Urban Public Transport Digital Planning based on an Intelligent Transportation System

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***Abstract*—there is presented an original concept of intelligent transportation system for public urban passenger transport advanced management, analysis and control. The proposed approach uses intelligent information technologies based on neural networks and methods of Big Data processing, allowing real time adaptation to dynamically changing conditions. Considering the up-to-date research results and technologies related to the transportation problem domain there is introduced a formal model that describes the public transport helping to reveal the main issues. Using the model there is presented a generalized route network planning algorithm. Description of the software implementation includes the specification of solution modules (components). The proposed solution is illustrated by an example of a transport model covering the territory of the Samara city district, Russia. The results of its probation and practical use prove the efficiency of the intelligent transportation system application for public urban passenger transport management.**

I. Introduction

Public urban passenger transport is an essential part of the city life support. Modern cities deal with a substantial increase of traffic routes in number and complexity due to constantly growing requirements of transportation industry from both suppliers and customers. Therefore there is identified a strong request to improve the efficiency of public urban passenger transport using modern digital technologies.

Following the development of urbanized areas the passenger flows have become complex: multi-directional, crossing, convergent and turbulent. The reasons of it are associated mainly with the development of the socio-cultural environment and the migration of labor activity centers of the population. To solve this problem there should be introduced a combination of effective methods, models and means of management of the public urban passenger transport system.

One of the possible solutions is an intelligent transport system that provides the opportunities of advanced management of transport infrastructure. It includes organizational, software and hardware components that improve the efficiency of public urban passenger transport system at present. However, critical issues of their implementation are concerned with integration into the intelligent transport system and adaptation to dynamically changing conditions, which are still not sufficiently developed.

In this paper, there is introduced an original approach to improve functioning of urban passenger public transport by optimizing the routes of transport and vehicles utilization. The proposed approach uses intelligent information technologies based on neural networks and methods of Big Data processing, allowing real time adaptation to dynamically changing conditions. The approach is implemented in the software complex, being embedded as a component of the intelligent transport system.

II. State of the Art

Managing the mobility of citizens through the public transport system usually involves the use of multimodal models that take into account the demand for movement [1]. Such models are intended to the attempts to achieve stability and steadiness of the transport system due to proper spatial planning [2] or using various types of analysis [3]. However, such solutions are efficient for only new and reconstructed parts of cities but are not applicable to existing urban development.

The paper [4] presents an in-depth study of this issue, which indicates the shortcomings of the available methods. The same article presents a tool that helps to make decisions in situations where there is a lack of economic resources and transparency. However, this method can only be applied when working with environmental and climate indicators. In [5], an original approach is proposed that takes into account road, institutional, and weather conditions that affect traffic flow. The traffic is represented by a macroscopic model that does not allow applying the approach to public transport moving on a given schedule.

In [6], a multilevel model of the transport system is used, which allows you to display the behavior of the transport system depending on the level of detail. This model provides an increase in the efficiency of urban mobility planning, but it cannot be used in dynamic planning.

Some experiments conducted in [7] show that high-speed bus transport systems can be successfully applied to increase the productivity of public transport, but modeling and decision making are required for each individual route. The work [8] indicates the problems that arise with the support of decision-making to determine public preference in bus traffic.

Valid information and decision-making performance are both important for managing the spatial mobility of the population. Intelligent transport systems can help solving most of the problems of information support for the population. In a review [9], it is shown that there is a lack of studies on the interconnections of transportation, especially in an interrelated urban environment. In addition, insufficient attention is paid to the cost of the proposed solutions. In [10], a new concept is proposed for a transport intermediary platform, which, through the automation of joint negotiations, makes it possible to make decisions on the coordination of transportation and their cost. However, the proposed concept is effective only for a fixed number of consumers, which is not always feasible in a modern urban environment.

To solve the problem of collecting valid information about population movements in the urban environment there are used social network analysis techniques [11], phone call data, and smart card data [12]. These technologies allow you to supplement the data obtained in the course of traditional population surveys. Their application requires the use of Big Data analysis techniques, data mining algorithms and natural language processing methods to extract information. These technologies are currently being actively developed and are close to reach the level available for practical use [13], [14]. Due to the structure and conditions of Big Data processing, its use for research and analysis remains still complicated [15].

