DEEP LEARNING - BASED OPTIMIZATION OF SMART TRAFFIC SIGNAL SYSTEMS

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Rezumat. *Această lucrare compară diverse tehnici de inteligență artificială aplicate sistemelor inteligente de trafic pentru optimizarea semafoarelor. Utilizarea algoritmilor de Deep Learning pentru actualizarea timpilor de semaforizare conduce la obținea de rezultate superioare abordării clasice cu timp fix. Rețeaua de trafic este conceptualizată ca o componentă modulară a infrastructurii rutiere urbane, facilitând analiza traficului în contextul unui sistem de management integrat. Studiul de caz prezentat analizează un scenariu cu multiple intersecții conectate, cu fluxuri de intrare variabile estimate pe baza datelor reale achiziționate din sistemul de management al traficului din București.*

Abstract. *This paper compares various artificial intelligence techniques applied to intelligent traffic systems for traffic light optimization. The use of Deep Learning algorithms for updating traffic light timings achieves superior results compared to the classical fixed-time approach. The traffic network is conceptualized as a modular component of the urban road infrastructure, facilitating traffic analysis in the context of an integrated management system. A case study analyzes a scenario with multiple connected intersections, with variable input flows estimated based on real data acquired from the Bucharest traffic management system.*

Keywords: Deep Learning, optimization, traffic light systems, variable cycle, number of cars, congestion

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1. Introduction

With the increase in the number of cars, the problem of congestion generated by road traffic in congested urban areas has become increasingly important. In the last two decades in Romania and all over the world, the number of road vehicles has increased greatly. The increase is largely due to urbanization and the development of activities within cities. Urban mobility has begun to pose numerous problems due to the lack of space, inevitably leading to traffic jams and undesirable effects such as air and noise pollution. The continuous increase in traffic leads to the need to adopt solutions that ensure sustainability in large cities.

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The general tendency of people in large cities such as those in the USA, Canada, Australia and Europe is to leave cities to settle in their proximity. The city, although seen by many as a crowded, noisy and polluted environment, has the capacity and potential to become a clean, safe and prosperous environment in which the quality of life is at the highest level (Banister 2000, Ilin 2009 [1-3]).

The shape of today's cities reflects the technologies and transport networks of different eras and stages of the development of human settlements. Current cities were designed for the low traffic of previous eras, gradually developing around points of great interest such as fairs or markets. The development of cities, carried out in an incremental manner, was not accompanied by an urban design adapted to the volume of contemporary traffic. This deficiency inherently generates the agglomeration felt by traffic participants. Modern research has concluded that sustainable cities must have the appropriate shape and size to ensure space for walking, special lanes for travel by alternative means (bicycles, electric scooters), efficient public transport and high-performance road transport. The city must be an instrument that facilitates social interactions and provides access to quality services. At the same time, land must be managed efficiently, the economy must be empowered to flourish, and toxic gas emissions must be kept at a certain level by increasingly using renewable energy sources. It is also necessary that policies for sustainable urban development lead to the facilitation of non-polluting and energy-efficient forms of transport and at the same time reduce the need for personal travel.

Urban traffic congestion is alleviated by various methods, the predominant ones being road infrastructure modifications, public/alternative transport development and intelligent traffic control, especially through traffic lights. Although infrastructure modifications can provide short-term solutions, their long-term benefits are limited [4]. The success of public transport depends crucially on passenger preferences, therefore, offering accessible and attractive alternatives can encourage the transition from private to public transport, thus alleviating agglomeration [5]. In the context of traffic flow control that depends on many parameters, artificial intelligence and machine learning algorithms (e.g. fuzzy logic, genetic algorithms, neural networks) have a very high potential to learn the characteristics of a specific road area and to be able to streamline traffic light times. The accuracy of traffic management can be significantly improved by using real-time data and intelligent traffic lights based on traffic density [6, 7]. Among the strategies presented, optimizing intelligent traffic light systems through traffic light control represents the least invasive approach from an infrastructure point of view, allowing for efficient control of vehicle flows on the road network.

2. Traffic and traffic light methods

2.1. Traffic light methods

In the field of traffic light systems, two main paradigms are distinguished: the classical approach based on fixed traffic light time, widespread globally, and the modern approach, with variable time. Both paradigms are defined in relation to the traffic light cycle, which is the combined duration of the green and red times.

