AN ADAPTATIVE SYSTEM FOR SIGNPOSTED INTERSECTION CONTROL: ASSINC

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Abstract

This paper deals with the development of intelligent and adaptative system for signposted intersection control. The role of such systems is to manage the existing infrastructure to ease congestion and respond to crises. The proposed system, named ASSINC, try to insure a more fluid traffic flow. ASSINC is based on case based reasoning (CBR) approach and fuzzy logic to consider imprecise information taken from some detector. In fact, the CBR is always considered as a cyclic paradigm of Artificial Intelligence and that is used to learning and problem solving based on past experience. The developed system is tested on a virtual junction and the obtained results are discussed.

1 Introduction

In our days, implementing, and maintaining optimally timed traffic signals becomes a major preoccupation of transport authorities around the world. For that reason, several adaptative traffic signal controls are developed. The aim of such system is the process by which the timing of a traffic signal is continuously adjusted based on the changing arrival patterns of vehicles at an intersection, usually with the goal of optimizing a given measure of effectiveness.

However, some existing controllers don't consider the dynamic state of the traffic. To improve the traffic fluidity, the controller have to generate the timing schedules based on the traffic conditions for a specific time of day and must maximize, for example, the bandwidth on arterial streets.

The development of adaptative traffic signal control uses information from sensor or detector (induction loops, camera, etc.) installed in the intersection. The intersection is said actuated. There are two types of actuated signal:

– Semi-actuated signals that have detectors on minor roads that detects when traffic is present. These detectors switch the green phase to the minor road to allow traffic to clear.

– Fully-actuated signals have detectors on all (major and minor) roads that detect the volume of traffic present. Based on the amount of traffic, the signal provides enough time to accommodate all of the vehicles.

In this paper, we consider fully actuated signal to develop an Adaptative System for Signposted INtersection Control, named ASSINC. This system use the case based reasoning - CBR - a technique taken from the artificial intelligence field. The aim of this system is to control an isolated intersection. The system can be extended in a future work to consider several intersections.

This paper is structured as follow: the section 2, came with a brief bibliographical survey of different works and studies made around traffic lights control. The section 3 presents the proposed system for traffic light control. The section 4 introduce the integration of imprecise data to the system. Finally, this system is developed and some obtained results are presented and analyzed in section 5. The paper is completed with a conclusion.

2   Related Works

In the last few years, new generations of traffic signal controller were developed and that considered as "adaptive" as opposed to the usual time plans. The aim of adaptive traffic control systems (ATCS) is generally to decrease the average delays and average queue lengths of vehicles in an intersection. ATCS allows the green time to vary as demand varies. In the literature, several systems was developed such as PASSER II [1] and TRANSYT-7F [2] that aimed at local optimal control of traffic signal system. Both of studies tried to find out optimal solutions for local traffic signal control system in each intersection.

Indeed, computer technology and artificial intelligence has been widely used to develop such controller that facilitate traffic movement. For example, some controllers were developed based on approaches that were inspired by biological systems and by their specific mechanisms to elaborate new models and approaches more adapted to the transportation systems with all their complexity. Artificial Immune Systems (AIS) is one of these approaches. Up to our knowledge, very few works were based on AIS to regulate and control urban traffic. AIS is based on the metaphor mechanisms of the vertebrate immune systems. Negi [3] proposed an artificial immune system capable of detecting abnormal situations of urban traffic such as congestion and proposed actions for the traffic regulation. Furthermore, Artificial Neural Network (ANN) is also deal with in [4] in order to develop a model-based method for the monitoring of a complex road intersection in the city of Nancy in France.

In some works, fuzzy logic were also used to integrate imprecise data in Traffic Management System. In fact, fuzzy logic provides an expressive language for working with both quantitative and qualitative descriptions of the traffic state and enables model to produce some complex behavioral phenomena and states. Recently, an increasing number of works use fuzzy logic for implementing Traffic Management Systems. In [11], authors described an approach to the analysis and modeling of traffic flow using a specific class of self-organizing fuzzy rule-based system known as the *Pseudo Outer-Product Fuzzy-Neural Network*. The fuzzy logic is also used with genetic algorithm in [12] to automatically detect incidents on a traffic network. Moreover, [13] describes an integrated system for incident management using this approach.

The Ant Colony Optimization (ACO) was also used to develop intelligent traffic controller. The self-organizing structure of ant colony algorithms is carried out via stigmergic communication such as communication by changing the environment. In the transportation field, the ACO was used to optimize traffic lights [22]. Other approaches were used to develop intelligent transportation systems such as Multi-agent systems (MAS). The challenge for using MAS is to increase the performance of actual systems with the consideration of real problems. For example, researchers have been applying agents' technology to develop traffic controller [5], to design a transportation regulation support system [6], to develop a strategy of bimodal urban traffic [7] and to control traffic light [9]. MAS is usually coupled with other approaches to integrate artificial intelligence in agents. For example, Fayech [10] adopted this approach with the integration a genetic algorithm. MAS was also associated with the fuzzy set theory. In fact, Kosonen proposed in [8] a traffic light control system, called HUTSIG, based on real-time simulation, multi-agent control scheme, and fuzzy inference.