Implementation of a combination of transport management methods in a solid information space can be provided using virtual decision points for intelligent transport systems that hide the real complexity of the lower-level subsystems [16]. Dynamic planning of traffic routes becomes relevant to the processes of active development of information services provided by intelligent transport systems. The approaches mainly apply dynamic control in case of emergency [17].

One of the main components of automated decision-making support systems are simulation and modeling tools [18], [19], which allow you to verify decisions made for the transport of goods and passengers before they are introduced into the real world. There is a model [20] that takes into account the influence of various road and weather factors but does not consider all the characteristics of the rolling stock of public transport, the location of transport stops and ways of approaching them for different categories of the population.

Development of the concept of "smart cities" modifies the traditional concept of "intelligent transport system" into "smart mobility" with three main characteristics [21]: focus on people, focus on data, and the "bottom-up" initiative. Thus, the adoption of artificial intelligence for the development of "smart cities" and "smart mobility" is necessary for the further sustainable development of society [22]. In [23], a new structure of the intellectual system of public transport based on the Internet of things is presented. Such a structure helps decision-makers improve planning. However, at present we are dependent on road transport [24], therefore, the development of solutions is required that allow us to operate in a historical situation.

The mentioned references overview helps concretization of the problem statement. This paper develops an approach to managing spatial mobility of the population using public transport (both traditional and promising), for which optimization methods are proposed. The approach can be used both for planning and for real-time control through the use of intelligent technologies and Big Data processing methods.

III. Approach Description

A. Model of public transport routes

In formalizing the model of traffic routes, a set-theoretic approach is used. Let us represent the transport network graph G as:

$$\mathrm{G} = (\mathrm{N}, \mathrm{A}),$$

where N – is the set of base points (nodes);

A – ensemble of transport connections (arcs).

The set of base points, which are stops of public transport and places of a possible change of direction, can be represented as:

$$\mathrm{N} = \left\{\mathrm{N_{i,j}} / \ \mathrm{i} \ = \overline{1, \mathrm{I}}, \mathrm{j} \ = \overline{1, \mathrm{J_i}}\right\},$$

where i – the route index;

j – the index of the route node.

We represent many arcs as:

$$\mathrm{A} = \left|\mathrm{a}_{\mathrm{i},\hat{\mathrm{i}}}^{\mathrm{j},\hat{\mathrm{j}}}\right|, \mathrm{i}, \hat{\mathrm{i}} \ \in \mathrm{I}, \mathrm{j}, \hat{\mathrm{j}} \ \in \mathrm{J_i}.$$

We represent vehicles of various classes used on routes as:

$$\mathrm{V} = \left\{\mathrm{V_{i,k,c}} / \ \mathrm{i} \ = \overline{1, \mathrm{I}}, \mathrm{k} \ = \overline{1, \mathrm{K}}\right\},$$

where k – the index of the vehicle of class c on route i;

c = {bus, trolley, tram, metro, minibus} – augmented many classes of vehicles engaged in transportation.

We declare the functions that determine the time required for the vehicle to pass one node of a certain class t_n or one arc t_a:

$$f_N\ (V_{i,k,c}, j, N_{i,j}) \rightarrow t_n,\ f_A\ (V_{i,k,c}, j, a_{i,\hat{i}}^{j,\hat{j}}) \rightarrow t_a. \quad (1)$$

Thus, the total travel time of the route will be the sum of these values:

$$t_f = \ \textstyle\sum_{\forall\, n} t_n + \sum_{\forall\, a} t_a.$$

We declare a function that determines the number of passengers carried at time t:

$$f_Q\ (V_{i,k,c}, j, t) \rightarrow q_t, \quad (2)$$

where q_t – the number of passengers carried.

