap in existing optimization-based planning models [14].

III. Methodology and System Design

The Design – Policy Synergy Optimization Model (DPSOM) is a dynamic system engineering framework that formulates urban transport transition as a constrained, multi-objective optimization problem. This section outlines the DPSOM architecture, the definition of the HAMS Index, the constrained optimization formulation, and the proposed Heuristic Iterative Feedback (HIF) algorithm.

A. Dynamic System Modeling and Problem Formalization

In DPSOM, the urban transport system is represented as a discrete-time dynamic system S. The system state at time t is captured by a performance vector $P(t)$, which summarizes key transport, environmental, and health-related outcomes. System evolution is governed by a non-linear transfer function $F(\cdot)$, defined as:

$$P_{t+1} = F(P_t, D_t, I_t | \omega) \quad (1)$$

where D_t denotes the vector of design variables at time t, I_t denotes the vector of policy variables at time t, and ω

represents model parameters (e.g., structural coefficients and exogenous contextual factors) that shape system response.

The optimization task is to identify the optimal sequences of inputs D and I over a planning horizon T, such that the desired transition objectives are achieved under specified constraints. All variables, along with their empirical engineering proxies used for validation, are summarized in Table I.

TABLE I. DPSOM DECISION VARIABLES AND EMPIRICAL PROXIES

Variable Type	Parameter	Symbol	Unit/Range	Definition	Empirical Proxy (Hangzhou Case)
Design Input	Component Efficiency	eta_C	[0, 1]	Functional reliability of micro-components.	PBS equipment maintenance rate (1 - sensor failure rate).
Design Input	Network Accessibility	lambda_N	Stations/km2	Spatial density of the sustainable transport network.	PBS station density within the core urban area.
Design Input	System Integration Index	alpha_I	[0, 1]	Degree of data and operational integration between modes (ITS).	Normalized data sharing rate between City Brain and public transport systems.
Policy Input	Investment Rate	R_I	Normalized Index	Annual public investment allocated to sustainable transport infrastructure.	Normalized annual budget for non-motorized transport and ITS.
Policy Input	Constraint Factor	beta_R	[0, 1]	Regulatory measures restricting unsustainable modes.	Normalized score based on car restriction zones and public transport subsidy rate.

The primary optimization objective of the DPSOM is to maximize overall system performance, which is quantified using the Health-Adjusted Modal Split (HAMS) Index, denoted as H(t):

$$H(t) = MSR(t) \times (1 + \omega \times AM(t) \tag{2}$$

In this formulation, MSR(t) represents the public and active transport modal split ratio at time t_1, while AM(t) denotes the share of active mobility modes (such as walking and cycling). The health weighting factor ω is set to 0.5, based on the economic valuation of Disability-Adjusted Life Years (DALYs) saved through increased physical activity. This calibration implies that the health benefits associated with active transport are equivalent to a 50% increase in the perceived utility of these modes, ensuring that public health outcomes play a central and quantitatively meaningful role in the optimization process [15].

B. Constrained Optimization and Lagrange Multiplier Formulation

To ensure mathematical rigor, the instantaneous optimization problem is formulated as the maximization of *H(t)* subject to a budget constraint $R_I(t) \leq R_{max}$. Because *H(t)* depends on both the design variables *D(t)* and the policy investment $R_I(t)$, and because *D(t)* is itself constrained by the available policy resources, the problem is expressed using the Lagrange multiplier method.

