



Using an Artificial Neural Network to Record and Analyse the Performance Indicators of a Transport Enterprise



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ABSTRACT

Recently, the issue of determining actual values of passenger flow processed by urban public and suburban transport on each section of the route in real time has become even more relevant since those values affect planning, organisation of operations and performance of transport enterprises.

It is not possible to assess the real volume of passenger flow with the number of tickets issued to passengers due to the large number of unaccounted passengers (the discrepancy between the number of tickets issued to passengers and the real number of passengers transported).

The objective of the study which results are described in the article was to develop an intelligent system for calculating and analysing the transport enterprise performance, which allows automatically collecting, processing and analysing information about passenger flows, calculating the passenger rotation ratio on the route, drawing up optimal bus schedules and timetables, adjusting vehicle traffic intervals, determining the need for rolling stock to minimise the likelihood that a passenger is denied boarding,

improving the quality of passenger service and reducing the operating costs of a transport enterprise.

Real-time calculation of passenger flow values for each vehicle on the route of urban public transport is carried out by a quantitative method based on artificial neural network technology, which allows automatic processing of a large amount of information from CCTV cameras installed in vehicle interiors.

The use of theoretical research methods helped to create an intelligent system capable to analyse and compare the number of tickets issued to passengers with the actual number of passengers transported on Samara city public transport route, the results were displayed through a graphical user interface. It was possible to reveal dependences of the number of unaccounted passengers on the route on the amount of passenger flow and the time of day.

A possibility of using the proposed intelligent system in commuter trains was noted, provided that the cars are equipped with video surveillance cameras.

Keywords: urban public transport, commuter train, artificial neural network, intelligent system, passenger flow, transport enterprise, performance indicators, unaccounted passengers, passenger tickets, need for rolling stock.

For citation: Moskvichev, O. V., Leonova, S. A., Vasiliev, D. V. Using an Artificial Neural Network to Record and Analyse the Performance Indicators of a Transport Enterprise. World of Transport and Transportation, 2023, Vol. 21, Iss. 2 (105), pp. 185–191. DOI: <https://doi.org/10.30932/1992-3252-2023-21-2-4>.

**The text of the article originally written in Russian is published in the first part of the issue.
Текст статьи на русском языке публикуется в первой части данного выпуска.**

INTRODUCTION

The activity of passenger transport enterprises are evaluated by quantitative and qualitative indicators characterising, among other things, the number of rolling stock and the level of its productivity [1–3].

Quantitative indicators determine the income of the enterprise from transportation activity, the number of passengers transported and passenger turnover. The values of passenger flow on each section of the route reflect the effectiveness of operation of certain vehicles.

The rate of technical readiness, the number of the units of the fleet, the coefficient of output, as well as duration of a vehicle operation, the mileage utilisation rate, and the speed on the route per line are related to the quality indicators of the work of the transport enterprise.

For transport enterprises, it is important to reduce operating costs and improve the quality of passenger service.

If we consider the example of urban public transport, then passengers make their choice in favour of a particular mode of transport based on regularity of traffic and occupancy of vehicles, especially during peak hours. The supply of vehicles should be carried out with such a quantity that will allow satisfying the entire passenger flow in each direction during «peak» periods and reducing the likelihood that a passenger is denied boarding. All this is possible only if accurate data on the magnitude and fluctuations of a passenger flow on each section of the route are available [4–5].

Collection and analysis of real time data on the number of passengers transported will allow making informed decisions about the number of vehicles operating on the route, rational planning of the work schedule of drivers and developing bus schedules in such a way as to satisfy all passengers during «peak» periods with proper quality of the service.

It is not possible to estimate the real size of passenger flow by the number of tickets issued to passengers due to the large number of unaccounted passengers (the discrepancy between the number of tickets issued to passengers and the real number of passengers transported). It is important to obtain data on the amount of passenger flow per each hour of the day on each section of the route to draw up optimal work schedules and timetables for vehicles, assess the efficiency of using the working fleet of vehicles and reduce the operating costs of the enterprise. At the same time, it is

necessary to analyse and process a large amount of information, calculate, and adjust quantitative and qualitative indicators, which is impossible without a modern intelligent system capable of automatically collecting, analysing, and updating data in real time.