Total number of passengers carried:

$$q_f = \ \textstyle\sum_{\forall\, t} q_t.$$

The general set of movements (route) for a particular vehicle is defined as a set:

$$R_V^* = (N^*, A^*).$$

Thus, it is required to determine R_V^*, at which it is achieved:

$$t_f \to min, q_f \to max.$$

In order to simulate the spatial position of a particular vehicle, we declare a function that describes the position of a particular vehicle in space at a discrete time instant *t*:

$$f_V\left(V_{i,k,c}, j, t\right) \to (a_{i,\hat{\imath}}^{j,\hat{\jmath}}, N_{i,j}, d),$$

where d – the distance from the beginning of the arc.

If the vehicle is on the site at the moment *t*:

$$a_{i,\hat{\imath}}^{j,\hat{\jmath}} = 0, d = -1.$$

If the vehicle is on the arc at the moment t:

$$N_{i,j} = 0.$$

B. Vehicle count calculation

Calculation of the required number of vehicles is carried out according to peak passenger traffic as follows:

$$S = \frac{Q}{q * \gamma} * t, \tag{3}$$

where: S – the amount of transport on the route;

Q – passenger flow in the most loaded area;

q – the nominal capacity of the vehicle;

γ – the filling ratio of the rolling stock;

t – the time of the round trip, the time during which the vehicle makes a complete turn over on the route.

C. Route network planning

A generalized algorithm of actions when forming a list of measures for reorganizing the route network, traffic schedules or rolling stock used for transportation is shown in Fig. 1. The algorithm can be used for adaptive dynamic planning in real time or static long-term scheduling.

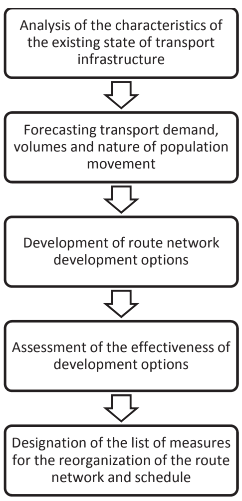

Fig. 1. Generalized route network planning algorithm

Algorithm steps are described below in detail.

Step 1. Analysis of the characteristics of the existing state of the transport infrastructure.

At this step, the passenger flows data are collected in the analyzed territory. The system provides analysis of information on population movements, the target structure of movements on various modes of transport, as well as the determination of patterns of use of transport. Also, information is collected and analyzed on the characteristics of the road network and traffic flows, traffic management schemes and traffic routes, locations, and characteristics of public transport stops, technical means of traffic management, including traffic lights and their characteristics that affect traffic on sections of the road network within the analyzed territory.

Step 2. Making a forecast of transport demand, volumes and nature of population movement.

At this step, the population's demand for relocation, the opening of new routes and transport infrastructure facilities, including the organization of "dynamic" transport hubs, is analyzed. A forecast is being made of the redistribution of traffic flows taking into account infrastructure facilities. The analysis of the transport behavior of the population, i.e. a set of patterns of use of transport infrastructure is revealed, which includes: the frequency of movement; distribution of movements by purpose and duration, as well as points of departure and arrival; a change in the nature of movement due to changes in weather conditions, the occurrence of temporary points of attraction, etc.

Step 3. Development of route network development options.

A step-by-step roadmap of the proposed changes to the integrated organization of transport services is being formed taking into account the prospects for using all types of urban public transport (metro, tram, trolleybus, bus) or promising modes of transport (electric bus, monorail, cable car, etc.). Three draft roadmaps are being formed – optimistic, pessimistic and balanced, the differences of which are in cost and speed of implementation.

Step 4. Evaluation of the effectiveness of development options.

At this step, the performance indicators of transportation routes are calculated. Indicators are described that describe the level of quality of public services, including the time spent on moving, the comfort of the trip, the need for transfers and long waiting times at stopping points. Another calculated group of indicators is indicators describing the efficiency of using rolling stock.

Step 5. Designation of the list of measures for the reorganization of the route network and schedule.

The obtained data are processed and, on their basis, a conclusion is prepared on the need (no need) to optimize the route network, traffic schedules and the number of vehicles.

To perform steps 1 and 2, methods of analyzing big data from state and industry data sources, social networks, media resources, and others are actively used. To complete step 2, a neural network is used, which allows one to carry out forecasts of controlled indicators, i.e. determine the types of dependence functions (1) and (2).

