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Towards sustainable traffic control: evaluation of learning traffic controllers

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ABSTRACT
Traffic control is a crucial component of urban transportation systems. In recent years, machine learning-based traffic controllers have been widely used in urban traffic control. This paper presents a comprehensive evaluation of the performance of traffic control systems on urban motorways and signalized intersection networks. By integrating sustainability criteria into the evaluation, this research contributes to the development of efficient and sustainable urban traffic control solutions. The proposed methodological evaluation framework is comprehensive and can be used as a roadmap for the implementation and testing of various ITS-based urban road transport solutions. In addition, future research directions are outlined that guide the evolution of sustainable and efficient traffic management solutions based on machine learning.

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1. Introduction

In the last decade, there has been a shift toward more complex and efficient transportation systems. With the constant rise in transport demand, traditional traffic control systems fail to properly handle the increased complexity of today's transportation systems. With the rise of Intelligent Transport Systems (ITS), new opportunities for the control and management of traffic become available [1]. Modern ITS based services allow the use of machine learning to further improve performance. ITS frameworks incorporate various sensing, communication, and decision-making technologies to optimize urban mobility. Machine learning-based adaptive traffic control can be embedded in ITS infrastructures to dynamically adjust signal timings, manage traffic flow, and reduce environmental impact. Previous research has demonstrated the effectiveness of combining machine learning with ITS data sources such as loop detectors, cameras, and GPS-based tracking to optimize signal phasing and reduce congestion [2]. In addition, ITS-enabled adaptive controllers have been shown to improve traffic efficiency when integrated with cooperative adaptive cruise control (CACC) systems [3]. Such systems enable the use of real-time data processing acquired from multiple sensors in the traffic network to select control actions to be applied in the network [4, 5]. Current state-of-the-art approaches are learning-based, meaning that their control policy is created during operation by exploring all possible state-action combinations and observing the traffic system's response.

The focus of this paper is the evaluation of traffic controllers on urban motorways and signalized intersections. In the case of urban motorways, two primarily used control strategies are ramp metering and Variable Speed Limit (VSL) control. Both approaches attempt to alleviate congestion on the main traffic flow by slightly reducing the traffic flow on motorway sections and on-ramps before the congestion, providing a total network benefit. Due to a trade-off between reducing congestion in one segment and decreasing traffic flow in another, it is difficult to properly evaluate the efficiency of both control strategies.

In the case of signalized intersections, the analyzed control strategy is Adaptive Traffic Signal Control (ATSC). The main principle of ATSC operation is the adjustment of intersection signal programs according to current traffic conditions. Similarly to urban motorways, there is a trade-off between allowing more mainstream flow and secondary flow, making the proper evaluation difficult, as total network benefits are always most apparent when the mainstream flow is increased. For this reason, metrics that consider access equity should be included in the evaluation.

Regardless of the control strategy and traffic problem to be solved, learning-based traffic controllers require additional evaluation metrics compared to traditional traffic controllers. Learning-based controllers require a large number of learning iterations to reach the optimal control policy. The number of required learning iterations is usually not known in advance, but is highly dependent on the defined learning parameters. Most

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learning-based controllers are trained offline in a simulated environment before being integrated with real-world control systems. Before real-world integration is performed, the controller performance must be evaluated to ensure good control behaviour in a large spectrum of traffic demand changes. In addition to classic performance measures, the controller should be evaluated according to learning speed, adaptability to new and previously not seen states, and computational complexity since the computations will need to be conducted in real-time.

Such learning-based traffic controllers are being intensively developed [6], and some versions are already being implemented in commercial applications. A good example is the City Brain system, which is widely based on different methods from the artificial intelligence domain [7]. The current traffic controller evaluation [8, 9] does not include all the metrics mentioned needed for the evaluation of all aspects of learning-based controllers and for their systematic comparison. This creates a gap in their further focussed development and possible real-world application, especially in complex, large-scale urban environments where they are mostly needed. Thus, this paper addresses this open problem by systemizing the criteria available for a systematic evaluation of all the needed aspects (traffic, ecology, and training criteria) and proposing criteria sets for the two most distinguished use cases: urban motorways and networks of signalized intersections. The motivation for this research lies in the need to develop comprehensive evaluation criteria that address both traffic efficiency and environmental factors, enabling more effective deployment of learning-based controllers in real-world urban environments. By proposing novel metrics and frameworks, this study aims to improve the adaptability and performance of ITS, ultimately contributing to smarter and more sustainable transportation systems.

To address the mentioned problems, this paper contains the following contributions:

(1) Proposal of traffic efficiency criteria for the analysis of learning adaptive traffic controllers;
(2) Proposal of environmental criteria for the analysis of learning adaptive traffic controllers;
(3) Conceptual approach for the evaluation of learning parameters in learning adaptive traffic controllers.

This paper is organized as follows. After the introduction, the second section elaborates on traffic control approaches applied in urban areas that can also be implemented using new machine learning approaches. The third continuing section gives information on the evaluation criteria applied from the point of view of traffic, followed by the fourth section that takes into account the perspective of ecology. The fifth section elaborates on the evaluation criteria typical for learning-based traffic controllers that are the focus of today's research. The proposal of evaluation criteria for learning urban traffic controllers is given in the sixth section, accompanied by a discussion. The last section concludes the paper by indicating possible future research directions.

2. Traffic control approaches

Road traffic networks serve traffic flows that can be conflicting. Resolving such conflicting traffic flows is essential to ensure smooth and safe traffic with a high Level of Service (LoS). This is especially the case in urban environments where severe recurring daily congestion appears. Depending on the characteristics of the road network (urban roads or signalized intersection networks), different traffic control approaches are needed. Representative traffic control approaches for urban motorways and signalized intersection networks in continuation are described in more detail.

2.1. Urban motorways

The motorways initially constructed as urban bypasses are strongly affected by recurrent congestion caused by local commuters and transit traffic [10]. Furthermore, with the growth of urban areas, they have become fully integrated into the urban traffic system, and therefore, are named urban motorways. Thus, recurrent congestion on them has become even more prominent [11]. The most prominent congestion locations are known as *effectual bottlenecks* and are located near the on- and off-ramps. They are critical for reduced throughput and safety on motorways due to the speed difference between on-ramp flow and mainstream flow. The described situation at *effectual bottlenecks* with increasing traffic demand can significantly increase the possibility of congestion and slowdowns. Thus, it is necessary to implement several control approaches for motorway traffic flows, since construction expansion of urban motorways is not feasible in most cases. The two most prominent control approaches on motorways are ramp metering and VSL control. To address the problem of the stochastic nature of traffic flows, one of today's successful approaches is to design controllers for both motorway control strategies based on machine learning models.

