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## APPLICATION OF NEURAL NETWORKS FOR OPTIMISATION OF SIGNALLING IN ROAD TRAFFIC

### ZASTOSOWANIE SIECI NEURONOWYCH DO OPTYMALIZACJI STEROWANIA SYGNALIZACJĄ ŚWIETLNA W RUCHU DROGOWYM

#### Abstract

This article presents a proposal for applying neural networks to control road traffic. The proposed solution makes it possible to determine durations of traffic signals at intersections so that the waiting time for transit is as short as possible. The variability of traffic intensity on all access roads and between analysed intersections was taken into account. The developed concept was compared with a method of determining the durations of lights based on the coefficient of intersection readiness, and the feasibility for practical applications of the method was assessed.

*Keywords: neural networks, road traffic, traffic signals*

#### Streszczenie

W artykule przedstawiono propozycję wykorzystania sieci neuronowych w sterowaniu ruchem drogowym. Proponowane rozwiązanie umożliwia wyznaczanie czasów trwania sygnałów świetlnych na skrzyżowaniach, tak aby czas oczekiwania na przejazd był najmniejszy z możliwych. W analizie uwzględniona jest zmienność natężeń ruchu na wszystkich drogach dojazdowych oraz między analizowanymi skrzyżowaniami. Opracowaną koncepcję porównano z metodą wyznaczania czasów trwania świateł opartą na współczynniku gotowości skrzyżowania i scharakteryzowano możliwości praktycznego zastosowania metody.

*Słowa kluczowe: sieci neuronowe, ruch drogowy, sygnalizacja świetlna*

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## Designations

$k_{gc}$	– readiness koefficient [–]
$T^{pc}$	– full light cycle time [s]
$T_{zi}$	– duration of green light [s]
$T_{zcz}$	– duration of yellow light and yellow and red light [s]
$T^{pp}$	– time for a vehicle to travel through the crossing [s]
$T_{sr}$	– mean waiting time in traffic [s]
$Q_i$	– intensity of vehicles [1/60 s]
$dt_{12}$	– temporary shift of signal display between crossings [s]
$l_{pr}$	– number of traffic lanes [–]

## 1. Introduction

The difficulties of vehicular road traffic are visibly onerous for all involved. Such phenomena are particularly severe in municipal agglomerations, where many drivers travel relatively short distances. This brings about a rise in exhaust emissions and excessive fuel consumption, both harmful to the environment. The dense road network most often found in municipal areas makes it possible to change direction quickly and reach any desired point in the city. On the other hand, the necessity for crossings decreases the capacity to accomodate intersecting directions of traffic, which leads directly to the formation of traffic jams and prolongation of travel time.

One solution applied to improve traffic capacity and to keep traffic moving is the construction of crossings with grade separations. However, these solutions are expensive, and their construction requires space, which is at a premium in the urban environment. Thus, crossings at grade level, with traffic controlled by signalling, are most common.

Below, a proposal for analysis of road traffic through the application of a neural network is presented. It was compared to analysis of the readiness coefficient presented in work [3] and the potential for its practical application was assessed.

## 2. Analysis of the coefficient of readiness for transit through intersections

Due to speed limits, organisation of traffic at crossings, the number of road lanes in a given direction, and the fact that cars that have stopped must resume driving, there is a theoretical limited number of vehicles that can travel through a given crossing within a unit of time. The effectiveness of signalling control at a given crossing is indicated by the actual number of vehicles coming from different directions that can traverse this crossing within a unit of time. The greater this number under given conditions of traffic variability, and the closer to the theoretical limit value, the more effective the control.

Due to the variability of traffic intensity over the course of a day, a week, or even a season, the most effective method of traffic management should be real-time continuous signalling control. To make this possible, it is necessary to apply systems to determine traffic

intensity on access roads to the crossing and to apply controls adapted to such intensities, so that the waiting time for travel through a crossing is kept as short as possible under given conditions for vehicles on all access roads.

