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Forecasting Transport Service Demand under Dynamic Conditions: A Scenario-Based Approach

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Abstract — **In transport systems theory, forecasting the demand for transport services is an essential task addressed by classical methods such as gravity and regression models, discrete choice models, and time series analysis. These approaches enable the estimation of passenger flows and the assessment of socio-economic factors. However, the dynamic development of the market and crisis situations necessitate more adaptive approaches, such as scenario modeling supported by machine learning algorithms and intelligent analytics.**

The aim of this study is to test a scenario-based approach to forecasting transport service demand under dynamic external conditions.

The paper proposes a modeling algorithm, conducts numerical calculations, and analyzes key transport demand indicators (average mobility, average travel time, travel losses, modal split). The results demonstrate high sensitivity of demand to crises of various origins and provide practical recommendations for optimizing the route network, enhancing the resilience, and improving the adaptability of the transport system.

***Keywords*— demand forecasting, transport services, scenario modeling, transport planning**

I. Introduction

Forecasting the demand for transport services is a key task of transport planning, as it directly affects the efficiency of transport systems. Traditional methods—gravity and regression models, discrete choice models, and time series analysis—form the basis of classical transport modeling [1,2]. These approaches allow for the estimation of passenger flows, the examination of demand factors, and the construction of baseline forecasts.

However, the dynamic development of the market, crisis situations, and socio-economic changes require more flexible tools capable of adapting to uncertainty. Modern digital technologies, particularly machine learning algorithms and intelligent analytics, create the prerequisites for applying scenario-based modeling, which improves forecast accuracy and enhances the adaptability of transport systems.

II. Problem Statement

Existing methods of demand forecasting have several limitations:

Gravity and regression models insufficiently account for spatio-temporal and socio-economic factors [4];

Discrete choice models require large volumes of high-quality data [2];

Time series and stochastic approaches are ineffective under conditions of rapid environmental change [3].

This gives rise to the task of developing an integrated methodology for demand forecasting that combines classical transport models with adaptive data analysis tools; enables the modeling of various development scenarios (economic recession, infrastructure failures, pandemics, tariff changes); and provides decision-makers with an instrument for risk assessment and decision-making in route network organization.

The aim of this study is to test a scenario-based approach to forecasting the demand for transport services under dynamic external conditions.

To achieve this goal, the study proposes:

– the integration of classical transport models with modern data analysis tools;

– modeling of key crisis scenarios (economic recession, infrastructure failures, tariff shocks, pandemic);

– evaluation of the impact of these scenarios on population mobility, average travel time, trip losses, and modal split;

– development of practical recommendations to improve the resilience and flexibility of transport systems.

III. Research Methods and Modeling Framework

To forecast the demand for transport services under dynamic conditions, this study proposes a modeling algorithm that integrates classical transport models with adaptive data analysis tools, thereby enabling the simulation of diverse crisis scenarios. The algorithm is designed to address the limitations of conventional forecasting techniques by incorporating flexibility and resilience into the modeling process. In particular, it facilitates the examination of how socio-economic shocks, infrastructural disruptions, tariff fluctuations, and pandemic-related constraints may influence transport demand patterns.

On the basis of the proposed framework, numerical experiments were conducted to model key indicators of transport demand across multiple developmental scenarios. These indicators include average mobility, mean travel time, trip losses, and modal split. The simulation results not only demonstrate the sensitivity of transport demand to external shocks but also provide insights that can inform the optimization of route networks and the enhancement of system adaptability under conditions of uncertainty.

The modeling algorithm is presented in Fig. 1.

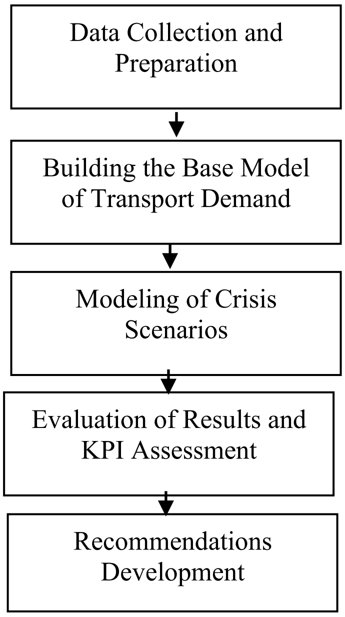

Fig. 1. Algorithm for Scenario Modeling of Transport Demand

This allows for the assessment of how economic, infrastructural, and social changes affect average population mobility, travel time, trip losses, and modal split.

