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APPLYING NEURAL NETWORK TECHNIQUES TO DETERMINE TRAFFIC FLOW REDIRECTION PROPORTIONS IN ROAD NETWORKS

Summary. This article explores traffic management strategies for addressing unpredictable events in transportation networks, focusing on situations where road segment capacity is reduced due to factors like traffic accidents or disruptions. The research aims to determine the proportion of traffic flow redistribution needed to maintain network efficiency under such conditions. A novel method is proposed to mitigate congestion by rerouting vehicles from heavily loaded roads, identified by high network load coefficients, to alternative routes. The approach also calculates the optimal volume of redirected traffic to avoid overloading other parts of the network, thereby minimizing the risk of secondary congestion. To achieve this,

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neural network-based survey and regression analysis techniques are utilized, offering precise and data-driven solutions for traffic redirection. The study highlights the potential of improving urban traffic flow through enhancements to indirect traffic control systems integrated into Intelligent Transportation Systems. By optimizing vehicle rerouting strategies, the proposed method seeks to increase ITS efficiency, especially in scenarios with high congestion risks or traffic accidents. This approach promises a more resilient and adaptive urban transportation network, ensuring smoother traffic operations and reduced congestion impacts.

Keywords: traffic management, intelligent transportation systems, intelligent neutral network, traffic flows.

1. INTRODUCTION

In the practice of traffic management, a number of different measures are used to solve the problems of low efficiency of the road transport network. The solutions proposed and tested in real conditions achieve certain results depending on the object under study and are able to improve various indicators of the road transport network. Among them, Intelligent Transportation System (ITS) is a widely used means for traffic management in large cities [1, 2]. Overcoming the limitations of this system in solving traffic congestion problems can simultaneously lead to an improvement in the quality of traffic functioning in many densely populated cities around the world.

Studies on traffic management highlight that redirecting traffic flow is accomplished through the efficient operation of the ITS and its indirect traffic flow management subsystem [3, 4, 5]. Research findings indicate that the success of the indirect traffic flow management approach largely depends on how well the proposed method aligns with the behavior and preferences of road network users (drivers).

Studies [8, 9] determine the volume of vehicle traffic within a transportation network by assessing the capacity of a given road section relative to its traffic intensity. The key metric for this evaluation is the remaining capacity of the route. Based on this value, traffic management decisions establish the maximum number of vehicles that can be redirected to the route.

The proportion of traffic flow redirection in the network depends not only on the capacity of individual road sections but also on drivers' route choices [6]. Therefore, traffic management scenarios must be designed to align with drivers' preferences and decision-making processes. This alignment is achieved by calculating and implementing road measures that reflect the priorities and behaviors of road users when selecting routes during traffic management.

To gather insights into driver route preferences, a survey method was employed. The collected data was then analyzed using a neural network approach, allowing for a deeper understanding of drivers' behavior and enabling the development of more effective traffic management strategies.

2. RESEARCH METHOD

The route choice of traffic participants during a traffic accident is influenced by numerous factors. As noted in [7], a driver's decision is shaped by both subjective and objective aspects of the transportation system. These include the distance to the destination, travel time, familiarity with the proposed route, organizational features of movement along that route, direction of travel, and final destination. However, the impact of these factors on the driver's decision varies and is determined by the significance coefficient assigned to each factor.

It is important to highlight that this significance coefficient is not fixed; it fluctuates depending on the driver's physical and psychological condition, as well as external influences at the time of decision-making. This variability underscores the complexity of modeling and predicting driver behavior under such circumstances.

In this study, *Vissim* is used to evaluate the throughput of an organized intersection with traffic lights [10]. *Vissim* modeling is used as a tool to determine the relationship between the values of traffic light cycles, the duration of the traffic light permissive phase, the intensity and speed of the traffic flow and the number of traffic lanes of the roadway (Fig. 1).

The conventional model of the street and road network consists of one main multi-lane road, five adjoining roads and one bypass road, which is parallel to the main road, having a capacity equivalent to the main road (among the roads considered adjoining the main road). Vehicles on the main road move along 4 lanes. Each adjoining road has two traffic lanes directed to the right relative to the main direction of traffic on the road. The redistribution of traffic flow from the main roads to the bypass road is carried out at intersections through a system of dynamic information boards and road signs, which better facilitates the process of redistribution and informing road users.