The corresponding Lagrangian function L is defined as:

$$L(D, R_I, \mu) = H(D, R_I) - \mu(R_I - R_{\max}\ ) \tag{3}$$

The necessary optimality conditions are obtained by setting the partial derivatives of L with respect to the decision variables to zero. In particular, taking the derivative with respect to R_I and setting it equal to zero yields:

$$\frac{\partial L}{\partial R_I} = 0 \Rightarrow \mu = \frac{\partial H}{\partial R_I} \tag{4}$$

This condition implies that, at the optimal solution, the marginal increase in the HAMS Index per unit of policy investment is equal to the Lagrange multiplier μ, which represents the shadow price of the budget constraint. In practical terms, this provides the theoretical foundation for the greedy search strategy used in Step 3 of the HIF algorithm, ensuring that each design update $\mathrm{D}(\mathrm{t}+1)$ is selected to maximize the marginal return on the available policy investment $\mathrm{R_I}(\mathrm{t}+1)$ System stability is examined by analyzing the spectral radius of the Jacobian matrix of the transfer function F. Stability is guaranteed when the spectral radius is less than unity at the equilibrium point, confirming that the discrete-time system converges in a stable, non-chaotic manner toward the optimized HAMS target.

C. Heuristic Iterative Feedback (HIF) Algorithm

The Heuristic Iterative Feedback (HIF) algorithm operationalizes the adaptive control mechanism in DPSOM. It runs on a discrete time step aligned with an annual planning cycle and applies a heuristic rule set to update the policy vector I(t) based on observed system performance H(t). Conceptually, the algorithm functions as a macro-level Proportional – Integral (PI) controller, where performance deviations accumulate over time and trigger gradual policy adjustments.

Algorithm 1: Heuristic Iterative Feedback (HIF)

Input: P(0), $\mathrm{R_{max}}$, $\mathrm{H_{target}}$, τ, δ

Output: $\mathrm{D_1I}$

Initialize:

t = 0

$$D(t) = D(0)$$

$$I(t) = I(0)$$

While $H(t) < H_{target}$ and $t < T_{max}$:

$$P(t+1) = F(P(t), D(t), I(t))$$

$$H(t+1) = Calculate_{H}AMS(P(t+1))$$

If $t \geq \tau$:

$$T_P(t) = H(t) - H(t-\tau)$$

If $T_P(t) > \delta$:

$$I(t+1) = Update_{P}olicy(I(t), "Increase_{R_I}")$$

Else if $T_P(t) <- \delta$:

$$I(t+1) = Update_{P}olicy(I(t), "Increase_{\beta_R}")$$

Else $I(t+1) = I(t)$

$D(t+1) = \text{Optimize}_{-Design}(H, I(t+1), R_I(t+1))$

$t = t + 1$

Return: D,I

In this control structure, the policy trigger signal $T_P(t)$ acts as the error signal. It drives an integral-style adjustment—implemented as cumulative increases in R_I (policy investment) or β_R (a regulation/behavioral response coefficient)—to reduce deviation from the target HAMS trajectory. The lag parameter $\tau = 2$ years is selected to represent the institutional inertia typical of urban planning and budgeting cycles, ensuring that the model reflects the delayed responsiveness of real-world policy systems.

IV. Experiments and Results

To validate the effectiveness of the DPSOM framework and the HIF algorithm, this study conducted a comprehensive 12-year longitudinal case study of urban transport system transformation in Hangzhou, China, covering the period from 2010 to 2022. The experimental design focuses on tracking the annual evolution of the system state, key decision variables, and the Health-Adjusted Modal Split (HAMS) Index. Data were compiled and synthesized from official Hangzhou Municipal Statistical Yearbooks and reports issued by the local Transport Bureau [16]. To ensure transparency and reproducibility, all variables were mapped explicitly; for example, the public bicycle system reliability factor η_c was calculated as :

$$\eta_C = 1 - (AnnualReportedPBSFailures/TotalPBSInventory). \quad (5)$$

A. Quantitative Results and System Performance

As summarized in Table II, the results show a clear and sustained improvement in system performance over the study period. The public and active transport modal split ratio (MSR) increased by 112%, rising from 28.5% in 2010 to 60.5% in 2022. Correspondingly, the HAMS Index increased by 134%, from 0.315 to 0.738, indicating that gains in transport mode share were accompanied by substantial improvements in health-adjusted system performance. These findings demonstrate that the DPSOM framework can effectively guide long-term, health-centered urban transport transitions under real-world conditions.