The following section presents the simulation results for the baseline scenario and four crisis scenarios, as well as a comparative analysis of key performance indicators (KPIs).

IV. Results

The study utilized data from a sociological survey (1,107 respondents) and traffic counts at 35 control points across the city [6,7]. Baseline OD matrices were constructed, accounting for temporal demand characteristics (morning and evening peaks), modal split, and socio-economic factors [5].

5.1. Scenario "Base" (BS).

Under stable conditions, the average level of population mobility is 2.2 trips per day per capita, as confirmed by survey data. The trip distribution exhibits two pronounced peak periods: the morning peak (07:00–09:30) accounts for 44% of trips, while the evening peak (15:30–19:00) accounts for 26%. The average travel time is 27–28 minutes. The modal split is dominated by minibuses (≈49%) and trolleybuses (≈21%), with the remainder distributed among buses, private cars, and walking.

The dynamics of changes in average mobility across different scenarios are shown in Fig. 2.

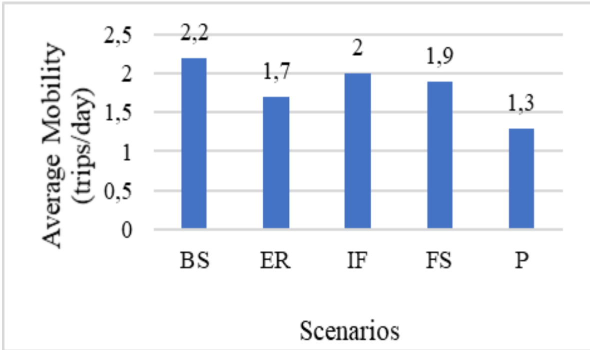

Fig. 2. Scenario-Based Changes in Average Mobility

5.2. Scenario "Economic Recession" (ER).

A decline in household income and purchasing power leads to a reduction in demand for public transport. It is estimated that the number of trips in low-income households decreases by 20–30%, reducing average mobility from 2.2 to approximately 1.7 trips per person per day. The share of walking trips increases (+5–7 percentage points), while the use of minibuses and taxis decreases.

5.3. Scenario "Infrastructure Failure" (IF).

Accidents, critical damage, and subsequent repairs of transport facilities (e.g., a bridge or a main line) result in local congestion on adjacent routes (up to +30% passengers during peak hours). Average travel time increases to 35–40 minutes (Fig. 3), and the share of lost trips reaches 10–15% within the affected area.

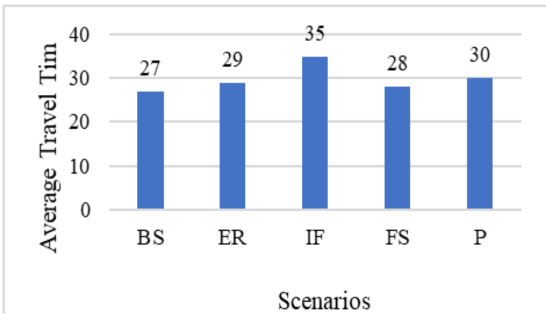

Fig. 3. Impact of Infrastructure Failures on Average Travel Time

5.4. Scenario "Fare Shock" (FS).

A sharp increase in fare prices by 30–50% without corresponding improvements in service quality reduces demand for public transport by 10–20%. Low-income passengers are the most sensitive to such changes. The share of walking and cycling trips increases (up to 18%), while minibuses lose up to 9 percentage points in the modal split structure (Fig. 4).

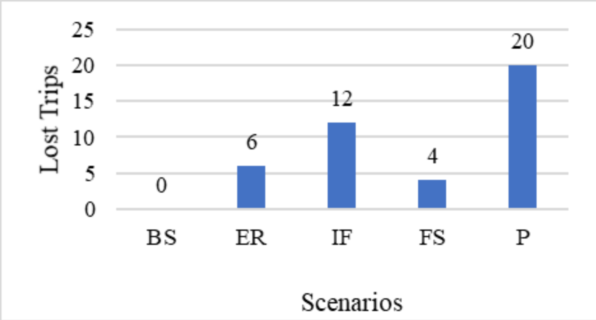

Fig. 4. Impact of Fare Changes on Modal Split

The change in modal split under fare adjustments demonstrates a high passenger sensitivity to travel costs and underscores the need for adaptive fare regulation and the maintenance of accessibility for socially vulnerable population groups.

