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Efficient Intersection Management Based on an Adaptive Fuzzy-Logic Traffic Signal

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Abstract: Traffic signals may generate bottlenecks due to an unfair timing balance. Facing this problem, adaptive traffic signal controllers have been proposed to compute the phase durations according to conditions monitored from on-road sensors. However, high hardware requirements, as well as complex setups, make the majority of these approaches infeasible for most cities. This paper proposes an adaptive traffic signal fuzzy-logic controller which uses the flow rate, retrieved from simple traffic counters, as a unique input requirement. The controller dynamically computes the cycle duration according to the arrival flow rates, executing a fuzzy inference system guided by the reasoning: the higher the traffic flow, the longer the cycle length. The computed cycle is split into different phases proportionally to the arrival flow rates according to Webster's method for signalization. Consequently, the controller only requires determining minimum/maximum flow rates and cycle lengths to establish if–then mappings, allowing the reduction of technical requirements and computational overhead. The controller was tested through a microsimulation model of a real isolated intersection, which was calibrated with data collected from a six-month traffic study. Results revealed that the proposed controller with fewer input requirements and lower computational costs has a competitive performance compared to the best and most used approaches, being a feasible solution for many cities.

Keywords: adaptive traffic signal; fuzzy logic; Webster method; microsimulation

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1. Introduction

Traffic congestion is one of the major problems of modern cities, causing time loss, pollution, and excessive fuel consumption [1,2]. This problem is encouraged by the steady population growth of vehicles and the lack of efficiency in traffic management [3]. Traffic signals are intended to regulate traffic at road intersections, and their efficiency depends on the ability to balance the alternation of vehicle flows without worsening waiting times, queues, and density [4,5]. However, due to inadequate signal timings, sometimes, traffic signals cause intersections to become traffic bottlenecks on the road network.

Most traffic signals operate in either pre-timed or traffic-actuated modes [6,7]. While pre-timed control is based on fixed signal timings, traffic-actuated control uses preset reductions and extensions to regulate the phases according to vehicle detection [8]. Unfortunately, due to the high uncertainty of the traffic arrivals, it is difficult to establish long-term optimum values for phases or extensions [9]. Moreover, due to their pre-set behavior, these schemes are unable to react to atypical events that disturb traffic [10]. As a consequence, such controllers are susceptible to cause long queues and excessive stops due to overestimated or underestimated timings.

Since traffic is frequently fluctuating, proposals for adaptive traffic controllers have chosen to address the signal timing issue as an adaptation problem instead of an optimization problem [11]. Adaptive controllers solve the deficiencies of pre-timed and actuated controllers by continuously sensing different attributes of the traffic stream and adjusting the signal phases accordingly [12]. For this purpose, these approaches incorporate self-adjusting mechanisms to modify their internal logic configuration.

Artificial intelligence methods have gained popularity to design adaptive controllers capable of addressing unpredictable traffic conditions. Numerous approaches have been proposed based on reinforcement learning (RL) [13–15], neural networks (NN) [16–18], deep reinforcement learning (DRL) [19–22], and fuzzy logic (FL) [12,23–34]. Due to their accuracy, computational requirements, as well as the supported amounts of states and actions, NN, DRL, and FL methods have demonstrated the best performances [35–37]. In practice, however, the main drawback of NN and DRL approaches is their complex designs and setup, whose understanding is difficult for operators. Conversely, fuzzy logic approaches are more intelligible, since they imitate human perception by using mappings between systems' inputs and outputs through verbal propositions and qualifying the scalar magnitudes with vague terms such as low, great, high, few, etc. [38]. In addition, such particular characteristics of fuzzy logic facilitate the inclusion of experts' knowledge in the controller design [35].

Typical FL-based controllers consider queue lengths, waiting time, traffic density, or flow rates as inputs and the green time for each phase as output. Nevertheless, in real traffic scenarios, flow rates can be easily measured with commercial vehicle counters, while the estimation of queue length, waiting time, or traffic density requires additional and sophisticated requirements [26,39–41], which are not suitable for many cities. Furthermore, it is well known that arbitrary extensions of green phase duration may cause longer cycles, increasing the delay in the system.

In this paper, an adaptive traffic signal FL controller for isolated intersections is proposed. The controller operates by using the arrival flow rate as the unique input to compute the proper cycle length. The computed cycle is proportionally split into the corresponding phases based on the effective green time estimation derived from Webster's method for signalization [42]. From this approach, the controller is capable of adjusting the signalization long enough to clear the queues formed during red intervals, improving the operational performance of the intersection by reducing waiting times, queue lengths, and densities. The proposed controller is based on a type-1 fuzzy logic, which only demands operators to know the minimum and maximum expected values for arrival flows and cycle lengths to establish if–then mappings. In addition, the algorithmic proposal is based on sequential instructions, such as basic arithmetic and if–then statements. Therefore, the execution time is constant, since it directly depends on the number of fuzzy sets and incoming traffic streams, whose size remains immutable during the execution. This last means the proposal could be implemented over simple microcontrollers becoming an affordable solution for many cities.

The controller performance was evaluated using a microsimulation model of a real-world intersection. The simulation scenario was calibrated on data collected from a six-month traffic survey. Using the simulated intersection as a test bench, the proposed controller (Proposed Adaptive FL) was compared against five approaches: (a) the existing pre-timed controller (Pre-Timed), (b) a time-gap-based actuated controller (Time-Gap), (c) a time-delay-based actuated controller (Time-Delay) [43,44], (d) a fuzzy system for green extension (FL Green-Extension), and (e) an adaptive FL-based method with modified Webster's formula (FL Phase-Adjustment) [34]. Simulation results show that the performance of the proposed controller is competitive with the most sophisticated and effective approaches, even without needing complex or expensive requirements for deployment and setup.

The remainder of the document is organized as follows. Section 2 summarizes the state-of-the-art on traffic signal controllers. Section 3 presents some background definitions. In Section 4, the proposed adaptive FL controller is described. In Section 5, the proposed controller is evaluated, and the findings are discussed. Finally, the main conclusions are stated in Section 6.

2. Related Work

Traffic signal controllers can be categorized as pre-timed, actuated, or adaptive, depending on how the allocation of the signal times is performed. The following sections provide a brief overview of the three types of controllers, highlighting the most relevant approaches.

2.1. Pre-Timed Signaling

Pre-timed control is the most basic type of control that can be implemented in a traffic signal controller. In pre-timed control, the cycle length, the duration of the phases, as well as the duration of each interval within each phase, are fixed values. The main drawback of pre-timed control is that the operation is not reactive to the traffic demand, meaning that the signals need to be optimized for a regular operation. Signal optimization has been widely studied [45–50]; however, due to the dynamic nature of traffic, it is difficult to set long-term values that satisfy any traffic condition.