2.1.1. Ramp metering

The ramp metering approach is a motorway control strategy, which controls the number of vehicles, which merge with the main motorway traffic flow from the on-ramps, by using a special traffic light containing only the red and short green phase. The ramp metering controllers use a much shorter cycle time to allow the inclusion of on-ramp flow to the motorway mainstream. Furthermore, the size of on-ramp flow per green phase can be the size of a single vehicle or a small platoon of vehicles (usually two or three vehicles). The metering rate is based on the traffic macroscopic parameters of the on-ramp adjacent mainstream flow and on-ramp queue (on-ramp traffic demand). The goal is to enable an optimal balance between on-ramp queues and mainstream throughput. However, ramp meters can also be used to control traffic flows between motorway mainstream flow and adjacent arterial urban roads [12]. The optimization of metering rates at all ramps with respect to their on-ramp queues and mainstream throughput can be difficult to model for one controller. Thus, there is a need to apply machine learning approaches to find/learn needed optimal control policies.

2.1.2. Variable speed limit control

VSL is the second motorway control strategy often used to improve the LoS on urban motorways. The main goal of VSL control is to improve traffic throughput by addressing the phenomenon of "capacity drop". This is done by reducing average speeds at mainstream flow. The speed reduction before the congested part of the motorway reduces the vehicle income over time to it [13]. Furthermore, the key control strategy for VSL controllers is the homogenization of vehicle speeds, which increases the value of critical density at particular motorway sections. Speed limits are calculated based on an algorithmic structure that uses data collected from static road sensors such as induction loops, video cameras, or radars as input. The computed speed limits can be posted at dynamic vertical traffic posts signalization known as Variable Messaging Signs (VMSs) or they can be imposed directly at the vehicle by using the Intelligent Speed Adaptation (ISA) framework and vehicle to infrastructure (V2I) communication. One has to bear in mind that by using the ISA framework, all vehicles equipped with an appropriate on-board unit can receive the information about the respective speed limit directly from the VSL controller, making the currently used VMS infrastructure obsolete.

2.2. Adaptive traffic signal control

In urban environments, intersections remain an essential component of urban traffic systems, as they allow for the controlled movement of vehicles and pedestrians following a defined set of rules to avoid collisions between conflicting traffic flows. Intersection traffic is primarily controlled by Traffic Signal Control (TSC) systems. The design of a TSC controller has a significant impact on the overall performance of the traffic network. Depending on the operational objective, the goal of TSC can be to reduce Travel Time (TT), minimize delays, or improve safety levels. However, if the TSC controller parameters are not set correctly, the controller can cause increased congestion, longer waiting times, and decreased safety. Today, there are three main types of TSC systems used [14]:

(1) Fixed-Time Signal Control (FTSC);
(2) Traffic Actuated Signal Control (TASC);
(3) Adaptive Traffic Signal Control (ATSC).

FTSC controllers operate using a predetermined signal program that is designed according to historical data. It allows for cost-effective intersection control that performs well in low- to medium-volume intersections that have repeating traffic patterns. In high-volume intersections, the FTSC controllers are less effective and can even cause congestion. Especially if the traffic flow has significant fluctuations.

TASC controllers use sensors to detect approaching vehicles and adjust the signal program to allow them to cross the intersection. The adjustment is preprogrammed into the controller and is activated only upon approaching vehicle detection. This allows the TASC controller to perform well in low- to medium-volume intersections. In high-volume intersections, vehicle actuation is almost constant, resulting in a performance similar to that of FTSC controllers [15].

ATSC controllers present the highest level of TSC with signal programs that are adjustable according to the current traffic conditions which are obtained in real-time by the use of multiple sensors placed on key locations in the road or intersection infrastructure. ATSC controllers perform well in high-volume intersections with fluctuating traffic flow as the signal program can be dynamically adjusted according to the desired operational objective. Multiple commercial ATSC systems are used today with the most notable being: SCOOT [16], SCATS [17], UTOPIA [8], and ImFlow [9].

2.3. Influence of connected autonomous vehicles

Recent advancements in traffic control have been significantly influenced by the development of Vehicular Ad Hoc Networks (VANETs), ITS, and the Internet of Vehicles (IoV). These technologies facilitate improved communication between vehicles and infrastructure, enabling more efficient traffic management and adaptive control strategies. VANETs allow for vehicle-to-vehicle (V2V) and V2I communication, providing real-time traffic data that can be utilized to enhance the efficiency of learning-based adaptive traffic controllers [18]. Studies have shown that integrating VANET-based data collection with Reinforcement Learning (RL) models can significantly improve the responsiveness of ATSC systems [19, 20]. Moreover, the predictive capabilities of machine learning can be enhanced by leveraging the high-frequency data exchange characteristic of VANETs, leading to better congestion management and accident prevention [21].

The evolution of IoV extends the capabilities of ITS and VANETs by incorporating cloud computing, edge computing, and artificial intelligence to provide a highly connected vehicular ecosystem. IoV-based traffic control strategies use extensive real-time traffic data from connected vehicles to predict congestion patterns and optimize traffic signals accordingly. Studies indicate that leveraging IoV for adaptive traffic control can lead to up to a 20% reduction in average travel time and a 15% decrease in fuel consumption [22]. Furthermore, deep RL models trained on IoV data have demonstrated superior performance in handling highly dynamic urban traffic conditions [23].

Following the development of Autonomous Vehicles (AVs) and Connected Autonomous Vehicles (CAVs), a lot of studies managed to derive fundamental diagrams based on AVs and CAVs car-following models that capture specific characteristics and communication capabilities of this new kind of vehicle [24]. Initially, AVs and CAVs will maintain longer distances between each other compared to traditional human-driven cars, as they exhibit more cautious behaviour [20]. This conservative approach will lead to a reduction in road capacity and an overall decrease in traffic speed. However, as AVs and CAVs become more prevalent and adopt cooperative driving techniques like platooning, they will enhance mobility, safety, and environmental benefits by decreasing the distances between each other.