The issue of determining the values of passenger flow on each section is relevant for commuter railways as well. It is important to record and track passengers in commuter trains, not only to ensure safety and security, but also to identify the demand for this direction, to determine a possibility of accounting for passengers transported between specific stations, to decide to add or reduce the number of cars in the commuter train.

The objective of the work is to develop an intelligent system based on an artificial neural network for calculating and analysing the transport enterprise performance, which allows processing and analysing information about passenger flows, data on occupancy of rolling stock per sections and along the entire length of the route, the results of calculating quantitative and qualitative indicators, comparing the number of tickets issued to passengers with the actual number of passengers transported on the route.

RESULTS

The proposed intelligent system consists of the following modules [6]:

1) A module that allows determining the real values of passenger flows by a quantitative method based on the use of artificial neural networks technology. At this stage, a database is created containing information on the number of boarding and disembarking passengers at stopping points during each period of time.

2) A module that allows comparing all conducted transactions with the coordinates of the location of the vehicle at each period of time. At this stage, we obtain a database on the number of issued travel documents on the public transport route.

3) An analytic module that allows, based on data from the previously described modules, evaluating quantitative and qualitative indicators of a transport enterprise, comparing the number of tickets issued with the actual number of passengers transported on the route. Flexible grouping per routes, days of the week, seasons is provided.

The first module allows automatic counting passengers on each section of the route of each

vehicle, solves the problem of systematising data on passenger flows with given parameters, determines the occupancy rate of the vehicle between stops, and calculates the passenger rotation rate on the route.

In general, the analysis of fluctuations in passenger flow makes it possible to obtain information about the demand regarding a particular direction and to identify patterns of formation of passenger flow both for each route separately and throughout the entire transport network.

The complexity of collecting such data is associated with the large volume and variability of information, as well as with the absence of special technical tools that allow collecting data on the number of passengers carried on each section of the route [7; 8]. Currently, the only acceptable way to collect data on the number of passengers transported on each section of Samara urban district route is a *tabular method* that allows recording passengers entering and leaving the vehicle.¹ The use of this method is associated with large financial costs in the case of using special technical means (sensors) installed in the doors of the bus, or significant labour and financial costs in the case of using a human resource: an employee who counts boarding and disembarking passengers must be located in the bus cabin, however the application of this approach is characterised by a large error in the output data associated with the human factor. In turn, it is necessary to regularly update information on passenger flows to make optimal decisions on the number of vehicles operating on the line, to develop the work schedule of drivers and ticket-checkers, to schedule traffic to meet the entire passenger demand during the «peak» period [9–11]. This is of particular importance in an environment of dynamically developing urban infrastructure and urban public transport network.

The paper, to identify passenger flows in real time, proposes a *method* based on the technology of artificial neural networks [12–15]. Artificial neural networks cover an array of popular machine learning methods that mimic the learning mechanisms inherent to biological organisms.

The input data for calculating passenger flows (module 1 of the developed intelligent system)

are data from video surveillance cameras in the interiors of vehicles, which, according to transport security requirements, are installed in almost every bus operating on the line and are directed to the passenger compartment and entrance doors.

An artificial neural network receives information from CCTV cameras aimed at the entrance doors and recognises passengers entering or leaving the vehicle. To increase the accuracy of identification, it is possible to rearrange cameras so that they shoot vertically downwards. This will reduce the likelihood of passengers overlapping the image.

The developed intelligent system within the framework of the first module is capable of tracking passengers, that is, determining the direction of movement of passengers: whether they are entering or leaving the bus. The system also eliminates the possibility of re-counting passengers since for each stop a temporary array is created with data on each passenger, which is cleared when the doors are closed. An intelligent system based on an artificial neural network, because of processing data from CCTV cameras, determines the number of passengers carried on each section of the route (Pic. 1).