IV. Software Implementation

Software implementation of the public transport management solution consists of two blocks of software modules: interaction unit and data analysis unit. Software implementation of solutions involves connecting additional modules and functions aimed at solving complex problems within a single architecture and space of information interaction, for example, providing planning tools for the development of route networks on a large scale.

Three software modules were developed that provide man-machine and machine-to-machine interactions: the visualization module "GUI", the interaction module "IO_Processor" and the control module "App". The modules interact with each other in client-server mode via TCP / IP. Modules are powered by Windows compatible operating systems. The software is implemented using the programming languages C # and Python.

The software of the visualization module "GUI" uses the shell of the open-source simulation environment "SUMO Gui" to visually represent the transport network, traffic lights, and individual vehicles. Software implementation provides visualization of modeling of transport processes with detailing to an individual vehicle. The input/output file format of the transport network and routes is XML. It is possible to download data of transport models prepared in the software PTV Vision, Matsim, Sumo.

The software of the "IO_Processor" interaction module provides sending commands to the interaction service and receiving responses. The "IO_Processor" interaction module implements the "Wrapper" design pattern. Interactions are carried out in asynchronous mode using the "Background Worker" pattern.

The "App" control module software provides visualization control and solution of applied problems. The control module forms transport areas, provides work with routes and bus stops, generates transport and pedestrian flows with specified characteristics, and generates requests for individual vehicles. The App control module allows you to use data on the number of transport units in operation when analyzing the current situation on the road network. It also takes into account the possibility of redistributing public transport units between routes in order to optimize traffic congestion and eliminate traffic congestion and their consequences. The "App" control module uses the visualization service through the interaction module. The control module provides the ability to enter new vehicles and driving routes during operation.

Two additional software modules provide input-output and data analysis. Modules interact with each other through a dynamic library call mechanism. Used input file types: XML, JSON, WKB, WKT.

The "Business_Logic" module implements business methods for accessing data and provides services for client applications. To access data, the technology of object-relational data mapping is used. The use of technology is justified by the use of a subject-oriented design pattern. The module uses electronic maps in the format of representing geometric primitives' well-known text and well-known binary. The module provides access to geodata using the query language, the choice of methods for storing and presenting geodata, as well as a set of procedures for manipulating objects and analysis.

The module "Business_Intelligence" provides processing and analysis of the collected structured and unstructured data using Big Data processing methods, determining the dependence of changes in the direction of flow and their distribution over the road network depending on various conditions: time of day, seasonality, weather conditions, holding public events, earlier decisions to change the organization of traffic, etc. The analysis can be performed by district or individual sections of the road network.

The developed software package was debugged in the Visual Studio 2017 environment, testing was performed using automated unit tests of the NUnit framework. Integration testing was conducted using the TeamCity continuous integration environment. As a result of stress testing of the software solution, it was revealed that work is supported while simulating the movement of up to 200,000 vehicles, up to 1000 public transport routes and up to 5000 public transport stops.

V. Application to Practice

A. *Performance criteria*

To assess the effectiveness of the solutions offered by the software package, we apply two indicators: a network indicator of mobility and a time index.

Network indicator of mobility (I_M), [minutes / km] characterizes the specific time spent on communication (average speed) and the temporary availability of territories:

$$I_M = k_{it} * \frac{1}{R_{it}} \sum_{r \in R_{it}}^{|R_{it}|} k_l \frac{\overline{T_{it}^r}}{L_r} + k_{pt} * \frac{1}{R_{pt}} \sum_{r \in R_{pt}}^{|R_{pt}|} k_l \frac{\overline{T_{pt}^r}}{L_r}, \quad (4)$$

where r – the route belonging to the set of routes when driving on personal transport R_{it}, or to the set of routes on public transport networks R_{pt}, respectively;

k_{pt} – coefficient of significance of trips on public transport;

k_{it} – the coefficient of significance of travel by individual transport;

k_l – weight coefficient, reflecting the importance of transport communications;

L_r – route length r, [km];

T_{it}^r – average travel time on individual transport along the route r, [h];

T_{pt}^r – average travel time on public transport along the route r, [h].

