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Efficient intersection management based on an adaptive traffic light controller

Tesis que para obtener el grado de

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presenta:

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Cuna de héroes, crisol de pensadores

Abstract

Most of the main urban intersections are managed by traffic lights, coordinated by prefixed times. However, such systems do not achieve a fair balance for the involved streams since they do not consider the variations of the traffic flow rates. Thereby, green/red phases can be overestimated or underestimated, causing queues formations or intersection's underutilization.

To solve this problems, proposals of adaptive traffic light controllers use queues length measurements to compute proper extensions for the phases' duration. Unfortunately, in real world, queue length is difficult to measure because the sensor's accuracy is affected by the space gap among vehicles. Moreover, arbitrary phase extensions may cause a longer traffic light cycle, increasing the waiting times for the involved traffic streams.

In this work it is proposed an adaptive fuzzy logic controller which use traffic flow rates measurements to compute the proper duration for whole cycles. Each computed cycle is proportionally divided into different phases according to the flow rates. The controller was tested through a microscopic-simulation of a real intersection and the results show that the controller reduces trip durations, waiting times, time losses and fuel consumption up to 16%, 51%, 41% and 22%, respectively; increasing average travel speeds up to 19%.

Keywords: *Adaptive controller, Traffic light, Fuzzy logic, Traffic management, Microscopic simulation.*

Resumen

La mayoría de las principales intersecciones urbanas se gestionan mediante semáforos, coordinados por tiempos pre-establecidos. Sin embargo, tales sistemas no logran un equilibrio justo para los flujos involucrados, ya que no consideran las variaciones de estado del flujo del tránsito. De esta manera, las fases de luz verde y roja pueden ser sobrestimadas o subestimadas, causando formación de colas o subutilización de la intersección.

Para resolver estos problemas, las propuestas de controladores adaptativos de semáforos utilizan mediciones de longitud de colas para calcular extensiones apropiadas para la duración de las fases. Desafortunadamente, en el mundo real, la longitud de la cola es difícil de medir porque la precisión del sensor se ve afectada por el espacio entre los vehículos. Además, las extensiones de fase arbitrarias pueden causar un ciclo de semáforo más largo, aumentando los tiempos de espera.

En este trabajo se propone un controlador adaptativo basado en lógica difusa que utiliza mediciones de flujo del tránsito para calcular la duración adecuada para el ciclo total. Cada ciclo calculado se divide proporcionalmente en diferentes fases según los flujos. El controlador se probó a través de una simulación microscópica de una intersección real y los resultados muestran que el controlador reduce las duraciones de los viajes, los tiempos de espera, las pérdidas de tiempo y el consumo de combustible hasta en 16%, 51%, 41% y 22%, respectivamente; incrementando las velocidades de circulación hasta en un 19%.

Palabras clave: *Controlador adaptativo, Semáforo, Lógica difusa, Gestión de interseciones, Simulación microscópica.*

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Dedicatoria

A mis padres, por darme todo el apoyo y el cariño incondicional para seguir cumpliendo mis metas...

Contents

Acronyms and Symbols

- ITS: Intelligent transportation System
- FIS: Fuzzy Inference System
- UAV: Unmanned Aerial Vehicle
- TFT: Traffic Flow Theory
- l_i = vehicle length (meters)
- x_i = longitudinal position
- $v_i = \frac{dx_i}{dt}$ = travel speed
- $a_i = \frac{dv_i}{dt} = \frac{d^2x_i}{dt^2}$ = acceleration
- g_{s_i} = space-gap
- g_{t_i} = time-gap
- h_{s_i} = space headway
- h_{t_i} = time headway
- PCU = Passenger Car Unit
- q = flow (vehicles per hour)
- N = number of vehicles passing a reference point
- T_{mp} = time interval
- k = density (vehicles per kilometer)

- K = length of the roadway (kilometers)
- CL = Cycle Length (seconds)
- C_0 = optimal cycle length (seconds)
- L = total lost time (seconds)
- n_p = number of phases
- Y_i = critical flow ratio in a phase (vehicles per hour)
- q_i = flow ratio (vehicles per hour)
- s_i = saturation flow (vehicles per hour per lane)
- e_p = effective green time per phase (seconds)
- e_c = effective green time per cycle (seconds)
- $f_A(x)$ = membership function of a fuzzy set A of elements of a domain or universe "X"
- L = left scalar values that delimit a fuzzy set
- C = central scalar values that delimit a fuzzy set
- R = right scalar values that delimit a fuzzy set
- b, c = boundaries of the range where the inputs have the largest membership to A
- COA = Centroid of Area method
- WA = Weighted average method
- $\bar{a_c}$ = the centroid of each symmetric membership function
- $SUMO$ = Simulation of Urban Mobility

- GPL = General Public License
- $TraCI$ = Traffic Control Interface
- $HBEFA$ = The Handbook Emission Factors for Road Transport
- TLC = Traffic Light Control

Chapter 1

Introduction

1.1 Motivation

Traffic congestion is one of the major problems of modern cities, causing excessive fuel consumption, time lost and pollution [ZRG17]. This phenomenon is originated, on the one hand, due to the constant increase in the number of vehicles, and on the other hand, by the lack of efficiency in traffic management.

Regarding traffic management, the regulation of intersections is one of the major open challenges. For the most crowded intersections, the frequently used traffic control method are still the based on traffic lights. However, traffic lights phases and offsets must be perfectly calculated to help reduce traffic congestion. Up to date, the most used system to control traffic lights are based on preset signal timings [AA96]. Unfortunately, such systems do not achieve a fair balance for the involved streams since they do not consider the variations of the traffic flow rate, which makes traffic behavior completely circumstantial. Therefore, the inadequate signal estimations causes a variety of conflicts, such as unnecessary interruptions in the traffic flow, queuing, and bigger travel times. These drawbacks have motivated the development of alternatives for the traffic lights control, where the most outstanding approaches operate considering the peak hour factor.

1.2 Problem description

Several approaches have been proposed to mathematically or computationally find appropriate configurations of traffic lights by optimizing phases times and offsets. [Kel12, ZC14, opt04, WVvVK04, MH01, VY86, LKG81]. Unfortunately, due to the random fluctuations of traffic flow, it is difficult and expensive to establish a long-term optimum value for the involved variables. Moreover, optimization methods do not detect atypical events that disturb traffic [Ger05]. With a prefixed time control it is easy to produce overestimated or underestimated phase times, causing queues formations or intersection's underutilization for certain times of day. An example of this problem is depicted through Figure 1.1, which shows a typical four-way intersection where the traffic light configuration causes that the traffic congestion takes place only in two involved lanes, while the remaining road elements present free flow conditions. Since traffic behavior is not stable, controlling traffic lights should not be addressed as an optimization problem, but as an adaptation problem [GR12]. In this sense, an adaptive controller is a system with variable inputs and a self-adjusting mechanism to regulate outputs. Thereby, for an adaptive traffic light, sensors deployment is required to constantly monitoring traffic conditions along with a mechanism to estimate the appropriate offsets or phases. Estimation of appropriate timings would be a hard task by traditional computational/mathematical stochastic techniques due to the high uncertainty of the system. Hence, most of recent proposals have chosen fuzzy logic as a tool to develop the required self-adjusting mechanisms. In this way, the estimation is performed through a decision-making process imitating the human perception.

Existing traffic light controllers, based on fuzzy logic [AUÖ12, PM77, HHlS, Kim97, LLLK95, TI12], use queue lengths as well as arrival frequencies measurements as inputs, which are translated to qualitative parameters. Then, the estimation is done by processing the qualitative parameters through logic infer-

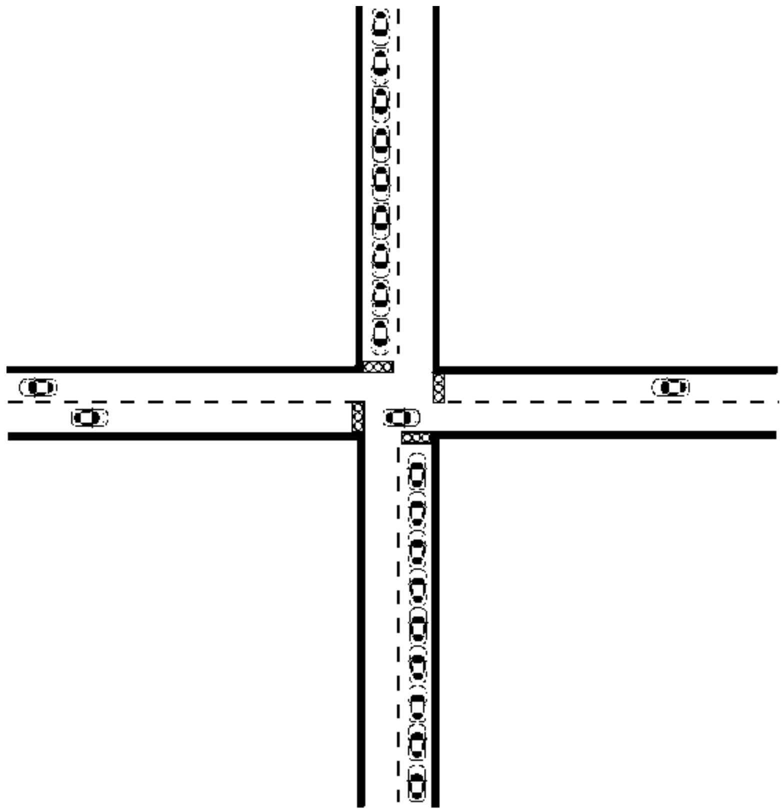


Figure 1.1: Ineffective green time usage state in a fixed time traffic light controller.

ence rules, following the reasoning *the greater flow, the longer green phase.* These schemes have shown successful analytical results, however, requirements of most of them are not always feasible for real world scenarios. While real-time traffic flow can be easily measured by induction loops, real-time queue length measurement is difficult and expensive. Furthermore, arbitrary extension of green phase durations cause longer cycles, increasing the waiting times for opposite traffic streams.

1.3 Proposed solution

In this work it is proposed an adaptive traffic light controller, governed by the computational intelligence of a fuzzy logic inference system. The controller uses the traffic flow rates measurement as a unique input to compute the proper duration for the whole cycle. The controller proportionally divides the computed cycle into different light phases according to the flow rates, avoiding the increasing of the waiting times. To achieve this design, an isolated junction was characterized based on the traffic volumes analyzed in the area of influence of a specific junction at the city of Morelia, Michoacán. The mobility analysis was done following the Intelligent Transportation Systems (ITS) prototype for traffic management and control [SR15, FJM$^+$01]. The prototype consists of three stages: crowd sourcing, information retrieval and development of intelligent traffic management systems. Crowd sourcing stage was achieved by deploying vehicular counting radars and aerial video recordings to retrieve traffic volumes. With these data, mobility patterns were determined at the junction and a simulation model was developed. Then, considering the mobility patterns, traffic volumes were classified as *very low*, *low*, *medium*, *high* and *very high*. Finally, by considering such classification, a fuzzy inference system was designed to compute the proper traffic light cycle duration.

The effectiveness of the controller was tested through the microscopic-simulation of a real intersection, comparing the proposed solution with different control methods using SUMO as a platform [KEBB12]. The simulation model was designed to reproduce a wide range of traffic states and control methods. These control methods include three approaches: a) the current fixed-time configuration, present, in the real intersection, b) an optimized signal configuration and c) an actuated control based on time-delay [EOW15a].

Each of the three approaches were tested through four simulation conditions. The first simulation was configured to reproduce the time-of-day with free-flow conditions. The second simulation is based on the time-of-day with congested traffic. For the third simulation it was assumed a time-of-day with an over saturated traffic, which represents an increasing of 30% over the congested traffic. Finally, the fourth simulation was done by combining the three time of days, generating fluctuations among free-flow, congested and over saturated traffic conditions.

Results show that the controller achieves the reduction of waiting times and time loss, fuel consumption, up to 50%, 40% and 16% respectively, and increasing travel speeds up to 19%. In addition, the pollution was estimated through an emission model resulting up to 17% improvements.

1.4 Objectives

1.4.1 The main objective

The main objective of this research work is:

To design an efficient and sustainable traffic management scheme at intersections, based on the design of an adaptive traffic light controller, which be capable to adapt the cycle length duration adapt to the current traffic flows.

1.4.2 Specific objectives

- To determine the characteristics of a real intersection as a case study.
- To develop a simulation model of the case study with the determined characteristics.
- To design a model of an adaptive traffic light based on a fuzzy inference method, which considers traffic flow at the intersection as input parameters.
- To develop a system of adaptive traffic light controller , based on the designed fuzzy model.
- To implement the system of adaptive traffic light controller in the simulation model, to evaluate it's efficiency.

1.5 Methodology

To achieve the stated objectives, it is proposed the following methodology:

- Characterization of an isolated intersection based on the real parameters of a case of study.
- Implementation of a crowd-sourcing strategy to gather data about traffic volumes, speeds, trip distributions, traffic light configuration and time of days; by deploying radar counters, inducted loops and UAV recordings.
- Implementation of an information retrieval strategy to retrieve useful information from the data corpus, obtained by crowd-sourcing. For this stage, the main task is to recognize traffic patterns through the creation of origin destination matrices, establish traffic flow time tables, time of days, turn-trip distributions, average weekly traffic volumes, average travel speeds and mean flows.
- Development of a microscopic simulation model, calibrated with the parameters and characteristics retrieves from previous stages.
- Classification of the traffic volumes in to different fuzzy sets.
- Definition of inference rules, considering the different established fuzzy sets, to develop a fuzzy inference engine to determine the proper cycle length duration for different traffic conditions.
- Development of an adaptive traffic controller mechanism which based on the fuzzy inference engine to dynamically manage the traffic light behavior.
- Evaluate the performance of the proposed solution in the simulation environment, and comparing it to different control methods.

1.6 Document organization

The content of this thesis is structured as follows: Chapter 2 gives an overview of traffic flow theory concepts and traffic engineering.

Chapter 3 is a survey of the recent developments in the literature about the design of traffic control strategies.

In Chapter 4 it is presented the design, development, calibration and evaluation of the adaptive traffic light controller based on fuzzy logic.

Finally, Chapter 5 presents the conclusions from the research and future research work.

