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Comparison of Forecasting Methods for Intercity Passenger Flows for Various Modes of Transport



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ABSTRACT

The article is devoted to methodological features of forecasting intercity passenger flows under the conditions of transformation of the transport system of Russia, namely, the emergence of a new type of rail transport which is high-speed rail. The objective of the article is to present the authors' methodology for forecasting passenger flows and to prove its higher efficiency relative to the methods used in Russia today. The article considers the historical aspect of forecasting passenger flows, analyzes strengths and weaknesses of existing approaches to forecasting and modelling passenger flows. The authors argue that it is impossible to simulate the number of trips with changes in transportation parameters only on the basis of patterns identified by retrospective data series (the most common approach to forecasting passenger flows in Russia).

The article proposes an alternative methodology based on the calculation of passenger's total costs of a trip, which depend on cost of travel, loss of time, frequency of departure of vehicles and their comfort, as well as considering the dynamics of key social-economic indicators. The technique allows minimizing measurement errors arising from the lack of primary information about some types of passenger transport, as well as calculating the induced demand for trips arising as a result of improved transportation characteristics. The authors identified and expressed in quantitative terms the main factors of redistribution of passenger flows to newly introduced types of transport.

The article discusses the experience of forecasting passenger flow according to the proposed method at the example of four itineraries where movement of high-speed trains of Lastochka type started. The forecasted results are compared with the actual volumes of transportation, on the basis of which conclusions are drawn about the effectiveness of the forecasting method and its applicability in modern realities of the Russian transport system. The advantages and disadvantages of the proposed approach to forecasting passenger traffic, as well as the possibilities of its implementation and further development in Russia are identified.

Keywords: *forecasting methods, passenger flow, transport demand, transport mobility of the population, high-speed train.*

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Introduction and statement of the research problem

Modern approaches to forecasting long-distance passenger flows are based mainly on mathematical models with multivariate regression dependencies.

Modern mathematical models for forecasting passenger flows, for the most part, are based on the classical four-stage model [1]. This approach, first used in the 1950s, allows getting a picture of passenger flow distribution over the network based on input prerequisites for generating travel demand and parameters of the transport system. Modelling is carried out in four stages:

1) identification of the points of generation and attraction of trips and their potential;

2) distribution of trips over the network;

3) selection of a mode of transport;

4) compilation of the zonal interchange (trip distribution) matrix «$Point_i$—$Point_j$» with the absolute value of the passenger flow for each of the modes of transport available for trips.

The distribution of the number of trips between the points of generation and attraction along routes and by modes of transport in the classical four-stage model are carried out according to the principle of minimizing transport costs and considering restraints of transit capacity of the infrastructure. That is, the passenger travelling from Point 1 to Point 2 will choose the shortest route and the cheapest mode of transport by the total transport costs until the capacity limit for this route and mode of transport is reached.

Further development of this concept of forecasting passenger flow was directed towards avoiding a formalized rational justification for a passenger's choice of a route or a mode of transport. The thesis of irrationality of the consumer behaviour has influenced the transformation of modelling algorithms. So, at the stage of distribution of trips by modes of transport and routes, it was not differentiation of the total cost of the trip that was taken into account, but differentiation of subjective significance of transportation parameters, determined on the basis of the regression dependence of the passenger flow on transportation parameters by a mode of transport and route within retrospective time series.

To solve the problems of modelling a passenger flow for the trip «Point 1—Point 2», models of analysis of time series ARMA (autoregressive moving average) and ARIMA (autoregressive integrated moving average, Box—Jenkins model), mathematically representing a generalization of the auto-regression model and the moving average model, have become very popular [2; 3].

In the framework of the approach based on the regression analysis of time series, the forecast of the passenger flow for the trip «Point 1—Point 2» in the case of introducing a new mode of transport (or changing the parameters of an existing one) is carried out as follows.

At the first stage, the total travel demand is estimated, which is determined by the characteristics of population mobility. The forecast of the total demand for travel between «Point 1—Point 2» is based on regression dependence of retrospective data of the passenger flow on the social-economic and demographic parameters of the departure and arrival points.