Unlike human drivers, who often display stochastic behaviour and are more hesitant towards risk, AVs and CAVS operate with deterministic driving behaviour, leading to predictable driving dynamics. Consequently, the parameters and constants used in current car-following models, such as the Wiedemann psycho-physical car-following model from 1974 or 1999 [25], will require revision to accommodate the unique characteristics of autonomous vehicles. Eventually, when AVs and CAVs become dominant, they will be able to achieve smaller time headway. Thus, the influence of those vehicles in mixed traffic scenarios on a fundamental traffic diagram needs to be analyzed.

Several eminent studies analyze AVs, and CAVs' influence on the Fundamental Traffic Diagram using none of the traffic control algorithms, and they are displayed in Table 1. In study [19], authors conducted simulations of how AVs influence traffic through various scenarios by using a network of Macroscopic Fundamental Diagrams (MFDs) in mixed traffic environments containing Human Driven Vehicles (HDVs) and AVs. Car following models for modelling behaviour for different automation levels of AVs were calibrated using OpenACC and Waymo Open datasets, which may not be universal for AVs in general. Following on that note, the authors of [19] concluded that AVs positively influence network capacity but behave too conservatively in the aspect of maintaining a larger space between vehicles, which influences negatively on critical accumulation. Thus, the study showed that AVs with different penetration rates resulted in capacity gains of up to 19.0% and critical accumulation decreases of up to 9.0%. Thus, the impact on the operational road capacity will be more significant with higher AVs penetration rates. AVs also increase the road network flow, but when their accumulation exceeds the critical accumulation and the traffic flow goes from an unsaturated to an oversaturated state, the AVs cause a rapid drop in the traffic flow and average speed.

A study conducted in [3] assessed the influence of AVs and CAVs on a network of national roads, existing motorways, and urban networks in the city centre of Dublin. According to the Society of Automotive Engineers (SAE) J3016 standard AVs were categorized as Level 2 automation, while CAVs equipped with Cooperative Adaptive Cruise Control (CACC) were categorized as Level 4 automation. The research evaluated a range of scenarios which included different penetration rates (0%–70%) and various levels of SAE defined automation. The results showed that CAVs experienced gradual safety and efficiency enhancements, and acceptable and feasible outcomes were achieved when penetration rates were approximately from 20% to 40%. The motorway situation demonstrated the highest impact of CAVs. At lower penetration rates, certain areas of the motorway network experienced increased traffic congestion and conflict situations.

Various traffic parameters such as the relation of flow and density, Time-to-Collision (TTC), distributions of acceleration rate, and distributions of speed variation were investigated under various CAVs penetration rates in [27]. The overall count of incidents in the heterogeneous traffic flow reduced with varying levels of CAV penetration. An increase in the traffic flow was observed to be approximately 2000 veh/h for a desired time headway of 0.5 s and close to 500 veh/h for the 1.1 s value. The acceleration and speed of the mixed traffic flow were found to improve as the penetration rates of CAVs increased. Furthermore, lane capacity was also studied for different penetration rates of AVs and CAVs [28]. Lane capacity was observed to increase by 8.6% with 100% AV penetration and by 188.2% with 100% CAV penetration rate. In the case of mixed traffic flow consisting of CAVs and HDVs, when the CAV penetration rate changed from 0% to 100%, lane capacity was found to increase linearly from 2046 veh/h/lane to 6450 veh/h/lane. On the other hand, the AVs impact on the fundamental diagram of mixed traffic flow analyzed in [29] found that an increase in AV penetration rates led to an increase in the network's capacity and the critical density (ρ_c) value on a single road. The ρ_c value increased by almost 48% as the AV penetration rate increased from only HDVs to 100% AVs in a mixed traffic flow. Furthermore, how the fundamental diagram of a single-lane road is influenced by CAVs was analyzed using the Cellular Automata (CA) model

Table 1. Impact analysis of AVs and CAVs on macroscopic traffic parameters [26].

Paper	Year	Penetration rate	Measured impact
[19]	2023	AVs from 0% to 100%	Increased network flow and capacity, decreased critical accumulation
[3]	2020	AV/CAVs from 0% to 70%	Conflicts and congestion improvement
[27]	2019	CAVs from 0% to 100%	Increased flow, reduced acceleration, and speed oscillations
[28]	2018	AV/CAVs from 0% to 100%	Improved capacity
[29]	2018	AVs from 0% to 100%	ρ_c value increased for 48%
[30]	2017	CAVs from 0% to 70%	ρ_c value increased for 60%, flow increased for 71%
[31]	2017	AVs from 0% to 100%	Free-flow speed increased for 32%, flow under ρ_c increased for 29%
[32]	2016	AV/CAVs from 0% to 100%	Enhanced throughput
[33]	2016	100% AVs	Flow increased 43.6%

in [30]. Cellular Automata (CA) was employed to segment the road into discrete cells, each capable of either containing or not containing a vehicle. The findings indicate that with a 70% penetration of Connected and Autonomous Vehicles (CAVs), the critical density value (ρ_c) experienced an increase of approximately 37%, and concurrently, the capacity at the critical density value was substantially improved by around 42%. The results were analyzed to observe the effect of AV penetration rates on the fundamental diagram in [31]. It was found that an increase in AV penetration rates shifted the speed-density curve to the right, leading to a higher ρ_c value and increased traffic flow. The free-flow speed increased by approximately 34% with 100% AV penetration rate, while the increase in capacity under ρ_c was about 30%.

In [32], the impact of Connected Vehicles (CVs) and AVs on traffic flow and density was analyzed under different penetration rates and three scenarios. The throughput showed an increase with higher penetration rates of both CV and AV, with no breakdown or scatter observed in the flow-density relationship at elevated penetration rates. The influence of AVs on throughput and scatter within the flow-density relationship mirrored that of the initial scenario, indicating a reduced scatter at 50% and 70% AV penetration rates. The impact of AVs and CVs on throughput and scatter within the flow-density relationship was examined in the third scenario. It was observed that the scatter in the flow-density relationship tended to increase when the number of CVs exceeded that of AVs, except in cases with high CV penetration rates. A study conducted in [33] analyzed the effect of AVs on fundamental traffic parameters such as traffic flow, density, and speed. The research revealed that under conditions where the penetration rate of AVs reached 100% and the headway time gap parameter was set to 0.5 seconds, the standard capacity value for a single lane, initially at 2200 veh/h, could potentially increase traffic capacity to approximately 3900 veh/h. The study authors highlighted that this brief following distance is already observed in up to 20% of cases, depending on traffic conditions.