The authors presented one form of signalling control in [3], proposing a method maximizing the coefficient of readiness determined for a single crossing. In this method, the duration of green lights is determined based on the maximisation of the crossing's readiness coefficient, which ensures minimisation of the mean waiting time for travel by vehicles heading in both directions. An additional condition was assumed: mean waiting times should be equal in both directions. The total coefficient of crossing readiness is the sum of coefficients for individual traffic directions, according to dependency [3]:

$$k_{gc} = \frac{T_{ziA}}{T_{pc} + T_{srA}} + \frac{T_{ziB}}{T_{pc} + T_{srB}} \quad (1)$$

$$k_{gc} = \frac{T_{ziA}}{T_{pc} + \frac{n_A(C) \cdot T_{pp} \cdot T_{pc}^2}{C \cdot l_{prA} \cdot T_{ziA}}} + \frac{T_{ziB}}{t_{pc} + \frac{n_B(C) \cdot T_{pp} \cdot T_{pc}^2}{C \cdot l_{prB} \cdot T_{ziB}}} \quad (2)$$

where:

- $T_{pc}$  – full light cycle time (constant),
- $T_{ziA}$  – duration of green light in traffic direction  $A$ ,
- $T_{ziB}$  – duration of green light in traffic direction  $B$ ,
- $T_{srA}$  – mean waiting time in traffic direction  $A$ ,
- $T_{srB}$  – mean waiting time in traffic direction  $B$ ,
- $t_{zcz}$  – duration of yellow light and yellow and red light,
- $C$  – time constant, e.g.  $C = 3600$  [s],
- $n_A(C)$  – intensity of vehicular traffic in traffic direction  $A$  relative to constant  $C$ ,
- $n_B(C)$  – intensity of vehicular traffic in traffic direction  $B$  relative to constant  $C$ ,
- $l_{prA}$  – number of traffic lanes in direction  $A$ ,
- $l_{prB}$  – number of traffic lanes in direction  $B$ ,
- $t_{pp}$  – time for a vehicle to travel through the crossing.

To solve the optimisation problem at assumed values of vehicular traffic intensity ( $n(C)$ ), the duration of green lights may be determined for intersecting traffic directions  $A$  and  $B$  [3].

In actual conditions, it is frequently observed that the formation of traffic jams does not only concern one crossing, but two or more. In this way, characteristic areas with significantly more difficult traffic and increased transit time are formed. To keep traffic moving to the extent possible in such an area, the need to consider traffic intensity and signaling at several adjacent crossings seems to be justified.

The computational model proposed below considers not one but two crossings as well as the number of vehicles arriving at them, constituting an introduction to the development of the problem involving a greater number of crossings. The duration of the appropriate signals determined according to the model makes it possible to minimise waiting times for transit through both crossings, under given conditions of traffic intensity, for all arriving vehicles. Such a solution makes it possible to improve traffic flow in the entire area, not only at one crossing.

In real conditions, both randomness and periodicity play a part in the variability of traffic intensity [1, 2]. To determine all traffic possibilities and find optimal solutions for them through signal control is difficult. Simplified solutions, based on the development of several control programmes for a given crossing, can be encountered in traffic control; such solutions are activated according to the traffic intensity or time of day [1].

The application of neural networks makes it possible to account for variability and randomness of traffic without first finding solutions for all possible scenarios, and to determine optimal durations for signals.

### 3. Characteristics of the method

A concept for signal control using artificial neural networks is presented below. The implementation of the proposed solution should enable easy, continuous, and fluid signal control in a given area, so that the transit time through this area for increased and variable traffic intensity can be reduced as much as possible.

The crossings presented in figure 1 include only one traffic direction for the main road and access for vehicles from subordinate roads only from the right side of this road. For the opposite direction on the main road, the situation can be considered analogously by accounting for the appropriate intensity of vehicular traffic on the main road and access roads which are opposite to their counterparts on Fig. 1. The computational model remains unchanged, except that the intersection marked 1 is marked 2 for the opposite direction, while intersection 2 becomes intersection 1. This model will still not account for conditional turns or left turns; however, the developed concept has broad possibilities for further development and improvement, which may lead to the full reflection of the nature of traffic in a given area and the determination of optimal control in subsequent steps. The first version of the solution presented here is provisional, and only after it has been positively verified will it be subjected to further modifications.

The intersection system accepted for analysis is shown in the graphic below.