Chapter 2

Background and definitions

2.1 Traffic flow theory

2.1.1 Microscopic traffic flow characteristics

Traffic on streets it is composed by individual vehicles, each one with their own characteristics. A microscopic traffic flow model simulates single vehicle-driver units, so the dynamic variables of the model represent properties like the position and velocity of single vehicles. The dynamic aspects of the microscopic environment are determined by the interaction between drivers and their behavior.

2.1.1.1 Vehicle related variables

For the microscopic traffic model, the vehicle-driver combination is modeled as a single entity considering the following individual on-road vehicle characteristics:

- vehicle length, denoted by l_i,
- longitudinal position, denoted by x_i and typically taken to be the position of its rear bumper (see Figure 2.1),
- speed, denoted by $v_i = \frac{dx_i}{dt}$,
- and acceleration, denoted by $a_i = \frac{dv_i}{dt} = \frac{d^2x_i}{dt^2}$

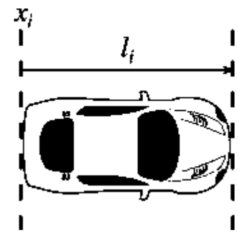


Figure 2.1: Vehicular variables

2.1.1.2 Traffic flow characteristics.

Referring to Figure 2.1, it can be considered two consecutive vehicles in the same lane in a traffic stream: a follower i and its leader $i+1$. Follower and leader are separated with a distance called *space gap*, denoted by g_{s_i} (see Figure 2.2). Considering the length of the follower l_i and the space gap, it is said that vehicle i has associated a *space headway*, denoted by h_{s_i}.

$$h_{si} = l_i + g_{s_i} \tag{2.1}$$

Definition 1 *Let x_i and x_{i+1} be the longitudinal position of two vehicles, leader $i+1$ and follower i, the space headway is the difference between x_i and x_{i+1} [May90].*

$$h_{si} = x_{i+1} - x_i \tag{2.2}$$

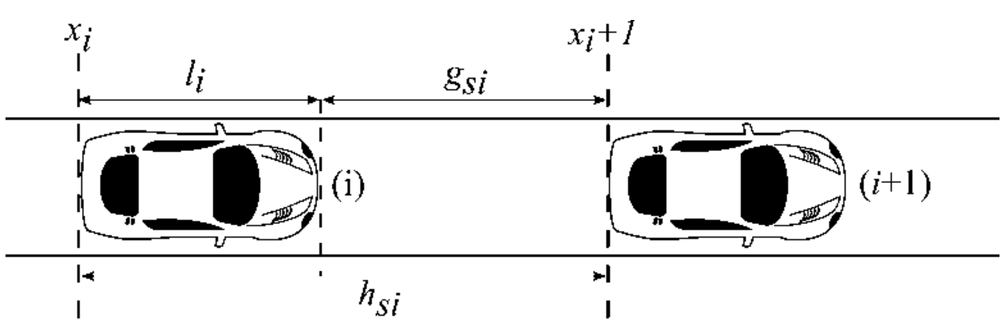


Figure 2.2: Space headway

Analogously to space gap, two vehicles are separated in a time-line with a *time gap*, which is the measure of the time that elapses between the departure of the first vehicle and the arrival of the second at the designated test point. It can be said that the time gap is a measure of the time between the rear bumper of the leader and the front bumper of follower. In this way, each vehicle also has a *time headway* h_{t_i}, consisting of a *time gap* g_{t_i} and an *occupancy time* τ_i:

$$h_{t_i} = g_{t_i} + \tau_i \tag{2.3}$$

Definition 2 *The space headway is a measure of the temporal space between two vehicles. Specifically, the space headway is the time that elapses between the arrival of the leading vehicle and the following vehicle at the designated test point [May90].*

Considering a discretization of a time-line and assuming that a vehicle travels over such time scale with certain speed, the spatial coordinate x_i of a vehicle can be computed as a functions of time t according to:

$$x_i(t + \Delta t) = x_i(t) + s(t + \Delta t)\Delta t, \forall i \in \{1, 2, ...\}; \tag{2.4}$$

where Δt refers to the constant updated time step, i.e., two registers of a traffic detector given two timestamps.

Therefore the interaction between drivers is reduced to reproducing a behavior that ensures that the *space gap* has values greater than 0, i.e. $g_{s_i} \geq \forall i \in \{1, 2, ...\}$ [Kra98].

2.1.2 Macroscopic flow characteristics

Definition 3 Passenger Car Unit (PCU). *PCU, is a numerical factor associated to the impact that a mode of transport has on the traffic flow compared to a single standard passenger car.*

For convention, there are different PCU values according to the vehicle type:

- private car = 1
- motorcycle = 0.5
- bicycle = 0.2
- bus = tractor = truck = 3.5

Definition 4 Flow rate. *The macroscopic characteristic flow, denoted by q, is the number of vehicles passing a reference point per unit of time, commonly expressed as vehicles per hour [May90].*

Flow describes how vehicles interact on a stream and define the efficiency operational level. Let N, be the number of vehicles passing a reference point and T_{mp} be a time interval, the flow q for a single lane stream is computed as follows:

$$q = \frac{N}{T_{mp}} \tag{2.5}$$

Definition 5 Density. *The macroscopic characteristic density, denoted by ρ, is the number of vehicles per unit length of a roadway, commonly expressed as vehicle per kilometer [May90].*

Density describes the traffic flow demand on the stream. Let N, be the number of vehicles passing a reference point and K be the length of the roadway, density k for a single lane stream is defined as follows:

$$\rho = \frac{N}{K} \tag{2.6}$$

2.2 Traffic engineering

2.2.1 Traffic light controllers

Traffic light controllers are implemented for the purpose to allow alternatively the movement of the current traffic flows at an intersection, to facilitate traffic and pedestrian management. The standard method is based on *phases*, which are the specific combinations of movements that receive simultaneous priority. A phase is the portion of the synchronized signal's cycle assigned to these sets of movements. Each phase is divided in *intervals*, which are the length of all the allowed signal movements that remain unaltered. A phase is typically composed on three intervals: green, yellow and red as shown in Figure 5.

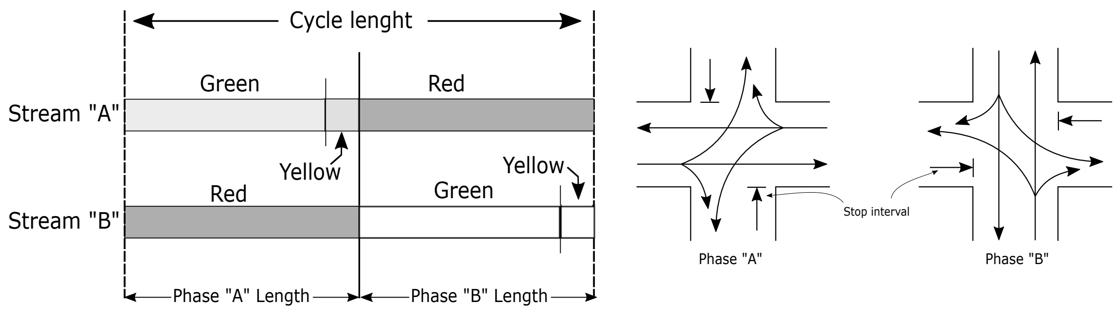


Figure 2.3: Phase-Cycle traffic light diagram

2.2.2 Control types

Traffic signal controls are implemented to reduce or eliminate conflicts at a intersection by allocating the usage of time among the streams at the intersection. The logic for this allocation of time vary from simple time-based methods to complex algorithms which calculate the allocation in real time based on traffic demand. There is a wide range of approaches by which signal phasing and timings can be controlled. Controllers can be categorized as fixed-time, actuated, or adaptive [KPR+].

Fixed-time control is the most basic type of control logic that can be implemented. In fixed-time control, the cycle length and the phase switching are set as fixed values, as well as the durations of each interval within each phase. Historical flow data is typically used to determine appropriate values for these parameters. The key attribute of fixed-time control is that the logic is not demand-responsive, meaning that the signals operate without regard to fluctuations in traffic demand.

Actuated control uses demand-responsive logic to control signal timings, with phase durations set based on traffic demand as registered by detectors on the intersection. The most common feature of actuated control is the ability to extend the length of the green interval for a particular phase. Three parameters are required: the minimum green time, the extension time, and the maximum green time. The *extension time* is often referred as the *gap time* because the interval will be extended if a vehicle has a time headway from the vehicle in front, that is less than this value. The extension time is usually set to be the travel time from the point of detection to the intersection, as this will extend the interval for just enough time, for a detected vehicle to be able to cross the intersection. However, the extension time can also be set to vary as a function of the elapsed green time, usually reducing the extension time as the maximum time is neared. Another common feature of actuated control is the ability to skip a phase if no demand, for that phase, is present. If there are no vehicles waiting for any movements of a certain phase (as determined by the detectors at the stop lines), the controller can skip over that phase and move directly to the next phase in the sequence.

Adaptive control, like actuated control, responds to traffic demand in real time, but its logic can change more parameters than just interval length. The most common adjustments made are to the cycle time and to the phase splits, which determine the allocation of the cycle time to the various phases. These strategies rely on traffic data collected for each approach upstream of the intersection, and this data is used by the controller to estimate conditions at the intersections and to respond to them in real-time. This logic is often optimization-based, allocating green time to maximize measures such as vehicle throughput or to minimize measures such as vehicle delays or stops. Adaptive logic can also be predictive, projecting future conditions based on detector inputs as well as historical trends and adjusting signal settings accordingly. Adaptive traffic control systems are becoming more widespread, both in application and in development.

2.2.3 Prefixed traffic light settings

Regarding to fixed-time control, the estimation of the effective green time could be seen as an optimization problem. If the total cycle length is known, the length of the amber and all-red periods can be subtracted from the total cycle length and end up with the total time available for green signal indications. However, for efficiency, the cycle length should be long enough to serve all of the critical movements, but no longer. If the cycle is too short, there will be so many phase changes during an hour that the time lost due to these changes will be high compared to the usable green time. But if the cycle is too long, delays will be lengthened, as vehicles wait for their turn to discharge through the intersection.

To solve this problem, Webster proposed a method to find the optimal minimum delay cycle.

Definition 6 Webster's optimum cycle. *Assuming that the effective green times of the phases were in the range of their respective flow ratio values, the optimal minimum delay cycle length is given by:*

$$C_0 = \frac{1.5L + 5}{1 - \sum_i^{n_p} Y_i}, \tag{2.7}$$

where C_0 represents the optimal cycle length (sec); L represents the total lost time (sec); n_p denotes the number of phases; and Y_i the critical flow ratio in a phase. Let q_i be the flow ratio (PCU/h) and s_i be the saturation flow (PCU/h), then Y_i is computed by $Y = \frac{q_i}{s_i}$, for a given lane.

Definition 7 Effective green time per phase. *Considering the optimal minimum delay cycle length, the effective green time per phase, denoted by e_p is computed by:*

$$e_p = \frac{Y_l}{\sum_i^{n_p} Y_i} e_c, \tag{2.8}$$

where $e_c = C_0 - L$ is the effective green time per cycle.

2.3 Fuzzy logic

Fuzzy logic is a form many-valued logic which is able to handle the concept of partial truth, where the truth value may range between completely true and completely false [NMP99]. This characteristic is used to computationally imitate human perception, which relies on the organization, identification, and interpretation of sensory information in order to represent and understand the environment [SGW11]. Its versatility have been used to develop intelligent technology to solve problems in many fields, such as robot control, traffic signal management, industrial control, and many other where it is not easy to find solutions using conventional mathematical models.

Fuzzy logic is based on the concept of fuzzy set, which is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership (characteristic) function which assigns to each object a grade of membership ranging between zero and one [Zad65] .

Definition 8 Fuzzy sets. *A fuzzy set A is a* membership function $f_A(x)$ *that maps the elements of a domain or universe X with the elements of the interval* $[0,1]$*:* $f_A : X \to [0,1]$*, 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.*

A fuzzy set A can be represented as a set of pairs of values: each element $x \in X$ with its grade of membership in A.

$$A = \{(x, f_A(x))|x \in X\} \tag{2.9}$$

Definition 9 Fuzzification *is the conversion of a precise quantity to a fuzzy quantity.*

Generally, the fuzzification of a real value is performed using intuition, experience and an analysis of the set of conditions associated to the system input variables. The most used fuzzifiers, are the based on triangular and trapezoidal functions:

- **Triangular function:** let L, C and R be real scalar values that delimit a fuzzy set A, and being C the input value that has the largest membership to A (see Figure 2.4), the membership function is computed by:

$$f_A(x) = max[min(\frac{x-L}{C-L}, \frac{R-x}{R-C}), 0]. \tag{2.10}$$

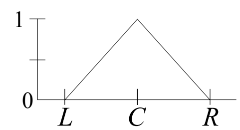


Figure 2.4: Triangular function

- **Trapezoidal function:** let L, U, b and c be the real scalar values that delimit a fuzzy set A, being b and c the boundaries of the range where the inputs have the largest membership to A (see Figure 2.5), the membership function is computed by:

$$f_A(x) = max[min(\frac{x-L}{b-L}, 1, \frac{U-x}{U-c}), 0]. \tag{2.11}$$

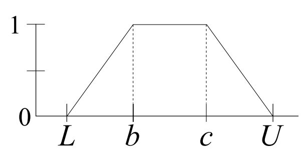


Figure 2.5: Trapezoidal function

Definition 10 Defuzzification *is the process of producing a quantifiable result, given fuzzy sets and corresponding membership degrees.*

Defuzzification can be performed in several ways; however, the most used defuzzification methods are the based on the called center of area or center of gravity.

- **Centroid of Area (COA) method.** This procedure is the most prevalent and physically appealing of all the defuzzification methods [Sug85, Lee90]; it is given by the algebraic expression:

$$COA = \frac{\int f_A(a_c) \cdot a_c \mathrm{d}a_c}{\int f_A(a_c)\mathrm{d}a_c}, \tag{2.12}$$

  where $\int$ denotes an algebraic integration.