At the second stage, a forecast is made for switching passenger traffic to a new mode (type) of transport. The classic tool for calculating switching is currently a model of discrete choice of a mode of transport. The principle of its operation is to use the revealed dependence of the passenger flow change on the change in transportation parameters. In other words, the model «learns» the reaction of demand for trips by various modes of transport to retrospective changes in travel time, cost of travel, transit frequency and comfort. Thus, the passenger flow elasticity is revealed by its sensitivity to the aforementioned parameters, which in case of their change determines the rate of passengers who switch to a new type of transport.

An alternative approach using the method of balance of generalized transport costs is currently used mainly as a corrective complement to the methods of regression analysis. However, in some cases, especially when forecasting the passenger flow for a fundamentally new type of traffic, this method plays a leading role. For example, the national company of French railways SNCF uses the method of balancing the generalized costs in forecasting passenger traffic switching to commissioned high-speed lines [4]. Optimal transit mode is determined for each individual passenger and for a specific trip. The optimality criterion is the minimum value of generalized costs, which is calculated by the formula:

$$C_g = (P_{journey} + P_{access}) + h \cdot (T_{journey} + T_{access}), \quad (1)$$

where C_g – generalized costs;

$P_{journey}$ – cost of the main trip, rub.;

P_{access} – cost of auxiliary trips (to access the main transport), rub.;

$T_{journey}$ – time of the main trip, min;

T_{access} – time of auxiliary trips, min;

h – time cost, rub.

Consequently, the newly introduced high-speed rail will attract the number of passengers for which it will turn out to be the most advantageous mode of transport in terms of generalized costs.

A separate stage in modelling the passenger flow change is the forecast of induced (or deinduced) demand for trips caused by a change in transport accessibility of Point 1 and Point 2 relative to each other. The change in total travel demand in this case is calculated according to the law of gravity, where the mass of respective Points 1 and 2 is the volume of effective demand concentrated in them, and the distance between them is the weighted average generalized (monetary and time) travel costs before and after simulated changes [5].

Speaking about the main problems of using generally accepted international approaches to modelling and forecasting intercity passenger flows [e.g. 6–9] in Russia, it is necessary to note the extremely high heterogeneity in development of infrastructure, the solvency of the population and, as a consequence, transport behaviour of residents. Therefore, the use of uniform sensitivity coefficients to measure changes in the parameters of modes of transport (primarily travel time, cost of travel, transit frequency, comfort level) for the entire territory of Russia is incorrect. It is at least necessary to cluster trips between different origin and destination points and calculate the sensitivity of the passenger flow to these indicators individually and there should be a lot of clusters in order to minimize the error. However, the more clusters are distinguished, the smaller becomes the training sample of trips' origin and destination points in each of them. In this regard, the methods for assessing the switching of passenger flows between modes of transport, based on the discrete choice model, may give incorrect results if the specified forecasted parameters of the modes of transport are beyond the range observed in the retrospective data.

Most of the models used in foreign countries for forecasting passenger flows are extremely demanding on quality of initial statistical data that are laid therein, and on the value of time series by which regression dependencies are determined. Unfortunately, in Russia, the advantage of using methodically more complex algorithms is offset by the fact that the volume and quality of the source data is significantly inferior to the statistical data of most European countries, the USA or Japan.

In Russia, reliable statistical information in the context of trips between specific origin and destination points (pairs of settlements) is only available for air and railway transport, which, unfortunately, is not enough to make a correct forecast of total transport demand. Information on bus transport is available only for a limited set of of origin and destination points, moreover, despite the fight against illegal carriers, in most regions the share of informal transportation in the structure of passenger flow is still high.

The assessment of passenger flows generated by private cars is a separate methodically difficult task, and official statistics on private car passenger traffic, even at the inter-regional level, do not exist. Thus, to completely assess the existing passenger flow, one has to resort to the use of sociological survey methods and large-scale field observations. Incorrect data on just one route in the training set can significantly distort the forecasting results.

Under these conditions, the use of simpler and more transparent algorithms, where at each stage of the calculations it is possible to evaluate the intermediate result (having physical meaning), gives an even more accurate forecasting result compared to more advanced and mathematically complex methods, which are rather a «black box» during the study.