2.2. Traffic-Actuated Controllers

In contrast to pre-timed control, traffic-actuated control can extend or terminate signal phases in response to vehicle actuation, which is detected by on-road sensors [51]. An actuated control is typically used for isolated intersections where the traffic signal control operates independently of any other traffic signal [52]. Generally, three parameters are required for this type of control: (1) the minimum green time, (2) the vehicle extension time (a.k.a., passage time), and (3) the maximum green time. Regardless of the traffic demand, green time is configured for at least a specified minimum duration. Then, by detecting whether a queue has been cleared or the gap between vehicles has increased, the green time is terminated. Additional extensions to the green interval can be applied until reaching the maximum green time.

While early actuated controllers were based on prefixed settings, most recent approaches have been focused on integrating an adaptive behavior by including methods to dynamically adjust the controller's parameters.

Zheng et al. [53,54] have proposed methods to determine optimal timing parameters by estimating future traffic demands. Hence, through a periodic optimization of such parameters, the controller's timing settings are dynamically updated. To achieve this, they formulated prediction algorithms to estimate the future arrival flow rate for each signal phase based on the available signal-timing data obtained from previous cycles.

Oertel and Wagner proposed a delay-time actuated traffic controller [43] which was designed to adjust the green times according to the vehicles' delay times. In this sense, they stated that a delay occurs when the vehicle's current speed is below a maximum achievable speed. Assuming that delays are captured, the controller extends the green intervals in such a way that a vehicle's platoon can cross the intersection, dissolving the queue. Otherwise, the green interval is interrupted. Therefore, the green intervals are bounded by the delay values. Their objective was to minimize delay times for users of motorized vehicles by allocating green times in a preferably efficient way. To measure the delay, this proposal suggested the use of video processing techniques, probe vehicle data as well as vehicle infrastructure integration.

By leveraging vehicle-to-infrastructure (V2X) communication [55,56], Erdmann et al. [44] proposed to improve the delay-time actuated traffic signal by integrating the Green Light Optimized Speed Advisory (GLOSA) application [57]. In addition to minimizing delay times, this approach gave speed recommendations to drivers based on the oncoming switching times. In this way, the controller outperforms the classic traffic actuated controllers by improving the vehicle's motion and signal switching.

Shiri and Maleki [58] proposed dynamically determining the maximum green times through a fuzzy control. They considered three inputs: (1) the maximum length of queues behind the red intervals, (2) the maximum queue length behind the green intervals, and (3) the arrival flow rate approaching green intervals. By considering these inputs, the system established the maximum green times to prevent long vehicle delays behind the red intervals, clear the queues, and serve the arrivals at the end of the green interval. The signal timing was adjusted by considering a time interval between the minimum and the maximum green time. Thus, each green interval was started with a specified minimum time, one second prior to the end, whilst the phase is extended according to the maximum extension determined by the fuzzy system. This proposal outperforms the traditional traffic actuated control method by automatically adjusting maximum green times for different timing plans of the day, avoiding the requirement of providing maximum green times for different times of the day.

2.3. Adaptive Controllers

Adaptive traffic signal controllers are characterized by continuously sensing the traffic conditions and adjusting the signal timing accordingly. Most of these controllers implement self-adjusting mechanisms with the ability to address unpredictable traffic conditions by modifying their parameters and internal logic.

Artificial intelligence has been widely applied to develop adaptive controllers. In the literature, a considerable variety of solutions mainly based on reinforcement learning (RL) [13–15,59,60], neural networks (NN) [16–18], deep reinforcement learning (DRL) [19–22], and fuzzy logic (FL) can be found. However, as has been surveyed by Araghi et al. [35], RL has the worst performance in terms of accuracy, speed, and capacity to manage a huge amount of data compared to the other approaches.

The main drawback of RL-based controllers is that they require the extraction of features from input data to create models to later identify useful information for the output. This procedure can lead to an overload of states, producing a performance decay as the amount of input data increases.

Unlike traditional RL techniques, DRL has the capacity to learn features and tasks directly from input data, allowing them to increase their performance as data increases. Most DRL-based controllers are based on decision-making models integrated by scalar representations for *states* (queue length, light timing, phases, vehicles' speed/position), *actions* (selected phase, phase splitting), and *rewards* (waiting time, queue length, phase transition) [37]. Due to these representations, a DRL approach requires that input data be expressed in a matrix or tensor formats [20,21]. Nevertheless, the effective computation of those formats requires nonlinear processing units, such as high-performance GPUs, and even the implementation of parallel computing techniques [19]. In addition, as was surveyed by Gregurić et al. [36], since DRL controllers need to learn from multiple levels of representation and abstraction, they require a significant amount of traffic data extracted and fused from multiple heterogeneous sources, which must be arranged into large sets of image-like representations. Many of the traffic agencies would have difficulties meeting the latter condition in the short and mid-term.

In practice, since FL systems are based on simple mappings between the inputs and the output, the result is more understandable and transparent for operators in comparison to NN, RL, and DRL approaches. Furthermore, FL systems are based on if–then rules with the capability to include experts' knowledge and experience in their design, without requiring the tuning of extra attributes for training, feedback, or reward functions. This advantage also facilitates the development of solutions with lesser computing requirements, allowing implementations over straightforward processing units, for instance, microcontrollers.

An FL-based controller relies on the definition of fuzzy sets and an inference system. Fuzzy sets are collections whose elements have degrees of membership that are used to mathematically describe the vagueness or uncertainty about a scalar magnitude. Such a description is done by using linguistics concepts such as *very low*, *low*, *average*, *high*, *very* *high*, which are named fuzzy values. Hence, the inference system consists of methods to translate scalar values to fuzzy values, and vice versa, which are supported by a base of rules (conditional statements) in the form: *if x is A then y is B*, where *A* and *B* are linguistic values determined by fuzzy sets.

Based on FL, the design of a basic traffic signal controller is conducted by the reasoning: *the higher the traffic demand, the longer the green time* [23,27,30,61]. For this purpose, arrival flow rates, queue lengths, and green interval lengths are commonly converted to fuzzy values to be used as the system's inputs and output, respectively.

Collota et al. [29] developed a sophisticated system architecture based on a Wireless Sensor Network (WSN) and multiple FL controllers. With the aim to find a low complex computational solution, they proposed the use of commercial off-the-shelf hardware to implement magnetometer sensors for the detection of queued vehicles, exchanging data through the IEEE 802.15.4 protocol. The system incorporated a phase-sorting module to compute the phase's execution order based on the queue lengths retrieved from an arrangement of magnetometers. Finally, a set of independent FL controllers (one controller for each phase) computed the appropriate green time duration. Using simulations, the authors showed that their proposal outperformed other FL solutions.