- **Weighted average (WA) method.** The weighted average method is the most frequently used in fuzzy applications since it is one of the more computationally efficient methods [Ros95]. The only restriction is that the output membership functions must be symmetrical. It is given by the algebraic expression:

$$WA = \frac{\sum f_A(\bar{a}_c) \cdot \bar{a}_c}{\sum f_A(\bar{a}_c)}, \tag{2.13}$$

  where $\sum$ denotes the algebraic sum and where $\bar{a}_c$ is the centroid of each symmetric membership function, for example C (see Figure 2.4). The weighted average method is formed by weighting each membership function in the output by its respective maximum membership value.

Definition 11 Linguistic variables. *Are variables whose values are represented using* linguistic terms *(*low*,* medium*,* high*,* very high*, etc.). The meaning of these terms is determined through fuzzy sets [Zad73]. A linguistic variable is characterized by* (v, T, X, g, m)*, where:*

- v *is the name of the variable*
- T *is the set of linguistic terms of* v
- X *is the universe of discourse of the variable* v
- g *is a syntactic rule to generate linguistic terms*

- *m is a syntactic rule that assigns to each linguistic term t its own meaning m(t), which is a fuzzy set in X*

2.4 Fuzzy inference system

A fuzzy inference system (FIS) is a way to transform an input space in an output space, using fuzzy logic. The FIS attempts to formalize the reasoning of human language, using the fuzzy logic [Lee90].

Generally, a FIS has four modules as depicted in Figure 2.6:

- *Fuzzification module*: transforms the system inputs, which are crisp numbers, into memberships to fuzzy sets. This is done by applying a fuzzification function.
- *Knowledge base*: stores *if-then* rules provided by experts.
- *Inference engine*: simulates the human reasoning process by making fuzzy inference on the inputs and *if-then* rules.
- *Defuzzification module*: transforms the memberships to fuzzy sets, obtained by the inference engine, into a crisp value.

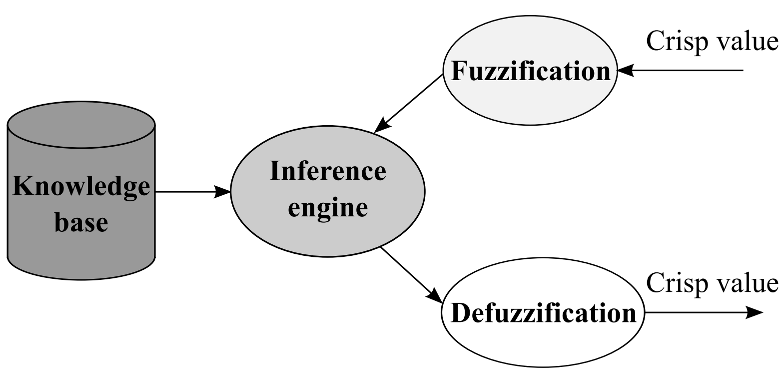


Figure 2.6: Typical FIS modules

The most used FIS are the Mamdani type [MA75] and the Sugeno type [TS85].

- In the Mamdani systems the inputs and the outputs of the inference engine are fuzzy, for example:

$$If\ x\ is\ A\ and\ y\ is\ B\ then\ z\ is\ V$$

- In the Sugeno systems, the inputs of the inference engine are fuzzy and the output is "crisp", for example:

$$If\ x\ is\ A\ and\ y\ is\ B\ then\ z = f(x, y)$$

2.5 SUMO (Simulation of Urban Mobility)

SUMO (Simulation of Urban Mobility) is an open source, highly portable, microscopic road traffic simulation package designed to handle large road networks [KEBB12]. It is mainly developed by employees of the Institute of Transportation Systems at the German Aerospace Center (DLR) [oTS17].

SUMO is licensed under the GPL. It allows to simulate how a given traffic demand, which consists of single vehicles, moves through a given road network. The simulation allows addressing a large set of traffic management topics. It is purely microscopic: each vehicle is modelled explicitly, has an own route, and moves individually through the network. Simulations are deterministic by default but there are various options for introducing randomness.

The software works on command line or can be used with the additional SUMO-GUI application which provides a graphical user interface to the simulation. Furthermore, SUMO has a list of additional tools like TraCI (Traffic Control Interface). TraCI giving the access to a running road traffic simulation, it allows to retrieve values of simulated objects and to manipulate their behavior "on-line". It can be used for adaptive traffic light control by a python script, for example.

SUMO is used in several traffic light research projects of the Institute of Transportation Systems at (DLR) like VITAL [OW11],[EOW15a]. In this VITAL project SUMO was used not only for the evaluation of new control approaches but also for the real-time compensation of missing detector information for the control approaches in the real field test. There are also thoughts to remote a real traffic controller directly by using SUMO and TraCI.

2.5.1 Emission model

The Handbook Emission Factors for Road Transport (HBEFA) [MK17], provides emission factors for all current vehicle categories (passanger vehicles, heavy duty vehicles, busses, etc), each divided into different categories, for a wide variety of traffic situations. SUMO is able to simulate vehicular pollutant emissions based on this database application. HBEFA contains information about other pollutants, as the following ones:

- Carbon monoxide (CO).
- Carbon dioxide (CO2).
- Nitrogen oxides (NOx), like nitric oxide (NO) and nitrogen dioxide (NO2).
- Particulate matter (PMx).
- Hydrocarbon (HC).
- Fuel consumption.

These emissions are considered the most problematic pollutant substances since are toxic (CO), cause cancer (PMx), are responsible for ground-level ozone increase and smog generation (NOx and HC) or are greenhouse gases (CO2). The implementation of this model into simulations allows to gain insights into the effects of the evaluated proposal on the environment, by measuring the impacts of ITS solutions or regulatory actions on the environment.

Chapter 3

Related work

3.1 Taxonomy of traffic light control systems

Traffic lights as traffic regulators are more efficient whether they can increase traffic flow and decrease waiting times [LMH+08]. Therefore, a traffic light controller is focused on to allocate the usage of time among the streams at the intersection. Depending on how such allocation is performed, controllers can be categorized as fixed-time, actuated, or adaptive [KPR+]. Based on this categorization, in this chapter it is presented a taxonomy of the recent approaches related to traffic light control systems. Figure 3.1 depicts the taxonomy of the approaches that are described in the following sections.

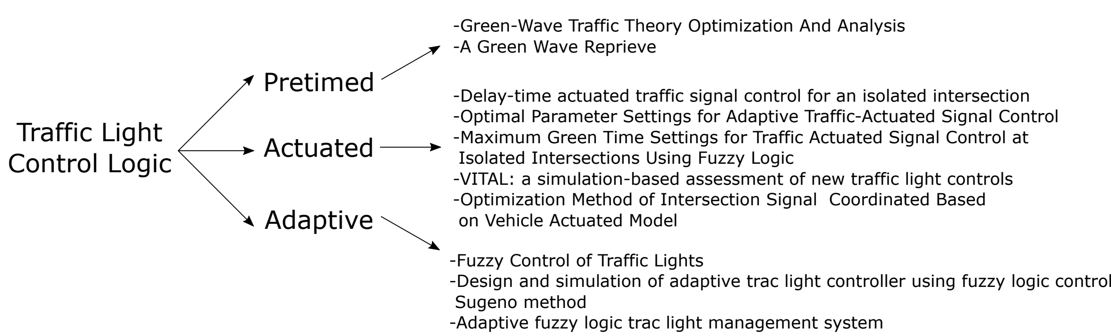


Figure 3.1: Taxonomy of traffic light control systems

3.2 Controllers based on fixed-time

Pretimed control is the most basic type of control that can be implemented in a traffic light controller. In pretimed control, the cycle length and the phases duration are fixed values, as well as the durations of each interval within each phase. The main drawback of pretimed control is that the operation is not reactive to the traffic demand, meaning that the signals need to be optimized for a regular operation.

3.2.1 Green-Wave Traffic Theory Optimization and Analysis

This method analyzed by Xiaoping Wu et al. [WDDM14], focuses on the optimization of the green wave method by using use two-phase cycles for the traffic lights of three-way and four-way intersections. To achieve this, authors propose the prohibition of left turn at intersections. Therefore, only straight traffic (main traffic direction) is remained, reducing the traffic flow directions within the intersection. Based on such constraints, each of the two-phase cycles is adjusted in such a way that be a signal point to coordinate the remaining green wave. This configuration allows the uniformity of traffic by the green wave method, reducing vehicle emissions, fuel consumption and improving road safety at intersections.

Due to the restriction of the left turns it is necessary to modify the infrastructure to allocate the new traffic flows, of left turns, into U-turns or additional lanes in the main stream. However this modifications are not always possible for all urban networks due the geometrical constraints. Moreover, the rerouting may cause longer travel times and increasing of other overheads.

3.2.2 A green wave reprieve

This work was proposed by Blaise Kelly [Kel12] and is focused on to reduce the stops and starts stages, which are the most wasteful stages of driving. To achieve this, the author created an origin-destination matrix of a corridor, of the Manchester city network, aggregated with the flow profiles of each of the involved intersections. Then, based on such a matrix and using the modeling language SCOOT [BKS08], a series of green waves along a main corridor were coordinated according to the respective flow profiles. Finally, the green waves of the signals on opposite sides of the network, which intersect the main corridor, were coordinated considering the direction of the green waves of the main corridor as the base temporal reference. In this way, working with a traffic simulation model, the author showed that it was possible to reduce excessive consumption of energy of start-stop phases through the coordination of multiple green waves. The results of this research were the reductions of emissions of CO2, nitrous oxide NOx and PM10 in a meaningful way, achieving an improvement in the reduction of travel times, fuel consumption and higher levels of service. Despite the findings of these approach, the model was only tested 5 times from 10 pm to 7 am, since the traffic flow profiles were more affordable than the obtained in other periods.

3.3 Actuated controllers

The actuated control differs from pretimed in that signal phases can be extended dynamically reacting to oncoming traffic. Traffic reactive method is used to control signal timings and phase durations according on the detections registered by sensors deployed upstream the intersection. It is generally used for an isolated applications, where the traffic light control operates independent of any other traffic light. Generally, three parameters are required for this type of control: the minimum green time, the extension time, and the maximum green time. Regardless of demand, green is configured for at least the specified minimum duration. If a vehicle is detected and an extension time was applied, it is possible to apply an additional extension; in some times producing longer cycle lengths.

3.3.1 Delay-Time Actuated Traffic Signal Control for Isolated Intersections

This approach proposed by Robert Oertel, and Peter Wagner [OW11] consists of control traffic signals at isolated intersections by capturing vehicles' delay times and utilize them to adjust the green times. Similar to a traditional vehicle actuated control a queue clearing policy is applied. Within the bounds of a minimum and a maximum green time, a running green phase is terminated as soon as the accumulated delay on an approach is dissolved. The delays needed for this type of control can be measured by video processing, probe vehicle data and vehicle infrastructure integration. Delay always occurs when the current speed of a vehicle has been below a maximum achievable speed. Sources of delay times differ in the penetration rate of actually captured vehicles.

This control method consists in the extension of the green phase according to the detected queue length, upstream the intersection, and the delays between platoons of vehicles. In these sense, a platoon is a coordinated group of vehicles traveling with a similar speed.

Considering the measured delay the green phase is extended in such a way that a complete vehicle platoon can cross the intersection, dissolving the queue. Green phase is interrupted as the delay interval reaches the intersection. Therefore the green phases are bounded by the delay intervals. Their objective is to minimize delay times for motorists by allocating green times in a preferably efficient way.

To assess the quality of the new method, a simulation study was performed which demonstrates that it outperforms the traditional approaches. The delay-based control is a good approach for large and medium demands, since utilizes the many new data surveys available, like video processing, probe vehicle data and vehicle infrastructure integration. However, this sources requirement is the main drawback of this approach, since it requires sophisticated hardware to accurately retrieve the delays and queue lengths.

3.3.2 Optimal Parameter Settings for Adaptive Traffic-Actuated Signal Control

Xing Zheng and Lianyu Chu [ZC08] proposed a real-time signal control to optimize time parameters based on the estimated flow for each signal phase in the upcoming cycle, by predicting the future arrival flow, at target intersections, according to available signal timing information.

The proposed control model incorporates a traffic flow prediction process to estimate approach volumes based on the outflows from upstream intersections, and to predict turning movements at the target intersection according to the turning ratios in previous cycles. Thus, the future flow rate associated with each phase at an intersection is decided by multiplying the estimated approach flow and the corresponding turning proportion.

Appropriate phase timing parameters are chosen in accordance with these estimated flow rates. Three parameters are optimized in the proposed model: unit extension, minimum green and maximum green. This model establishes a relationship among the parameter settings. Optimal minimum green and maximum green are determined based on the optimized unit extension. The unit extension is determined first by solving a nonlinear optimization problem. Minimum green is formulated as a function of unit extension based on the queue theory, and is expected to be a green period required to clear the queue of vehicles formed at the stop line.

The proposed signal control model was tested using the microscopic simulation package Paramics to test it against of various algorithms and evaluation of various

Intelligent Transportation Systems. Authors found that the network under the proposed control performs better in all three scenarios: drivers spend less time in the network, but travel more distance with improved traveling speed. The control model was formulated based on Poisson arrival pattern, various traffic demand levels have different impacts on the optimal parameter settings.

In the real world, however, traffic conditions in a network are not consistent with the Poisson process as hypothesized in this approach. Therefore, alternative flow patterns needs to be taken into account. The major disadvantage of these systems is that they have a limited traffic-responsive behavior during significant traffic flows because of the limited incremental changes of signal settings.

3.3.3 Maximum Green Time Settings for Traffic Actuated Signal Control at Isolated Intersections Using Fuzzy Logic

In this paper MJ Shirvani Shiriand and Hamid Reza Maleki [SM17], defined maximum green times determined by fuzzy control approaches. First, it monitors the whole intersection traffic conditions and then dynamically adjusts maximum green times. The advantage of the proposed approach is its capability to adjust maximum green times which are responsive to real time traffic condition in isolated intersections. The fuzzy controller was applied to dynamically determine traffic actuated control maximum green times. The developed method accounts for sudden changes and fluctuations of the traffic, traffic intensity of the waiting for service vehicle queues, and the complexity of traffic behavior joined with difficulty of exact modeling of maximum green times impact on signal control performance.

This paper assumes that the length of vehicles queue on each approach is available from traffic sensors. The basic timing parameters of each phase include unit extensions, minimum, and maximum greens. At the beginning of any phase green duration, a specified minimum green is devoted to the green duration. If the traffic demand is insufficient, the green time can be extended to the maximum green in several steps. After green extension, the signal group can go to red or hold green until a conflicting phase receives green.