The *objective* of this article is to develop a set of necessary initial data and algorithms that minimize, from the point of view of the authors of this article, the risk of significant errors in forecasting intercity passenger flows and to test them at the example of recently introduced high-speed rail routes.

Research methods

It is proposed to use the following data sets as initial data for modelling and forecasting passenger flows for different itineraries:

1. Information about the existing passenger flows and the parameters of activity of modes of transport.

1.1. Retrospective data on passenger flows by modes of transport.

The proposed methodology uses data series for 2005–2018, as only within this period the authors could use reliable statistics. Among the modes of transport, air, bus, private cars and railway transport are assessed[1]. Due to strong heterogeneity, the latter is considered separately for classes: shared open compartment carriages (open compartment sleeping cars, but also sitting cars and day coaches, excluding cars in high-speed and accelerated trains), compartment carriages (passenger flow in cars of the first class, luxury and upholstered beds categories also applies) and high-speed trains.

1.2. Parameters of activity of modes of transport averaged over the annual period for forecasted itineraries for the period from 2005 to 2018: travel time, fare, transit frequency, carriage or vehicle comfort for passengers[2].

2. Social and economic indicators.

2.1. Information on gross regional product (per constituent entities of the Russian Federation);

2.2. Information on the structure of the population by income groups per constituent entities of the Russian Federation in accordance with the classification of the Federal State Statistics Service (the number of inhabitants of the region having respectively income of less than 7 thousand rubles, from 7 to 10 thousand rubles, from 10 to 14 thousand rubles, from 14 to 19 thousand rubles, from 19 to 27 thousand rubles, from 27 to 45 thousand rubles, from 45 to 60 thousand rubles, more than 60 thousand rubles);

2.3. Information on the population size of passenger flow generation points (settlements or urban agglomerations).

The source of data on social and economic indicators is the Federal State Statistics Service (Rosstat).

The passenger flow forecasting unit according to the interchange zonal matrix in the context of modes of transport consists of three main components:

- forecasting the total demand for passenger transportation by all modes of transport by each itinerary;
- distribution of the total passenger flow by a mode of transport;
- forecasting induced demand.

The total demand for passenger transportation depends on several social and economic indicators. According to the results of the factor analysis, the gross regional product (r = 0,88) showed the greatest correlation with the transport mobility of residents of regions[3]. Based on retrospective data, a regression relationship between the transport mobility of the population and GRP was revealed.

With an increase in GRP, the transport mobility of the population also increases, therefore, ceteris paribus, the total passenger flow by an itinerary also grows. Thus, the total passenger flow for the forecast year can be determined by the following formula:

$$F_{forecast} = F_{current} \cdot GRP_{\Delta} \cdot k_{grp\text{-}flow} \cdot Pop_{\Delta}, \quad (2)$$

where $F_{forecast}$ and $F_{current}$ are respectively forecasted and current total passenger flow for an itinerary, persons;

GRP_{Δ} – increase in GRP of regions connected by the itinerary;

$k_{grp\text{-}flow}$ – coefficient of sensitivity of changes in transport mobility of the population to GRP[4];

Pop_{Δ} – population growth of cells connected by an itinerary.

Increase in GRP of regions connected by an itinerary is calculated using the following formula:

$$GRP_{\Delta} = X \cdot \frac{GRP_{future\ 1}}{GRP_{current\ 1}} + Y \cdot \frac{GRP_{future\ 2}}{GRP_{current\ 2}}, \quad (3)$$

where GRP_{Δ} – increase of GRP of regions for the corresponding year;

$GRP_{future\ 1}$, $GRP_{future\ 2}$ – forecasted GRP in region 1 and region 2;

$GRP_{current\ 1}$, $GRP_{current\ 2}$ – current GRP in region 1 and region 2;

X and Y – passenger flow shares, generated by region 1 and region 2.

If the settlements of the route are located within one and the same region, the calculations use data only for this region.

[1] When necessary any other mode/types of transport with their respective parameters can be added to the model.