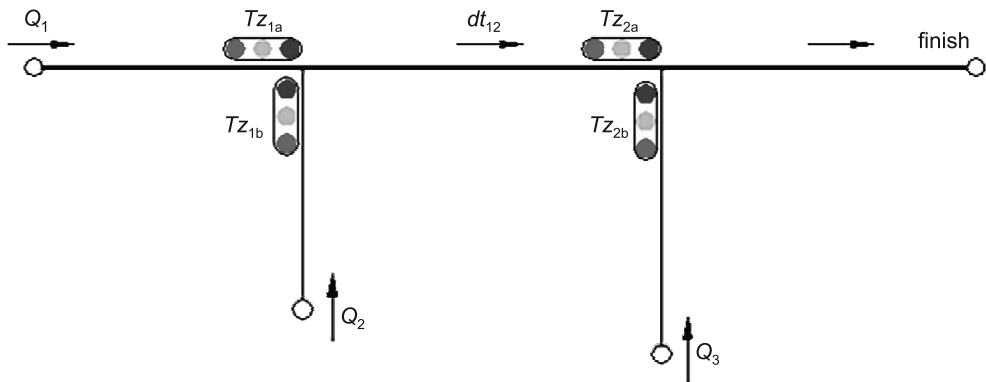


Fig. 1. Schematic of the intersection system accepted in the computing model

Because the proposed model is a simplification of actual road traffic, it is necessary to define specific assumptions:

- the total duration of the green and red light at each intersection is equal to 120 [s] (a yellow light is equivalent to a red light, in accordance with valid road traffic regulations) in both directions,
- optimisation is conducted according to the criterion of the minimum mean value of transit time of vehicles arriving from 3 directions over a time of 30 [min.],
- the distance between intersections is 200 [m],
- the main road is one-way, with one lane, and cars arriving from the two subordinate roads must turn right,
- conditional turns are not taken into consideration.

In the conducted simulations of vehicular traffic, the following are variable values:

- $Q_1$  – intensity of vehicles arriving from starting point 1 [1/60s],
- $Q_2$  – intensity of vehicles arriving from starting point 2 [1/60s],
- $Q_3$  – intensity of vehicles arriving from starting point 3 [1/60s],
- $T_{z1}$  – green light duration at crossing 1 [s],
- $T_{z2}$  – green light duration at crossing 2 [s],
- $dt_{12}$  – temporary shift of signal display between crossings 1 and 2 [s].

The computer programme simulating vehicular traffic calculated the mean transit time of all cars for various configurations of the above variables. Given the duration of each simulation, it is not possible to verify all cases, so variable values are assumed at certain numerical intervals in successive tests. Next, time cases  $T_{z1}$ ,  $T_{z2}$ ,  $dt_{12}$  are selected for the minimum transit time at determined traffic intensity values  $Q_1$ ,  $Q_2$ ,  $Q_3$ .

Such a parameter set, for which a minimum mean transit time exists, has been used to ‘teach’ the neural network presented in Fig. 2.

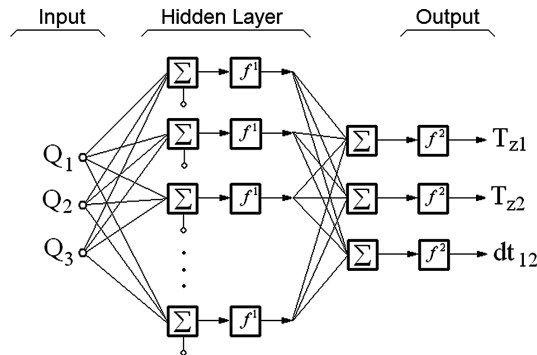


Fig. 2. Schematic of the artificial neural network for signal control

Input and output data were scaled to the range (0; 1) at the beginning in order to ensure their homogeneity.

The learning process was conducted using the gradient method [4–7]. It is based on inputting successive learning vectors into the network and adjusting weight values depending on the error of the obtained network response, so that in further learning steps,

the mean square error for the entire learning set decreases. The achievement of a minimum value, which remains unchanged during successive learning steps, means that the learning process has been concluded. In the analysed case, the error decreased only after the 25<sup>th</sup> learning step, after which its value did not change.