Some authors also have proposed two-stage fuzzy systems to determine changing the phases' order, with the aim of deciding whether to extend or terminate a current phase [32]. Ge [12] proposed a method based on an urgency degree computed in the first stage. The urgency was inferred from the number of vehicles queued during the red intervals and the duration of such intervals since the last green interval. Hence, the red interval with the greatest urgency is selected as the next phase. Then, in the second stage, the green interval delay was computed according to the number of vehicles on the current phase and the next phase. Jiang et al. [33] proposed a fuzzy system for the phases' order selection and green interval delay computation, which was optimized through a traffic flow prediction based on a wavelet NN.

Chiou and Huang [26] argued that in most of the FL-based controllers, the methods for formulating the rule base and the fuzzy sets are subjectively preset and therefore not optimally solved. Hence, they proposed a stepwise genetic fuzzy logic controller that considers traffic flows and queue lengths as state variables and the green extension as a control variable.

Ali et al. [34] proposed an adaptive method based on FL and the modified Webster formula [62,63]. Using a fuzzy system, the method dynamically adjusted the green interval during its execution. When the green reaches the interval of the remaining 15 s, proper extensions or reductions were computed. This process was repeated at each remaining second until the green interval finishes or the extension overpasses 130% of an estimated maximum green time. At the end of each cycle, the next cycle length, as well as the effective green times, are computed through the modified Webster's formula. The method was tested using a microsimulation model in SUMO [64] with outstanding results.

Most FL controllers are based on the also called type-1 fuzzy sets, where an expert should determine the degree of achieving the characteristics of the object. Many researchers argue these models are susceptible to producing inaccurate results by incorrect handling of the environmental uncertainties and disturbances. In response, some solutions, based on the called type-2 fuzzy sets, have been proposed [24,28,31]. In type-2 FL, an expert cannot determine exactly the degree of achieving the characteristics, requiring incorporating uncertainty to represent a fuzzy set. Nevertheless, since type-2 fuzzy sets are three-dimensional, they are computationally complex. To tackle this problem and improve the performance of signal controllers, Bi et al. [28] and Khooban et al. [31] proposed two type-2 FL approaches. Bi et al. proposed a system which is optimized by differential evolution. Khooban et al. proposed a general type-2 FL system whose parameters are optimized by a heuristic algorithm called *modified backtracking search algorithm*. Although the theoretical improvements of type-2 FL systems are encouraging, the number of parameters required for tuning is bigger than that of type-1 FL, which can lead to an increase in the time and computational complexity during the optimization process.

2.4. Summary

In this section, different traffic signal controllers have been reviewed, focusing on the actuated and adaptive schemes including the use of fuzzy logic. Most of the proposed approaches are based on requirements that are unfeasible for real traffic scenarios. On the one hand, for some approaches, the algorithms demand high requirements and computational power for start-up, processing, and maintenance. On the other hand, data retrieval for input sources, training, and reward functions demands a high cost in terms of hardware and technical resources (e.g., sensors and data storage). Additionally, some assumptions such as the generic strategy based on the computation of green phase extensions may produce a larger cycle length that results in an increase in waiting time.

3. Background

3.1. Traffic Signal Timing

A traffic signal cycle is a set of phases, which are the specific combinations of movements that receive the right-of-way simultaneously. Commonly, each phase is divided into three intervals: green, yellow, and red clearance (if applicable). Figure 1 shows a traffic signal cycle comprised of two phases each with green and yellow intervals.

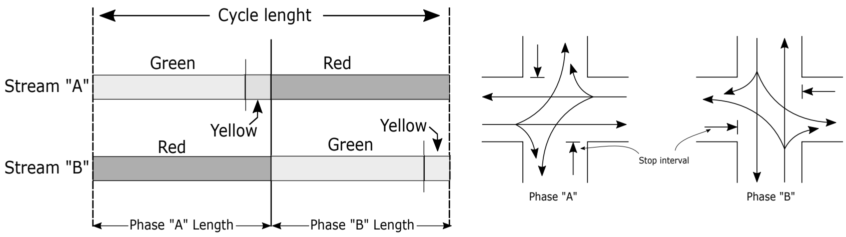

Figure 1. Phase-cycle traffic signal diagram.

According to Webster's method for signalization [42], if it is assumed that the effective green times of the phases were proportional to their respective flow ratio values; thus, the optimal cycle length C_0 is given by:

$$C_0 = \frac{1.5L + 5}{1 - \sum_{i}^{n} y_i}, \tag{1}$$

where L represents the total lost time, n denotes the number of phases, and y_i is the critical flow ratio in phase i. Let q_i be the flow ratio and s be the saturation flow; for a given lane, y_i is computed by:

$$y_i = \frac{q_i}{s}. \tag{2}$$

Therefore, the effective green time per phase, denoted by g_i, is computed by:

$$g_i = \frac{Y_i}{\sum_{i}^{n} y_i} C_0 - L. \tag{3}$$

3.2. Fuzzy Logic

Fuzzy logic is a form of many-valued logic that is able to handle the concept of partial truth, where the truth value may range between completely true and completely false [65]. Fuzzy logic is based on fuzzy sets, which are classes of objects with continuum grades of membership, ranging between zero and one [66].

A fuzzy set A is defined as a membership function $f_A(x)$ that maps the elements of a universe of discourse X with the elements of the interval $[0,1]$: $f_A : X \rightarrow [0,1]$, representing the grade of membership of x in A. The closer the value of $f_A(x)$ to 1, the higher the grade of membership of x in A.

Input scalar values are mapped to the fuzzy interval $[0,1]$ through a *fuzzification* process. Many types of curves can be used for fuzzification, of which the triangularly shaped membership functions are the most common.

Let x be an element of a set A; then, its triangular membership function is computed by:

$$f_A(x) = max[min(\frac{x-L}{C-L}, \frac{R-x}{R-C}), 0], \quad (4)$$

where L, C and R are real scalar values that delimit A (see Figure 2).

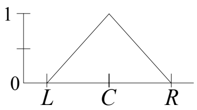

Figure 2. Triangular function.

The reversible process in which a fuzzy value is converted to a scalar is called defuzzification. The most common method for defuzzification is the centroid of area, which is the most prevalent and physically appealing [67,68]. Let x be the sample element and its discrete membership function $f_{A_i}(x)$; then, the defuzzified value is computed by:

$$WA = \frac{\sum_{i=1}^{n} \bar{x}_{A_i} f_{A_i}(x)}{\sum_{i=1}^{n} f_{A_i}(x)}, \quad (5)$$

where n represents the number of sets to which the element belongs, and $\bar{x}_{A_i}$ is the element with maximum membership function in a set A_i. This method, also referred to as weighted average (WA), is the most frequently used in fuzzy applications due to its efficiency [69].

4. Proposed Adaptive Traffic Signal Controller Based on Fuzzy Logic

The proposed traffic signal controller is composed of two modules: a fuzzy inference system (FIS) and an adaptive mechanism. The inference system is intended to compute the proper length of the signals' cycle according to the traffic flow rate. The adaptive mechanism is designed to split the computed cycle length into the required phases, based on Webster's method, as well as dynamically change the phases' duration.