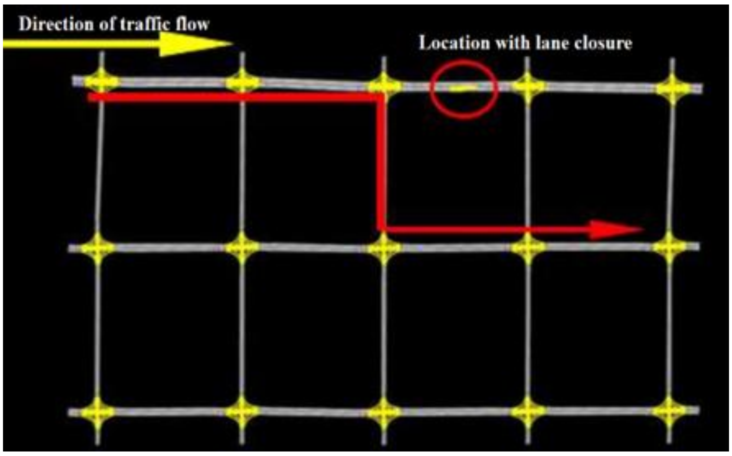
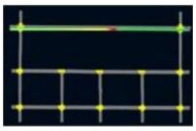
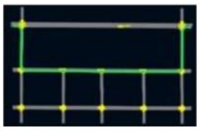
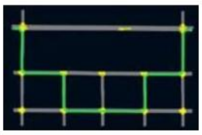
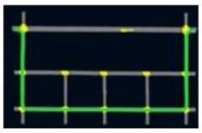


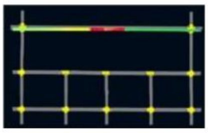
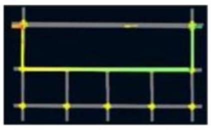
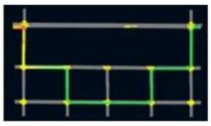
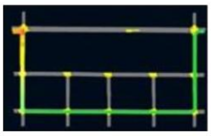
Fig. 1. The diagram of the studied reference model of the transport network in Vissim

A study was conducted to investigate the factors influencing drivers' decision-making in situations with a high risk of congestion. A survey of 111 drivers of various groups, including women and men, professional and private drivers, and representatives of different age and experience categories, provided valuable data on drivers' preferences and priorities when choosing a route [Fig. 2]. The main conclusion drawn from the analysis of the survey results is that drivers' choices depend on the relative differences between different routes, rather than on the characteristics of each route individually. That is, drivers evaluate the "benefit" of the differences between the proposed routes.

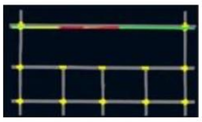
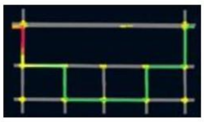
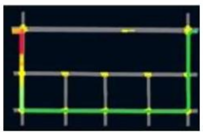
The study examined four distinct traffic conditions (*A1, A2, A3, A4*), represented by changes in the network load coefficient (z). These scenarios included the following cases: $z < 0.5$, $0.5 < z < 0.7$, $0.7 < z < 0.9$, and $z > 0.9$. To enhance comprehension, the variations in the z coefficient were visually depicted through changes in the color scheme, reflecting the assessment of traffic conditions. This visualization allowed participants to evaluate road scenarios more effectively.

No	Route	Traffic pattern	Train time	Route length	Number of nodes	Level of service
A1	No1		15 -- (1)	5.2 -- (1)	2 -- (1)	C -- (0)
	No2		15 -- (1)	7.8 -- (1.5)	7 -- (3.5)	C -- (0)
	No3		15 -- (1)	10.5 -- (2)	7 -- (4.5)	C -- (0)
	No4		15 -- (1)	10.5 -- (2)	9 -- (4.5)	B -- (+1)

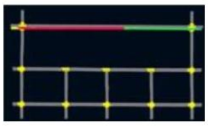
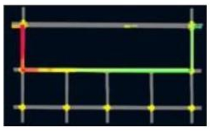
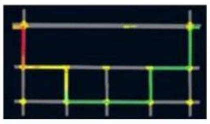
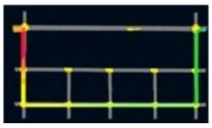
a)

No	Route	Traffic pattern	Train time	Route length	Number of nodes	Level of service
A2	No1		25 -- (1)	5.2 -- (1)	2 -- (1)	D -- (0)
	No2		20 -- (1.25)	7.8 -- (1.5)	7 -- (3.5)	C -- (+1)
	No3		16.5 -- (1.5)	10.5 -- (2)	7 -- (4.5)	C -- (+1)
	No4		14.5 -- (1.75)	10.5 -- (2)	9 -- (4.5)	B -- (+2)

b)