The maximum green represents the largest interval time which is associated with any specified phase. Maximum green is applied to limit the delay of temporary stopped vehicles as well as guarantee the maximum possible cycle length. It also prohibits undesirable long green times due to continuous demands. For this approach fuzzy logic was applied in order to achieve a way to manage the uncertainty related to the behavior of drivers, traffic flow, intersection service rate, and complex relation between maximum green times and signal control performance.

The proposed fuzzy control is able to resolves the response variations of the predefined fixed controllers. Furthermore, this controller distribute green split based on the total condition in an isolated intersection. Simulation results show the efficiency of the proposed method compared with the traditional traffic actuated control method. Nevertheless the main disadvantage of this approach is that requires to know the queue lengths upstream the intersection, which is not always feasible to measure.

3.3.4 VITAL: a simulation-based assessment of new traffic light controls

Jakob Erdmann et al. [EOW15b], developed a control method that do not need a loop detector at all, but can use data provided by the vehicles driving across the intersection. These data consists of the trajectory of each of the vehicles near the intersection, which can be retrieved by vehicle to infrastructure communication (V2X) or by video processing.

The proposed scheme was named delay-based intersection control. The delay-based approach consists in using the speed of the vehicles and assuming that the traffic light controller has access to the speeds and positions.

A simulation with SUMO has been set-up to test the approach (data-acquisition and traffic signal control). For this, firstly the phase was optimized and based on this optimization it was used to test the new method against it. The optimized approach and the new method were compared through four different demands. The demands have been extracted from the data of the intersection, and the four scenarios are a low demand scenario (half the daily average, normalized per hour), a medium demand scenario (daily average), a large demand scenario (the peak hour demands) and a very large demand scenario which is 1.5 times the peak hour demand.

In simulations, this delay-based traffic actuated works better than the classic headway-based methods. The controller outperforms the classic traffic actuated controllers only for large enough demand. However, these gains depend on the scenarios for big demands. Moreover, it requires at least one detector per connection to be installed, for small demands, it does not fully utilize the detailed demand pattern since it reacts immediately to the headways, while for large demands it has difficulties to measure a queue length from a free-flow scenario, since they become very similar.

3.3.5 Optimization Method of Intersection Signal Coordinated Control Based on Vehicle Actuated Model

Chen Zhao-Meng et al. [ZMXMWX15] proposed a coordinated control method for variable cycle time green wave bandwidth optimization integrated with traffic-actuated control. For the coordinated control, green split is optimized in real time by the measured presence of arriving and/or standing vehicles in each intersection and simultaneously green waves along roads are guaranteed. Specifically, the dynamic bound of green wave is firstly determined and is further adjusted by two algorithms. These two algorithms called green early-start and green late-start accommodate the fluctuations in vehicle arrival rates in each phase.

The green early-start algorithm adjusts the traffic-actuated green wave control as follows. If the running time of non coordinated phase does not reach the initial design time, the saved green time is assigned to the coordinated phase for obtaining greater green wave bandwidth. Meanwhile, its start time of the green light in the coordinated phase is moved up.

The green late-start algorithm adjusts the system to the randomness and variability of the traffic flow, in terms of the non-coordinated phase in traffic-actuated control if the initial allocation of green time may be lower than the actuated green time. Therefore, the green light time is extended to meet the traffic demand in the non-coordinated phase. When the sum of all the green times for non-coordinated phase is larger than the sum of those, at the initial allocation time, the start time of green light in coordinated phases will have to be postponed.

This method improves green time, expands green wave bandwidth, and reduces queuing, compared to the original green wave method, consequently leading to an increase in the road network efficiency. However, this method requires to compute the adequate minimum and maximum dynamic bounds for a whole corridor, including different intersections, which is not always feasible, since traffic conditions are exposed to abrupt changes cause by extraordinary events.

3.4 Adaptive controllers

An adaptive controller is a system with adjustable inputs and outputs with a mechanism for altering them with a self-adjusting strategy. For a traffic light, however, self-adjustment rely on the real-time estimation of the resulting traffic behavior after a variation of the periods/phases. Hence, a fair adjustment requires a decision-making process similar to the qualitative judgment done by a traffic officer.

Fuzzy logic have been widely used to develop applications, intended to imitate human though processes, to find solutions in complex systems where it is not easy to find solutions using mathematical models. Based on fuzzy logic, adaptive traffic light controllers have been developed by qualitatively modeling the traffic situation, around an intersection, and the corresponding variations of lights durations. In the following sections, some adaptive controllers, based on fuzzy logic, are described.

3.4.1 Adaptive Fuzzy Control to Design and Implementation of Traffic Simulation System

Ibrahim and Aldabbagh proposed a methodology and a generic engine which allows to build fuzzy controllers to develop adaptive traffic lights [IA16]. Their engine is oriented to find short-term optimizations for green phase durations that constantly are adjusted according to the traffic flow variations. The developed controllers requires the deployment of two sensors: one at the head of the lane queue and another upstream the lane. The goal of this deployment is to obtain real-time arrival frequencies and queue lengths, as the input of the controller. These measurements are transformed into natural language words, called linguistic variables, in order to qualitatively classify traffic conditions through vague terms such as *very short*, *short*, *medium*, *high* and *very high*.

In this way, the vague terms are used to qualitatively classify traffic conditions and deduce an appropriate green phase duration. Traffic conditions are classified into vague terms by using previous knowledge about the behavior of the intersection. The deduced phase duration is evaluated by simulating the intersection with the current traffic conditions, by using the SUMO microscopic simulator[KEBB12]. With the simulation results it is computed a new phase duration suitable for the resultant traffic state. This processes is iteratively executed each traffic light cycle.

Following this methodology users can calibrate the engine, modifying linguistic variables and range values, in order to optimize the output parameters for the traffic fuzzy controller. Simulations were carried out to show the performance of the developed controllers, obtaining reductions on waiting times, vehicle emissions and fuel consumption. The main drawback of this approach is that is based on the assumption that the is always feasible to measure the queue lengths. In addition, the system is designed to estimate phases extensions. However, phase extensions could lead in to the increase of waiting times for the involved streams.

3.4.2 Fuzzy Control of Traffic Lights

Robert Hoyer and Ulrich Juhar [HJ94] proposed to use fuzzy logic to control traffic lights for an intersection with twelve addresses or movements. Depending on traffic situations the fuzzy rule set decides on the activation of a two-state, three-state or four-state control. In this way the merits of each of these control schemes are combined.

The controller operates with then fuzzy input variables and two output variables. Traffic density of different lanes and elapsed time since last state change were chosen as inputs. Outputs are on the one hand, the extension of time after the precalculated moment of state change, and on the other hand, the selection of next state. The varying linguistic fuzzy logic controllers are; density of traffic, intensity of traffic, relative performance, space of time between vehicles, congestion, average speed, etc.

The method works by time intervals of ten seconds with the input and output variables decide if it should extend the period of the green phase. With the help of five rules for each period of ten seconds in which the variables are modified in the period of decision. There are three levels of hierarchy proposed in this study, the operational level, the tactical level and the strategic level. Strategic or novel macroscopic level refers to the total set of the network or parts of it. The one which activates different stages plans an extended period depending on the time or the density of the traffic. The tactical or microscopic level is a subordinated level. It reacts more quickly to changing traffic situations. On the operational level the presence of every single car in front of the traffic light is considered.

Fuzzy logic helps to solve the typical problem presented at the intersections that is the time control of distance between vehicles, to decide if the green phase should be extended or shortened. The objective of knowing the time space between vehicles is to contain and group vehicles in the green wave to improve traffic flow using fuzzy logic controller. Another problem is the adaptability of the phases of control, due to the changeable conditions of the traffic flow throughout the road network, optimized signals with phase with settings of parameters (cycles, length of phase and delay times) are assigned to certain situation. According to the distribution of the traffic control on the controller at the strategic level it can successfully be controlled by fuzzy logic.

The result obtained from this approach, was an improvement of the efficiency of the traffic control in comparison to the current systems in use, achieving flexible change of phase change, reduction of time losses. However the large number of input variables needed for the system sometimes are not feasible to measure. Another drawback is that since the outputs are based on time extensions and multiple state configurations, the approach may produce longer waiting times due to a short interval sampling.

3.4.3 Design and simulation of adaptive traffic light controller using fuzzy logic control Sugeno method

Prasetiyo et al. proposed an adaptive traffic light controller using fuzzy logic with a Sugeno method [PWS15], in order to determine the length of green time at an intersection. This system has two input variables, number of vehicles arriving in to the green phase and queue length at the segment of a red phase. The output of this system is the decision whether to extend or not the green time during the phase in the green phase. This method relies on the type of output membership function as they are linear or constant values. This system is used as a decision maker in controlling the traffic lights depending on the traffic flow condition at the intersection. The duration of the green time is a decision which is took based on the rules in the fuzzy logic control system.

Simulation was carried out by creating an application that consist on two systems, which are the fuzzy system and fixed time system. This application is developed to compare the performance between the adaptive traffic light controller using fuzzy logic control Sugeno method and traffic light control system using fixed time. The results shown that the system using fuzzy logic control Sugeno method can work adaptively according to the traffic condition around the intersection.

However, using this method result in the increase of waiting times, this because of the longer extensions on the green phase. Moreover, simulation was carried out using singles lanes and very ideal vehicular behavior.

3.4.4 Adaptive fuzzy logic traffic light management system

I. Adam et al. analyzed the traffic light switching scheme to adapt the inconsistency in number of vehicles arrivals addressed by fuzzy logic controller [AWY+14]. The adaptive traffic light is responsible for controlling the duration of green light timing scheme according to traffic conditions. Using fuzzy logic system, the green light timing will be determined by terms and rules set.

The controller was designed for an isolated single lane three junctions with to input variables to the traffic light controller, number of vehicles and percentage of vehicles. The output fuzzy variable as the green light timing scheme that will vary according to the number of vehicles approaching the intersection.

The fuzzy logic controller formulates the output based on the input and fuzzy rules to come out with ideal green light time scheme. The performance of the controller is evaluated by comparing it with the fixed time traffic light system. This was carried out using mathematical models to simulate the real-time traffic behavior on the two systems. They concluded that using fuzzy logic system contributes on the green light timing scheme providing better performance in terms of total waiting times as well as total moving time.

However, the simulation environment considers only single lanes and no light/right turns ignoring real life traffic behavior that could affect directly to the fuzzy logic traffic light system performance.

Chapter 4

Adaptive fuzzy logic traffic light controller

In this chapter it is presented an adaptive traffic light controller, which is based on an inference system that imitates the human perception to dynamically estimate the appropriate signal cycle length, according to the traffic flow rate registered over the upstreams of an intersection. The developed inference system use fuzzy logic to relate the traffic flow measurements to the cycle duration under the following reasoning:

"The highest the traffic flow, the larger the cycle lenght".

4.1 System model

For this work it is considered a five-way regular intersection with the following characteristics:

- The five crossing roads are denoted as r_1, r_2, r_3, r_4 and r_5.
  - r_1 is a two-lane dual roadway with west-east and east-west traffic.
  - r_2 and r_3 are two-lane single roadways with north-south traffic.
  - r_4 and r_5 are two-lane single roadways with south-north traffic.
- Left turn it is allowed in roadway r_5, allowing the incorporation of vehicles to r_1, r_2, r_3, r_4.

- Right turn it is allowed in roadway r_1, allowing the incorporation of vehicles to r_2 and r_3.
- Left turn it is allowed in roadway r_1, allowing the incorporation of vehicles to r_4 and r_5.
- Roads are grouped as three streams A, B and C.
  - Stream A is composed by r_2, r_3 and r_4.
  - Stream B is composed by roadway r_1.
  - Stream C is composed by roadway r_5.
- For each traffic light it is considered three seconds for amber light.
- Three upstreams sensing points, at streams A, B and C, located up to 190 m before the intersection, similar to the deliberative traffic light proposed to Zapotecatl et al. [ZRG17] (see Figure 4.1). For sensing the traffic flow it is assumed the deployment of on-road traffic counters such as piezoelectric sensors, magnetometers or radars [CCV04, CW99].

Figure 4.2 shows the configuration of the intersection. The current traffic light configuration has 3 phases. Phase I controls the movements of flow on stream A. Phase II represents the movements of stream B, being this phase being the most critical. Phase III represents the incorporation of a left turn from stream A to the different lanes at the junctions.

4.2 Fuzzy inference system

The proposed adaptive controller is a control system based on a Mamdani fuzzy inference system (see section 2.4) that analyzes the flow rates at streams A, B and C (retrieved by on-road sensors) as its three analog input values. The single output of the control system is the value for the traffic light cycle length D.

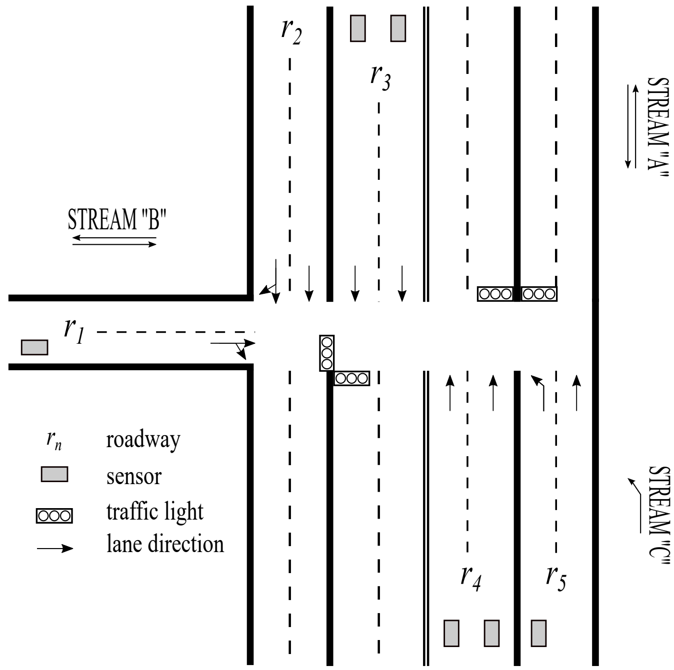


Figure 4.1: System model

4.2.1 Fuzzification process

For the fuzzy system, it is necessary to interpret the output and the three analog input values as degrees of membership to different fuzzy sets. To achieve this, the following four linguistic variables are defined:

- Flow A (FA), is the variable whose universe of discourse is the average number of vehicles per time period over lanes of stream A.
- Flow B (FB), similar than FA, refers to the traffic flow on stream B.
- Flow C (FC), is the average number of vehicles per time period on the left lane of stream C.
- Cycle length (D), whose universe of discourse is the duration of the set of phases which controls the vehicle movements allowed in an intersection.