4.1. Fuzzy Inference Description

A Mamdani-type FIS [70] was designed to compute the cycle duration based on the following reasoning:

The higher the traffic flow, the longer the cycle length.

Within an intersection, however, there is an inherent contention among the incoming traffic streams. For this reason, the proposed FIS computes the cycle length by relating all the possible combinations of flow rates among the involved streams.

For a χ-way intersection with n incoming traffic streams ($n \leq \chi$), there is a set of input variables $S = \{s_1, s_2, \ldots, s_n\}$. Each $s_i \in S$ has a scalar value in vehicles per hour (veh/h), which is related to the upstream traffic flow rate retrieved by on-road sensors. These inputs are fuzzified by using c triangular membership functions or fuzzy sets $f_{Q_1}(x), f_{Q_2}(x), \ldots, f_{Q_c}(x)$, which are defined in the universe of discourse established by the interval $[q_{min}(s_i), q_{max}(s_i)]$, which describes that the range the traffic flow may fluctuate between the minimum ($q_{min}(s_i)$) and maximum ($q_{max}(s_i)$) expected rates. Here, these minimum and maximum expected flow rates may be established from an in situ traffic count survey. For practicality's sake, each fuzzy set $f_{Q_j}(x)$, $j \in \{1, 2, \ldots, c\}$, is identified by a linguistic term that qualifies the traffic flow with adjectives such as *very low*, *low*, *medium*, *high*, *very high*, and so on.

For the cycle length cl, there are defined m triangular membership functions $f_{T_1}(x)$, $f_{T_2}(x), \ldots, f_{T_m}(x)$ in the universe of discourse established by the interval $[t_{min}, t_{max}]$, whose values are expressed in seconds. Analogously to the membership functions for flow rate, the membership functions f_{T_h}, $h \in \{1, 2, \ldots, m\}$ are related to linguistic terms as *very low*, *low*, *average*, *extended*, *very extended*, and so on.

Based on the fuzzy sets defined for the inputs and the output, the knowledge base of the FIS is defined by a set of if–then rules $r_1, r_2, \ldots, r_k, \ldots, r_z$, each one of the form:

$$r_k : s_1 \text{ is } f_{Q_j} \wedge s_2 \text{ is } f_{Q_{j'}} \wedge \ldots \wedge s_n \text{ is } f_{Q_{j''}} \Rightarrow f_{T_h}.$$

As an example, a first rule r_1 would be interpreted as:

if s_1 is very low and s_2 is very low, ... and s_n is very low, then the cycle length is very low.

These rules are established by considering all the expected traffic conditions at the intersection. Among the i incoming streams, not all the combinations of flow rates are possible, therefore, the total number of rules is less than c^n.

The inference module is specified through Algorithm 1, which uses the Mamdani fuzzy implication [71] to compute the inference rules (see lines 7 to 9). Since the fuzzy sets associated with cl are defined by triangular membership functions, the algorithm defuzzificates the system's output by the weighted average method (see line 10).

Algorithm 1 Fuzzy inference module

1: **procedure** FUZZYINFERENCE($S = \{s_1, s_2, \ldots, s_n\}$)
   * *Fuzzification with triangular functions*
2: **for each** input value $s_i \in S$ **do**
3:     **for each** fuzzy set $f_{Q_j}(x), j \in \{1, 2, \ldots, c\}$, **do**
4:         $v_{i,j} = max(min(\frac{s_i - L_j}{C_j - L_j}, \frac{R_j - s_i}{R_j - C_j}), 0)$
5:     **end for**
6: **end for**
   * *z inference rules ($z < n^c$)*
7: $r_1 = min(v_{1,j}, v_{2,j'}, \ldots, v_{n,j})$
⋮
8: $r_k = min(v_{1,j}, v_{2,j'}, \ldots, v_{n,j})$
⋮
9: $r_z = min(v_{1,j}, v_{2,j'}, \ldots, v_{n,j})$
   * *defuzzification with the WA method*
10: $cl = \frac{\sum_{k=1}^{z} \sum_{h=1}^{m} r_k \cdot \bar{x}_{T_h}}{\sum_{k=1}^{z} r_k}$
11: **return** cl
12: **end procedure**

4.2. Adaptive Mechanism Description

Reconfiguring a traffic signal at every cycle would be infeasible and inefficient. A short-time traffic monitoring would lead the system to be susceptible to magnifying specific conditions of the dynamics among vehicles, such as sudden delays, underestimating or overestimating the current traffic condition. Conversely, extremely long-time traffic monitoring periods could hide some fluctuations, reducing the reaction capacity of the system. To solve this problem, the proposed controller uses a mechanism that performs the traffic signal reconfiguration every τ cycles, where $3 \le \tau \le 10$. As a result, the FIS computes the cycle length cl by using the flow rates monitored during the time period bounded by τ, allowing the inference to take into account the effects of the previous configuration.

For the adaptive mechanism, the traffic signal configuration is defined as a tuple $TL = (P, D)$, where $P = \{p_1, p_2, \ldots, p_n\}$ is a set of phases' descriptors and the set $D = \{d_1, d_2, \ldots, d_n\}$ contains the duration assigned to each phase. Each $p_i \in P$ specifies the combinations of movements allowed/disallowed during a time d_i (i.e., green, red, yellow). The combinations of movements and sequence of phases are assumed to be fixed, since both the performance and the safety of a traffic signal can be compromised by the ordinary expectations of local users.

To achieve a fair traffic signal configuration for the incoming vehicle streams, the computed cl is proportionally split into the p_n phases according to the flow rates. Such a distribution is derived from the effective green time given by Equation (3). In this sense, the arrival flow rate of each stream s_i, retrieved from the on-road sensors, is assumed as the critical flow ratio, and the phase duration d_i is computed by:

$$d_i = \frac{s_i}{\sum_{k=1}^{n} s_k} cl + y, \tag{6}$$

where $s_k \in S$ and y is a predefined value for the duration of yellow interval.

The mechanism also includes a security rule implemented to avoid the appearance of too short cycles. This rule consists of the establishment of an average preset cycle in the case of atypical values measurements, which are retrieved by the on-road sensors. The aim of this rule is to restrict phases with duration tending to zero. As a result, a minimum phase duration is defined based on a safe pedestrian crossing time when there is no presence of vehicular flow at one of the incoming streams.

The adaptive mechanism is shown in Algorithm 2.

Algorithm 2 Adaptive mechanism module.