The occupancy of the vehicle on each section is calculated as follows:

$$H_{i-(i+1)} = H_{(i-1)-i} + B_i - C_i, \quad (1)$$

where $(i-1)$ and i – stopping points;

$H_{(i-1)-i}$ – the number of passengers transported through a given section (data obtained by counting passengers by the proposed intelligent system);

B_i – the number of people entering the vehicle at the stopping point i ;

C_i – the number of people exiting at the stopping point i .

The second module allows displaying in the graphical user interface the data on the number of tickets sold for each vehicle, indicating the date, time, stop where the ticket is purchased.

The input data for the second module are arrays of transactions and data on the location of vehicles received from the GLONASS navigation satellite system.

The third module allows, based on the data generated by the previously described modules, assessing quantitative and qualitative indicators of operation of a motor transport enterprise, calculating operating costs, drawing up optimal

¹ Public transport of Samara region. [Electronic resource]: <http://www.samaratrans.info>. Last accessed 03.12.2021.





Pic. 1. Automatic calculation of incoming and disembarking passengers [performed by the authors].

Table 1

Data on occupancy of the bus of the route 41 of Samara city district
[performed by the authors]

Stopping point	Disembarked, pass.	Embarked, pass.	Occupancy, pass.	Disembarked, pass.	Embarked, pass.	Occupancy, pass.
15 th «А» mikroraion [microdistrict]	0	9	9	0	4	4
Karla Marksa pr.	4	11	16	1	6	9
.....						
«Yunost» univermag [department store]	10	0	0	5	0	0

schedules and timetables for buses, adjusting vehicle traffic intervals, and determining their occupancy to minimise the likelihood of a passenger being denied boarding, getting a comparative analysis of the number of issued tickets with the actual values of the number of passengers travelling along the route.

The probability of denial to board a passenger P_{den} is the proportion of passengers who, due to overcrowding of the vehicle, decided to stay at the stopping point, and passengers who boarded the vehicle despite the inadequate quality of the transport service provided:

$$P_{den} = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} \exp\left(-\frac{y^2}{2}\right) dy \quad (2)$$

$$\text{at } x = \frac{q + 0,5 - I \cdot \lambda}{\sqrt{I \cdot \lambda}} \text{ and } x \leq y \leq \infty,$$

where q – maximum capacity of the vehicle, pass. (value determined by the design of the rolling stock);

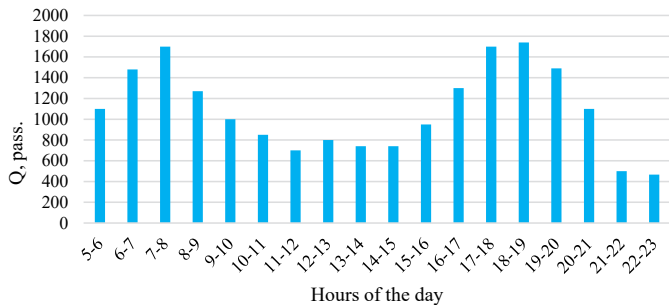
λ – average intensity of passenger flow on a certain section of the route, pass/min;

I – traffic interval [interval between the buses following the same route], min.

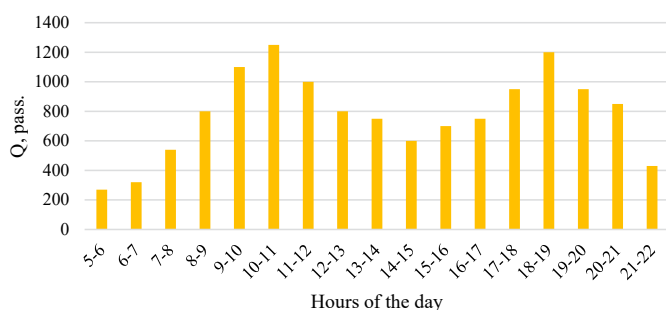
For the purpose to obtain $P_{den} \rightarrow \min$, the system proceeds with an accurate calculation of the passenger flow, adjustment of the traffic intervals of vehicles and their timetable.