No	Route	Traffic pattern	Train time	Route length	Number of nodes	Level of service
A3	No1		40 -- (1)	5.2 -- (1)	2 -- (1)	E -- (0)
	No2		32 -- (1.25)	7.8 -- (1.5)	7 -- (3.5)	D -- (+1)
	No3		27 -- (1.5)	10.5 -- (2)	7 -- (4.5)	D -- (+1)
	No4		23 -- (1.75)	10.5 -- (2)	9 -- (4.5)	C -- (+2)

c)

No	Route	Traffic pattern	Train time	Route length	Number of nodes	Level of service
A4	No1		60 -- (1)	5.2 -- (1)	2 -- (1)	F -- (0)
	No2		48 -- (1.25)	7.8 -- (1.5)	7 -- (3.5)	E -- (+1)
	No3		35 -- (1.75)	10.5 -- (2)	7 -- (4.5)	D -- (+2)
	No4		30 -- (2)	10.5 -- (2)	9 -- (4.5)	C -- (+3)

d)

Fig. 2. Questionnaire for choosing a scenario for moving through networks of vehicle drivers with different values
a) $z < 0.5$; b) $0.5 < z < 0.7$; c) $0.7 < z < 0.9$; d) $z > 0.9$

3. RESULTS AND DISCUSSION

The results presented in the Tab. 1 and Fig. 3 indicate that as traffic conditions worsen, the dominant (selected) route becomes increasingly attractive compared to other routes. This preference is primarily due to a reduction in travel time, despite a slight increase in mileage. In these scenarios, the dominant route consistently represents the one where the reduction in the cost of movement for road users approaches its maximum value as $z \to 1$.

Tab. 1

The result of the survey on the choice of scenario for movement through the networks of vehicle drivers

Choice of drivers (%)	Route No1	Route No2	Route No3	Route No4
$z < 0.5$	72	18	14	8
$0.5 < z < 0.7$	14	26	13	12
$0.7 < z < 0.9$	2	12	6	6
$z > 0.9$	12	44	67	74

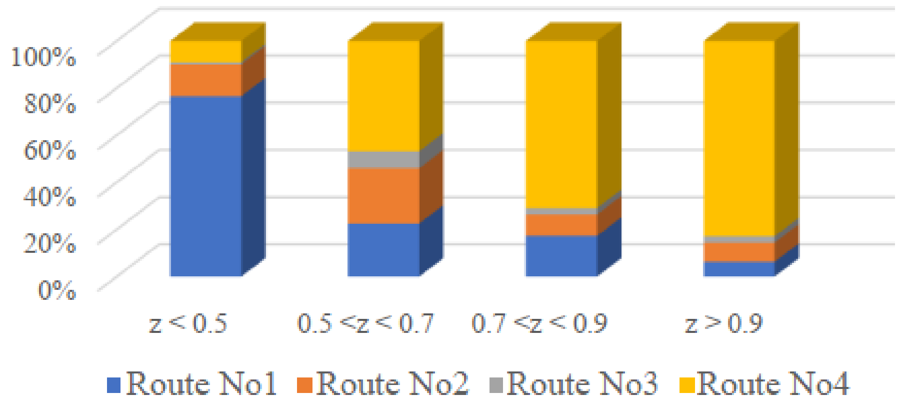


Fig. 3. The result of the survey on the choice of scenario for movement through the networks of vehicle drivers

As the *z* value increases, drivers initially consider alternative routes. However, a transition to the dominant route occurs as it offers the most favorable balance of reduced travel cost, even under heightened traffic conditions. This dynamic highlights the interplay between travel time, mileage, and cost-efficiency in route selection under varying traffic loads.

The survey results and their analysis reveal that drivers' decision-making regarding traffic patterns is influenced by multiple factors acting simultaneously. To uncover general trends in drivers' route choices, the regression method is essential for determining the impact of each factor on decision-making behavior. The use of neural network methods is justified by prior studies highlighting their effectiveness in analyzing complex, multifactorial data.

Artificial neural networks are employed to process the survey results and identify patterns in drivers' route choices. The structure and parameters of the neural network are tailored to the specific characteristics of the survey data. For this analysis, *Matlab-Simulink 2021b* software is utilized, enabling effective modeling and interpretation of the data (refer to Fig. 4 and 5). This approach ensures a robust analysis of the interplay between various factors influencing route selection.