Input: $TL = (P, D)$
Output: Phases configuration
while true **do**
  for all traffic streams $s_i \in S$ **do**
    $s_i = $ SENSORS.RETRIEVEFLOWRATE(i)
  end for
  if TRAFFICLIGHT.CYCLEREMAININGTIME() = 0 **then**
    $num\_cycles += 1$
  end if
  if $num\_cycles == \tau$ **then**
    $num\_cycles = 0$
    $cl = $ FUZZYINFERENCE(S)
    * *cycle length distribution*
    for each phase $p_i \in P$ **do**
      $d_i = \frac{s_i}{\sum_{k=1}^{n} s_k} cl + y$
      * *complementary security rule*
      if $d_i <$ min_phase_duration **then**
        $d_i =$ min_phase_duration
      end if
    end for
    TRAFFICLIGHT.SETNEWPROGRAM(P, D)
  end if
end while

5. Evaluation and Discussion

5.1. Implementation of the Proposed Controller

The setup of the proposed controller is explained with a case study, which is performed by taking into account the characteristics of an isolated intersection located in the city of Morelia, Mexico. The analyzed intersection is depicted in Figure 3 and is described below.

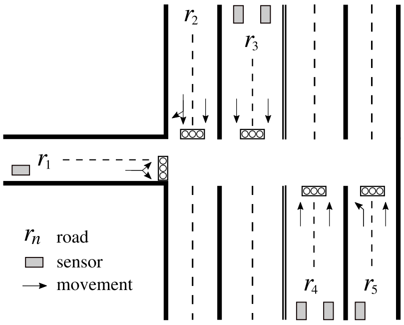

Figure 3. System model.

The case study consists of a four-leg intersection, where the intersecting roads are denoted as r_1, r_2, r_3, r_4 and r_5. These roads have three main characteristics:

1. r_1 is a two-lane dual road with west–east and east–west traffic. In addition, r_1 has two turning movements: a permitted right turn allowing the incorporation of vehicles to r_2 and r_3, and a protected left turn for the incorporation of vehicles to r_4 and r_5.
2. r_2 and r_3 are two-lane single roads with north–south traffic.
3. r_4 and r_5 are two-lane single roads with south–north traffic. Moreover, r_5 has a protected left turn to allow the incorporation of vehicles to r_1, r_2 and r_3.

All the allowed movements are grouped in three incoming traffic streams A, B, and C:

1. Stream A is composed by the through movements of r_2, r_3, r_4 and r_5, along with the permitted right turn of r_2.
2. Stream B is composed of the two movements of r_1, a protected left turn and a permitted right turn.
3. Stream C is composed of both movements of r_5, the protected left turn and the through movement.

Based on the streams A, B, and C, three phases are allocated within a traffic signal cycle. Figure 4 depicts the phases' setting.

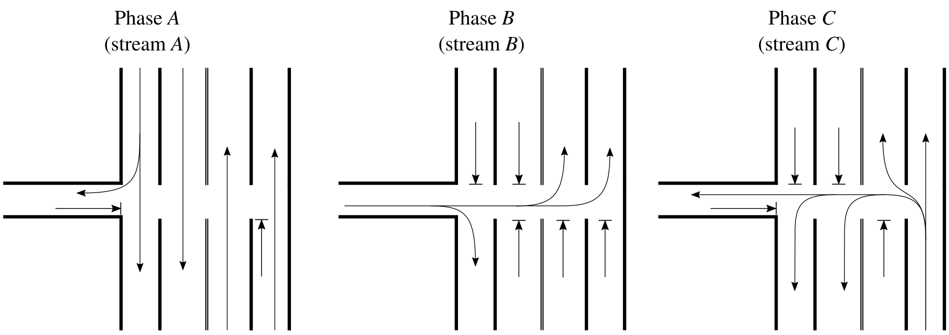

Figure 4. Traffic signal phases.

For sensing the traffic flow, we assumed the deployment of on-road traffic counters such as piezoelectric, which were located upstream 150 m before the corresponding intersection approach.

By considering the traffic streams A, B, and C as the system's inputs and the cycle length as the output, four linguistic variables are defined:

1. Flow A (FA) is the variable whose universe of discourse is the traffic flow rate of stream A.
2. Flow B (FB) is the input related to the flow rate of stream B.
3. Flow C (FC) is related to the flow rate of stream C.
4. Cycle length (Cl) is the variable whose universe of discourse is the duration of the set of phases in the traffic signal.

Linguistic variables are fuzzified and labeled with different linguistic terms as follows:

1. Flows A and B are fuzzified through five fuzzy sets: *very low* (VL), *low* (L), *medium* (M), *high* (H), and *very high* (VH).
2. Since Flow C has the less traffic flow rates, only three membership functions are defined: *low* (L), *medium* (M), and *high* (H).
3. The cycle length is fuzzified with five functions: *very short* (VS), *short* (S), *average* (A), *extended* (E), and *very extended* (VE).

Fuzzy sets, related to the four linguistic variables, are bounded as shown in Figure 5. The maximum and minimum values for flow rates were obtained from a six-month traffic survey performed in the study site. Consequently, the boundaries for the flow rate, in vehicles per hour per lane (Veh/h/lane), are set as: $q_{min}(FA) = 0$, $q_{max}(FA) = 700$, $q_{min}(FB) = 0$, $q_{max}(FB) = 1100$, $q_{min}(FC) = 0$ and $q_{max}(FC) = 500$. The values for the cycle length were defined by considering the recommendations included in the HCM [72] and the values obtained from the Webster method for averaged traffic conditions. The boundaries for the cycle length are set as $t_{min}(Cl) = 30$ and $t_{max}(Cl) = 90$.

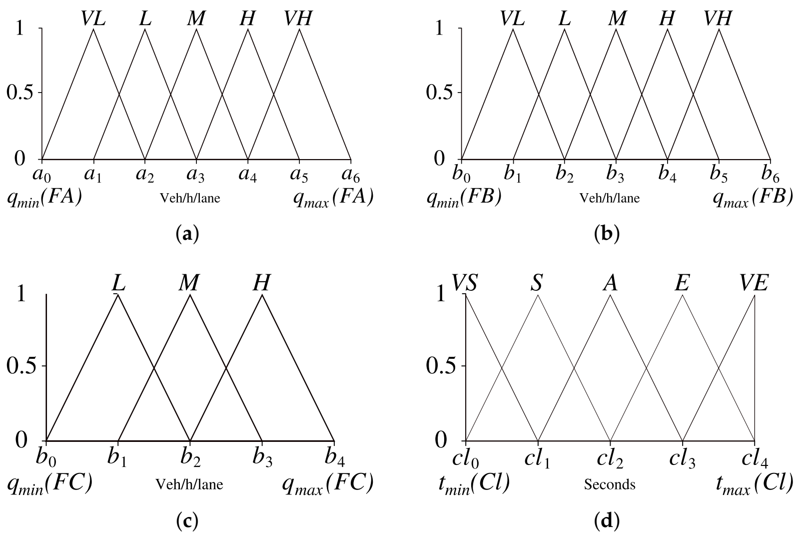

Figure 5. Fuzzy sets for the four linguistic variables: (**a**) flow rate in stream A, (**b**) flow rate in stream B, (**c**) flow rate in stream C, and (**d**) cycle length Cl.