2.4. Influence of electric vehicles

The impact of Electric Vehicles (EVs) on traffic flow plays an important role in future traffic flows with the tendency of an increased number of EVs, in the near future. Recent papers on EVs impact on traffic have mixed findings. In [34], the evaluation of real traffic flows and existing charging infrastructure with EV uptake impacts on electric energy infrastructure and traffic congestion was analyzed. The findings indicate that the existing charging infrastructure could not manage to withhold the slightest rise in the number of EVs. Furthermore, TT and waiting times for larger EV penetration rates at each station level were greatly increased. Furthermore, positive impacts of EVs in mixed traffic flows were observed in [35]. In mixed traffic flow scenarios regarding adding EVs, increased density resulted in reduced fuel consumption, CO, and NO_2, and the EVs electricity consumption. With the increase of the EV penetration rate, the fuel consumption, CO, and NO_2 decrease. The impact of EVs on total energy consumption, fuel consumption, and exhaust gas emissions was analyzed in [36]. RL based optimization criteria were set to reduce total energy consumption. The results showed that the proposed Q-learning VSL algorithm managed to reduce all measured parameters in a congested motorway at all analyzed EV penetration rates.

Nevertheless, negative effects of increasing EV penetration rate were observed in [2]. The findings indicate that the coexistence of EVs and classic gasoline vehicles in mixed traffic flow scenarios may increase waiting time and congestion occurrence during analyzed morning rush hour. Furthermore, EVs were used for the urban distribution of goods, and the corresponding environmental impacts were measured in the study [37]. The selection of delivery vehicle routes in a case study of the city of Bogotá, Colombia showcased that the route with the minimum economic cost is not necessarily also an environmentally friendly route with minimal emissions. The authors also concluded that the CO_2 emissions vary significantly, dependent on the vehicle type (traditional internal combustion engine or EV).

3. Traffic related evaluation criteria

The operational effectiveness of urban networks has a significant impact on urban road transport sustainability in terms of efficiency, accident rate, delay, and emissions. Depending on the purpose and scope of the traffic operation analysis, as well as the traffic alternatives and/or traffic signal operation of traffic control systems, various numerical outputs and traffic performance metrics of effectiveness can be used for analysis.

The basic set of Measures of Effectiveness (MoEs) used to quantify the success of traffic operations goals or traffic control systems goals are the following:

- TT;
- Speed;
- Delay;
- Queues;
- Number of Stops;
- Density;
- Travel Time variance;
- LoS;
- Volume/Capacity (V/C) ratio.

TT, speed, and delay are closely related measures of the amount of time that people and goods must spend to complete their trips from their origin to their destination. Queues indicate congestion on the network or road segments where capacity inefficiencies and/or safety problems may exist. Number of stops, delay, and speed play crucial roles, as inputs, in traffic signal timing optimization algorithms, as well as fuel consumption and air pollutant emission computations. Density is an essential parameter to compute the LoS for uninterrupted flow facilities. TT variance refers to the variability or dispersion of TT experienced by vehicles or travellers along a given route or corridor. It provides insights into the consistency and predictability of TT, reflecting the reliability of the transportation system.

The Highway Capacity Manuel (HCM) is a widely accepted guidebook used to evaluate and predict the operational and capacity characteristics of various highway facilities [38]. In its current form, it serves as a fundamental reference for concepts, performance measures, and analysis techniques for evaluating the multimodal operation of streets, highways, freeways, and off-street pathways [38]. The LoS is a key concept in the HCM, which categorizes the quality of traffic flow on a scale from A to F. The LoS grades represent different levels of congestion and delays experienced by drivers. Generally, a higher LoS grade (e.g. A or B) indicates good traffic flow with minimal delays, while a lower LoS grade (e.g. E or F) represents congested conditions with significant delays.

The V/C ratio is a metric that compares the traffic volume on a roadway or facility to its capacity. Volume refers to the actual number of vehicles using the facility within a given time period, while capacity represents the maximum number of vehicles that the facility can accommodate without excessive delays. The V/C ratio is calculated by dividing the volume by the capacity. A V/C ratio less than 1 indicates that the facility is operating below its capacity, while a ratio greater than 1 suggests that the facility is experiencing congestion and potentially operating above its capacity.

Table 2. Urban motorway operational objectives.

Operational objective	Candidate MoEs
Increased LoS	TT, Total Time Spent (TTS), speed traffic density, traffic flow, Average travel speed
Harmonized flow	Average Travel Speed, Speed Ratio, Coefficient of Variation of Speed
Mitigation of bottlenecks	TT, TTS, bottleneck outflow, Average travel speed
Managing on-ramp queues	Total delay time, TTS, Number of queued vehicles, Merging area density

Both the HCM LoS and the V/C ratio provide valuable information to decision-makers regarding the performance of a transportation facility. These indicators help assess the level of congestion, delays, and overall efficiency, aiding in making informed decisions about potential improvements, traffic control strategies, and capacity enhancements.

3.1. Urban motorways

As mentioned, urban motorways are designed to serve a high traffic demand compared to urban roads. They facilitate a large number of on- and off-ramps and are designed to operate at a high capacity. Even though they are designed in that way, the traffic demand often surpasses the operational capacity of the urban motorway resulting in reduced LoS and congestion.

One way to alleviate the occurrence and the effects of congestion and reduced LoS is by applying appropriate traffic control methods to increase the LoS, reduce TT, harmonize mainstream traffic speeds, and reduce on-ramp queues [39]. This can be achieved by employing the above mentioned control methods such as ramp metering and VSL.

Evaluating those control methods is essential for analyzing the performance of the control system that aims to reduce congestion, TT, ramp queues, and harmonize mainstream traffic flow speeds. Quantification of the impacts of control methods is commonly done by running a set of simulations on a real-world data based simulation model and applying the control method on the controlled urban motorway segment. The evaluation of the proposed control method is done by measuring a number of MoEs as indicators of the influence of the control method on an operational objective as mentioned above. Table 2 summarizes the aimed objectives and candidate MoEs for an urban motorway [40].