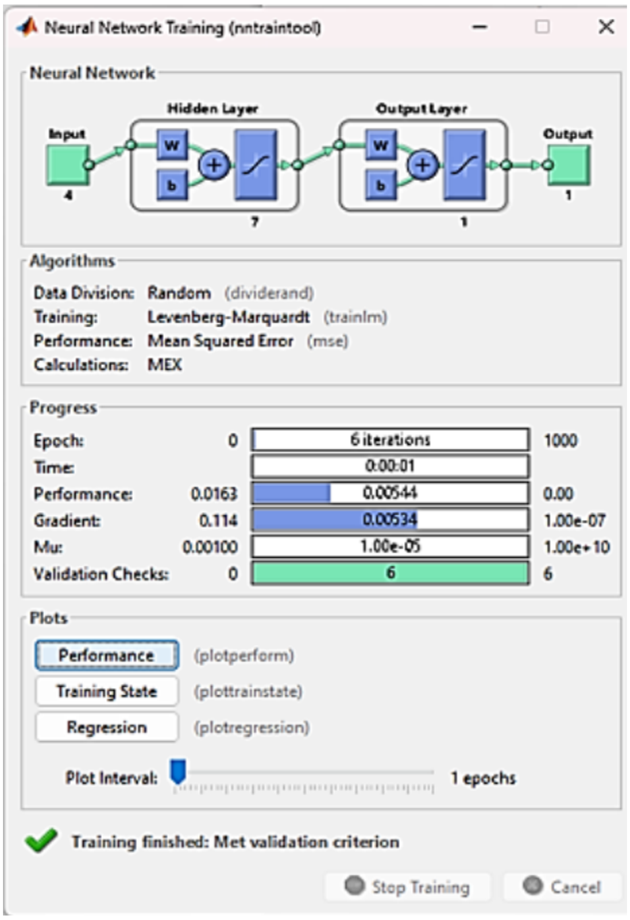


Fig. 4. The structure of the constructed neural network

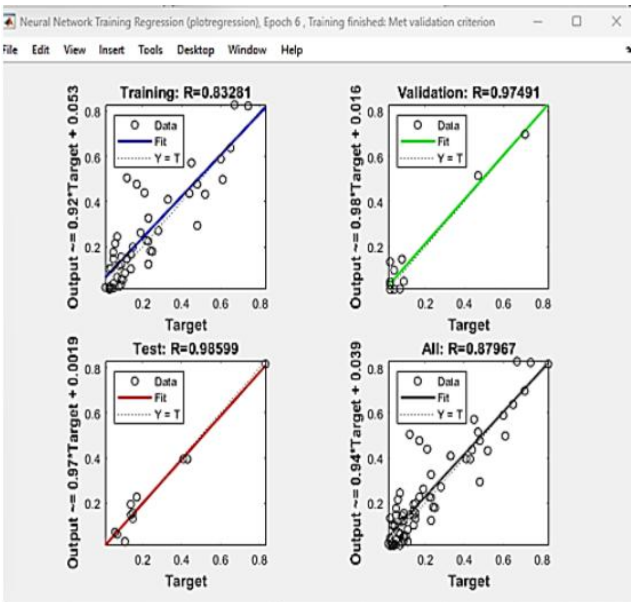


Fig. 5. Results of the survey data processing process

The following parameters define the neural network constructed based on the analysis of the survey results.

$$w_{11} = \begin{bmatrix} 0.26267 & -0.5081 & 1.5453 & -1.925 \\ 1.9102 & 0.7391 & 0.6658 & 0.4869 \\ -1.7488 & 1.4663 & -0.9371 & 4.397 \\ 1.5325 & -1.3515 & -1.7418 & 0.4875 \\ -2.2678 & 1.4337 & -0.7665 & 0.5061 \\ -1.6669 & 2.6745 & 2.7268 & 0.11 \\ 0.1563 & -0.9559 & 1.0245 & -2.9124 \end{bmatrix}$$

$$w_{21} = \begin{bmatrix} 0.7806 \\ 1.5956 \\ 1.3788 \\ 1.5746 \\ 2.4696 \\ 2.8742 \\ 2.1658 \end{bmatrix}; b_1 = \begin{bmatrix} -1.8137 \\ -0.3488 \\ 0.2745 \\ -0.1085 \\ 1.4703 \\ -3.5024 \\ -0.0564 \end{bmatrix}; b_2 = [0.96566].$$

The overall regression coefficient reached $R = 0.879$, with a maximum value of $R = 0.986$ observed in the test sample. These findings demonstrate that the constructed neural network effectively models the desired relationships.

The training results show that the correspondence coefficient between the input parameters and the forecasted outcomes exceeds 87%, which is considered an acceptable level. The observed differences between the neural network's predictions and the survey results can be attributed to the complexity of the input parameters, variations in driver behavior when choosing routes, and differences in traffic network structures, even under identical traffic conditions.