For the Mamdani fuzzy inference system, the inputs and the output are fuzzified using triangular membership functions according to Definition 4.2.1. For each

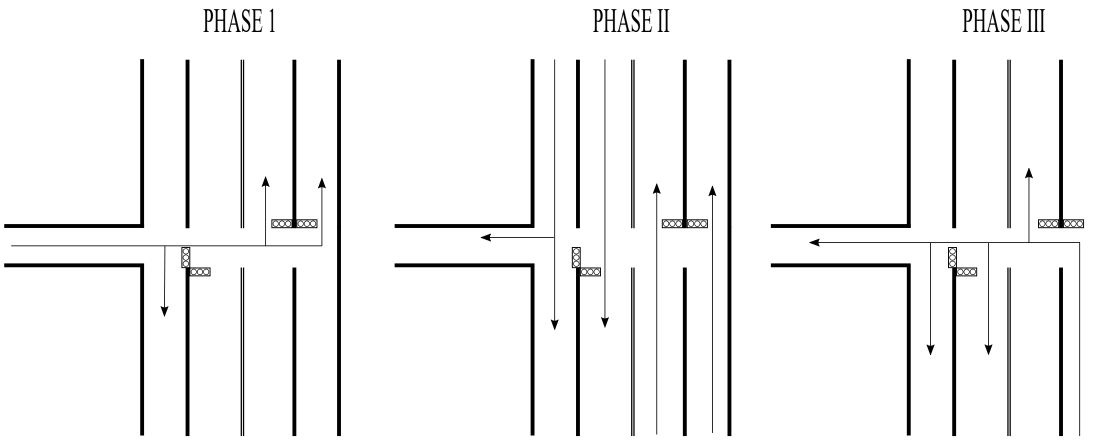


Figure 4.2: Current traffic light phases

linguistic variable, five triangular membership functions (fuzzy sets), related to five linguistic terms, are defined as follows:

- for flow A: VL related to *very low*, L related to *low*, M related to *medium*, H related to *high*, VH related to *very high* ;
- for flow B: VL related to *very low*, L related to *low*, M related to *medium*, H related to *high*, VH related to *very high* ;
- for flow C: L related to *low*, M related to *medium*, H related to *high* ;
- and finally for the cycle length D: VS related to *very short*, S related to *short*, A related to *average*, E related to *extended*, VE related to *very extended*.

Considering these linguistic terms, the different fuzzy sets are delimited as shown in Table 4.1. The values of the intervals A_0 to A_6, B_0 to B_6, C_0 to C_4 and D_0 to D_4 must be chosen using previous knowledge about traffic volumes under certain traffic light configuration. Thus, intervals A_0 to A_6, B_0 to B_6 and C_0 to C_4 are determined by the number of vehicles per time period entering stream A, B and C, respectively; while D_0 to D_4 are the optimal cycle lengths, calculated by the Webster method (see definition 6) according to different traffic conditions.

Table 4.1: Values of variables used in definition of membership functions

Universe of discourse	Set	L	C	R
Flow A	VL	A_0	A_1	A_2
	L	A_1	A_2	A_3
	M	A_2	A_3	A_4
	H	A_3	A_4	A_5
	VH	A_4	A_5	A_6
Flow B	VL	B_0	B_1	B_2
	L	B_1	B_2	B_3
	M	B_2	B_3	B_4
	H	B_3	B_4	B_5
	VH	B_4	B_5	B_6
Flow C	L	C_0	C_1	C_2
	M	C_1	C_2	C_3
	H	C_2	C_3	C_4
Cycle length D	VS	–	D_0	D_1
	S	D_0	D_1	D_2
	A	D_1	D_2	D_3
	E	D_2	D_3	D_4
	VE	D_3	D_4	–

In this way membership functions are used symmetrically to describe the different classifications of the traffic volumes into fuzzy sets. This means that each fuzzy set includes all of those similar measurements within the universe of discourse.

The graphical representations of the fuzzy sets are shown in Figure 4.3.

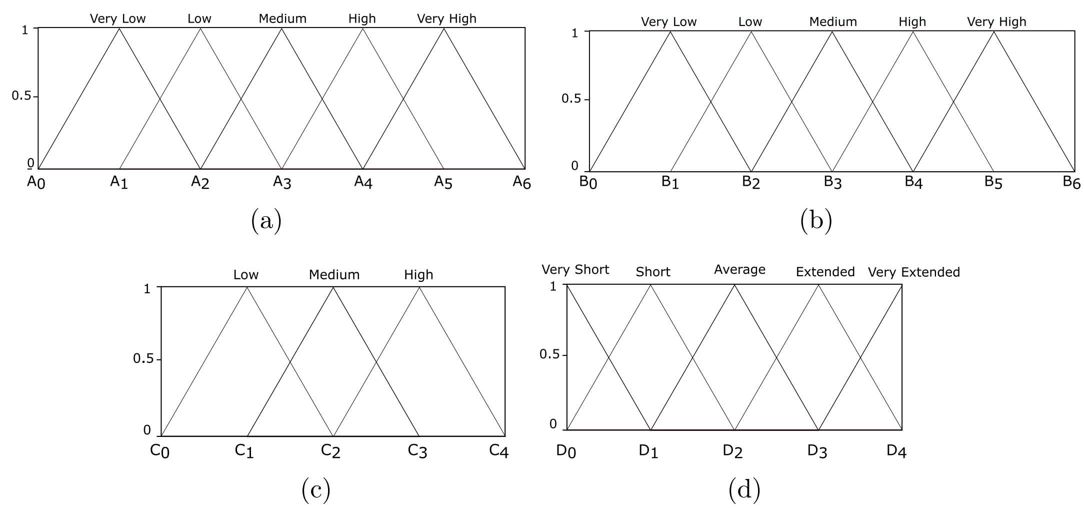


Figure 4.3: Fuzzy sets for the four linguistic variables: (a) flow rate in stream A, (b) flow rate in stream B, (c) flow rate in stream C, (d) cycle length D

4.2.2 Fuzzy inference and defuzzification

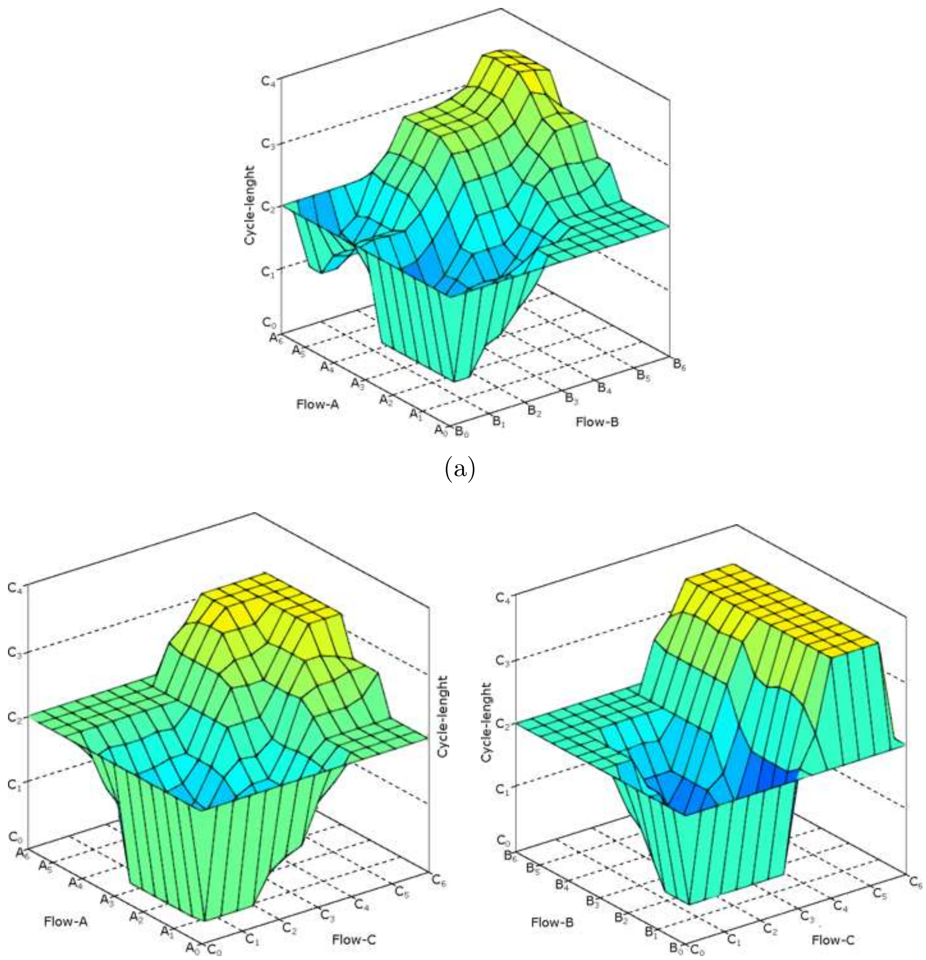
Once the inputs and outputs variables were fuzzified, the cycle length is determined by a Mamdani fuzzy inference system. The Mamdani system consists of 75 if-then rules that have been defined to include all possible scenarios for each cycle length. The 75 combinations of flow rates are shown in Table 4.2. Each row of the table 4.2 specifies a rule, where Flow A, Flow B and Flow C are the fuzzy inputs and Cycle is the fuzzy output. For example if Flow A is medium (M), Flow B is very high (VH) and Flow C is low (L) then the cycle length is extended (E).

The outputs of the inference system are linguistic terms, therefore, it is necessary to translate such outputs into numerical values through a defuzzification process. For this work it was chosen the Weighted Average method (see Definition

Table 4.2: Inference rules

Rule	Input			Output	Rule	Input			Output
	Flow A	Flow B	Flow C	Cycle		Flow A	Flow B	Flow C	Cycle
1	VL	VL	L	VS	38	M	M	M	A
2	L	VL	L	VS	39	H	M	M	A
3	M	VL	L	S	40	VH	M	M	E
4	H	VL	L	A	41	VL	H	M	A
5	VH	VL	L	A	42	L	H	M	A
6	VL	L	L	VS	43	M	H	M	E
7	L	L	L	VS	44	H	H	M	VE
8	M	L	L	S	45	VH	H	M	VE
9	H	L	L	A	46	VL	VH	M	S
10	VH	L	L	A	47	L	VH	M	A
11	VL	M	L	VS	48	M	VH	M	E
12	L	M	L	VS	49	H	VH	M	E
13	M	M	L	S	50	VH	VH	M	VE
14	H	M	L	A	51	VL	VL	H	S
15	VH	M	L	A	52	L	VL	H	S
16	VL	H	L	A	53	M	VL	H	A
17	L	H	L	A	54	H	VL	H	A
18	M	H	L	E	55	VH	VL	H	E
19	H	H	L	E	56	VL	L	H	S
20	VH	H	L	VE	57	L	L	H	A
21	VL	VH	L	A	58	M	L	H	A
22	L	VH	L	A	59	H	L	H	A
23	M	VH	L	E	60	VH	L	H	E
24	H	VH	L	E	61	VL	M	H	A
25	VH	VL	L	VE	62	L	M	H	A
26	VL	VL	M	VS	63	M	M	H	A
27	L	VL	M	S	64	H	M	H	E
28	M	VL	M	A	65	VH	M	H	VE
29	H	VL	M	A	66	VL	H	H	A
30	VH	VL	M	A	67	L	H	H	A
31	VL	L	M	VS	68	M	H	H	E
32	L	L	M	S	69	H	H	H	E
33	M	L	M	S	70	VH	H	H	VE
34	H	L	M	A	71	VL	VH	H	A
35	VH	L	M	A	72	L	VH	H	E
36	VL	M	M	VS	73	M	VH	H	E
37	L	M	M	S	74	H	VH	H	VE
–	–	–	–	–	75	M	M	M	A

10) since it have been defined symmetrical membership functions. Therefore, by defuzzification the linguistic terms, obtained from the inference, the magnitude of the inferred cycle length is established in seconds. The overall input-output surface corresponding to the inference systems is depicted in Figure 4.4.



(a)

(b)

(c)

Figure 4.4: FIS input/output variables using centroid defuzzification method

4.3 Adaptive mechanism

The fuzzy engine computes a proper cycle length according to a specific traffic flow measurement. However, during an operational day, traffic flow behavior is constantly changing. Therefore, it is necessary that the traffic controller be able to dynamically change its configuration every time interval.

To compute a new configuration signal each traffic light cycle would be not feasible and efficient by two reasons; on the one hand, short time evaluations periods would lead to produce short cycles lengths caused by anticipated estimations, on the other hand, long time evaluations periods could miss the dynamism of traffic, causing longer waiting times or time losses.

To solve this problem, for the controller it was designed an adaptive mechanism, which performs the traffic lights reconfiguration every n_C cycles, where $3 \leq n_C \leq 10$, which could be represented a time interval between 30 and 60 seconds. This mechanism is composed by three stages that are described below.

1. The first stage relies on to read the traffic flow measurements from the involved streams. These measurements can be obtained from radar trackers, induction loops or magnetometers.

2. Then the fuzzy engine classifies the traffic flow measurements according to the five linguistic terms (see section 4.2.1). With this classification, the duration of the cycle length is inferred through the Mamdani fuzzy inference system.

3. The inferred cycle duration is proportionally divided in to the number of involved streams. This distribution is computed by the Webster method.

4. Finally the resulting phases are set in the traffic light at the beginning of the next cycle.

These three stages are iteratively repeated every n_C cycles. Figure 4.5 shows the flow diagram of the adaptive mechanism.