These aspects highlight the existence of the following traffic light methods:

- Fixed cycle traffic lights: This method operates with predefined durations for the green and red lights – in the case of the specified example, these durations are equal. As illustrated in Figure 1 - Fixed cycle, the traffic lights that manage the arteries ab and cd of an intersection use constant signal times that do not depend on the number of cars involved in the traffic. The green and red times have the same value for the adjacent arteries [10].
- Improved fixed cycle traffic lights (semi-intelligent): This approach introduces partial adaptation, identifying periods of heavy traffic. During these periods the traffic light is programmed to extend the green times, then reverting to the default fixed cycle (Figure 1 - Improved fixed cycle) [10].
- Intelligent variable cycle traffic lights (variable duration): The duration of the green time is calculated dynamically according to the number of vehicles in the queue at the intersection. The times are automatically updated at each traffic light cycle based on an algorithm that takes into account the number of vehicles in traffic. According to Figure 1 - Intelligent cycle, the green and red times are complementary between adjacent arteries [10].

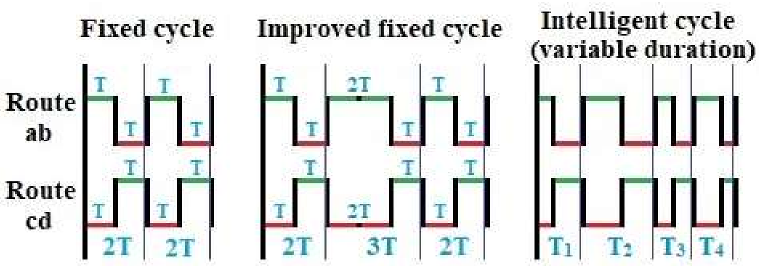

Fig. 1. Types of traffic light methods [10]

2.2. Traffic situation in the city of Bucharest, Romania

In 2024, Bucharest, the capital of Romania, ranked fifth globally in the TomTom Traffic Index [8] as the city with the highest congestion, a result based on the analysis of 501 cities from 62 countries. The direct consequence for the inhabitants of Bucharest is an estimated annual loss of 150 hours spent in traffic. Urban expansion has directly contributed to the increase in vehicle volume and, implicitly, to the intensification of urban jams. Several factors including poor road infrastructure, lack of synchronization of traffic lights, dependence on personal cars at the expense of public transport, road incidents and an often chaotic driving style aggravate this problem.

For the subsequent simulations, the traffic analysis was focused on the specific context of Bucharest. To ensure the realism of the modeling, we examined the traffic flow on the segment Calea Ștefan cel Mare - Piața Victoriei (bounded by the intersections with Barbu Văcărescu and Calea Floreasca) an area known for its high level of agglomeration during the week in the city of Bucharest. As can be seen in Figure 2, the traffic flow monitoring took place between 4:00 and 23:00, recording the number of vehicles every 15 minutes to calculate the average flow per second. The graph indicates a traffic flow range from 0.4 to 1.6 cars/s. The maximum value recorded is 1.6 cars/s, which is the maximum flow value for the following simulations of peak traffic conditions.

Fig. 2. Traffic flow evolution in Bucharest, during the week

In this paper, the necessary data were simulated taking into account the information obtained from real traffic in Bucharest (see Figure 2). In the following simulations we will use an intersection model with 4 or 3 routes (a, b, c, d) and two directions of travel: ab and cd, as shown in Figure 3. We consider that during the red time, cars accumulate at the traffic light, and during the green time, cars leave the traffic light going to another intersection.

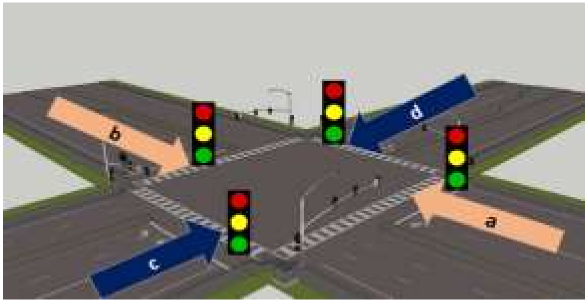

Fig. 3. Example of intersection with complementary directions ab and cd

We will interconnect 6 intersections (A,B,C,D,E,F, 22 arteries, 101 traffic light cycles) in the configuration of a city for which we will generate, using a traffic generator, vehicle input flows into the system (the constraints are described in (1)). We will also calculate the car transfers from one intersection to another (the total number of cars, the number of cars leaving during the green time, the number of cars accumulated during the red time and the number of remaining cars that fail to pass in the first green interval of the traffic light) and the traffic light times based on a recurrent neural network within Deep Learning for each artery of each intersection. The data will be generated according to the following constraints:

$$\begin{cases} [T_{g\,min}, T_{g\,max}] = [20\,s, 40\,s];\ [T_{r\,min}, T_{r\,max}] = [20\,s, 40\,s]; \\ N_{min} = 12\ cars;\ N_{max} = 61\ cars; \\ q_{min} = \dfrac{N_{min}}{N_{max}} = 0.6\ cars/s \\ q_{max} = \dfrac{N_{min}}{N_{max}} = 1.6\ cars/s \end{cases} \tag{1}$$

where:

- $T_{g/r\,min}, T_{g/r\,max}$ represent the minimum/maximum green/red time;
- N_{min}, N_{max} represent the minimum/maximum number of cars;
- q_{min}, q_{max} is the minimum/maximum traffic flow.

3. Deep Learning Algorithm

Deep Learning (DL) is a subclass of Machine Learning (ML) that is based on the use of multi-layer neural networks capable of emulating the learning and decision-making processes of the human brain. Within DP, recurrent neural networks (RNNs) of the Long Short Term Memory (LSTM – see Figure 4) type prove to be extremely efficient in identifying long-term dependencies in sequential data, thus finding extensive application in numerical time series analysis. Creating a Deep Learning model involves going through four fundamental stages: data selection and preprocessing, defining the network architecture, training and finally testing.

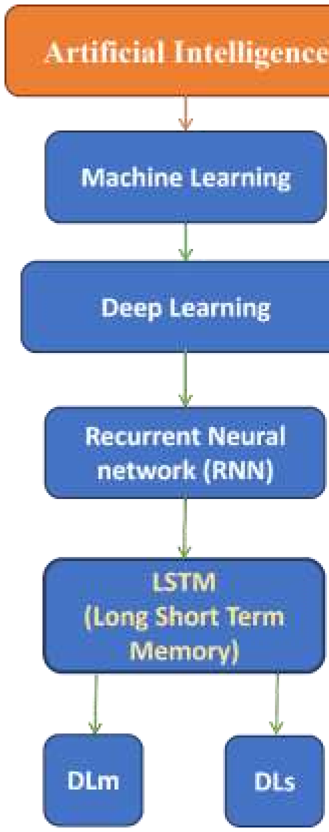

Fig. 4. Algorithms Machine Learning

3.1. Data selection and preprocessing

In the study, we used a dataset consisting of 30,240 traffic flow records from various urban areas [9]. These data were organized according to four directions of movement (a,b,c,d) and subsequently, each group was labeled into two classes: 'Green duration extension' and 'Green duration modification'. The labeling was performed using two distinct methodologies, which allowed the training of two separate algorithms:

- DLm: The 'Green duration extension' label was applied when the maximum value between flows a and b was greater than or equal to the maximum value between flows c and d ($\max(a,b) \geq \max(c,d)$). Otherwise, if ($\max(a,b) < \max(c,d)$), the 'Green duration modification' label was assigned.
- DLs: The label 'Green duration extension' was applied when the sum of flows a and b was greater than or equal to the sum of flows c and d ($\mathrm{sum}(a,b) \geq \mathrm{sum}(c,d)$). In the opposite situation, if ($\mathrm{sum}(a,b) < \mathrm{sum}(c,d)$), the label 'Green duration modification' was assigned.

3.2. Defining the network architecture

The DL network architecture is composed of six distinct layers (see Figure 5). The first layer is the input layer, designed to receive a traffic vector structured based on the four directions of movement. Next comes the second layer, which integrates the Long Short Term Memory (LSTM) algorithm, specialized in identifying and learning dependencies in time series. The third, fourth and fifth layers play an important role in ensuring interconnectivity, helping to prevent overfitting and transforming intermediate data into probabilities. Finally, the last layer is the classification layer, which is formed by a set of two classes: 'Green Duration Extension' and 'Green Duration Modification'. The Long Short Term Memory (LSTM) algorithm is a specialized variant of recurrent neural networks (RNN) designed to solve the vanishing gradient problem and capture long-term dependencies in sequential data. Unlike traditional RNNs, LSTMs have a more complex internal structure that continues as memory cells and allows the network to retain or forget information for long periods of time. Each LSTM cell is equipped with three main gates:

1. Forget Gate: It decides what information from the previous memory cell state should be forgotten.
2. Input Gate: It decides what new information from the current input and the previous hidden state should be stored in the state of the memory cell.
3. Output Gate: It decides what part of the current cell state should be displayed as the layer's output [11].