Thus, using the developed intelligent system based on an artificial neural network, within the framework of the first module, a preliminary analysis of data on ten urban routes of the motor transport enterprise of Samara city district was performed. An array of data on occupancy of buses operating on each route was obtained. For example, Table 1 shows a fragment of the database on occupancy of the bus operating on route 41 of Samara city district and making the first trip on a weekday.

The proposed intelligent system processes a large array of data on the number of passengers transported by each vehicle on each section of the route per journey, shift, day, etc. It is possible



Pic. 2. Cartogram of distribution of passenger flows by hours of the day on a weekday [performed by the authors].



Pic. 3. Cartogram of distribution of passenger flows by hours of the day on a weekend [performed by the authors].

to collect, organise and present data in any convenient format: in the form of tables, diagrams, schemes, drawings, etc. for any period.

So, for example, Pics. 2 and 3 show cartograms of distribution of passenger flows for route 41 of Samara city district by hours of the day.

With the help of an intelligent system, the rates of non-uniformity of passenger flow

(regarding hours of the day, directions of travelling, duration of the journey) as well as the rate of the use of bus capacity on each route, etc., were revealed.

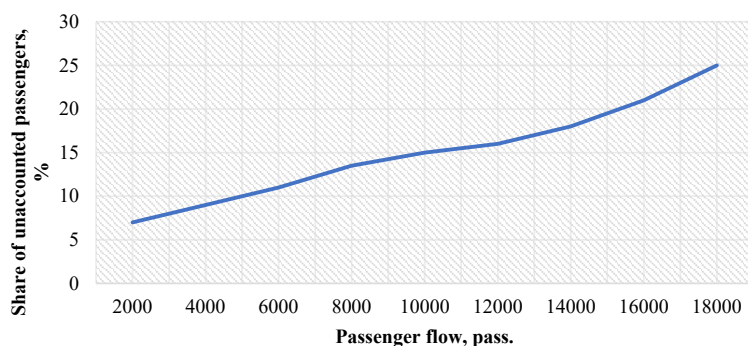
As part of the operation of the second module, a database was obtained on the number of issued travel documents for each vehicle, indicating date, time, stop of ticket purchase. These data are compared with data

Table 2

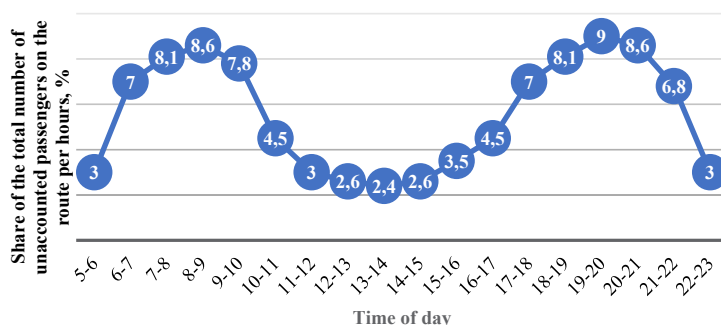
Data on routes of the Samara city district [performed by the authors]