In figure 4.5, $flow\_A$, $flow\_B$ and $flow\_C$ refers to the traffic flow measurements in the corresponding streams; cl is the cycle length inferred by the

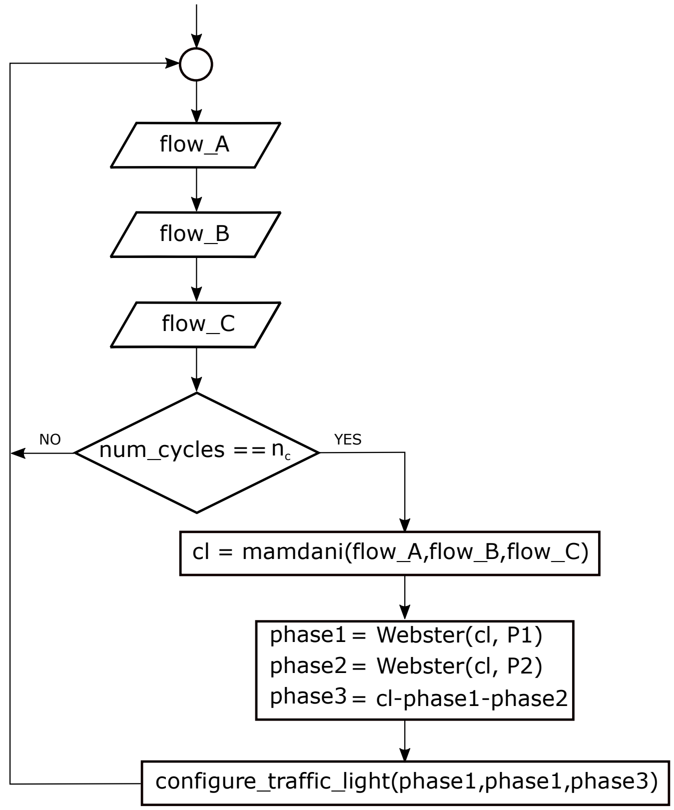


Figure 4.5: Flow diagram of the adaptive mechanism

Mamdani system and P_1, P_2 and P_3 are the appropriate cycle length proportion for each phase; Webster refers to the formula to find the effective green time per phase.

4.3.1 Functional description of the proposed system

To achieve a better understanding of the fuzzy inference system, consider the following example.

Suppose that the intersection depicted in Figure 4.1 have been characterized in such a way that the fuzzy sets for Flow A are bonded between 0 and 600 veh/h, for Flow B between 0 and 720 veh/h, for Flow C between 0 and 320 veh/h, and for the cycle length between 20 and 50 seconds. Thus, the different linguistic terms are instanced as depicted in Figure 4.12.

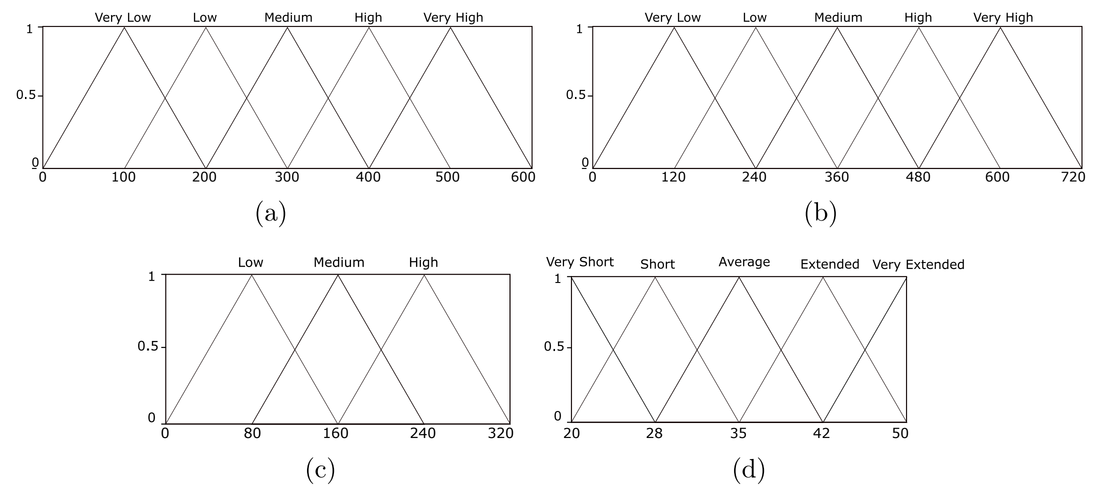


Figure 4.6: Fuzzy sets for the four linguistic variables: (a) flow rate in stream A, (b) flow rate in stream B, (c) flow rate in stream C, (d) cycle length D

Assuming that in a certain instant of the day, in the mentioned intersection were registered the following hypothetical vehicular flow rates:

- $Flow\ A = 300\ veh/h$,
- $Flow\ B = 240\ veh/h$,
- and $Flow\ C = 80\ veh/h$;

the analog input values are fuzzified as follows:

- for $Flow\ A = 300\ veh/h$:

$$
\begin{aligned}
f_A(300) &= max\left[min\left(\frac{300-200}{300-200}, \frac{400-300}{400-300}\right), 0\right] \\
&= max\left[min\left(\frac{100}{100}, \frac{100}{100}\right), 0\right] \\
&= max[min(1,1), 0] \\
&= max[1, 0] \\
&= 1, \qquad (4.1)
\end{aligned}
$$

(0 for the remaining four sets);

- for *Flow* $B = 240\ veh/h$:

$$\begin{aligned} f_B(240) &= max\left[min\left(\frac{240-120}{240-120}, \frac{360-240}{360-240}\right), 0\right] \\ &= max\left[min\left(\frac{120}{120}, \frac{120}{120}\right), 0\right] \\ &= max[min(1,1), 0] \\ &= max[1, 0] \\ &= 1, \end{aligned} \tag{4.2}$$

(0 for the remaining four sets);

- and for *Flow* $C = 80\ veh/h$:

$$\begin{aligned} f_C(80) &= max\left[min\left(\frac{80-0}{80-0}, \frac{160-80}{160-80}\right), 0\right] \\ &= max\left[min\left(\frac{50}{50}, \frac{50}{50}\right), 0\right] \\ &= max[min(1,1), 0] \\ &= max[1, 0] \\ &= 1, \end{aligned} \tag{4.3}$$

(0 for the remaining two sets).

These three membership values means that the value *Flow* $A = 300\ veh/h$ completely belongs to the set "Medium", the value *Flow* $B = 240\ veh/h$ completely belongs to the set "Low"and the value *Flow* $C = 80\ veh/h$ completely belongs to the set "Low".

The next stage is to use the knowledge base, that is the Mamdani system, to classify all possible scenarios for the traffic states at the intersection. According to the defined inference rules stated in Table 4.2, the inferred cycle length is *Short*.

To defuzzificate the inferred cycle length to a scalar value, the membership degrees to the sets Flow A, Flow B and Fow C, are related by using the Weighted

Average Method (see Definition 10) to estimate the membership degree to the set Short of the cycle length.

$$\begin{aligned} WA &= \frac{(1\cdot 35 + 1\cdot 35 + 1\cdot 35)(35)}{1(35) + 1(35) + 1(35)} \\ &= \frac{3675}{105} \\ &= 35. \end{aligned} \tag{4.4}$$

From equation 4.4 it is obtained the value of the cycle length in seconds. This means that the appropriate traffic light cycle length for $Flow\ A = 300\ veh/h$, $Flow\ B = 240\ veh/h$, and $Flow\ C = 80\ veh/h$, is 35 seconds.

Once the crisp value is obtained form the defuzzification process, the final step is to divide proportionally that cycle length according to the demand of each stream. This is obtained by computing the effective green time per phase by applying the Webster method (see Definition 7) as follows:

- for the phase of Flow A:

$$\begin{aligned} FlowA(greenphase) &= \frac{300}{300 + 240 + 80} 35 \\ &= 17, \end{aligned} \tag{4.5}$$

- for for the remaining phases, Flow B and Flow-C:

$$\begin{aligned} FlowB(greenphase) &= \frac{240}{300 + 240 + 80} 35 \\ &= 13 \end{aligned} \tag{4.6}$$

$$FlowC(greenphase) = 35 - A - B = 5. \tag{4.7}$$

Therefore, the total cycle is divided in a green phase of 17 seconds for Flow A, a green phase of 13 seconds for Flow B and a green phase of 5 seconds for Flow C.

4.4 Evaluation of the controller

The performance of the proposed controller was evaluated through a microscopic simulation model of a real intersection. The simulation was developed with the SUMO software [KEBB12]. Tacking advantages of the SUMO modules, the developed model considers accurate vehicle and road characteristics, car-following models as well as route and vehicle type distributions.

4.4.1 Simulation model

In order to calibrate the microscopic simulation model, traffic volumes were recovered from a real scenario in the city of Morelia, Michoacan, by using a crowdsourcing strategy [AAYE+12]. For this strategy there were deployed automated radar trackers and inducted loops to count and classify the upstreams in the intersected roads. In addition, to achieve an accurate origin-destination distributions, several videos were captured through an Unmanned Aerial Vehicle (UAV). All the retrieved data was represented in different time intervals as times-of-day and average daily traffic. Tables 4.3 and 4.4 summarize the retrieved traffic volumes.

Table 4.3: Weekly traffic volumes

	Roadways				
	r_1	r_2	r_3	r_4	r_5
Avg. weekly traffic	4,765	5,393	8,652	9,450	4,664
Avg. travel Speed	32.20	28.30	42.30	57.90	26.40
Mean Flow	451	329	554	770	226

Table 4.3 shows the weekly amount of vehicles, the registered average travel speeds (*kilometers/hour*) and the mean flow (*vehicles/hour*), on each of the involved upstreams. Table 4.4 displays the distribution of origin-destination trips, which determines the different movements inner the intersection.

Table 4.4: Volume trip 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%	–	–	–	–
	r_3	–	–	–	–	–
	r_4	–	–	–	–	–
	r_5	74.62%	11.19%	13.43%	0.74%	–

Table 4.5 shows the flow amounts in the involved roads, hourly distributed along a operational day.

4.4.2 Simulation results

The fuzzy controller was compared against two approaches: a) the current fixed-time configuration, present in the real intersection, and b) an optimized signal configuration based on the Webster method [Web58].

Each of the two approaches was tested through four simulations. The first simulation was configured to reproduce the time-of-day with free-flow conditions. The second simulation is based on the time-of-day with congested traffic. For the third simulation it was assumed a time-of-day with an over saturated traffic, which represents an increasing of 30% over the congested traffic. Finally, the fourth simulation was done by combining the three time of days, generating fluctuations among free-flow, congested and over saturated traffic conditions.

Table 4.5: Time table of traffic flows at the intersection

		Roads					
		r_1	r_2	r_3	r_4	r_5	*Average*
Flows(veh/hr)	$7:00-8:00$	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

From the simulations were obtained different traffic flow patterns, such as: average waiting times, average loss time, average trip duration, average travel, as well as pollution parameters based on the emission model eplained in 2.5.1. The average measures, of the obtained flow patterns, are summarized on Tables 4.6, 4.7, 4.8 and 4.9.

Table 4.6: Current fixed-time traffic light configuration

	Free flow hour	Congested hour	Over-saturated hour	Combined
Trip duration (sec)	103.61	126.93	169.04	155.13
Waiting time (sec)	11.26	34.75	72.68	59.98
Time loss (sec)	22.01	51.34	94.78	79.88
Speed (m/s)	9.03	7.45	5.61	6.10
Queue length (m)	11.65	300.46	462.67	462.67

Table 4.7: Optimized fixed-time traffic light configuration

	Free flow hour	Congested hour	Over-saturated hour	Combined
Trip duration (sec)	103.05	100.99	149.83	124.69
Waiting time (sec)	9.64	10.40	43.95	26.83
Time loss (sec)	21.51	25.42	74.16	48.77
Speed (m/sec)	9.08	9.36	6.29	7.57
Queue length (m)	10.59	42.29	140.59	140.59

Figure 4.7 give a graphical representation of the average waiting times, obtained from each of the tree compared approaches. It must be noted that the increasing of the trip duration is close to linear growth in both fixed time config-

Table 4.8: Adaptive fuzzy logic controller traffic light configuration

	Free flow hour	Congested hour	Over-saturated hour	Combined
Trip duration (sec)	99.45	102.07	106.68	104.6
Waiting time (sec)	6.12	11.57	14.68	13.07
Time loss (sec)	17.84	26.5	30.97	28.57
Speed (m/sec)	9.41	9.26	8.86	9.03
Queue length (m)	4.50	48.00	65.64	65.64

Table 4.9: Emissions results

	CO (tonnes)	CO2 (tonnes)	HC (tonnes)	PM10 (tonnes)	NOX (tonnes)	FUEL (liters)
Current fixed-time	0.04559	1.56616	0.00024	2.98479E-05	0.00065	673.24
Optimized fixed-time	0.02652	1.30102	0.00015	2.27797E-05	0.00052	559.26
Adaptive fuzzy logic	0.02124	1.20673	0.00012	2.04875E-05	0.00048	518.72

urations, once the traffic volume exceeds their design capacities. By contrast, the fuzzy controller allows constant trip durations.

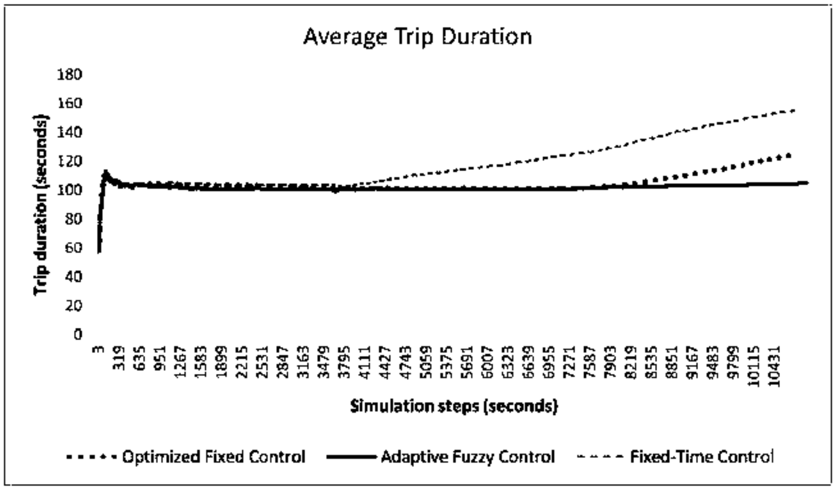


Figure 4.7: Average trip durations

Figures 4.8 and 4.9 show the average time loss obtained by the tests the three approaches. Both fuzzy controller and optimized configuration are compared against the current fixed time configuration.