This can be attributed to the social characteristics of the respondents, which do not conform to a universal pattern but are significantly influenced by the individual subjective factors unique to each respondent.

To verify the achieved results, a neural network is used to determine the proportion of vehicles that should be redirected in situations where the coefficient $z > 0.9$ at a traffic intensity of 4500 vehicles/hour. 4 traffic management scenarios with the values of traffic flow and trip characteristics shown in Tab. 2. The results (the proportion of each scenario chosen by road users, %) are also presented in the table.

Tab. 2

Result of applying a neural network to determine the share of traffic flow redirection through the network

Traffic flow diagram	Load level	Reduction in travel time (min.)	Extension of overrun (km.)	Improving the quality of service	Shares of choice(%)
No1	$z > 0.9$	26	1.41	3	80.71
No2	$z > 0.9$	22	1.15	1	7.58
No3	$z > 0.9$	17	1.17	1	1.54
No4	$z > 0.9$	15	1.18	1	1.09

In the presented congestion situation ($z > 0.9$), the proportion of traffic sce-narios chosen by the participants and offered to drivers is determined using the neural network algorithm (as shown in the table) and is consistent with the observed patterns of choice in the previous survey. The total number of choices that do not reach 100% - reflecting the inconsistent randomness of drivers' choices, which are influenced by factors not considered in this survey (familiarity with the traffic route, personal predictions of traffic conditions, drivers' personal routes,...) – accounts for 9.08%.

The direction of such a volume of vehicles in modern conditions is carried out by components of the intelligent transport system, including indirect traffic management subsystems, which can be implemented using dynamic information boards or different types of road signs.

4. CONCLUSION

When traffic accidents or other unforeseen incidents take place, leading to the temporary closure of one or more traffic lanes and a substantial reduction in the capacity of a road section, congestion inevitably develops within the transportation network. This congestion disrupts the normal flow of vehicles, increases travel time, and can have broader economic and environmental consequences. To minimize these adverse effects, appropriate traffic management strategies must be implemented. These strategies involve redirecting vehicles onto alternative routes that have sufficient capacity to handle the additional traffic, thereby preventing further congestion from forming on these roads.

Advanced traffic control systems, particularly those utilizing neural network methods, can play a crucial role in optimizing the redistribution of traffic flow. By analyzing real-time traffic data, driver behavior, and habitual route choices under congested conditions, these systems can determine the most efficient way to divert vehicles. This ensures a smoother traffic flow across the transport network, reducing delays, improving overall road efficiency, and enhancing commuter experience.

References

1. Zhankaziev S.V. 2010. *Concept of creating an intelligent transport system on federal highways*. NIR. 83 p.
2. Nguyen X.H. 2018. „Status of road traffic, ITS existing solutions and level of development of intelligent transport systems in Vietnam”. *Avtomobil'. Doroga. Infrastruktura* 2(16). 9 p.
3. Vu T.V.A. 2024. „Prevention of traffic congestion with the help of subsystems of directive and indirect traffic flow management”. *Bulletin of MADI* 4(79): 82-88.
4. Buslaev A.P. 2003. *Probabilistic and simulation approaches to the optimization of road traffic*. Russian Academy of Sciences V. M. Prikhodko. Moscow: Mir. 368 p.
5. Gazvan A.H. 2006. „International models for assessing the level of road safety”. *Science and technology in the road industry* 3: 3-9.
6. Efimenko D.B. 2012. „Methodological foundations of building navigation systems of dispatch control of transportation processes on road transport (e.g. urban passenger transport)”. *Diss. doctor of technical sciences.* 05.22.08. Moscow. 479 p.

7. Kosolapov A.V. 1992. „Increase of efficiency of information support of road traffic participants in the cities”. *Diss. candidate of technical sciences.* 05.22.10. Moscow. 178 p.
8. Kocherga V.G. 2001. „Estimation and forecasting of the road traffic parameters in the intellectual transportation systems”. *Rostov n/D: Rost. State Construction University*. 130 p.
9. Utkin A.V. 2006. „Modeling of driver behavior and quality assessment of a mixed traffic flow”. "Organization and traffic safety in large cities"”. In: *Collection of reports of the 7th International Conference. St.-Petersburg*. P. 84-86.
10. Xuan Can Vuong, Rui-Fang Mou, Trong Thuat Vu, Hoang Van Nguyen. 2021. „An adaptive method for an isolated intersection under mixed traffic conditions in Hanoi based on ANFIS using VISSIM-MATLAB”. *IEEE Access* 9: 166328-166338. DOI: 10.1109/ACCESS.2021.3135418.

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