The time index (I_T) is characterized by the additional specific time spent on movement due to the increased congestion of the road network and a decrease in the reliability of the message:

$$I_T = \frac{1}{\sum N_i} \sum \left(\frac{T_r^{peak}}{T_i^C} * N_i \right), \quad (5)$$

where N_i – the volume of motion for element i;

T_r^{peak} – travel time during the peak period along the route r, [h];

T_i^c – travel time in conditions of free movement on element i, [h].

B. Transport model creation

To test the proposed solution, a transport model was developed covering the territory of the Samara city district, Russia (Fig. 2). 22 tram routes, 14 trolleybus routes, 48 bus routes, 160 minibus routes and 10 metro stations operating in Samara were introduced into the transport model.

Fig. 2. Territory for building a transport model

After making a forecast of transport demand, the volume and nature of population movement, transport areas are identified (Fig. 3).

Fig. 3. Transport areas

The model is accurately calibrated and takes into account the various possible options for movement for one route. For example, Fig. 4 shows a typical situation in which public transport is in a traffic jam surrounded by private vehicles. When trying to increase the number of passengers traveling on this route by public transport, the traffic jam situation is not allowed (Fig. 5), since the resulting "window" is used by vehicles that previously traveled along other routes.

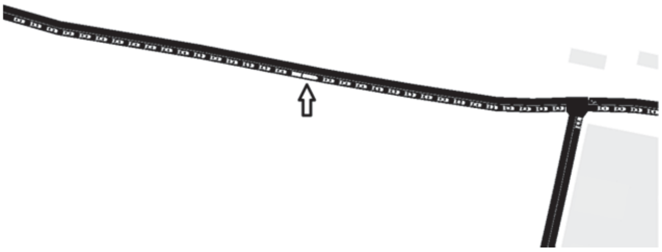

Fig. 4. Modeling: moving mainly by personal transport

Fig. 5. Modeling: moving mainly by public transport

C. A practical problem solving

The work of the solution was tested during the development of the scheme of public transport using trolleybuses with autonomous running (electric buses) up to 10 km in the territory of the urban district of Samara, Russia. In the research process, the following options for using electric buses were used:

- expansion of existing trolleybus routes;
- replacement of bus routes partially passing through sections equipped with a contact network;
- adaptation of the route of the trolleybus to the traffic situation: detour of accidents, congestion, repair areas, etc.
- combination of unprofitable and profitable routes;
- introduction of new routes up to 10 km, mainly passing through sections without a contact network and using the contact network only for recharging.

The following source data obtained from open sources were used:

- registers of routes and stops of public transport;
- location of routes and stops on an electronic map;
- performance characteristics of public vehicles;
- the composition of the fleet of vehicles;
- information about the passenger turnover and the level of load of the vehicle;
- power circuits and sectioning of the contact network;
- technical characteristics of traction substations.

The generalized process of obtaining results using the proposed solution is shown in Fig. 6.

Thus, as a result of the work, a geoinformation model of public transport services for the population is constructed based on a detailed electronic map in the form of a software system with the ability to conduct simulation experiments.

For practical use, a project document is formed, made in the form of an explanatory note and a graphic part, containing a set of interrelated scientifically-based systematic measures to improve public transport services using trolleybuses with autonomous travel up to 10 km.

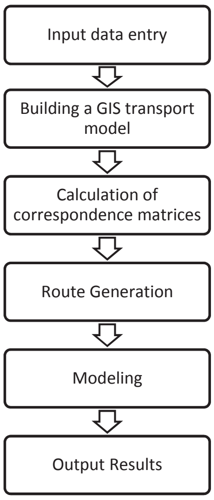

Fig. 6. The generalized output process

The study was conducted in the area “City Center” – “Kryazh” – “South City” – “Novokuybyshevsk” (Fig. 7). There are 4 transport hubs in this region: Provincial market, Groznenskaya street, South City, Novokuybyshevsk.