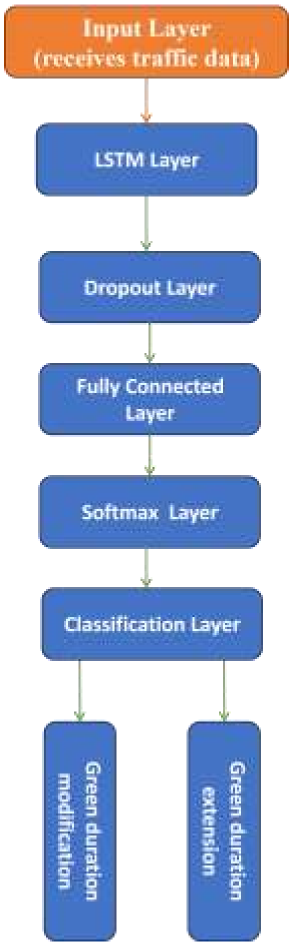

Fig. 5. Deep Learning Network Architecture

3.3. Training and testing

After configuring the layer architecture, we chose the training options for the network. We used the adam optimization algorithm to adjust the network weights during training. The maximum number of epochs (MaxEpochs) for which the network was trained was 100 with a MiniBatchSize of 32, which means that the network will process 32 data examples simultaneously before updating the weights. The Learning rate was chosen to be 0.001, Shuffle (every epoch - the order of the data examples in the training set will be randomized at the beginning of each new epoch), and GradientThreshold was chosen to be 1e5 (if the gradient norm exceeds this value, the gradient is scaled down to prevent the explosive gradient problem). The network was trained using the two preprocessed datasets, resulting in two distinct models: DLm and DLs. Both models demonstrated remarkable accuracy: DLm reached 97.49%, and DLs recorded an accuracy of 95.11%.

The test was performed on a network of 6 interconnected intersections (A, B, C, D, E, F). Depending on the traffic conditions detected on the four main directions (a,b,c,d) within each intersection, the system classifies the situation into one of two decision categories: 'Green duration extension' (the green time is increased by a constant value) or 'Green duration modification' (the green time is increased or decreased according to a function that takes into account the number of vehicles in traffic).

In Figure 7 we represented the result of testing the DLm algorithm (this algorithm was trained to adjust the timing of the traffic lights according to the maximum traffic volume on the two arteries in order to manage the congestion on the complementary artery) for intersection B on the 2 arteries (ab and cd). Here the traffic light signal oscillates, recording an initial increase-decrease, followed by a new increase for peak hours. A significant reduction is observed in the maximum number of remaining vehicles (18 for DLm compared to 90 for the classic fixed-time method – see Figure 6) and in the maximum number of vehicles involved in traffic (203 for DLm compared to 334 for the classic method – see Figure 6). In Figure 6 the classic method has a positive effect only on one artery and introduces a very large agglomeration on the complementary artery. In Figure 7 a notable aspect is the uniform distribution of congestion (yellow graph) on both arteries. The colors in the graph have the following meaning:

- black: The total number of vehicles accumulating at the red light;
- blue: The number of cars that leave the traffic light when it turns green;
- yellow: The number of cars that fail to leave the traffic light after the green signal ends and must wait for at least one more green cycle;
- green/red: The duration of the green/red traffic light;
- flow: Maximum traffic flow (set at a value of 1.6 cars per second);
- Min./Max. green light: Minimum/maximum green light duration. The minimum/maximum red light duration is identical.