3.2. Signalised intersections

One of the primary goals of traffic signal operations at intersections is to reduce congestion and keep traffic

Table 3. Candidate MoEs for intersection performance evaluation.

Operational objective	Candidate MoEs
Smooth Traffic Flow	Route travel time, Link travel time, delay, speed, Green bandwidth on route, Percent arrivals on green, Platoon ratio, Number of stops per mile or kilometer
Access equity	Phase green to occupancy ratio, V/C ratio by movement, Queue length by movement
Manage queues	Queue length by movement, Number of stops per mile or kilometer, Time to process equivalent volume
Throughput	Time to process equivalent volume, Traffic volume

flowing smoothly. This can be achieved by optimizing signal timings, coordinating signals along corridors, and implementing strategies such as traffic signal priority (preemptive TSC strategy) for certain movements or transit vehicles. Traffic signal operations should consider long-term variability and adapt signal timings in real-time as needed to accommodate changing traffic demands and patterns. This can be achieved by using the above mentioned ATSC approach.

ATSC systems perform changes in traffic signal operations in real-time and, therefore, they are often so-called "live" systems. The impact of the signal operations of ATSC systems is often underestimated or overlooked and due to that it is not possible to know, with certainty, the efficiency of the applied control strategies. In the absence of information for the performance of applied ATSC, the quality of traffic signal operations cannot be determined and the functionality of the control strategies cannot be validated.

To evaluate the impact of ATSC systems effectively, researchers typically employ a combination of field data collection, simulation models, and statistical analysis. This multifaceted approach allows for a comprehensive assessment of the benefits and challenges associated with implementing ATSC systems in different contexts. ATSC systems often operate at a network level, coordinating signals across multiple intersections. To quantify the impact of ATSC on traffic conditions expended set of MoEs should be determined, and the defined measures should reflect real-time "responses" of adaptive control to the traffic process. Thus, Table 3 summarizes candidate MoEs for each operational objective regarding signalized intersections [41, 42].

4. Ecological criteria

Along with future EU transport policies with respect to sustainable development and clean urban environments, the recommendations for the transport professionals/sector are in the view of a transport system design that will minimize the negative environmental impact of heavy goods vehicles and enhance the quality of life in urban environments. In other words, the driving idea is to keep the communities' activity in a safe manner, to enable them to live in environmentally friendly surroundings, to maintain their mobility, and to provide them to be well served. Thus, ecological criteria in transport analysis refer to evaluating the environmental impact and sustainability of transportation systems and practices. Considering ecological criteria is essential for assessing the environmental consequences of transport activities and making informed decisions to minimize their negative effects. The reference levels for pollutants are commonly used as guidelines for air quality monitoring and management. Thus, key pollutant parameters commonly used in transport analysis are depicted in Table 4.

Table 4. Reference levels of pollutants [43].

Pollutant	Reference value
PM_{10}	$> 50\ (\mu g/m^3)$
CO_2	250–350 ppm
CO	4 ppm
NO_2	$> 200\ (\mu g/m^3)$

In continuation, more details of the pollutants given in Table 4 are explained. They are the most important pollutants when assessing air quality near roads in urban environments.

- PM_{10}: The reference level for PM_{10} is typically set at more than 50 micrograms per cubic meter $\mu g/m^3$ as an annual average. This level indicates the threshold at which elevated levels of PM_{10} may pose health risks, particularly to vulnerable populations such as children, the elderly, and individuals with respiratory conditions;
- CO_2: Reference levels for CO_2 are expressed in parts per million (ppm). The range 250–350 ppm, generally represents the natural background concentration of CO_2 in the atmosphere. However, it is important to note that CO_2 levels have been steadily increasing due to human activities, particularly burning of fossil fuels. Efforts are being made to mitigate CO_2 emissions and stabilize atmospheric concentrations to prevent further impacts of climate change.
- CO: The reference level for CO is typically set at greater than 4 ppm as an 8-hour average. Elevated levels of CO can be harmful to human health, as they reduce the oxygen-carrying capacity of blood. CO is primarily emitted from the incomplete combustion of fossil fuels in vehicles and industrial processes. Measures such as improved vehicle emissions standards and better combustion technologies help reduce CO emissions.
- NO_2: The reference level for NO_2 is set at greater than 200 micrograms per cubic meter $\mu g/m^3$ as a daily average, or greater than 40 $\mu g/m^3$ on a yearly average. The effect of NO_2 on human health is significant and prolonged exposure can have adverse

effects. The primary sources of NO_2 in urban environments are combustion processes in vehicles and industrial activities.

Monitoring pollutant levels against these reference levels helps identify areas of concern and guides transport policy and mitigation efforts to reduce pollution and maintain acceptable air quality standards. CO_2, CO, PM_{10} and NO_2 are pollutants that are directly related to the combustion process in internal combustion engines, which are predominant in road traffic. Other environmental parameters such as ozone (O_3) are important, but may not be as tightly connected to specific traffic emissions. For example, O_3 is a secondary pollutant that forms when NO_x and volatile organic compounds react in sunlight, but the formation of ozone is influenced by multiple environmental variables, not just traffic. The ecological advantages of focussing on PM_{10}, CO_2, CO and NO_2 lie in their direct and measurable impacts on quality of life in urban areas. These pollutants are closely associated with traffic emissions, making them the most important indicators to assess the environmental sustainability of urban transport systems.

5. Evaluation of learning-based controllers

Currently, most of the machine learning methodologies used in traffic control are based on the RL approach. It is most convenient for control purposes of highly stochastic systems such as traffic since it uses a trial-and-error approach in exploring possible state-action space. This state-action space is explored using the Bellman equation shown below with Equation 1 [44]. It is a recursive formula that shows how the value of being in a certain state depends on the rewards received and the value which will emerge in future states.

$$v(s) = \max_a \left[R(s,a) + \gamma \sum_{s'} P(s' \mid s,a) v(s') \right] \quad (1)$$

Thus, the equation breaks down the problems into smaller ones. This enables computing the best way to make decisions when outcomes depend on a series of actions. A critical part of all RL approaches is the design of the reward system. Thus, it is necessary to use adequate traffic evaluation criteria related to the final goal of the traffic control method and the configuration of the controlled traffic system. Additionally, the state action space can explode, with respect to its dimensionality, due to the prominent stochastic nature of traffic flows and interactions between them. RL approaches such as Q-learning, which computes quality values for each state-action pair, can be computationally infeasible in such cases. Thus, it is necessary to replace those Q-tables with Artificial Neural Networks which conduct the approximation of the Q-function encoded in those Q-tables by learning the patterns from traffic scenarios presented in simulation frameworks. This type of RL is usually known as the Deep Reinforcement Learning (DRL) technique since it does not require the assessment of every possible state action pair for favourable control results. Every traffic control unit with one of the implemented RL approaches can be considered an agent that interacts with the traffic system by repeating the cycle of sensing traffic data and providing action based on them.