Based on the eighteen fuzzy sets depicted in Figure 5, the Mamdani FIS is defined by seventy-five if–then rules that have been stated to include all the possible traffic conditions. Some of these rules are shown in Table 1. By defuzzificating the linguistic terms obtained from the FIS, the magnitude of the inferred cycle length is established in seconds.

Table 1. Example of the if–then rules used for the fuzzy inference system.

Rule	Input			Output
	Flow A	**Flow B**	**Flow C**	**Cycle Length**
1	Very Low	Very Low	Low	Very Short
2	Low	Very Low	Low	Very Short
3	Medium	Very Low	Low	Short
4	High	Very Low	Low	Average
5	Very High	Very Low	Low	Average
6	Very Low	Low	Low	Very Short
7	Low	Low	Low	Very Short
8	Medium	Low	Low	Short
9	High	Low	Low	Average
...	...	...	...	...
75	Medium	Medium	Medium	Average

The performance of the proposed adaptive FL controller was evaluated using the case study as a test bench. A microsimulation model was developed with the SUMO software [64].

5.2. Simulation Model

Algorithms 1 and 2 were codified in python and embedded in the simulation environment through the Traffic Control Interface (TraCI) API provided by SUMO [73,74].

In SUMO, the microscopic simulation is based on the behavior of the driver–vehicle units. Because of this, vehicles are modeled by considering the length, maximum speed as well as acceleration/deceleration profiles.

The calibration of the SUMO model was carried out by setting the parameters required by the lane change model LC2013 [75] and the Krauß car-following model [76]. These parameters were obtained through in situ measurements, which were retrieved from radar trackers and road tube counters that were deployed to count and classify the traffic volumes in the study site. In addition, the GEH statistic was used to ensure that the calibrated microsimulation model was representative of the observed traffic conditions [77]. A summary of the collected traffic data is shown on weekly average daily traffic metrics and average hourly flow rates in Tables 2 and 3, respectively. In Table 2, the average travel speed was estimated from the corresponding observations as the 85th percentile of the entire sample. Table 4 displays the average directional movement distribution through an OD-Matrix.

Table 2. Weekly average daily traffic metrics.

	Roads				
	r_1	r_2	r_3	r_4	r_5
Traffic volume (veh/day)	4765	5393	8652	9450	4664
Avg. travel speed (km/h)	32.20	28.30	42.30	57.90	26.40
Mean flow rate (veh/h)	451	329	554	770	226

Table 3. Summary of the traffic survey, focusing on the average hourly flow rates per road.

		Roads					
	Hour	r_1	r_2	r_3	r_4	r_5	Avg.
Flow rate (Veh/h)	7:00–8:00	417	221	543	686	201	422
	8:00–9:00	386	252	502	759	212	414
	9:00–10:00	347	157	450	644	190	358
	10:00–11:00	344	209	445	602	175	355
	11:00–12:00	341	207	475	547	172	348
	12:00–13:00	323	220	517	561	197	364
	13:00–14:00	312	234	597	613	226	396
	14:00–15:00	324	238	608	537	233	388
	15:00–16:00	356	234	543	597	555	457
	16:00–17:00	321	223	513	605	202	373
	17:00–18:00	347	219	494	641	194	379
	18:00–19:00	359	221	550	615	198	389
	19:00–20:00	417	232	557	546	222	395
	20:00–21:00	255	226	528	409	208	325

Table 4. Average directional movement distribution.

		Destination				
		r_1	r_2	r_3	r_4	r_5
Origin	r_1	—	3.64%	6.16%	16.81%	73.38%
	r_2	18.23%	81.77%	—	—	—
	r_3	—	—	100%	—	—
	r_4	—	—	—	100%	—
	r_5	74.62%	11.19%	13.43%	—	0.74%

For the traffic demand, three vehicle types were defined in the microsimulation model: *car*, *van*, and *bus*. The type *car* represents private vehicles characterized by a length of 4.5 m, an acceleration of 2.6 m/s^2, a deceleration of 4.6 m/s^2, and a maximum speed of 80 km/h. Meanwhile, *van* and *bus* types were incorporated into the simulation, since they are the vehicles that provide public transport in the zone. The type *van* is characterized by a length of 5 m, an acceleration of 1.5 m/s^2, a deceleration of 3.6 m/s^2, and a maximum speed of 60 km/h. The type *bus* is characterized by a length of 7 m, an acceleration of 1.5 m/s^2, a deceleration of 3.6 m/s^2, and a maximum speed of 42 km/h. In addition, for all vehicles, a standard deviation of 10% up and down from the maximum speed was considered to reproduce real-world fluctuations as well as a sigma value of 0.5 mimicking drivers' stochasticity.

5.3. Comparison against Other Approaches

The calibrated microsimulation model was used as a test bench to compare the proposed adaptive FL controller against five approaches: (1) the existing Pre-Timed controller (see Figure 6), (2) a Time-Gap controller [78,79], (3) the Time-Delay controller proposed by Oertel and Wagner [43,44], (4) an FL Green-Extension controller based on the works of Nasser et al. [23] and Shiri and Maleki [58], and (5) the adaptive FL-based method with modified Webster's formula proposed by Ali et al. [34], which is hereinafter referred to as the FL Phase-Adjustment controller.

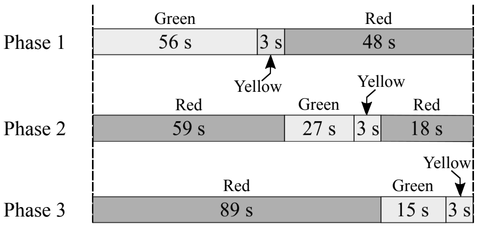

Figure 6. Configuration of the current pre-timed control at the case study.

From the in situ retrieved traffic volumes, eleven levels of arrival flow rate were simulated to mimic the observed variations from free-flow to congested traffic conditions. For each level of arrival flow rate, a ten-hour simulation period was carried out comprising at least 300 traffic signal cycles. The simulation outputs (e.g., performance metrics) were fine-grained configured using 5-min intervals, excluding the first and the last simulated hours to ensure steady-state conditions. Finally, all the collected registers were averaged to reduce the stochastic fluctuation.

Traffic density and waiting time were selected as performance metrics. Figure 7a–c depict the performance of the six signal controllers tested with respect to the traffic density as a function of the averaged system's arrival flow rate. Similarly, Figure 8a–c show the waiting time as a function of the averaged system's arrival flow rate.