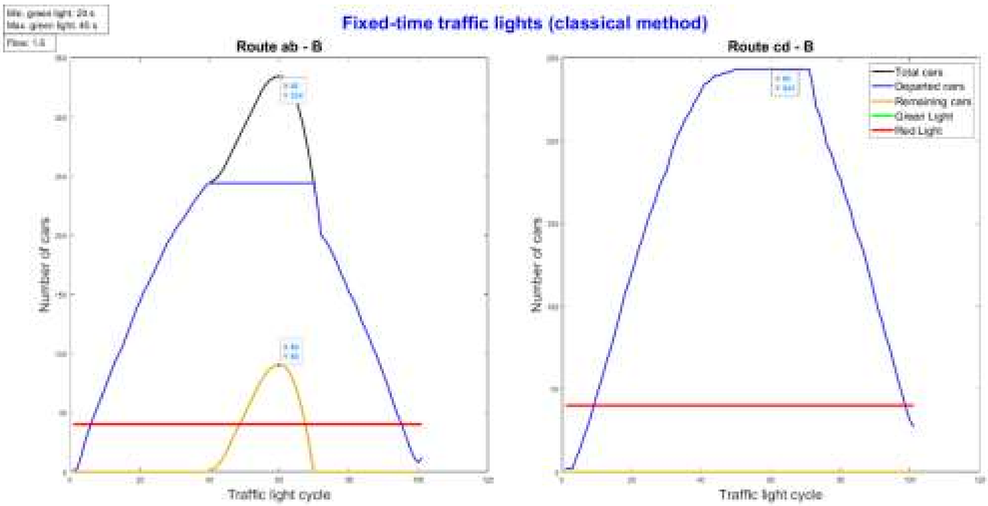

Fig. 6. Intersection B, arteries ab – cd, classic traffic lights with fixed time

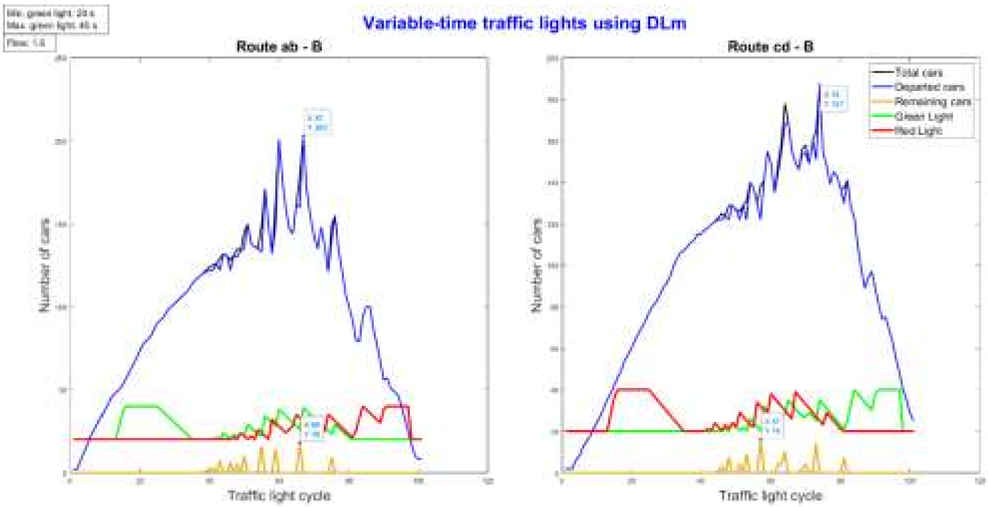

Fig. 7. Intersection B, arteries ab – cd, traffic lights using DLm

4. Experimental Results

In this section, we have presented various comparisons for the three methods used: Fixed cycle, DLm and DLs. Figure 8 shows the evolution of the average number of vehicles remaining after the green cycle of the traffic light, on the 22 arteries from the six intersections over the total duration of the 101 traffic light cycles. It is observed that DLm and DLs achieve a substantial reduction in congestion, compared to the classic method with fixed duration. The simulated experiments, carried out at flows ranging from 1.55 to 1.7 vehicles per second, indicate a very good performance of the DLm algorithm for any type of flow. DLs has a fairly good performance for the flow of 1.6, where the number of remaining vehicles decreases compared to Fixed cycle by 212. At a flow of 1.7 vehicles/s, DLm maintains an average number of remaining vehicles of only 156, a value significantly lower than the over 1000 vehicles recorded by the other methods. On the other hand, under low flow conditions (1.55 vehicles/s), all three strategies, including the fixed-time one, efficiently manage traffic volumes (the highest value is DLs-131 vehicles remaining, but it is lower than in the case of the 1.6 flow). However, a significant intensification of traffic flow will force the traffic light to operate at maximum capacity, ultimately generating a jam situation comparable to that of the classic fixed-cycle scenario.

