User-Centric Congestion-Aware Multimodal Optimization Routing System

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***Abstract*—This work proposes a public transport multimodal trip recommendation methodology that considers user preferences while reducing public transport infrastructure congestion. The system adheres to Behavior-enabled IoT (BeT) principles. BeT is a novel architectural paradigm for cyber-physical self-adaptive Smart Cities applications to balance QoE and QoS.**

***Index Terms*—Smart Mobility**

I. Introduction

Current multimodal public transportation applications mainly rely on user preferences (travel time, distance, habits, service cost) for route suggestion, often ignoring the congestion infrastructure stress [1], [2], [3], [4]. This work presents a framework for such a system, leveraging real-time congestion data and user-specific criteria to optimize travel experience and improve load distribution. This solution aligns with Behavior-Enabled IoT (BeT) principles [5] for balancing user experience (QoE) and service quality (QoS) through continuous adaptation. This work demonstrates the applicability and advantages of the BeT paradigm in smart mobility, considering the real-world use case of Lyon's public transport network.

II. BeT paradigm and modeling process

A BeT system involves a *human agent* and a *system agent* interacting through a *QoE-QoS balancer*. Each agent uses a *sensing interface* to update its behavioral model (user interactions for the human agent, cyber-physical data for the system agent). The balancer uses these models to optimize QoE and QoS. Outputs include *actuating operations* (modifying the physical process) and user *suggestions* (via a *recommending interface* to influence behavior and reduce system pressure). The BeT modeling process for designing architectures includes: 1) **QoE/QoS Analysis** to identify stakeholders, translate their needs into metrics or constraints, and analyze trade-offs. 2) **Behavior Modeling and Balancing Strategy Definition** to identify observable properties needed to extract QoE/QoS metric and constraints, and controllable resources (e.g. smartphones or on-board/in-station validation machines); to develop behavior models to predict human and system behavior, and creating a balancing strategy to optimize QoE/QoS within constraints, defining action outputs and recipients. 3) **BeT Concrete System Design** to translate the architecture into specific components with defined responsibilities and tailor the framework to the application scenario.

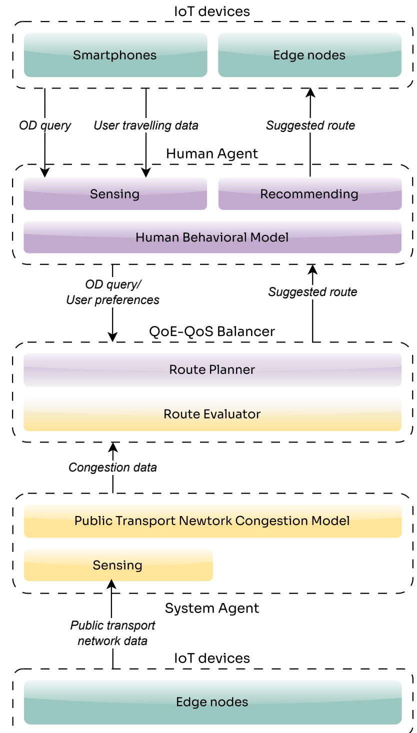

Fig. 1. BeT-driven architecture for public transport recommendation systems

III. BeT-driven multimodal transport system

The concrete BeT architecture is composed as follows. The *human agent* receives the user's *Origin-Destination (OD) query*, for which the user seeks a recommendation. In addition, the *Sensing interface* is responsible for collecting all user travel data to compute the QoE metrics. Our *Human behavioral model* is a probabilistic profile of user preferences based on travel time, frequency, preferred routes, and modes, obtained by mining the validation data. By analyzing interaction frequency within 10-minute intervals at specific locations, the model calculates a Behavior Index (BI), representing the proportion of a user's visits during that time, thus reflecting their habitual commuting patterns. Other QoE metrics used to evaluate a path are travel time and the number of line changes. At the same time, the *system agent* collects the public transport network data to feed the related congestion model. The latter uses a 5-minute moving average to estimate crowd levels on