Currently, most advanced RL models applied in traffic control are related to the Actor-Critic architecture. The actor selects actions using the current traffic system state and learns the control policy (continuous function for mapping states with actions) based on values computed by the Temporal Difference (TD) function. The Critic computes a value function which estimates the expected cumulative reward based on the current traffic state affected by Actor actions, and the reward which are inputs for the TD function. Additionally, this approach improves the data sampling efficiency due to the usage of a fixed replay memory buffer. It is possible to divide Actor-Critic models into two broader categories regarding their implementation in traffic control systems. One is related to learning-deterministic policies which directly map states to actions. Representatives of this model category are: Deep Deterministic Policy Gradient (DDPG) and Twin-Delayed Deep Deterministic Policy Gradient (TD3). The second group of models is related to stochastic learning policies. They are based on learning the probability distribution for mapping states with actions. The most prominent representatives of this model group are Advantage Actor-Critic (A2C), and the Proximal Policy Optimization (PPO) [45]. Additionally, it is possible to have a multi-agent system in which each agent has a different role in the traffic control process. In addition, they can exchange data with each other to carry out cooperative control actions. Those actions within a multi-agent RL framework are governed by a joint reward system defined by specific criteria for improving traffic safety and efficiency which depend on the traffic network type.

Traffic networks are complex systems due to the stochastic nature of interactions between traffic flows on them. This behaviour is even more prominent in the case of complex traffic networks, such as dense urban traffic networks and multi-lane motorways with numerous nodes that contain a lot of on- and off-ramps. Such traffic networks must be modelled and simulated based on the measured or synthetic traffic demand. In the case of microscopic traffic simulation environments, it is necessary to run several simulations under different seeds to compute baseline traffic scenarios without any type of traffic control. Thus, any type of traffic controller should provide improved performance over such no control baseline scenario. In addition, current reactive and static open-loop traffic controllers should be evaluated within simulations. The average results of their performance provide an additional baseline scenario that presents the conventional control methodology. Furthermore, if those baseline scenarios induce improved performance compared to the no-control traffic scenario, this represents the proof that current traffic scenarios can be improved. The usual performance metrics for all traffic systems are average speed, TT, TTS, delay, etc. They are all computed discretized during the simulation run and cumulative for the entire simulation. The cumulative performance of the simulation run is important for all learning-based controllers since they should improve their control performance during the learning period. The learning period contains numerous simulations on which the learning-based controller should gradually improve its performance compared to the basic traffic scenarios [21]. There can be a large amount of variability in each analyzed learning-based controller on different simulation runs. Thus, to provide a more comprehensive comparison of the controllers analyzed, the same controller must be run multiple times on these simulations [46]. In the case of RL-based traffic controllers, there are three statistical evaluation approaches for the assessment of the achieved cumulative reward function curve:

- The asymptotic slope provides insight into the control policy efficiency after the training of a controller has converged or ended;
- The minimum of the curve shows how much simulations with cumulative rewards provide the worst results compared to base-line scenarios before the improvement;
- The zero crossing shows how many simulations are needed until the controller has recouped its cost of learning.

The last two evaluation approaches are used when both positive and negative rewards are available. It is necessary to have a balance between them in order to have a positive evaluation of their control efficiency.

5.1. Evaluation under different traffic demand scenarios

The learned control policy is heavily dependent on the presented state-space or, in this case, the traffic demand scenarios based on which the simulation environment is tuned. In order to learn a robust and more consistent control policy, it is necessary to use several distinctive traffic demand scenarios in the simulation environment. Such traffic demand scenarios can be created based on real-world data (measured during weekends and working days, peak hours, and in time between them, etc.) and synthetic data or modifiers which can be applied to both previously mentioned sources of traffic demand data. Thus, learning-based traffic controllers can be evaluated separately for each traffic demand scenario. This enables a more comprehensive approach to the evaluation of learning-based traffic controllers. Additionally, this evaluation approach can be used to improve the learning performance of those controllers by adding more traffic demand scenarios in the learning loop under which the learning controller underperforms.

Thus, in this case, the same learning-based traffic controller is learned upon the mixture of all used traffic demand scenarios. Furthermore, the learning-based traffic controller can be learned exclusively at one of the user traffic demand scenarios. Thus, each learned traffic controller can be evaluated as a specialist in tackling a particular traffic demand profile. Most studies on learning-based traffic controllers use three distinct traffic demand profiles which are based on low, medium, and high traffic load [23]. One must perform an additional evaluation in the case of low and high traffic demand with respect to the performance of conventional traffic controllers on them. Hence, those scenarios can be too intense to be tackled by any controller, e.g. a very low number of vehicles where each control action disrupts the free flow state or generates an unrealistic too-high number of vehicles which quickly induces a state of permanent congestion.

5.2. Impact of traffic network scalability on evaluation

The analyzed traffic network itself can be very complex with respect to the number of intersections in the urban traffic network, or it can be in the form of a very long motorway with a lot of nodes with numerous on- and off-ramps. It is necessary to provide an initial evaluation of the learning based controller at one control unit in the analyzed traffic system, e.g. one intersection or one on-ramp, which is in line with the development workflow of learning based controllers. In the case of a large urban traffic network, the cumulative and average values attained by control over all intersections are mandatory for evaluation within each analyzed traffic demand scenario. This represents the overall impact of learning-based traffic controllers on the entire traffic network. Depending on the number of controlled intersections, it is possible to evaluate them individually or group them into districts in the case of city-wide traffic networks. Grouping intersections for evaluation should be avoided since it reduces the resolution of the analysis. Especially if the learned control policy of each intersection is learned based on the local state. Additionally, cooperative learning controllers require periodic evaluations of each intersection's performance. Thus, underperforming intersections cannot be isolated accurately. It is also necessary to provide an evaluation that highlights the worst- and best-performing intersections. Additionally, it is possible to evaluate the cumulative performance of the entire urban traffic network, which is not directly related to intersections but to all traffic network segments such as average TT, delay, speed, etc. [22]. This enables the evaluation of the synergic effect of locally learned intersection controllers or the assessment of the global performance of cooperative learning controllers.