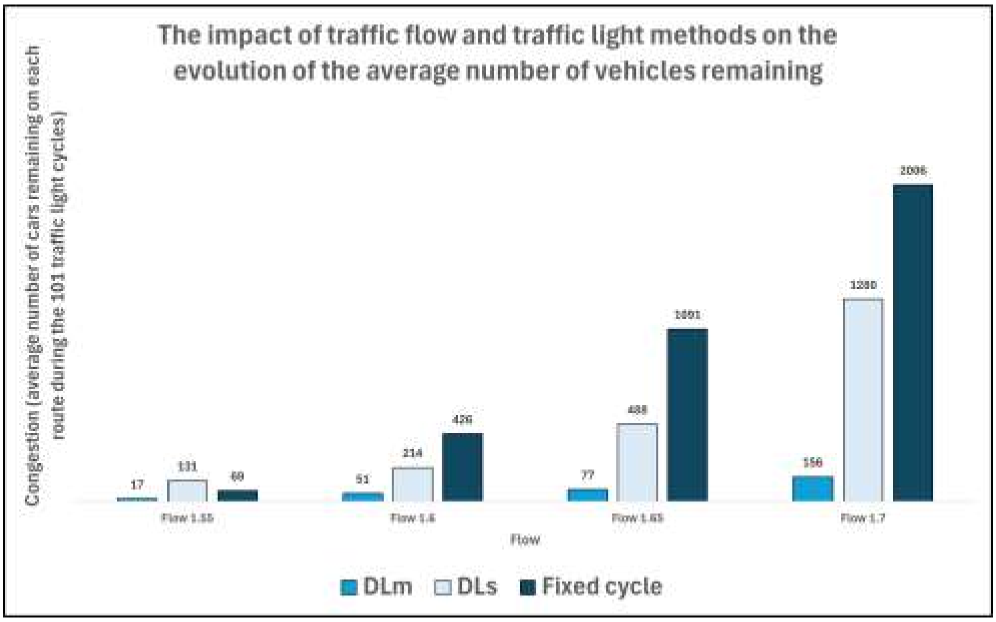

Fig. 8. Evolution of the number of cars remaining depending on traffic flow

The analysis of the time required to travel a distance of 10 km within the city is presented in Figure 9. Regarding the estimation of travel time in the classic case with fixed time, we performed measurements in Bucharest for the time spent in traffic when traveling a 10 km segment during peak hours. For traffic lights using DL, the time estimate was based on the product of the average duration of a traffic light and the number of traffic lights over a distance of 10 km, to which was added the time required to travel the distance in the absence of traffic and the delays caused by maneuvers that depended on the percentage of cars remaining in traffic. It is remarkable that DLm streamlined the duration of a 10 km trip to 24 minutes. The concept of 'traffic-free' represents the ideal duration to travel 10 km, without the influence of congestion or traffic lights. It is obvious that the implementation of traffic optimization methods (DLm and DLs) has a positive impact, reducing both the accumulation of vehicles per cycle and the total time spent in traffic at the urban level.

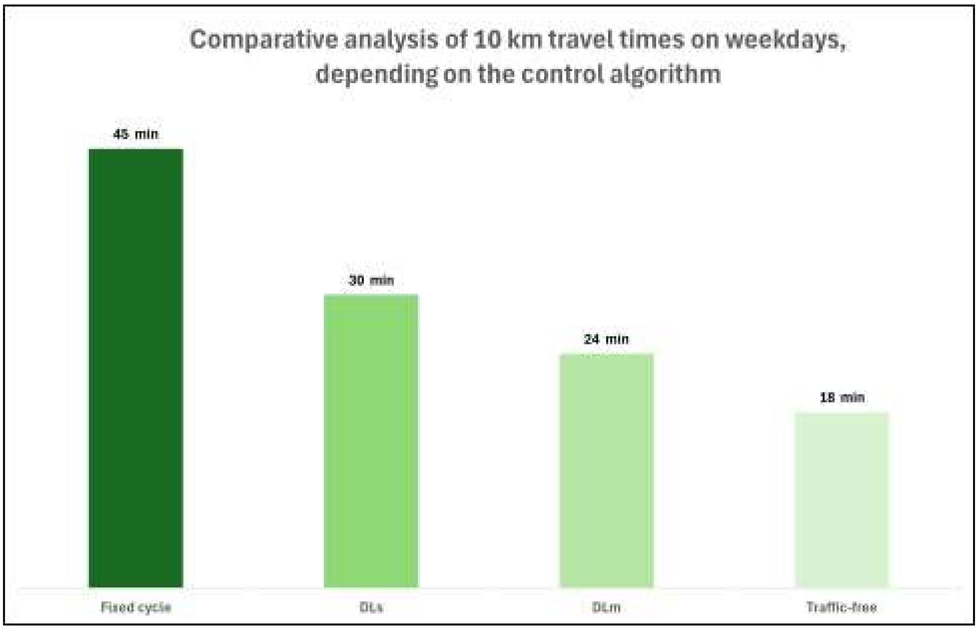

Fig. 9. Evolution of travel times for a distance of 10 km in Bucharest during peak hours