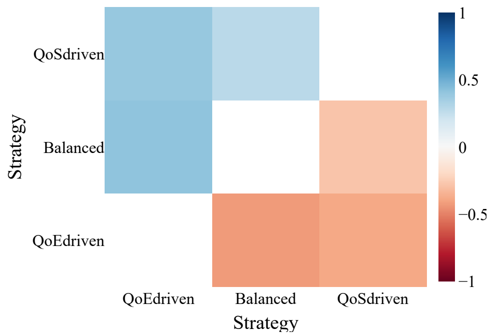

Fig. 2. Approach Comparison for Trams

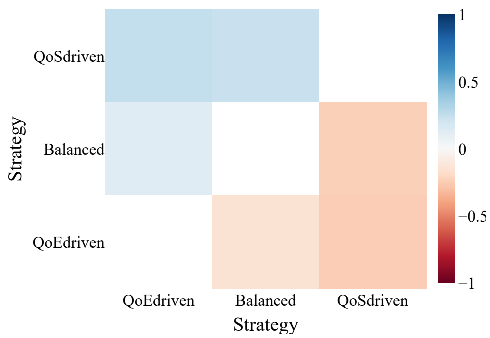

Fig. 3. Approach Comparison for Metros

public transport vehicles. The Congestion Index (CI) is the ratio of passengers on a vehicle to its capacity. The QoE-QoS balancer comprises two modules, a *route planner* and a *route evaluator*. The route planner is responsible for generating multiple candidate routes exploiting different modes of transportation (buses, trams, and metro). The route evaluator filters routes through a two-step process: first, identifying less congested options (prioritizing QoS), and then ranking the remaining ones based on BI, travel time, and line changes (promoting QoE). The route with the highest overall score is then suggested to the user. The suggestion is transmitted to the end-user through the recommending interface. We extended the MnMS[1] traffic simulator to validate the application of the BeT architecture on this scenario.

IV. Experiments and results

We are conducting ongoing experiments on public transport in Lyon (FR) using November 2019 validation data to represent typical congestion. After cleaning the data, OD trips were inferred by applying heuristics. We chose the morning peak (07:00-09:00 AM) for testing, with an average departure rate of 624 every 30 seconds. **QoE-driven** approach selects routes that satisfy user preference, travel time, and line changes. The **Balanced** approach implemented the proposed QoE-QoS adaptation strategy. **QoS-driven** suggests the less congested route. The simulations tracked a CI value for each vehicle at every time step. To compare two approaches j and k, we

1 https://github.com/licit-lab/MNMS

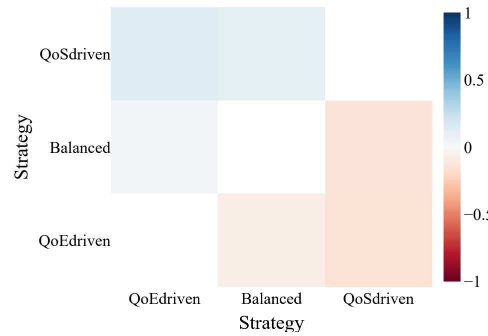

Fig. 4. Approach Comparison for Buses

defined a score $\rho_{j,k} = \frac{\sum_{v \in V} \gamma^v_{j,k} * \eta^v_{j,k}}{N_V}$ using p-value (π) and effect size (η) from a Wilcoxon test on paired CI at vehicle stops, considering the 'less than' alternative hypothesis. In particular, $\gamma^v_{j,k} = 1$ if $((\eta^v_{j,k} > 0 \wedge \pi^v_{j,k} \leq 0.05) \vee (\eta^v_{j,k} < 0 \wedge \pi^v_{j,k} \geq 0.95))$ else 0. A significant p-value and positive effect suggest one approach reduces congestion; conversely, a significant p-value and negative effect with swapped operands indicate the opposite. The score $\rho_{j,k}$ is normalized by the number of compared vehicles (N_V). We score performance per vehicle type (bus, metro, tram) to see strategy impacts on each, Fig.2, Fig.3, Fig.4. As expected, the QoS-driven approach is the most effective, while the balanced approach provides an acceptable middle ground. The QoE-driven approach performs worse. The strategy's impact varies by vehicle class, with trams significantly affected and metros slightly affected. The concentrated demand for metro and tram services in the city center obfuscates the impact of the strategy on the bus network (280 lines), which caters to a wider area and is less popular. The findings indicate that prioritizing congestion in public transport strategies effectively reduces infrastructure stress, with the Balancing approach showing as the best compromise. It is important to note, however, that this validation focused on the methodology itself, rather than on a complete real-world system. As such, aspects like the dynamic evolution of travel demand, system scalability, and data freshness were not considered and remain open for future research and implementation.

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