Larger traffic networks reduce learning convergence since they induce a larger traffic state space. The same approach can be used for motorways. In this type of traffic network, the grouping for the purpose of evaluation must also be avoided for one dense motorway node with numerous on- and off-ramps. Thus, the individual evaluation of on-ramps is needed. Additionally, the motorway can be divided into segments that involve several or one on-ramp depending on the size of the entire motorway network. This enables the evaluation of on-ramp control at their adjacent section of motorway mainstream flow. The VSL learning-based controllers are evaluated in their respective speed limit zones and at the level of the entire motorway network regardless of its complexity.

5.3. Evaluation of computational efficiency

The models used for learning-based traffic controllers can be complex and, therefore, computationally demanding. Different models can be evaluated by comparing learning loss or reward with overall performance in the same time interval. The best ratio between those two parameters should be taken as the optimal control solution. Additionally, different dimensionality reduction approaches should be evaluated in terms of their impacts on the overall performance of the learning based controller in terms of computational efficiency. This is especially important in the case of RL based traffic controllers. All models used in learning-based traffic controllers should be compared in terms of the duration of one learning iteration and the entire learning process. In this evaluation, the same server specifications applied for controller learning must be used. The described proposed conceptual approach for the evaluation of learning-based traffic controllers can be seen in Figure 1.

6. Discussion and criteria proposal

In the case of an urban motorway, the most prominent criterion for the evaluation of the efficiency of the controller is the total TTS after each evaluation cycle (one simulation run). This criterion metric is the most comprehensive, since it takes into account waiting time at the on-ramps as well as the throughput of the mainstream flow. Furthermore, the motorway networks are projected to sustain higher speeds of vehicles. Thus, reducing the values of TTS over the learning process denotes that vehicles are achieving higher speeds at mainstream flow while simultaneously the duration of queueing time at on-ramps is reduced. This is the case since all vehicles spend less time in the overall motorway network. It is possible to conclude that TTS should converge towards the smaller values over the learning process. The shorter TTS achieved by the evaluated controller induces lower fuel consumption, and therefore, implies a reduced impact on negative emissions. This is especially noticeable near the effectual bottleneck in the proximity of on-ramps where the slowdowns are most noticeable at motorways if the learned control policy is poor. The TTS generally can have a larger value if the total number of vehicles on-ramps is much larger than those on the main flow. Thus, large waiting queues at on-ramps can significantly increase the TTS.

Furthermore, TT can also be included as the criteria metric for the evaluation of learning based controllers that are dedicated to motorway control. This metric of criteria is especially useful for VSL controllers that control the speed of mainstream flow in its specific segments. Thus, TT can be easily computed for the major traffic flow in real-life cases, as well as in a simulation environment. TT as the main criteria metric in the case of learning-based controllers for ramp metering can provide results that converge towards over-restricted on-ramp flows to improve the mainstream throughput. This criterion metric steers the learning process towards control policies which create a large on-ramp queue in the case of ramp metering application. Thus, in the case of ramp metering controllers, it is imperative to include more comprehensive metrics which include the behaviour of on-ramp queues such as delay, average on-ramp queue length, or additional travel times which are computed from the start of each on-ramp to the end of the controlled motorway section.

In the case, where a learning-based controller must achieve improved safety on motorways, the most prominent criterion for mainstream flow should be Time to Collision (TTC). It is defined as the time before a collision occurs between involved vehicles if their speeds and paths do not change. This criterion is important in mainstream flow, as it ensures that the learned control policy enables great progress between the mainstream vehicles. The large average headway between mainstream vehicles is critical for avoiding severe crashes since they give the driver more time to react to the sudden slowdowns that can occur at effectual bottlenecks.

In the case of urban intersection networks, the criteria are similar to urban motorways. The main criterion is the reduction in TT and/or TTS. When TTS is globally reduced, total vehicle emissions are also reduced, as there is usually a correlation between them. However, care should be taken to ensure access equity between