As it can be observed from Figures 4.8 and 4.9, in the worst case, the time loss produced by the fuzzy controller is less to the half of the obtained by the optimized configuration.

Figures 4.10 and 4.11 depict the resultant waiting times. As it can be noted, the fuzzy controller significantly reduces the waiting times, which implies that the continuity of the trips is increased.

In Table 4.10 it is shown the overall results form the simulation, comparing the fuzzy logic controller against the fixed-time controllers, showing the percentage of improvement on all the traffic parameters measured.

From the results showed in Table 4.10, it can be observed that the adaptive fuzzy controller reduces the waiting times, time losses and allows a higher travel speeds, increasing drastically the efficiency of the intersection. In real life, this

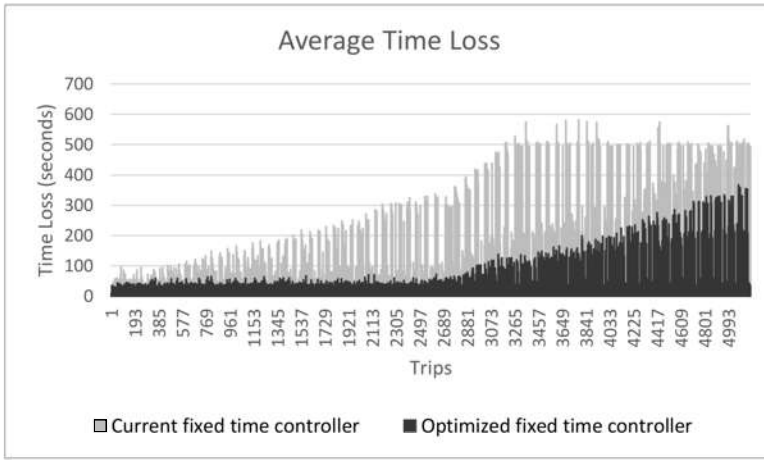


Figure 4.8: Average time loss obtained by the optimized fixed-time controller vs. the obtained by the current fixed-time controller

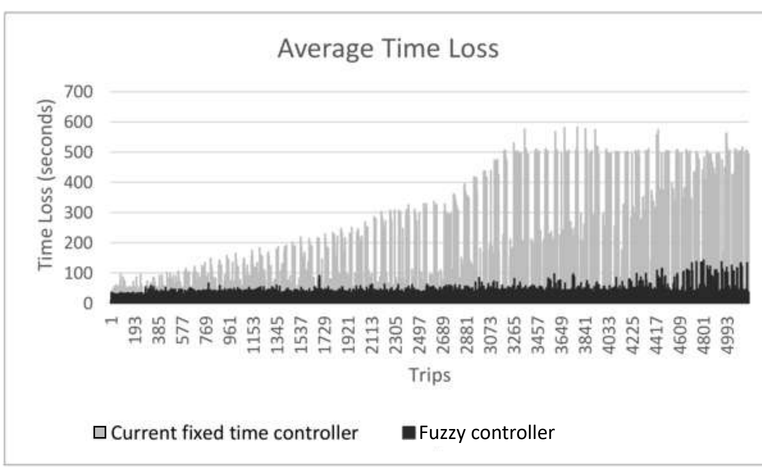


Figure 4.9: Average time loss obtained by the fuzzy controller vs. the obtained by the current fixed-time controller

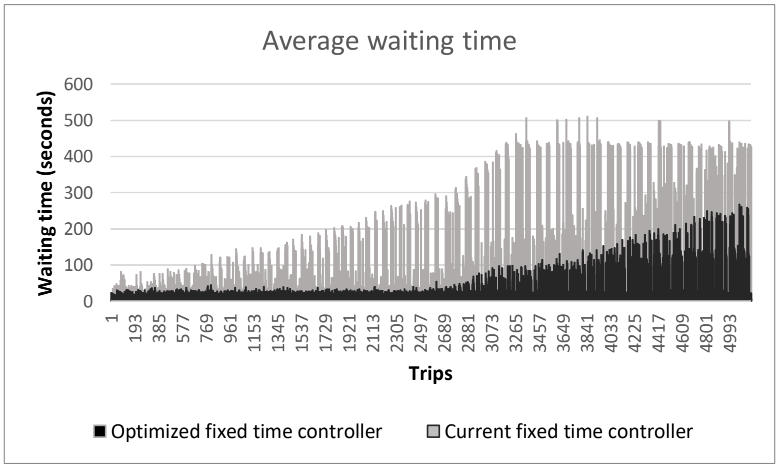


Figure 4.10: Optimized fixed-time controller vs. Current fixed-time controller

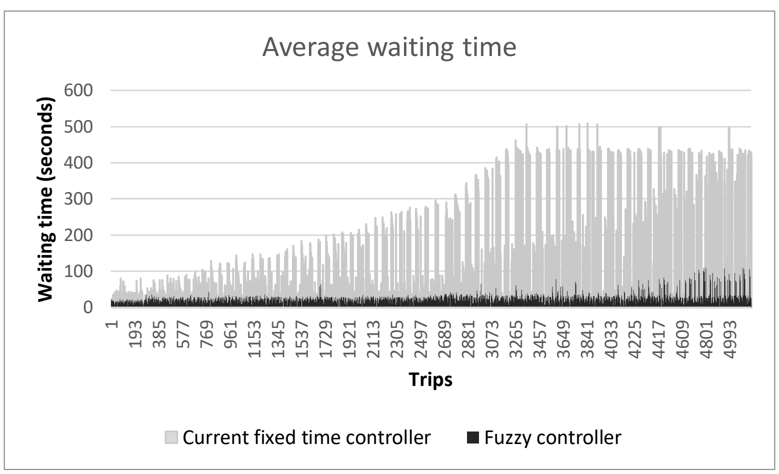


Figure 4.11: Fuzzy controller vs. Current fixed-time controller

translates into less traffic congestion. This would impact to urban mobility, improving the operation of a network by efficiently managing and regulating the approaching traffic to intersections, reducing the fuel consumption and the emissions. In Figure **??** it is shown the simulation representation of the comparison of the adaptive fuzzy logic controller and the pretimed traffic light controller.

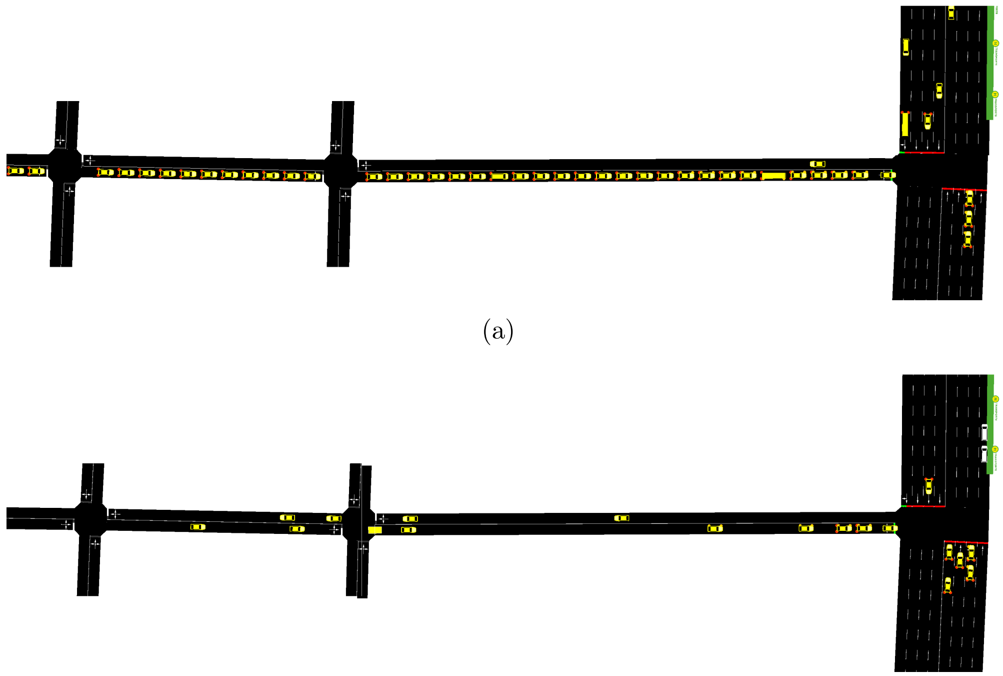
4.4.3 Fuzzy logic controller vs. actuated controller

In this section we describe the performance of the proposed fuzzy logic controller against an actuated controller. The actuated controller [EOW15b] operates using a demand-responsive logic to control signal timings, with phase durations set based on traffic demand registered by detectors on the intersection approaches and by vehicles using V2X communication.

The most common feature of actuated control is the ability to extend the length of the green interval for a particular phase. For example, when a vehicle is

Table 4.10: Overall results

	Fuzzy logic controller	
	Improvement (%) over the current fixed-time controller	Improvement (%) over the optimized fixed-time controller
Average trip duration (sec)	32.57 %	16.11 %
Average waiting time (sec)	78.21 %	51.29 %
Average time loss (sec)	64.23 %	41.42 %
Average travel speed (m/sec)	48.03 %	19.29 %
Queue length (m)	85.81 %	53.31 %
Fuel consumption (liters)	22.95 %	7.25 %
CO emissions (tonnes)	53.42 %	19.92 %
CO2 emissions (tonnes)	22.95 %	7.25 %
HC emissions (tonnes)	48.92 %	17.42 %
PM10 emissions (tonnes)	31.36 %	10.06 %
NOX emissions (tonnes)	25.64 %	8.23 %



(a)

(b)

Figure 4.12: (a) Current situation, (b) adaptive controller implementation

approaching a signal that is close to change to yellow, it allows the vehicle to pass through the intersection without stopping. For this approach, three parameters are required: the minimum green time, the extension time, and the maximum green time. The extension time is often referred to as the "gap time ", because the interval will be extended if a vehicle has a time gap (headway), from the vehicle in front it, that is less than this value.

The fuzzy logic controller was tested against the actuated controller by using the same parameters as the simulation scenarios previously described. Tables 4.11, 4.12 and 4.13 shows the simulation results.

For this simulation scenario it can be observed that the performance of the fuzzy controller is greater at high traffic demands. This is achieved because the fuzzy controller is based on to compute the total cycle length instead of to compute phase extensions, which allows an equilibrium between the green phase and the

Table 4.11: Adaptive fuzzy logic controller traffic light configuration

	Free flow hour	Congested hour	Over-saturated hour	Combined
Trip duration (sec)	104.25	104.60	108.68	106.90
Waiting time (sec)	7.15	12.10	15.08	13.54
Time loss (sec)	18.63	26.73	31.05	28.68
Speed (m/sec)	9.44	9.02	8.68	8.84
Queue length (m)	4.50	48.00	65.64	65.64

Table 4.12: Actuated controller traffic light configuration

	Free flow hour	Congested hour	Over-saturated hour	Combined
Trip duration (sec)	101.69	102.57	120.75	110.79
Waiting time (sec)	4.17	10.17	25.02	16.36
Time loss (sec)	15.66	24.48	43.17	32.42
Speed (m/sec)	9.69	9.20	7.81	8.53
Queue length (m)	4.66	49.74	68.02	68.02

Table 4.13: Improvement results (%) of the fuzzy logic control over the actuated controller

	Fuzzy controller vs. Actuated controller
Average trip duration (sec)	3.51 %
Average waiting time (sec)	17.24 %
Average time loss (sec)	11.54 %
Average travel speed (m/sec)	3.63 %
Queue length (m)	3.63 %

waiting times spent in the red phases. Figures 4.13 and 4.14 shows the average trip durations as well as the time loss for each type of controller.

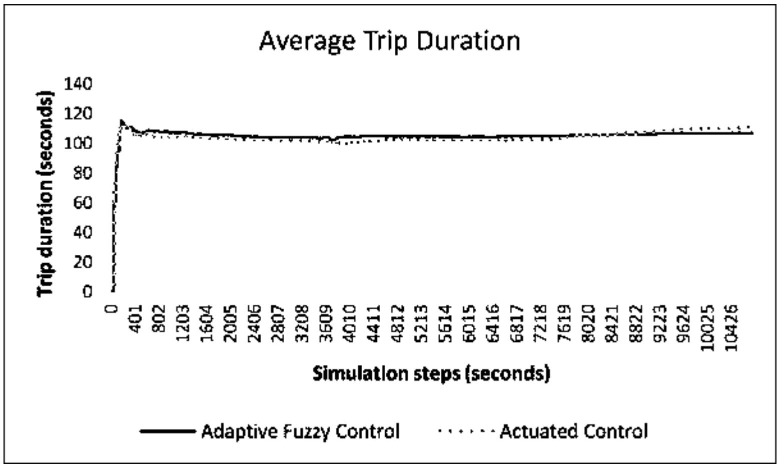


Figure 4.13: Fuzzy controller vs. Actuated controller

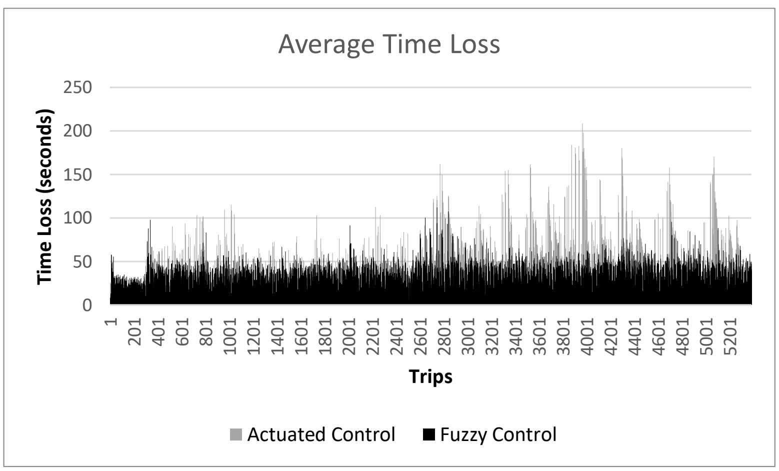


Figure 4.14: Fuzzy controller vs. Actuated controller

We can conclude that the extension of one phase is not the most efficient way to evaluate the traffic demand at an intersection, is not a problem of optimization, it has to focus on the adaptivity for the whole streams in order to have a fair time usage for each phase, in this case a proper total cycle duration.