No. of the route	Average passenger flow per day, pass.	Working hours	Traffic intervals	Number of vehicles on the line	% of unaccounted passengers
1	6882	Daily: from 6 a. m. till 10 p. m.	Weekday: 8–20 min, weekend: 16–35 min. In the evening (after 7 p. m.): 20–60 min	Weekday 18–20, weekend 10–14	13,1
2	4619	Daily: from 6 a. m. till 10 p. m.	Weekday: 8–17 min, weekend: 12–40 min. In the evening (after 8 p. m.): 25–76 min	Weekday 10, weekend 7	9,6
22	1897	Daily: from 6 a. m. till 10 p. m.	Monday, Tuesday, Thursday: 10–28 min, Wednesday, Friday: 20–40 min, weekend: 14–60 min.	Monday, Tuesday, Thursday 7, Wednesday, Friday 5, weekend 4	7,7
23	3909	Weekday: from 5 a. m. till 11 p. m. Weekend: from 7 a. m. till 10 p. m.	Monday, Tuesday, Thursday: 14–30 min, Wednesday, Friday: 18–39 min, weekend: 13–69 min.	Monday, Tuesday, Thursday 12, Wednesday, Friday 10, weekend 6	8,9
34	17715	Weekday: from 5 a. m. till 11 p. m. Weekend: from 6 a. m. till 11 p. m.	Weekday: 3–8 min, weekend: 6–12 min. In the evening (after 8 p. m.): 15–46 min.	Weekday 38, weekend 18–23	24,3
37	6061	Daily: from 6 a. m. till 10 p. m.	Weekday: 8–21 min, weekend: 10–25 min. In the evening (after 7 p. m.): 15–40 min.	Weekday 20, weekend 10	10,5
41	17978	Weekday: from 5 a. m. till 11 p. m. Weekend: from 5 a. m. till 10 p. m.	Weekday: 4–10 min, weekend: 5–12 min. In the evening (after 8 p. m.): 15–30 min.	Weekday 35, weekend 24–28	25,1
50	6652	Daily: from 6 a. m. till 11 p. m.	Weekday: 10–22 min, weekend: 12–25 min. In the evening (after 8 p. m.): 25–60 min.	Weekday 18–20, weekend 10	11,8
67	17379	Daily: from 5 a. m. till 11 p. m.	Weekday: 4–8 min, weekend: 6–12 min. In the evening (after 8 p. m.): 10–26 min.	Weekday 35–40, weekend 26–30	23.4





Pic. 4. Dependence of the number of unaccounted passengers on the magnitude of the passenger flow [performed by the authors].



Pic. 5. Dependence of the number of unaccounted passengers on time of day [performed by the authors].

on actually transported passengers on the routes under consideration.

The execution of operations within the framework of the third module supposes an automatic calculation and evaluation of quantitative and qualitative indicators of the transport enterprise, a comparison of the number of passengers, supplied with tickets, with the actual value of passengers transported on the route.

The proposed intelligent system compiles optimal schedules and timetables for circulation of buses, adjusts the traffic intervals, determines the need for operated rolling stock depending on passenger flow (Table 2) to minimise the likelihood of denial to board a passenger and reduce the operating costs of a motor transport enterprise.

The average values of discrepancy between the actual number of passengers transported and the data on transactions carried out were obtained for ten urban routes of the motor transport enterprise of Samara city district, which are shown in Table 2. The percentage of unaccounted passengers is calculated for each vehicle operating on the route during each period. It is also possible to evaluate the conscientiousness

of drivers based on data on unaccounted passengers for each shift on the route in question.

As a result of data analysis, we obtain the dependence of the number of unaccounted passengers on the route on the size of the passenger flow (Pic. 4) and on the time of day (Pic. 5).

Thus, we can conclude that the number of unaccounted passengers can reach 25 % of the total number of passengers transported on the route per day.

The more significant is the passenger flow on the route, the greater is the discrepancy between the number of actually transported passengers and the data on transactions.

It should also be noted that most of the unaccounted passengers fall on the «peak» periods of the day.

CONCLUSION

The proposed intelligent system for calculating and analysing the performance of a transport enterprise, based on the use of artificial neural network technology, allows calculating the values of passenger flow in real time for each vehicle on the route of urban public transport, analysing quantitative and

qualitative indicators of operations, comparing the number of issued tickets with the actual number of passengers transported on the route with the further output of the results to a graphical user interface. This, in turn, makes it possible to draw up optimal schedules and timetables for circulation of vehicles, adjust the traffic intervals, determine the need for vehicles to minimise the likelihood of denial to board a passenger and reduce the costs of a transport enterprise.

The application of the proposed system is also possible on commuter railways to create a possibility to account the number of passengers transported between specific stations, decide to add or reduce the number of cars within a commuter train.

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Article received 28.02.2023, approved 15.05.2023, accepted 18.05.2023.