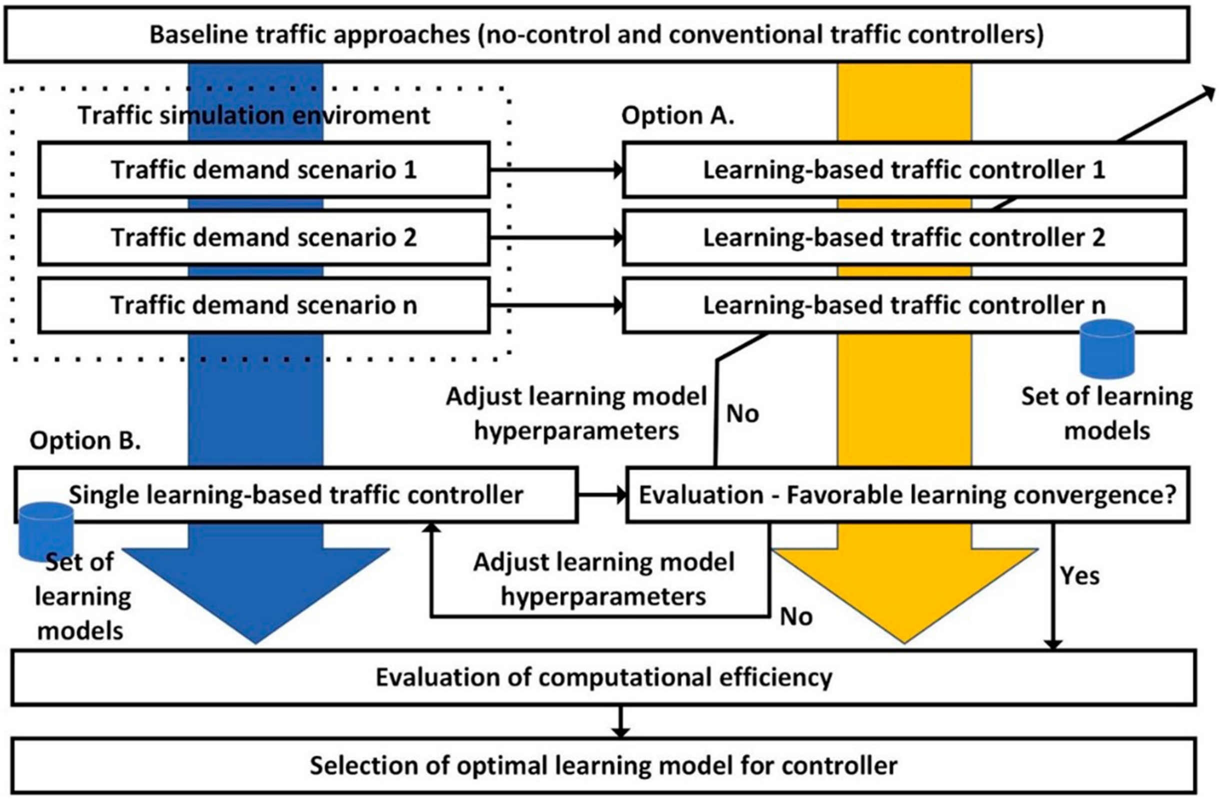

Figure 1. Conceptual approach for the evaluation of learning-based traffic controllers.

conflicting intersection approaches. This can negatively impact the global TTS, but can prevent long queues of idling vehicles on secondary intersection approaches. In addition, if environmental criteria are considered, preemption techniques at signalized intersections can ensure that heavy vehicles that generate large amounts of emissions do not stay idle for long. Another good indicator of the losses generated in intersection networks is vehicle delay, which can be used to calculate the LoS by HCM.

Despite their popularity and success, the new control approaches and strategies that are based on a variety of computational intelligence techniques are challenging open-ended problems for which learning and adaptation mechanisms need to be investigated and tested to deal with disturbances in an intelligent manner. Additionally, to demonstrate the efficiency of the different control strategies, we need to assess their performance under different traffic scenarios in real, or at least realistic, situations with competitive performances. Based on the analysis presented above (Sections 3 and 4), the following MoEs are proposed that address traffic efficiency and environmental criteria of signalized intersections:

- Traffic efficiency criteria: TTS, delay, HCM LoS, and the V/C ratio, due to their ability to provide valuable information to decision makers on the level of congestion and overall efficiency.
- Environmental criteria: for the impact assessment of the conventional traffic flow structure, the pollutants PM_{10}, CO_2, and CO should be analyzed. In mixed traffic flow scenarios where electric vehicles are added, the impact assessment should include the NO_2 pollutant.
- The proposed methodological evaluation framework is comprehensive and can be used as a roadmap for the implementation and testing of various ITS-based urban traffic management solutions.

Traffic and ecological parameters can be obtained from three most commonly used microscopic simulators, SUMO, VISSIM, and AIMSUN. SUMO simulator [47] uses the TraCI Python API [48] to obtain vehicle data in real time, or to parse output files such as tripinfo.xml and emissionoutput.xml for post-simulation analysis. VISSIM simulator [49] uses the COM interface [50] to interact with the simulation and extract vehicle data, such as speed, position, and potentially emissions data via external modules. AIMSUN simulator uses the AIMSUN API to obtain real-time vehicle data and analyze traffic flow and emission data, as well as post-process output files for further analysis [51]. Each of these simulators provides flexible tools for accessing both traffic and environmental data, and using their respective APIs or output files is key to getting detailed insights.

The proposed traffic and ecology related evaluation criteria and methodology for ensuring optimal learning models for the learning-based traffic controllers contribute to their wider inclusion into newly developed large-scale smart city management systems. In such systems, modules related to data gathering, processing, and archiving are the common base for all smart city services [6]. An important service is related to transportation, namely traffic control, including short-term (tactical) and long-term (strategical) interventions in the urban transport network. Thus, the evaluation of the transportation module with the criteria and methodology proposed in this paper alleviates the inclusion of newly developed learning-based traffic controllers in real-world systems. An important aspect is that before the deployment of the chosen traffic controller learning model in a real-world application, its suitability can be systematically evaluated and the best approach for a particular urban area can be selected between the evaluated ones. Thus, the goals for efficient and sustainable management of the urban transport network that rely more and more on additional criteria for the quality of life of the environment and citizens can be fulfilled.

7. Conclusion and future work

By applying artificial intelligence and machine learning approaches to traffic control, learning-based traffic controllers are created. By interacting with the traffic environment, such controllers can learn to control the traffic network optimally in real-time. However, a prior evaluation of learning-based traffic controllers is necessary to assess their effectiveness prior to integration into real-world traffic networks. The proposed approach to controller evaluation includes a comparison with traditional traffic controllers by comparing traffic and environmental MoEs under different traffic demands and traffic network scales. In addition to traffic related MoEs, the computational efficiency should also be evaluated with respect to learning parameters such as training loss, obtained reward, and overall performance which can help identify scenarios where the controller is performing sub-optimally. In general, the proposed evaluation framework provides an approach to assess the performance of learning-based traffic controllers, which ultimately leads to more efficient, safe, and sustainable traffic networks.

The benefits of this research include improved traffic management, adaptability and real-time decision making, comprehensive evaluation, and real-world applicability. By developing new evaluation criteria for learning-based controllers, this research shows the know-how to more effective traffic management strategies, reducing congestion and optimizing traffic flow on urban motorways and signalized intersections. The proposed criteria for both traffic efficiency and environmental impact offer a more holistic view of controller performance, addressing trade-offs that are often overlooked in existing evaluation methods. By considering the challenges of real-time processing and adaptability to new traffic scenarios, this research makes machine learning-based traffic control systems more viable for integration into real-world urban traffic environments. Although the proposed evaluation metrics are an advancement compared to current metrics, they may not cover all possible cases or traffic scenarios that could arise, limiting their applicability in some unique or extreme traffic conditions.

Potential future directions for learning-based traffic controller evaluation include conducting field tests and real-world deployment to gather more insight into controller performance in real traffic scenarios. Such scenarios could also include CVs and AVs for both real-time data collection and evaluation utilizing their communication capabilities. Since multiple parameters are used for the evaluation, the learning-based traffic controller could also be modelled using a multiobjective optimization problem, which can then be leveraged between multiple conflicting MoEs. Finally, human perception of proposed controllers can be analyzed to ensure that learning-based controllers remain user-friendly and safe for interaction with human and artificial drivers.

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