[2] Approach to calculation of integral trip comfort index will be described below.

[3] The number of trips outside the settlement, made by all modes of transport per capita.

[4] Determined according to the results of training of the model on retrospective data.

Similarly, the population growth of the territories connected by the itinerary is calculated:

$$Pop_{\Delta} = X \cdot \frac{Pop_{future\ 1}}{Pop_{current\ 1}} + Y \cdot \frac{Pop_{future\ 2}}{Pop_{current\ 2}}, \qquad (4)$$

where Pop_{Δ} – population growth of cells connected by the itinerary for the corresponding year:

$Pop_{future\ 1}$, $Pop_{future\ 2}$ – forecasted population number of cells 1 and 2, persons;

$Pop_{current\ 1}$, $Pop_{current\ 2}$ – current population number of cells 1 and 2, persons;

X and Y – passenger flow shares, generated by region 1 and region 2.

The distribution of the total forecasted passenger flow by a mode of transport is based on a combination of four factors affecting the choice of a passenger: travel time, cost of travel, transit frequency, and comfort level.

Each of the indicators is converted into value terms and affects the indicator of the total transport costs of the trip for this passenger for this itinerary. The total transport costs are calculated for each mode (type, class) of transport separately.

The indicator of total transportation costs is calculated as the sum of cost of travel and the cost of time spent.

$$TTC = C_{travel} + C_{time}, \qquad (5)$$

where TTC – total transportation costs, rub.;

C_{travel} – cost of travel[5], rub.;

C_{time} – cost of time spent (adjusted to the level of trip comfort), rub.;

$$C_{travel} = C_{t1} + NCT + C_{t2}, \qquad (6)$$

where C_{t1} – average weighted cost of travel from the departure point to the station/bus station/airport at which the main segment of the trip begins, rub.;

NCT – average cost of travel on the main segment of the trip, rub.;

C_{t2} – average cost of travel from the station/bus station/airport, on which the main segment of the trip of this itinerary to the destination point ends.

The cost of time spent depends on travel time, transit frequency (and, as a result, the average waiting time for departure of the vehicle), as well as on the income level of the passenger (calculated for each group of passengers by income level). Also, the cost of time spent is adjusted to the level of discomfort that the passenger experiences during the trip when using a certain mode (type) of transport and for a certain duration of the trip.

The cost of time spent is calculated according to the following formula:

$$C_{time} = (T_{travel} \cdot K_{comf} + (1/Fr) \cdot (1 - K_{fr})) \cdot I_h, \qquad (7)$$

where C_{time} – cost of time spent (adjusted to the level of the trip comfort), rub.;

T_{travel} – average travel time of a passenger from the departure point to the destination point, min;

K_{comf} – coefficient of trip discomfort;

Fr – transit frequency (number of trips per day), units;

K_{fr} – coefficient of elasticity with regard to transit frequency[6];

I_h – average cost of a working hour for a passenger belonging to a particular income category.

Travel time of a trip is composed of several trip segments:

$$T_{travel} = T_{t1} + T_{waiting} + NTT + T_{t2}, \qquad (8)$$

where T_{travel} – travel time of a passenger from the departure point to the destination point, min;

T_{t1} – average travel time from the departure point to the station/bus station/airport, on which the main segment of the trip of this itinerary starts, min;

$T_{waiting}$ – average time required for a passenger for transfers when changing modes of transport during the trip, min;

NTT – net travel time on the main segment, min;

T_{t2} – average travel time from the station/bus station/airport of arrival to the destination point, min.

The point of departure and destination for the territorial cell is the geometric center of the cell settlement system.

The trip comfort index depends on the comfort level of the vehicle itself and the coefficient of elasticity to the comfort level[7]. The comfort coefficient is determined for each type of transport and gets values from 0 to 1. The value is calculated based on the results of social surveys of passengers

[5] Full travel cost for public transport (with account of cost of travel between stations/bus stations/airports and point of departure/destination), or calculated cost of travel for private car trip, which includes: 1) cost of fuel used, 2) cost of technical maintenance per 1 km of run, multiplied by the length a route; 3) cost of infrastructure use, in case, it is charged.