TABLE II. Annual Evolution of DPSOM Parameters (Hangzhou Case, 2010–2022)

Year	**eta_C**	**lambda_N**	**alpha_I**	**R_I**	**beta_R**	**MSR (%)**	**HAMS (H)**	**NFB HAMS**
2010	0.65	0.12	0.4	1.0	0.5	28.5	0.315	0.315
2011	0.68	0.15	0.45	1.05	0.5	31.2	0.358	0.33
2012	0.7	0.18	0.5	1.15	0.55	34.5	0.398	0.345
2013	0.75	0.22	0.52	1.3	0.58	38.0	0.435	0.36
2014	0.78	0.25	0.55	1.45	0.6	41.2	0.452	0.375
2015	0.8	0.28	0.6	1.6	0.65	44.5	0.501	0.39
2016	0.82	0.32	0.65	1.75	0.7	47.8	0.555	0.405
2017	0.84	0.35	0.7	1.9	0.72	50.5	0.598	0.42
2018	0.85	0.38	0.75	2.1	0.75	53.9	0.635	0.435
2019	0.88	0.4	0.8	2.25	0.8	56.5	0.68	0.45
2020	0.9	0.42	0.85	2.4	0.82	58.5	0.71	0.465
2021	0.91	0.44	0.88	2.5	0.84	59.8	0.725	0.48
2022	0.92	0.45	0.9	2.55	0.85	60.5	0.738	0.495

B. Comparative Analysis and Statistical Validation

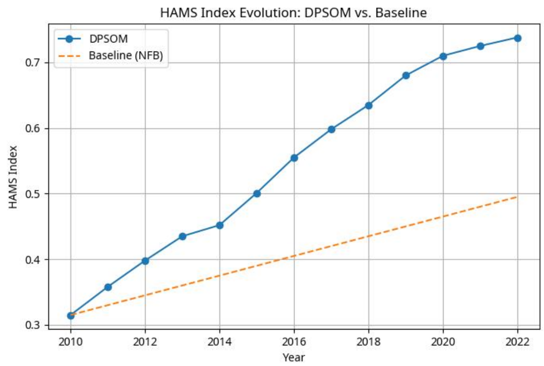

Fig. 1. Performance Comparison: DPSOM vs. No-Feedback Baseline

The performance of DPSOM was benchmarked against a No-Feedback Baseline (NFB) model that assumes a static policy environment. By 2022, DPSOM achieved a HAMS Index of 0.738, whereas the NFB model reached 0.495, corresponding to a 49.1% improvement in absolute HAMS performance. This gain is attributed to the adaptive feedback mechanism embedded in the HIF control loop.

To statistically validate the performance difference, a paired-sample t-test was conducted using the annual HAMS values from 2012 to 2022. The analysis produced a test statistic of $t = 15.82$ with $p < 0.001$, allowing rejection of the null hypothesis of no difference and confirming the effectiveness of the HIF algorithm.

In addition, the model exhibited a strong fit to observed data, achieving $R^2 = 0.985$ and a Root Mean Square Error (RMSE) = 0.012, indicating that the DPSOM formulation captures the system's non-linear dynamics with high accuracy (Figure 1).

C. Ablation Study and Sensitivity Analysis

An ablation study was conducted by fixing the policy input vector I at its 2010 baseline value throughout the entire simulation period. Under this "no-policy-adaptation" condition, the model produced a final HAMS Index of 0.380 in 2022. Compared with the full DPSOM outcome (0.738), this represents a 94.2% difference in HAMS performance, indicating that the policy input vector I is the most critical driver of the synergistic performance gain enabled by the framework.