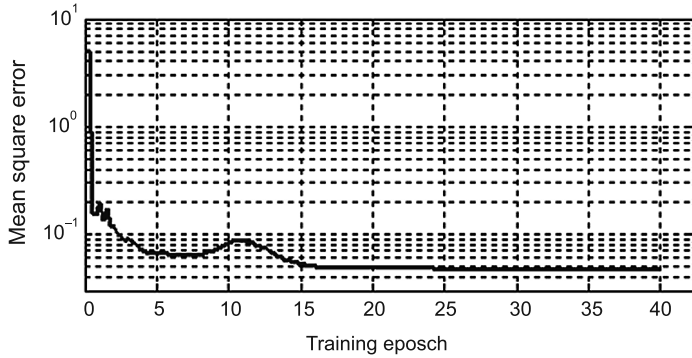


Fig. 3. Mean square error in learning process

One of the conditions guaranteeing the efficiency of the network is the provision of the appropriate amount of learning data, which should be greater than twice the number of weights in the network. In this case, the number of data sets is equal to 100, and the number of variables, for 4 neurons in the hidden layer, is 28, which means that the network will not learn enough based on the analysed data, which in turn could cause the calculation of incomplete time values for signalling changes.

Following the learning process, weight values are not subject to change and become constant values. A network taught in this way, with defined weight values, can then be simulated with any input values. Simulation of an artificial neural network means that data vectors with any values are input and conversion takes place according to constant weight values. In this case, the actual number of vehicles coming from individual directions and on the basis of this number, signalling is controlled continuously based on traffic intensity.

The primary advantage of artificial neural networks is their ability to acquire and generalise, that is, to approximate data. Thus they enable the calculation of the signal changing time in cases of vehicular traffic intensity not found in the learning set during the learning process but which may occur under actual traffic conditions. This makes it possible to control road traffic continuously in real time, using for example, induction sensors built into the road to measure the number of vehicles coming from particular directions.

#### 4. Verification and interpretation of obtained results of calculations

Calculations according to the presented method were carried out for the assumed traffic intensities on individual roads according to Fig. 1. The accepted numerical values are presented in Table 1 and in Fig. 3. It was assumed that the light cycle time at each intersection is equal to 120 [s].

Table 1

Vehicular traffic intensity on individual roads

Vehicular traffic intensity [veh./min.]	Case number											
	1	2	3	4	5	6	7	8	9	10	11	12
$Q_1$	12	12	12	12	6	12	18	24	12	12	12	12
$Q_2$	6	12	18	24	6	6	6	6	6	6	6	6
$Q_3$	6	6	6	6	12	12	12	12	6	12	18	24

After doing the simulation calculations using the neural network (according to Fig. 2), results were obtained as durations of green lights in individual traffic directions, which, according to the presented method, should ensure the shortest mean time of transit for all vehicles through the analysed area from Fig. 1. The obtained results are presented in Fig. 5.

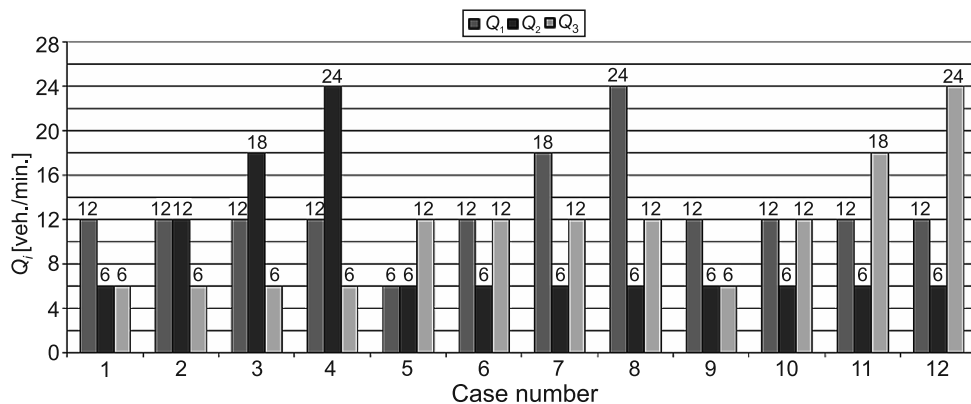


Fig. 4. Vehicular traffic intensity on individual roads accepted for calculations