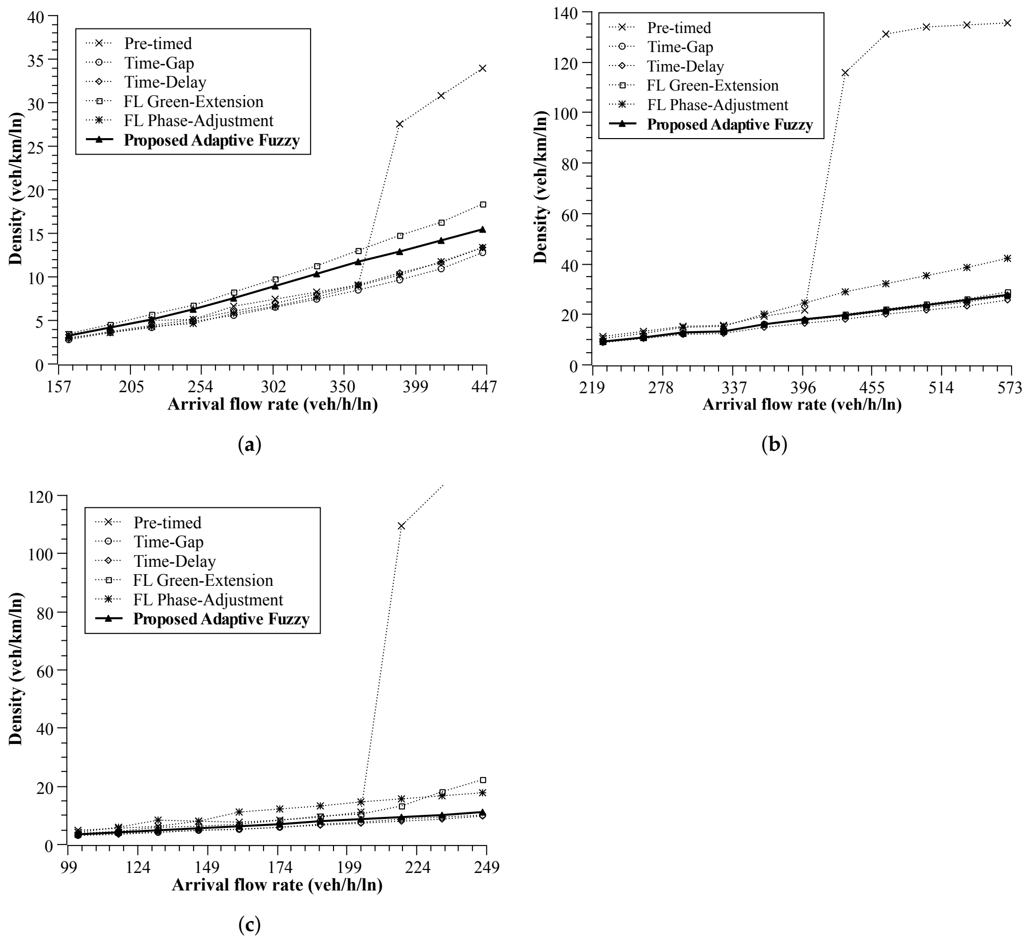

Figure 7. Traffic density as a function of the averaged system's arrival flow rate: (**a**) stream A, (**b**) stream B, and (**c**) stream C.

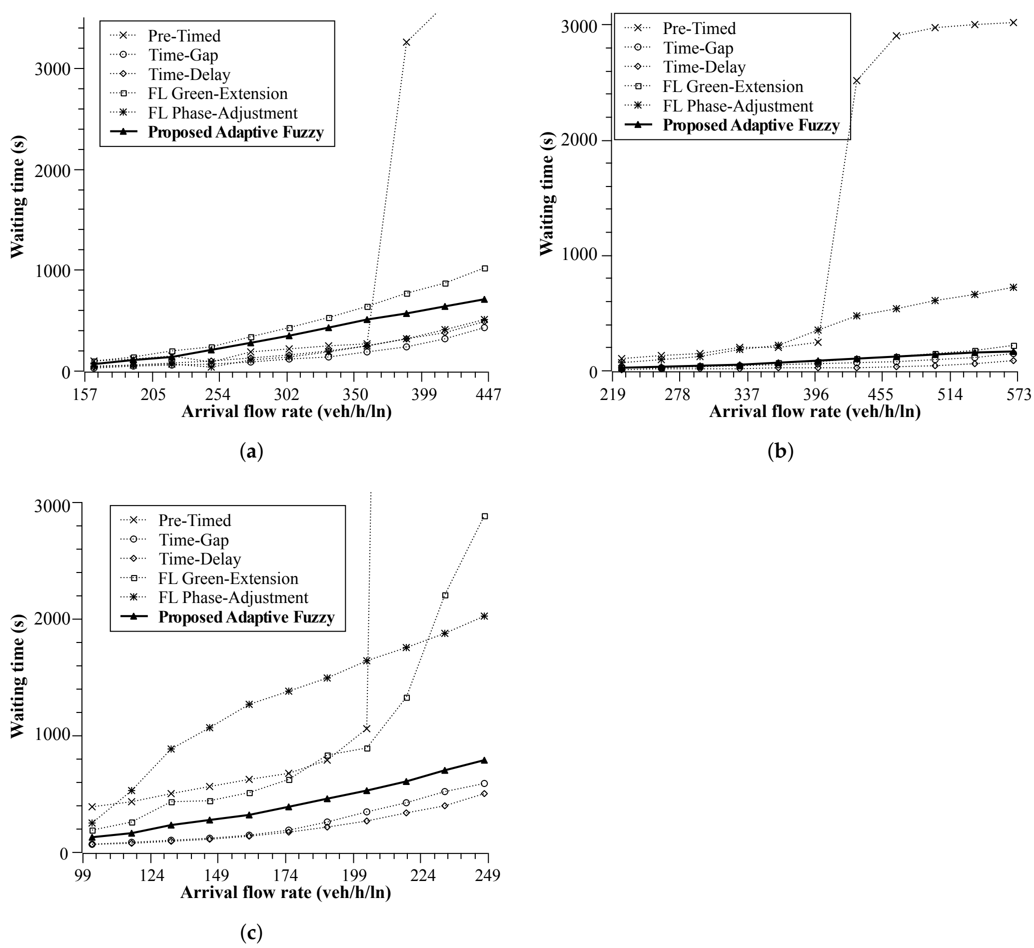

Figure 8. Waiting time as a function of the averaged system's arrival flow rate: (**a**) stream A, (**b**) stream B, and (**c**) stream C.

Plots of Figures 7 and 8 depict the efficiency boundaries, which were established from the performance achieved by the studied traffic signal controllers.

By considering the three incoming streams in the worst-case scenario, which is an arrival flow of 447 veh/h/ln for stream *A*, 573 veh/h/ln for stream *B*, and 249 veh/h/ln for stream *C*, the highest efficiency level is reached by the Time-Gap approach. So, Time-Gap achieves a density of 12.7 veh/km/ln and waiting time of 431.69 s for stream *A*, 27.3 veh/km/ln density and waiting time of 147.02 s for stream *B*, and 10.2 veh/km/ln density and waiting time of 593.91 s for stream *C*.