Figure 10 illustrates a comparison of the average number of remaining vehicles – calculated as an average over the 6 intersections during the 101 traffic light cycles for the methods: Fixed cycle, DLs and DLm. This analysis was performed for a maximum traffic flow of 1.6 cars/s. Of these, the classic variant, with fixed time (red graph), generates the most significant agglomeration reaching an average of 90 remaining cars, which fail to pass in the first traffic light cycle and must wait for at least one more green cycle. In contrast, the DLm variant (represented in blue) manages to reduce traffic to 22 cars remaining during the peak period. The DLs algorithm (yellow) is an intermediate variant with an average maximum number of 33 remaining cars during the peak period. The classic variant with fixed time of the traffic light induces jams during the peak traffic period. As peak traffic intensity decreases, the efficiency of all three methods becomes similar. This is because at low traffic volumes, any optimization strategy, including the traditional one, can manage the flow adequately, the traffic problem being reduced to the peak period when the number of cars increases greatly.

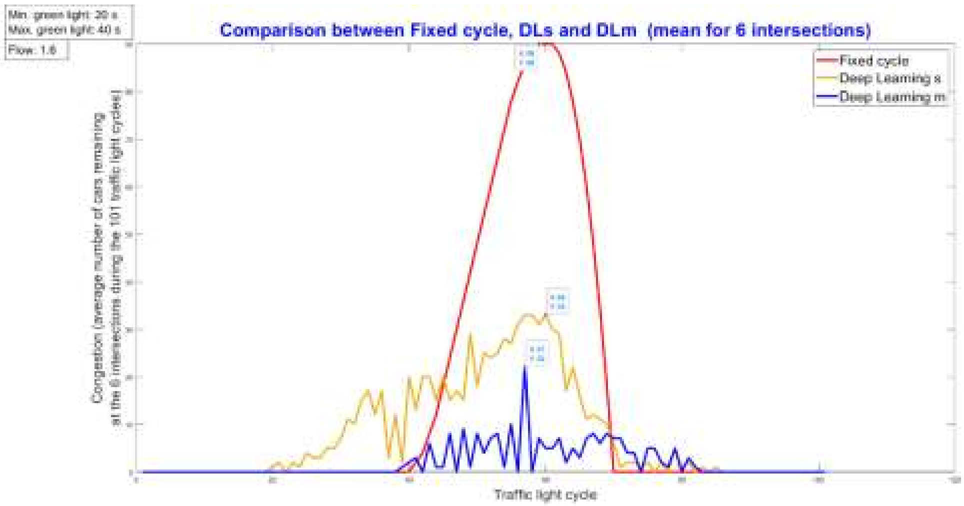

Fig. 10. Comparison between the average total number of vehicles for the fixed cycle, DLs and DLm

5. Conclusions

Efficient traffic management is a major global mobility challenge, affecting all developed communities. This paper examines two Deep Learning-based optimization algorithms and compares them with the existing fixed-cycle traffic light system. These methods help reduce traffic by generating traffic light times that use the number of cars involved in the traffic. As can be seen in Table 1, using DLs the number of remaining cars was reduced by 50% compared to the classic method, and for DLm the reduction was 88% (analysis performed for a maximum flow of 1.6 cars/s – Figure 10).

Table 1. Results on congestion and travel time reduction compared to classic fixed-cycle traffic lights

Algorithm	Reducing congestion (%)	Reducing travel time (minutes)
DLs	50 %	15
DLm	88 %	21

Additionally, the use of optimization methods contributes to shortening travel times for a distance of 10 km: for DLs we have a 15-minute reduction in travel time compared to the classic fixed-cycle variant, and for DLm 21 minutes. In conclusion, traffic management is a fundamental aspect of contemporary urban functioning. The present study highlighted two optimization methodologies based on Machine Learning, the implementation of which led to beneficial effects in terms of reducing jams and increasing mobility in cities.

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