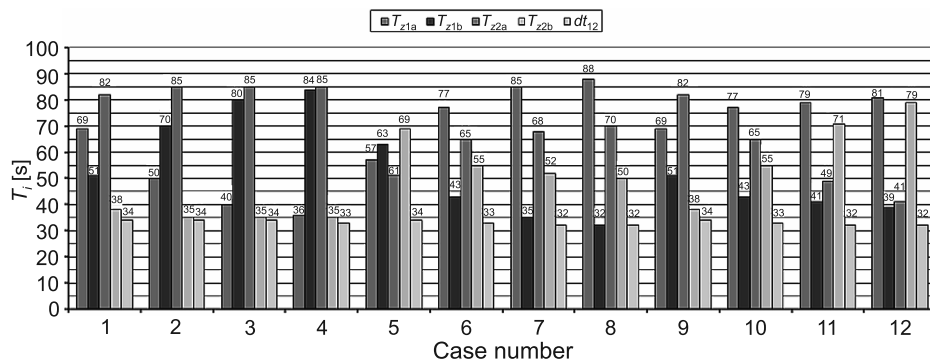


Fig. 5. Green light durations determined by the neural network

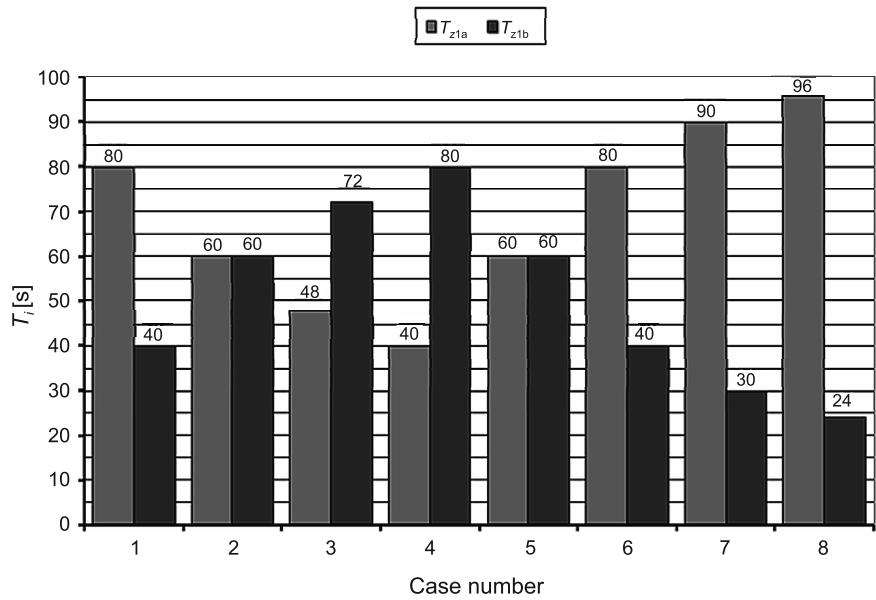


Fig. 6. Green light durations according to the readiness coefficient method

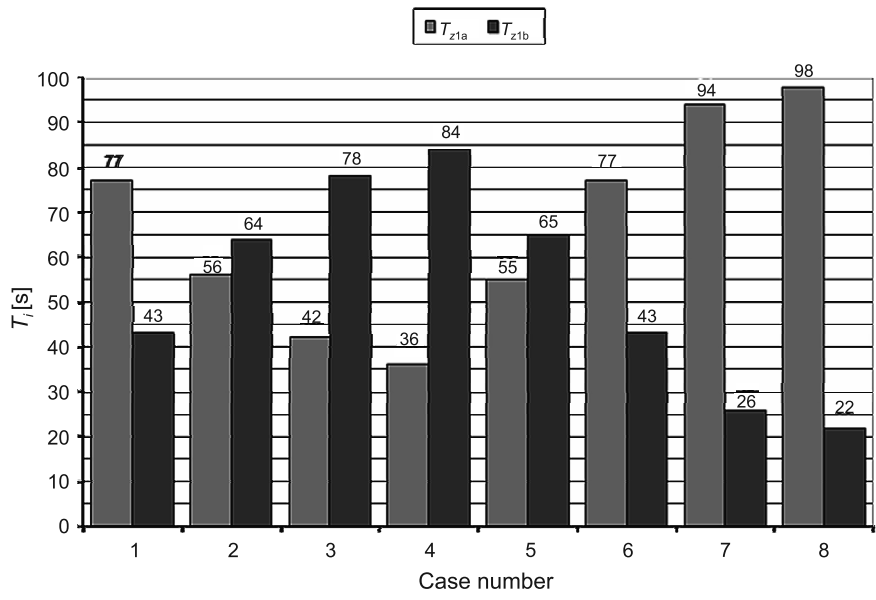


Fig. 7. Green light durations according to the neural network method



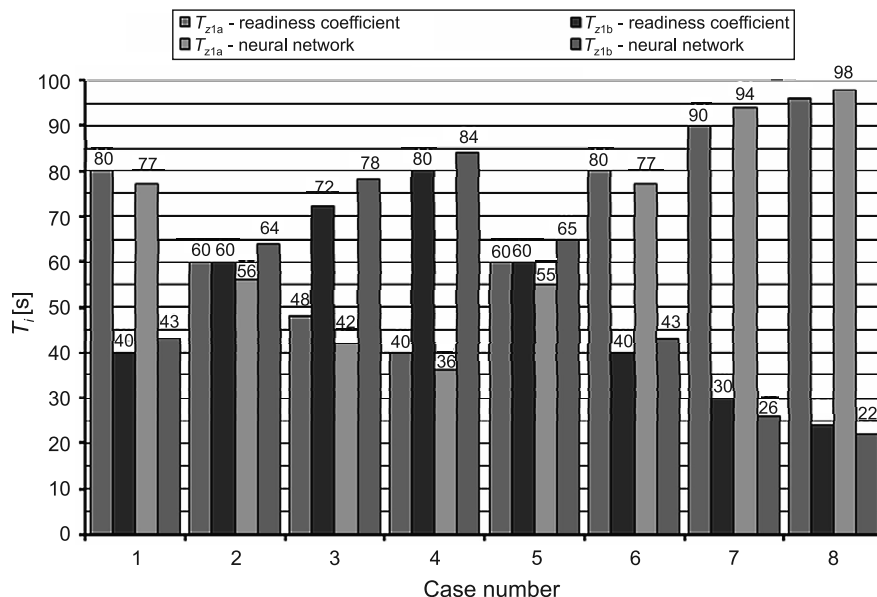


Fig. 8. Results of calculations according to the readiness coefficient and neural network methods

It can be seen that the obtained results indicate the need to prolong the duration of the green light as vehicular traffic intensity increases in a given direction, which is in accordance with reality and expectations. The neural network used for calculations also accounted for the fact that the time of  $T_{z2a}$  must ensure transit of vehicles that are found between crossings 1 and 2, comprising streams  $Q_1$  and  $Q_2$ . To obtain the effect of minimising waiting time for transit in this situation given the assumed distance between intersections, time lags between signals at intersections 1 and 2 are required (Fig. 5).

In order to compare the obtained results with the method according to the readiness coefficient mentioned in section 2, calculations were carried out for the case of a single intersection. Calculations were done for the first 8 cases according to Table 1, involving intensities  $Q_1$  and  $Q_2$  only, since only one crossing was being considered. The obtained results are presented in Fig. 6, 7 and 8.

It can be seen that the results obtained by the two computing methods are very similar. The maximum difference was equal to 15%. Most results differed by less than 10%. However, the method using the neural network is more flexible, enabling solutions for cases not considered earlier and the consideration of a greater number of crossings.

## 5. Conclusion

The traffic analysis methods presented above are two of the many ways to search for solutions of vehicular traffic control through signalling. Their practical applicability determines their efficiency. The adaptation of the presented methods to actual conditions

requires the consideration of a greater number of crossings and of intersecting two-way traffic.

Following analysis of the problem, practical verification of such methods and their further development in terms of adaptation to real conditions is warranted. The presented methods may be useful in the analysis and control of road traffic.

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