[6] Determined based on the results of training of the model on retrospective data.

[7] Determined based on the results of training of the model on retrospective data for each mode of transport and itinerary.

regarding the trip comfort when using different modes of transport.

The average cost of a working hour depends on the average monthly income level of a passenger in a given population group and the average number of working hours per year:

$$I_h = \frac{I_m}{\frac{247}{12} \cdot 8}, \quad (9)$$

where I_m – average monthly income of a passenger of a particular population income group, rub.;

247 – average number of working days per year;

12 – number of months per year;

8 – average number of working hours per day.

At the next stage, the ratio of the indicator of total trnasportation costs for this mode of transport is calculated in relation to the minimum indicator among all modes of transport:

$$K_{TTC} = TTC_i / TTC_{min}, \quad (10)$$

where K_{TTC} – coefficient of ratio of the total transportation costs for a given mode of transport to the minimum value among all modes of transport;

TTC_i – total transportation costs for this mode of transport, rub.;

TTC_{min} – minimal value of total transportation costs among all modes of transport for this trip, rub.

The probability coefficient for choosing a mode of transport is calculated as follows:

$$K_p = \frac{1}{K_{TTC}^{Kettc}}, \quad (11)$$

where K_p – probability coefficient for choosing a mode of transport;

K_{ettc} – coefficient of elasticity of passenger flow to the change in total transportation costs[8].

The total forecasted passenger flow is distributed in accordance with the coefficient of probability of choosing a mode of transport:

$$F_i = \frac{K_p}{\sum_{i=1}^{n} K_p} \cdot F_{forecast}, \quad (12)$$

where F_i – forecasted passenger flow on this mode of transport, people;

K_p – coefficient of probability of choosing a mode of transport;

$F_{forecast}$ – forecasted total passenger flow for an itinerary, persons.

[8] Determined based on the results of training of the model on retrospective data.

Thus, for each mode (type, class) of transport forecasted value of the passenger flow on the correspondence is calculated.

If any parameters of the modes of transport change over time, the weighted average total transportation costs will also change. If the total transportation costs as a result of changes in travel time, fare, transit frequency, and comfort level decrease, then there is an induced demand (passengers begin to travel more often, or those who have not traveled at all begin to use this itinerary for their trips). If the total transportation costs increase, the opposite situation arises (demand decreases). In general, the formula for calculating induced demand is as follows:

$$F_{ind} = F_{forecast} \cdot \left(\left(\frac{TTC_{base}}{TTC_{model}} \right)^{K_{ttc}} - 1 \right), \quad (13)$$

where F_{ind} – forecasted induced demand, persons;

TTC_{base} – average weighted total transportation costs with existing parameters of modes of transport, rub.;

TTC_{model} – average weighted total transportation costs for modelled parameters of modes of transport, rub.;

K_{ttc} – coefficient of elasticity to total transportation costs.

The volume of forecasted induced demand is summed up with the base forecasted passenger flow by the mode of transport, due to which there was a decrease in the total transportation costs for this itinerary. This value will be the final volume of the forecasted passenger flow for this mode of transport and itinerary.

Research results

The above-described passenger flow forecasting technique has been used in research projects related to development of large-scale infrastructure projects, in particular, of Moscow–Nizhny Novgorod and Moscow–St. Petersburg high-speed rail projects, of a promising high-speed road network of Avtodor Group of Companies. Transport projects partially implemented to date, and based on the forecast made using the methodology, comprise the route network of fast (express trains with higher speeds) electric trains Lastochka. Fast electric trains Lastochka are assigned to intercity routes on the network of JSC Russian Railways since 2012. In 2014, LLC Center for Economics of

Table 1

Estimated transportation parameters for 2018, used as input data for passenger flow modelling