Chapter 5

Conclusions and future work

5.1 Summary

In this work it was formally described the design of an adaptive fuzzy traffic control system. This system uses traffic flow rates measurements to compute the proper duration for whole traffic light cycles. The proposed controller is characterized to compute the duration of the whole cycle instead of specific phases' offsets or lengths, reducing the waiting times among phases.

By using fuzzy logic the cycle length is computed following the reasoning: "the highest the traffic flow, the larger the cycle length". For this it was designed a 75 if-then rules Mamdani inference system, including all possible scenarios for different traffic fluctuations. Each computed cycle is proportionally divided into different phases according to the flow rates.

Since it would be not be feasible and efficient to change the signal configuration each traffic light cycle, in addition to the inference system, an adaptive mechanism was developed to reconfigure the traffic light every certain number of cycles. Therefore, the cycle length considers the traffic flow rates registered in a specific period.

To determine the effectiveness of the controller, it was developed a microscopic-simulation model of a real intersection. The model was calibrated by using *in situ* measurements retrieved through crowd-sourcing strategy for which were deployed inductive loops, radar counters and UAV's recordings.

The proposed controller was compared with different control methods in the same simulation model, by using SUMO as platform. In such environment were reproduced a wide range of traffic states and control methods. These control methods included three approaches: a) the current fixed-time configuration, b) an optimized signal configuration and c) an actuated control based on time-delay.

The simulation results showed that the fuzzy logic traffic control system, allows a more efficient traffic management at intersections compared to the other two control schemes. We conclude that the adaptive fuzzy-logic controller can successfully adapt to the dynamic behavior of vehicular traffic. The proposed controller allows the reduction of trip durations, waiting times, time losses and fuel consumption up to 16%, 51%, 41% and 22% respectively, in different traffic conditions such as, free flow, congested and over-saturated hours. Moreover, the results showed that the controller allows to increase the average travel speeds up to 19%. Even though the vehicular pollutant emissions analysis was not one of the objective of this work, we include a simulated emission model which showed that the approach allows the reduction of CO, CO2, HC, PM10 and NOX up to 7%, 17%, 10% and 10% respectively.

5.2 Future work

The proposed controller was tested only in an isolated intersection, however, the behavior of the solution considering consecutive intersections was not analyzed. Another limitation is that the fuzzy controller currently does not consider traffic light signals for pedestrians. Considering these limitations and considering future extensions, the future work of this research includes:

- **The inclusion of pedestrian signals within the traffic light cycle**. To represent the real conditions for traffic safety in the interaction between infrastructure and pedestrian behavior it is necessary to modify the inference system as we as the simulation models to include flow rates of people interacting in the intersection. Nevertheless, to reproduce the real behavior of pedestrian in a real intersection imposes different unsolved challenges.

- **Analysis of the fuzzy inference system towards a self-organizing traffic light control**. To increase the efficiency of the urban network, beyond a single intersection, the inclusion of consecutive adaptive fuzzy controllers could lead to a self-organizing system, without an explicit coordination strategy among traffic lights. To achieve this, it is necessary to develop more complex simulation models, calibrated with network global parameters besides to only consider microscopic parameters.

- **Physical implementation of the fuzzy controller**. A main extension of this work is to develop the hardware and the software required to control a real traffic light.

- **Physical adaptations of the traffic light device**. Two possible extensions for this work rely on the use of preventive lights signals to improve the reaction time for the driver prior the green phase and the inclusion of public transport priority behavior which can be achieved with the addition of detectors for special vehicles (transport, emergency and patrols).

Bibliography

[AA96] Dunn Engineering Associates and United States. Federal Highway Administration. *Traffic Control Systems Handbook*. U.S. Department of Transportation, Federal Highway Administration, 1996.

[AAYE+12] K. Ali, D. Al-Yaseen, A. Ejaz, T. Javed, and H. S. Hassanein. Crowdits: Crowdsourcing in intelligent transportation systems. In *2012 IEEE Wireless Communications and Networking Conference (WCNC)*, pages 3307–3311, April 2012.

[AUÖ12] A Aksaç, E. Uzun, and T. Appl Ötzyer. A real time traffic simulator utilizing an adaptive fuzzy inference mechanism by tuning fuzzy parameters. *Applied Intelligence*, 32:698–720, April 2012.

[AWY+14] I. Adam, A. Wahab, M. Yaakop, A. A. Salam, and Z. Zaharudin. Adaptive fuzzy logic traffic light management system. In *2014 4th International Conference on Engineering Technology and Technopreneuship (ICE2T)*, pages 340–343, Aug 2014.

[BKS08] Nicolas Blanc, Daniel Kroening, and Natasha Sharygina. *Scoot: A Tool for the Analysis of SystemC Models*, pages 467–470. Springer Berlin Heidelberg, Berlin, Heidelberg, 2008.

[CCV04] Sinem Coleri, Sing Yiu Cheung, and Pravin Varaiya. Sensor networks for monitoring traffic. In *In Allerton Conference on Communication, Control and Computing*, 2004.

[CW99] Michael J. Caruso and Lucky S. Withanawasam. Vehicle detection and compass applications using amr magnetic sensors, 1999.

[EOW15a] J. Erdmann, R. Oertel, and P. Wagner. Vital: A simulation-based assessment of new traffic light controls. In *2015 IEEE 18th International Conference on Intelligent Transportation Systems*, pages 25–29, Sept 2015.

[EOW15b] Jakob Erdmann, Robert Oertel, and Peter Wagner. Vital: a simulation-based assessment of new traffic light controls. In *Intelligent Transportation Systems (ITSC), 2015 IEEE 18th International Conference on*, pages 25–29. IEEE, 2015.

[FJM+01] L. Figueiredo, I. Jesus, J. A. T. Machado, J. R. Ferreira, and J. L. Martins de Carvalho. Towards the development of intelligent transportation systems. In *ITSC 2001. 2001 IEEE Intelligent Transportation Systems. Proceedings*, pages 1206–1211, 2001.

[Ger05] Carlos Gershenson. Self-organizing traffic lights. *Complex Systems*, 16(1):29–53, 2005.

[GR12] C. Gershenson and D. A. Rosenblueth. Self-organizing traffic lights at multiple-street intersections. *International Journal of Scientific and Research Publications*, 17:23–39, March 2012.

[HHlS] Serge Hoogendoorn, Sascha Hoogendoorn-lanser, and Henk Schuurman. Fuzzy perspectives in traffic engineering.

[HJ94] Robert Hoyer and Ulrich Jumar. Fuzzy control of traffic lights. In *Fuzzy Systems, 1994. IEEE World Congress on Computational Intelligence., Proceedings of the Third IEEE Conference on*, pages 1526–1531. IEEE, 1994.

[IA16] Laheeb Mohammed Ibrahim and Mohammed A. Aldabbagh. Adaptive fuzzy control to design and implementation of traffic simulation system. *International Journal of Scientific and Research Publications*, 14(4):228–246, April 2016.

[KEBB12] Daniel Krajzewicz, Jakob Erdmann, Michael Behrisch, and Laura Bieker. Recent development and applications of SUMO - Simulation of Urban MObility. *International Journal On Advances in Systems and Measurements*, 5(3&4):128–138, December 2012.

[Kel12] Blaise Kelly. A green wave reprieve. *Traffic Engineering & Control*, 53:55–58, February 2012.

[Kim97] Jongwan Kim. A fuzzy logic control simulator for adaptive traffic management. In *Proceedings of 6th International Fuzzy Systems Conference*, volume 3, pages 1519–1524 vol.3, Jul 1997.

[KPR+] Koonce, Peter, Lee Rodegerdts, Kevin Lee, Shaun Quayle, Scott Beaird, Cade Braud, Jim Bonneson, Phil Tarnoff, and Tom Urbanik. Traffic signal timing manual. In *Traffic Signal Timing Manual*. Federal Highway Administration, U.S. Department of Transportation.

[Kra98] Stefan Krauß. *Microscopic Modeling of Traffic Flow: Investigation of Collision Free Vehicle Dynamics*. PhD thesis, 1998.

[Lee90] C.-C. Lee. Fuzzy logic in control systems: fuzzy logic controller. parts I and II. *IEEE Transactions on Systems, Man and Cybernetics*, 20(2):404–435, 1990.

[LKG81] DC Little, MD Kelson, and NH Gartner. Maxband: A program for setting signals on arteries and triangular networks us dept.

Transport of Washington DC Transport Research Record (795), 1981.

[LLLK95] Jee-Hyong Lee, Keon-Myung Lee, and Hyung Lee-Kwang. Fuzzy controller for intersection group. In *Proceedings IEEE Conference on Industrial Automation and Control Emerging Technology Applications*, pages 376–382, May 1995.

[LMH+08] H. X. Liu, W. Ma, H. Hu, X. Wu, and G. Yu. Smart-signal: Systematic monitoring of arterial road traffic signals. In *2008 11th International IEEE Conference on Intelligent Transportation Systems*, pages 1061–1066, Oct 2008.

[MA75] E. H. Mamdani and S. Assilian. An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, 7(1):1–13, 1975.

[May90] A.D. May. *Traffic Flow Fundamentals*. Prentice Hall, 1990.

[MH01] Pitu Mirchandani and Larry Head. A real-time traffic signal control system: architecture, algorithms, and analysis. *Transportation Research Part C: Emerging Technologies*, 9(6):415 – 432, 2001.

[MK17] Benedikt Notter Mario Keller, Philipp Wüthrich. Handbook emission factors for road transport, 2017.

[NMP99] Vilém Novák, Jirí Mockor, and Irina Perfilieva. *Mathematical principles of fuzzy logic*. Kluwer international series in engineering and computing science. Kluwer, Boston, MA, 1999.

[opt04] Optimized traffic flow at a single intersection: traffic responsive signalization. *Journal of Physics a: Mathematical and General*, 37:561â576, October 2004.

[oTS17] Institute of Transportation Systems. Sumo (simulation of urban mobility), 2017.

[OW11] Robert Oertel and Peter Wagner. Delay-time actuated traffic signal control for an isolated intersection. In *Transportation Research Board 2011 (90th Annual Meeting)*, number EPFL-CONF-181089, 2011.

[PM77] C. P. Pappis and Ebrahim H. Mamdani. A fuzzy logic controller for a traffic junction. *IEEE Transactions on Systems, Man, and Cybernetics*, 7:707–7217, October 1977.

[PWS15] Erwan Eko Prasetiyo, Oyas Wahyunggoro, and Selo Solistyo. Design and simulation of adaptive traffic light controller using fuzzy logic control sugeno method. *International Journal of Scientific and Research Publications*, 5:1–6, April 2015.

[Ros95] Timothy J. Ross. Properties of membership functions fuzzification and defuzzification. In *Fuzzy Logic with Engineering Applications*. McGraw Hill, New York, NY, USA, 1995.

[SGW11] D.L. Schacter, D. T. Gilbert, and D. M. Wegner. *Psychology (2nd Edition)*. Worth, New York, 2011.

[SM17] MJ Shirvani Shiri and Hamid Reza Maleki. Maximum green time settings for traffic-actuated signal control at isolated intersections using fuzzy logic. *International Journal of Fuzzy Systems*, 19(1):247–256, 2017.

[SR15] María Teresa Sánchez-Rico. *Data mining, optimization and simulation tools for the design of Intelligent Transportation Systems*. PhD thesis, Universidad de Castilla-La Mancha, 2015.

[Sug85] Michio Sugeno. An introductory survey of fuzzy control. *Information Sciences*, 36(1-2):59 – 83, 1985.

[TI12] Mohammad A. Taha and Laheeb Ibrahim. Traffic simulation system based on fuzzy logic. *Procedia Computer Science*, 12,:356–360, October 2012.

[TS85] T. Takagi and M. Sugeno. Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on Systems, Man and Cybernetics*, SMC-15(1):116–132, 1985.

[VY86] R. A. Vincent and C. P. Young. Self-optimizing traffic signal control using microprocessors: the trrl mova strategy for isolated intersections. In *2nd International Conference on Road Traffic Control*, pages 102–105, London, UK, May 1986.

[WDDM14] Xiaoping Wu, Shuai Deng, Xiaohong Du, and Jing Ma. Greenwave traffic theory optimization and analysis. *World Journal of Engineering and Technology*, 2(03):14, 2014.

[Web58] F.V. Webster. *Traffic Signal Settings.* Road research technical paper. H.M. Stationery Office, 1958.

[WVvVK04] M. Wiering, J. Vreeken, J. van Veenen, and A. Koopman. Simulation and optimization of traffic in a city. In *IEEE Intelligent Vehicles Symposium, 2004*, pages 453–458, June 2004.

[Zad65] Lofti A. Zadeh. Fuzzy sets. *Information and Control*, 8:338–353, 1965.

[Zad73] Lotfi A Zadeh. Outline of a new approach to the analysis of complex systems and decision processes. *IEEE Transactions on systems, Man, and Cybernetics*, (1):28–44, 1973.

[ZC08] Xing Zheng and Lianyu Chu. Optimal parameter settings for adaptive traffic-actuated signal control. In *Intelligent Transportation Systems, 2008. ITSC 2008. 11th International IEEE Conference on*, pages 105–110. IEEE, 2008.

[ZC14] Zhanhong Zhou and Ming Cai. Intersection signal control multi-objective optimization based on genetic algorithm. *Journal of Traffic and Transportation Engineering (English Edition)*, 1(2):153 – 158, 2014.

[ZMXMWX15] Chen Zhao-Meng, Liu Xiao-Ming, and Wu Wen-Xiang. Optimization method of intersection signal coordinated control based on vehicle actuated model. *Mathematical Problems in Engineering*, 2015, 2015.

[ZRG17] Jorge L. Zapotecatl, David A. Rosenblueth, and Carlos Gershenson. Deliberative self-organizing traffic lights with elementary cellular automata. *Complexity*, 2017:1–15, May 2017.