5.5. Scenario "Pandemic" (P).

The spread of a pandemic led to a decrease in mobility of approximately 40%, with the average number of trips declining to 1.3 per person per day. Additionally, 68% of respondents reported being unable to board due to overcrowding and capacity restrictions. Average travel time increased to 30–32 minutes, and the modal split shifted toward walking and cycling trips. This created significant challenges in ensuring transport accessibility.

5.6. Comparative Analysis of KPIs

The aggregated key performance indicators (KPIs) of transport demand across scenarios are presented in Table 1.

Table 1

Comparative Analysis of KPIs

Indicator	*BS*	*ER*	*IF*	*FS*	*P*
Average Mobility (trips/day)	2,2	1,7 (-23%)	2,0 (-9%)	1,9 (-4%)	1,3 (-0%)
Average Travel Tim	27–28 min	29–30 min	35–40 min	28–30 min	30–32 min
Lost Trips	≈0%	5–7%	10–15%	3–5%	до 20%
Share of Walking Trips	12%	17%	14%	18%	22%
Share of Minibus Trip	49%	43%	46%	40%	38%

As shown in the table, each scenario exhibits specific changes in key transport demand indicators. Economic recession reduces average mobility by 20–30% among low-income population groups. Infrastructure failures lead to an increase in travel time to 35–40 minutes and trip losses of up to 15%. Fare shocks decrease demand by 10–20%, whereas the pandemic causes the largest reduction in mobility and shifts the modal split toward walking and cycling. These findings provide the basis for further discussion of practical implications and recommendations for adaptive management of the transport system.

5.7. Discussion.

The obtained results demonstrate a high sensitivity of public transport demand to crises of various types. For transport planning, this implies the need for: flexible adjustments of schedules and routes during peak hours; implementation of reserve capacities to respond to capacity restrictions; promotion of alternative mobility modes (bicycles, micromobility) as compensatory mechanisms; and the use of scenario-based forecasting as a tool for risk assessment and timely managerial decision-making.

CONCLUSIONS

Conducting scenario-based modeling of transport service demand under dynamic conditions is a necessary prerequisite for ensuring the efficiency, resilience, and adaptability of urban transport systems. The integration of classical transport models with modern data analysis methods allows for the assessment of the impacts of various crisis scenarios—such as economic recession, infrastructure failures, fare shocks, and pandemics—on average population mobility, travel time, trip losses, and modal split.

Thus, the application of a scenario-based approach enhances the reliability of forecasts, enables risk assessment, and supports the development of practical recommendations to improve the resilience and adaptability of transport systems

REFERENCES

[1] Moreau, A., Côme, E., & Oukhellou, L. (2024). Modeling COVID-19 impact on Paris metro demand with regression mixtures. arXiv preprint arXiv:2402.12392. https://arxiv.org/abs/2402.12392

[2] Verroen, E., & Jansen, G. (1991). The Scenario Explorer for passenger transport. https://consensus.app/papers/the-scenario-explorer-for-passenger-transport-verroen-jansen/89f5ba1404cd500cb418342180241603/?utm_source=chatgpt

[3] Stephenson, J., & Zheng, L. (2013). National long-term land transport demand model. https://consensus.app/papers/national-longterm-land-transport-demand-model-stephenson-zheng/a985e03b8977591ea259d89b942da4de/?utm_source=chatgpt

[4] Davidich, Y. O., Ivanov, S. M., & Kuznetsova, N. P. (2019). Study of the attraction function of residents for assessing demand for transport services in cities. Urban Utilities, (4), 56–61. http://k-tsl.com

[5] Fornalchik, Y. U. (2020). Transport flow modeling: A textbook. Lviv: Novyi Svit – 2000. http://mybook.biz.ua

[6] Ponkratov, D., Kopytkov, D., Davidich, Y., Kush, Y., & Nykonchuk, V. (2025). An estimation of the public transit quality of service based on travel fatigue modeling approach. In IOP Conference Series: Earth and Environmental Science, 1499(1), 1–15. https://iopscience.iop.org/article/10.1088/1755-1315/1499/1/012069

[7] Nykonchuk, V. M., Krystopchuk, M. E., Khitrov, I. O., et al. (2024). Theory and practice of development of transport systems and transport infrastructure objects [Monograph]. Lutsk: Vezha-Druk.