Itinerary	Type of transportation	Cost of travel, rub.	Travel time, hours	Transit frequency, trips per day
Moscow–Kursk	Shared open compartment	1324	7,2	10,3
	Compartment	2444	7,2	9,3
	Lastochka	982	5,7	2,0
	Bus	850	9,0	3,3
	Private car	1208	6,7	Unlimited
Moscow–Oryol	Shared open compartment	1179	5,3	11,3
	Compartment	1861	5,3	9,3
	Lastochka	697	4,1	4,0
	Bus	650	6,5	10,0
	Private car	936	4,5	Unlimited
Moscow–Smolensk	Shared open compartment	950	5,8	7,0
	Compartment	1 652	5,8	7,0
	Lastochka	900	4,1	3,0
	Bus	900	6,5	34,0
	Private car	1082	4,8	Unlimited
Moscow–Tver	Shared open compartment	722	2,2	8,0
	Compartment	1018	2,2	8,0
	Lastochka	510	1,7	12,0
	Suburban train	390	3,0	7,0
	Private car	447	2,6	Unlimited

Source: compiled by the authors.

Table 2

Forecasted and actual values of passenger flow for 2018

Itinerary	2018 (forecast)	2018 (fact)
Moscow–Smolensk	342359	356426
Moscow–Kursk	311173	327171
Moscow–Oryol	417989	434179
Moscow–Tver	2292005	2407746

Source: compiled by the authors.

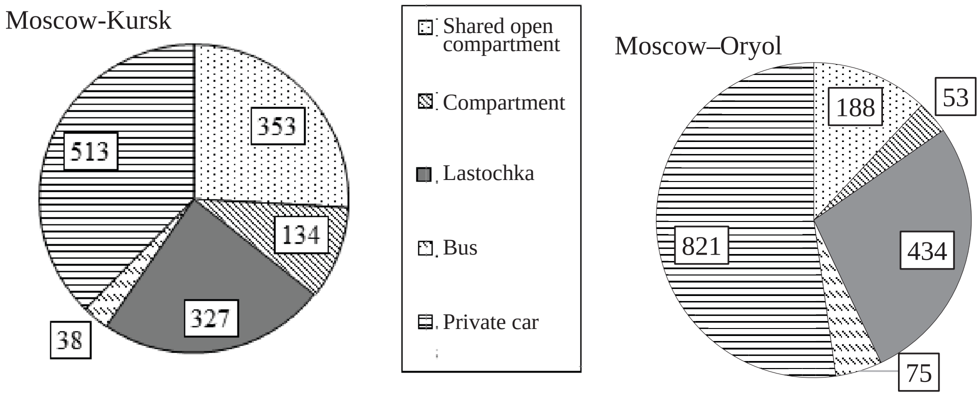
Infrastructure carried out research work on a plan for development of Lastochka train route network, within the framework of which a forecast was made of passenger flow on promising high-speed train routes for the period until 2035 in the context of station-to-station trip distribution.

Let's consider the forecasted and actual values of the passenger flow for 2018 according to the main itineraries of four express routes that were put into operation with the parameters closest to those used for forecasting. To carry out a passenger flow forecast for the itineraries under study, a database of parameters of existing modes of transport was compiled and promising parameters of fast rail transportation were set (Table 1).

Table 2 contains the forecasted and actual values of the passenger flow served by express trains Lastochka on the main point-to-point segments of the above routes. Actual passenger flow deviates from the forecast made as part of the research by no more than 5 %.

Discussions of results

It follows from the forecasting results that fast trains Lastochka on the itineraries under study should have occupied from 25 to 50 %



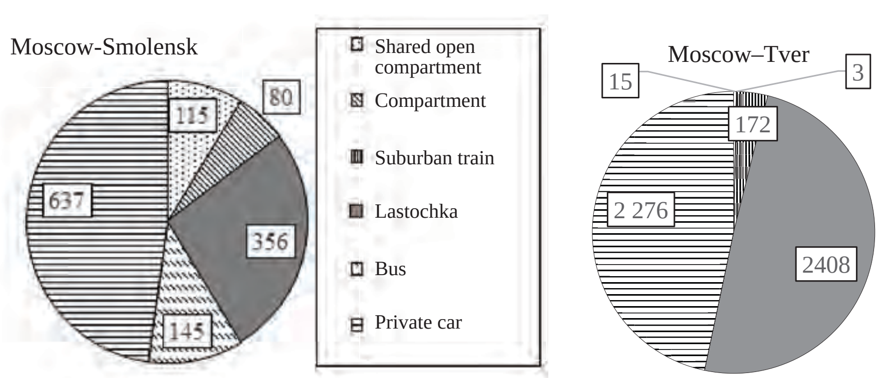
Pic. 1. The actual structure of passenger flow on the itineraries Moscow–Kursk and Moscow–Oryol, 2018, thousand passengers. Source: compiled by the authors.