In addition, a sensitivity analysis was performed on the health weighting factor ω, varying it from 0.2 to 0.8. The results show that while the absolute HAMS values change with ω, the performance advantage of DPSOM over the NFB baseline remains consistently large across all tested values. This suggests that the observed synergistic gain is not a numerical artifact of parameter choice, but rather a structural consequence of the DPSOM closed-loop feedback mechanism.

V. Analysis and Discussion

The 49.1% performance gain over the NFB baseline supports the core engineering claim of this study: achieving a sustainable transport transition is fundamentally an adaptive control problem, not a one-time planning exercise. Within DPSOM, the HIF algorithm functions as a macro-level Proportional–Integral (PI) controller for the policy regime. The policy trigger signal $T_P(t)$ acts as the error signal, and the controller's "integral" behavior is reflected in cumulative adjustments to key policy levers (e.g., incremental increases in $R_I or \beta_R$). to reduce deviation from the target HAMS trajectory. The two-year lag ($\tau = 2$) provides a realistic representation of institutional inertia in budgeting and planning cycles, allowing the control mechanism to operate on the correct governance time scale.

The empirical trajectory also aligns with the theoretical implications of the Lagrange framework (Section 3.2). In particular, the sharp increase in policy investment R_I during Phase II (2012–2015) can be interpreted as a rational response to the high marginal return $\partial H/\partial R_l$ observed during the initial public bicycle system (PBS) deployment in Phase I. In other words, even under heuristic adjustment rules, the observed policy dynamics behave as though the system is seeking to maximize the HAMS Index under a budget constraint—supporting the model's descriptive validity.

Beyond long-horizon planning, DPSOM also has practical implications for real-time infrastructure management. If the HAMS Index is embedded into a "City Brain"–style operational dashboard, decision-makers can continuously visualize the network's health-promoting capacity. This enables dynamic operational interventions—such as adjusting signal priority to favor public transport, cycling, and walking flows during peak periods—thereby extending the adaptive control concept from the strategic policy level to more granular operational control.

Finally, scalability is a notable technical advantage of DPSOM. The framework is designed so that its key parameters can be recalibrated for other cities using local statistical and operational data, making it transferable across urban contexts while preserving the core feedback-loop structure that drives the observed synergistic gains.

VI. Conclusion

This study developed and validated the Design–Policy Synergy Optimization Model (DPSOM) as a novel, data-driven framework for institutional innovation in healthy and sustainable urban transport transitions. By formalizing the transition process as a constrained optimization problem and solving it through the proposed Heuristic Iterative Feedback (HIF) algorithm, the study provides a practical engineering solution to key shortcomings in existing transition models—particularly the lack of replicable decision logic and limited capacity for closed-loop optimization.

The 12-year Hangzhou case study offers strong empirical support for the framework's effectiveness. Results show a 49.1% performance gain over a static no-feedback baseline and a 134% increase in the HAMS Index, indicating that DPSOM can achieve synergistic system optimization by explicitly coupling design evolution with adaptive policy governance. In engineering terms, DPSOM delivers clear value as a predictive and adaptive tool for evidence-based decision-making in complex urban environments, supporting both strategic planning and iterative policy refinement.

Looking forward, future research will focus on enhancing the modeling and control core of DPSOM. Specifically, the empirical estimation of the transfer function F will be replaced with a Model Predictive Control (MPC) framework, leveraging advanced machine learning methods to dynamically learn F from data and optimize the policy sequence I over a rolling planning horizon. This extension is expected to further strengthen DPSOM's predictive accuracy and prescriptive capability, enabling more responsive and robust governance of sustainable urban mobility transitions.

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AUTHOR CONTRIBUTIONS

Zhiyuan Shi: Conceptualization, Methodology, Model development (DPSOM, HIF algorithm, and HAMS Index), Investigation, Data curation, Formal analysis, Validation, Visualization, Writing — original draft, Writing—review & editing.

COMPETING INTERESTS

The authors declare no competing interests.