Here, is important to note that the proposed adaptive FL controller shows a performance close enough to the highest, achieving 15.6 veh/km/ln density and waiting time of 715.73 s for stream *A*, 27.7 veh/km/ln density and waiting time of 168.48 s for stream *B*, and 11.1 veh/km/ln density and waiting time of 791.54 s for stream *C*.

Another interesting result is that the fuzzy green-extension system, as well as the FL Phase-Adjustment controller, achieved a sound performance level only for some scenarios. On the one hand, by considering the resultant conditions with respect to stream *B*, it is noticed that the fuzzy green-extension system also matches the performance of Time-Gap and Time-Delay. On the other hand, by considering the waiting time for stream *A*, the FL Phase-Adjustment controller has a similar performance to Time-Gap and Time-Delay, and it even overcomes both the proposed mechanism and the fuzzy green-extension system. Nevertheless, behind such relative achievements exists an unbalanced phases distribution, which is highlighted when the waiting times for stream *C* are analyzed. Note that for stream *C*, at a flow rate from 215 veh/h/ln, the FL Phase-Adjustment controller achieves waiting times above 882.88 s, which are higher than the achieved by the proposed controller in the worst case, which is 791.54 s with a flow rate of 249 veh/h/ln. Phase imbalance is aggravated by the green-extension approach, producing waiting times above the triple of the obtained with the Proposed Adaptive FL. This poor performance is explained by the fact that strategies based on phase extension lead to long signal cycles and consequently longer waiting times. Such an effect is worsened when traffic signal reconfiguration is executed every cycle, since overestimation/underestimation is promoted by sporadic traffic conditions such as the well-known phantom jams [80]. Furthermore, in the case of the FL Phase-Adjustment controller, performance results were more affected by the use of a fixed value for saturation flow, which is an essential adaptive parameter.

Unlike the latter approaches, the proposed adaptive FL controller reaches an outstanding performance while preserving a fair balance among phases. This equilibrium is reached since the proposed controller adaptively computes the cycle length, which is proportionally split into different phases, instead of estimating phase extensions. Since cycle length is computed through a fuzzy inference, it does not depend on fixed/pre-established values such as saturation flow that may lessen adaptability to the controller. Moreover, the proposed adaptive FL controller avoids underestimations/overestimations by creating a virtual buffer of at least three signal cycles to contain sporadic effects such as phantom jams.

5.4. Prospective Strengths of Proposal

As discussed above, the proposed adaptive FL controller is competitive when compared to Time-Gap and Time-Delay approaches, which are still two of the best and most used approaches today; they are successfully implemented in different cities and included in global projects and initiatives such as VITAL and MAVEN [81–83]. This achievement is remarkable, since the proposed design only considers data retrieved from simple vehicle counters, such as widely used piezoelectric, avoiding the use of more sophisticated sensors such as those required by Time-Gap or Time-Delay controllers, which assume data-harvesting from video processing and even from vehicle probes through a V2X communication.

Regarding technical requirements for setup and maintenance, since the proposed controller is defined through a type-1 fuzzy logic, it only requires operators to know the minimum and maximum expected values for arrival flows and cycle lengths to establish if–then mappings. This advantage severely contrasts against the technical requirements involved with the definition of scalar states, actions, and rewards, besides the specifications for data collection, aggregation, formatting, and storage, as required for approaches based on NN or DRL. In addition, since fuzzy sets for input mappings consider a single input domain, the proposed adaptive FL controller effortlessly can include larger values than those usually retrieved from traffic surveys, overcoming the major drawback attributed to FL-based controllers [37].

In terms of computational efficiency, since the proposed adaptive controller is based on sequential and conditional instructions, such as basic arithmetic and if–then statements, the execution time is directly proportional to the number of fuzzy sets and incoming traffic streams (converging roads), which are constant values. For example, by considering an intersection with three incoming traffic streams and five linguistic terms for fuzzification, such as the case study depicted in Section 5.1, in the most demanding conditions (i.e., without rule trimming), the controller executes 90 arithmetic operations and 30 comparisons to fuzzify the input values, 125 comparisons for the FIS, and 625 arithmetic operations for defuzzification. This means the controller executes up to 870 $O(1)$ operations every τ traffic-light cycles. Exploring even a more complex scenario, for instance, a six-way intersection and five fuzzy sets without rule trimming, the controller executes up to 78,365 $O(1)$ operations. These low complexity bounds significantly contrast against the computational costs involved in most machine-learning-based controllers (e.g., NN, DRL, etc.) whose complexity bounds are above $O(n^2)$, in addition to the storage requirements [37]. In summary, due to its design principles, the proposed adaptive FL controller can be implemented over simple microcontrollers (e.g., a US$2 SAM D21 chip), which makes the proposal an affordable option for many cities, especially in developing countries.

6. Conclusions

This paper has described and tested a proposed model of an adaptive traffic signal controller based on fuzzy logic. The aim of the proposed model is to achieve a traffic signal with a balanced distribution of the signalization, without requiring expensive or complex requirements. The model was designed to compute the whole cycle duration instead of specific phase lengths or extensions as occurs with most traditional approaches. That is, the cycle duration is adjusted according to traffic demand determined by the arrival flow rate, which is retrieved from simple vehicle counters. Through a type-1 fuzzy inference system, the cycle length is computed following the reasoning: the higher the traffic flow, the longer the cycle length. Subsequently, the computed cycle is proportionally split into different phases based on the effective green time estimation derived from Webster's method for signalization.

The proposed adaptive FL controller was evaluated through a microsimulation model of a real intersection, using SUMO as a platform. Using the microsimulation model as a test bench, the proposed controller was compared against five different controllers found in the literature. Simulation results showed that the proposed adaptive FL controller closely matches the performance of the most sophisticated approaches and even overcomes other approaches based on fuzzy logic, despite having fewer requirements. In this regard, the proposed controller only requires knowing the minimum and maximum values for flow and cycle lengths for setup. Moreover, the algorithmic design has a low-constant computational overhead, since it depends on the number of fuzzy sets and incoming traffic streams, whose values remain immutable during the execution. This also allows implementations over the cheapest/simple microcontrollers. In summary, due to the lower requirements in hardware and setups, the proposed model becomes an affordable solution for traffic signal timing for most cities, especially those in developing countries.

The current approach has been focused exclusively on regulating traffic operation in isolated intersections. It is hypothesized that the controller could also be scalable for multi-intersection scenarios in a self-organizing scheme, as this is assumed to be independent and decentralized. Therefore, further work will be oriented to extend the capacities of the controller to achieve adaptive traffic signal corridors.

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