of the passenger transportation market by 2018, which actually happened. In addition to significant switching of passengers from other modes of transport, passenger flow was influenced by a significant induced demand for trips: from 10 to 15 % of passengers of Lastochka trains would not have traveled at all if there were no fast trains.

Due to the intensity of business, cultural and domestic relations and high incomes of the residents of the capital city, there is a high demand for «morning» or «evening» trips between Moscow and neighboring regions that allow not to loose a night or a daytime for the trip. Passengers making such trips are extremely sensitive to travel time. The launch of Lastochka trains, combined with their convenient departure and arrival times, made it possible to make such trips to Moscow from Smolensk, Oryol and Kursk, and greatly simplified the possibility of making such trips from Tver.

Switching of passengers to fast trains was carried out from all alternative modes of transport, including private cars. On the first three routes, the greatest outflow of passengers was suffered by bus and traditional railway (shared open compartment class) transport. On the Moscow-Tver route, classical suburban electric trains were the main source for passenger switching to Lastochka trains: as the result of the launch of faster trains suburban trains lost about 90 % of the annual passenger flow.

This forecast could not be correctly carried out using the model of discrete choice of the mode of transport, based on the regression retrospective dependence of changes in passenger flow on changes in transportation parameters, since in this case the demand for a fundamentally new transport service is simulated. Lastochka trains travel along the above routes much faster than alternative modes of transport, while ensuring competitive



Pic. 2. Actual structure of the passenger flow on the route Moscow–Smolensk and Moscow–Tver, 2018, thousand passengers. Source: compiled by the authors.

cost of travel (Table 1). In addition, those trains can offer higher level of comfort relative to competing buses and traditional railway services. There was no database for correct training of the regression model, with which it would have been possible to forecast the demand for the Lastochka trains at the time the forecast was made, since there had been previously few similar innovations.

Moreover, depending on the type of the itinerary and the degree of competition with other types of transportation, the same changes in parameters might lead to different changes in the structure and total volume of passenger flow. For example, reducing travel time of a night train from 10 to 7,5 hours (by 25 %) will cause a smaller increase in passenger flow than reducing travel time of a day express train from 4 to 3 hours (by the same 25 %), because the cost of time for a night passenger trains is lower than the cost of time for a day express passenger. So it is impossible to forecast without considering such a parameter as the cost of a unit of time of a passenger.

Conclusion. The proposed methodology for forecasting passenger flows coincides with the most common mathematical approaches based on the regression analysis of time series in the field of forecasting the total demand for trips. However, the approach under consideration is more transparent in terms of calculating distribution of passengers between modes of transport. The advantage of the proposed method is the quantitative expression of transportation parameters through the total cost of the trip for differentiated groups of passengers. The model distributes the passenger flow not according to the training results on retrospective data, but on the basis of total passenger transportation costs per trip. This allows to more accurately simulate changes in the transportation parameters that have had no analogues in retrospect. The forecast of the passenger flow for new routes of fast Lastochka trains showed that the sensitivity of the passenger flow to changes in travel time and travel comfort can be different depending on the scale of changes in these parameters, since different transportation parameters determine the transport behaviour of different groups of passengers. In particular, competent accounting of cost of travel time of passengers made it possible to identify the «hidden potential» of faster transportation at the stage of forecasting passenger flow, which is not considered using the regression-analytical approach. The main disadvantage of the proposed methodology is underestimation of irrationality of the consumer behaviour. Certain modes of transport for certain itineraries might be economically unreasonably popular or, conversely, not popular, due to the particular mental characteristics of passengers (for example, habits of using a certain mode of transport).

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