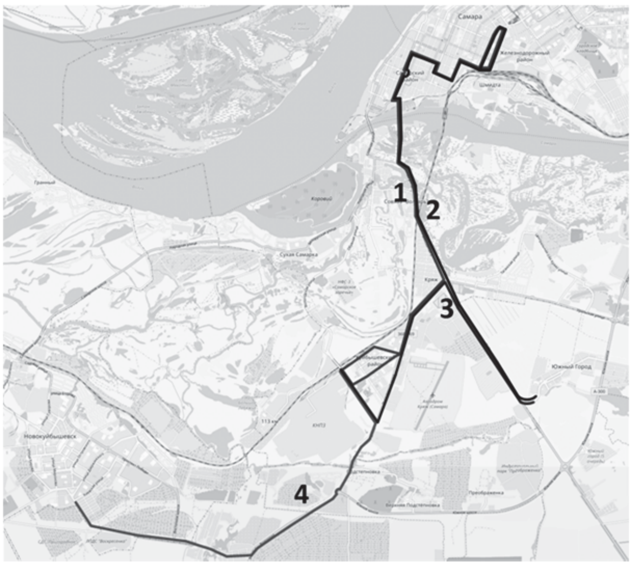

Fig. 7. The study area and the generated routes

The achieved indicators for improving transport mobility, calculated in accordance with (4), (5) and step 3 of the generalized route network planning algorithm, are shown in Table I.

TABLE I. PERFORMANCE INDICATORS FOR VARIOUS ROUTE NETWORK OPTIMIZATION OPTIONS

Performance indicator	Performance indicator value			
	Current	**Optimistic**	**Balanced**	**Pessimistic**
Network indicator of mobility (I_M), [minutes/km]	1.9	1.6	1.7	2.0
Time index(I_T)	2.1	1.2	1.3	2.4

Thus, taking the balanced option as the main one, a route network is generated. The routes generated by the application of the developed software are shown in Fig. 7:

1) The route “Provincial market – Groznenskaya street” is marked in red (“1”);

2) The route “Provincial market – South City” is marked in black (“2”);

3) The route “South City – Groznenskaya street” is marked in blue (“3”);

4) The route “Groznenskaya street – Novokuybyshevsk” is marked in purple (“4”).

Characteristics of the generated routes are shown in Table 2.

TABLE 2. CHARACTERISTICS OF THE GENERATED ROUTES

No.	Maximum passenger flow, [passengers]	Flight time, [h]	Distance, [km]	Average speed, [km / h]
1	560.0	2.1	33.0	15.7
2	420.0	2.0	31.8	16.2
3	270.0	1.2	18.8	15.2
4	300.0	1.5	24.1	17.3

The number of vehicles involved in regular transportation on the indicated routes, and the intervals of their movement are calculated in the developed software in accordance with (3) (Table 3).

TABLE 3. NUMBER OF ELECTRIC BUSES ON A REGULAR ROUTES

No.	Route	Number of electric buses	Interval of movement, [minutes]
1	“Provincial market – Groznenskaya street”	14	12
2	“Provincial market – South City”	10	15
3	“South City – Groznenskaya street”	4	13
4	“Groznenskaya street – Novokuybyshevsk”	6	17

Thus, decision support is provided for optimizing the route network using new generation vehicles – electric buses. Achievement of a 10% reduction in the network mobility indicator and a 38% decrease in the temporary efficiency indicator

VI. CONCLUSION

Using the research results provides an increase in the efficiency and sustainability of the functioning of the city's transport system, an increase in the safety, quality and comfort of public transport services, an improvement in environmental conditions and an increase in the profitability of public transport. The developed software solution provides high reliability of the results when making decisions on making changes to the location of stops and the route scheme of public transport.

The results of the work in the form of software are intended for use in state and municipal enterprises, specialized organizations involved in the process of managing transportation in urban passenger transport.

The solution can be implemented as part of a new generation of intelligent transport systems. The results of the work are applicable for solving the following applied problems:

- assessment of the performance of public transport through modeling;
- identification of public transport routes to be adjusted;
- dynamic and static adjustment of routes in order to increase spatial mobility of the population;
- dynamic and static adjustment of the number of vehicles transporting along the route.

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