The case based reasoning (CBR) is a relatively recent technique used in the transportation filed. The CBR is always considered as a cyclic paradigm of Artificial Intelligence and that is used to learning and problem solving based on past experience. The past experience is stored in a "case base" in the form of solved problem called "case". The solution of each new problem is based on the adapting of solutions of stored similar cases (problems). This technique is used in few works to develop decision support systems for real time traffic routing. How-

Table 1. Some of developed traffic light control systems

Used methods	Some papers
2*Multi-Agent Systems	Balan and Luke[5], Balbo and Pinson[6], Haciane and Bhouri[7], Kosonen [8], Bazzan et al.[9], Fayech, [10]
2*Fuzzy logic	Quek et al. [11], Srinivasan, et al. [12], Hawas, [13], Kosonen [8]
Petri nets	Tolba et al. [14], Dotolia and Pia Fanti [15], Di Febrarro et al. [16]
Metaheuristics	Shenoda and Machemehl[17], Turky et al. [18] Ceylan and Bell[19]
Case based reasoning	Elkosantini et al.[20], Elkosantini et al. [21]
Artificial Immune Systems	Negi [3]
Artificial Neural Network	Messai [4]
Ant Colony Optimization	Chen et al.[22],

ever, up to our knowledge, this approach is rarely used in the traffic light control. In a previous paper [20], we proposed a first version of a controller and that is improved in this paper.

3 The proposed system - ASSINC

Let us remember that , in this paper, the proposed system aims at maximizing the flows $F_{i,j}(t)$ where $F_{i,j}(t)$ is the flow of vehicles of the ith lanes of the jth road at the moment t. So, we adopted the CBR approach to improve the fluidity of the traffic in signposted intersections.

3.1 Variables

According to the principle of the CBR, regulation actions of new problems can be found based on existing situations stored in the case base by calculating the similarity degree between the new problem and solved ones. In this work, a problem is characterized by the following vector:

$$Pb =< P, L_{i,j}, Light_{i,j}, S_{i,j}, i, j >$$

Where: P is the period of the day. $P \in \{P1, P2, P3\}$ where

– $P1$ Traffic light is inactive.

– $P2$ Peak hour.

– $P3$ Normal situation.

$L_{i,j}$: The length of the vehicles queue at the ith lanes of the jth road. This variable is expressed in

meter. $Light_{i,j}$: is the light of the ith lanes of the jth road and $S_{i,j}$: average speed of the vehicles flow in the lane i of the road j.

Next paragraph is devoted to the presentation of the architecture of proposed system.

3.2 The system architecture

The architecture of the proposed system, named ASSINC - Adaptative System for Signposted INtersection Control - is represented in the figure 1. It is important to note that in this paper we focus only on fully-actuated signals. This means that the intersection is equipped with detection. The first part of the system is the search of the most similar case (using a similarity measurement funtion - see paragraph 3.1) from the case base. In the second step, the obtained case is presented to the regulator that can validate it or adapt it according to the actual state of the intersection. Each modification is stored in a separate data base and the adapted case is stored in the case base.

3.2.1 The Case base

The initial "case base" of the proposed controller contains several "cases" having the following structure:

Problem description ⇒ Regulation action

The first part of this rule is the problem which describes the state of the intersection and the second is the regulation action that resolves this problem.
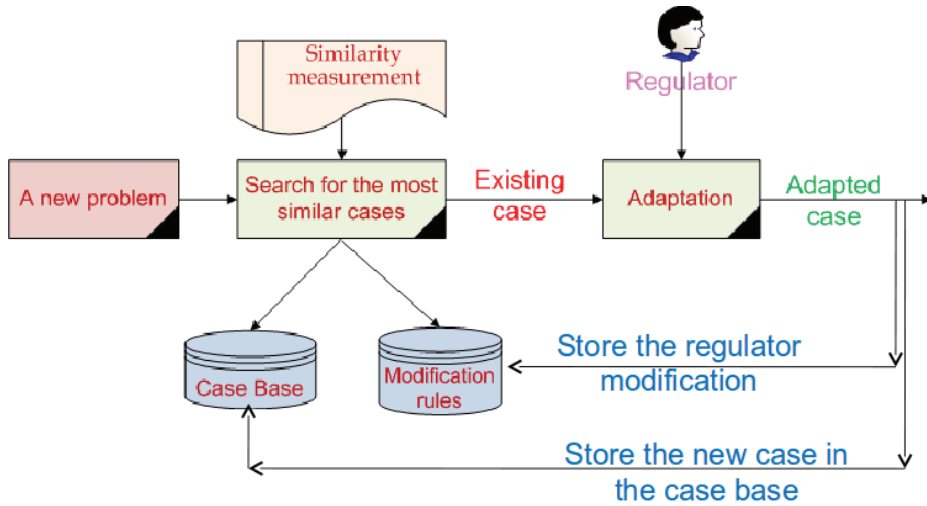
Figure 1. ASSINC architecture.

More formally, a case is structured as $Pb \Rightarrow A$ where Pb is the problem and A is the regulation action. This formulation can be translated to following sentence: if the period is P, the traffic light of the the ith lanes of the jth road is $Light_{i,j}$, the length of the jth road is $L_{i,j}$ and the average speed of the vehicles flow in the lane i of the road j is $S_{i,j}$ then the regulation action that must be considered is A.

3.2.2   The similarity measurement

In the CBR cycle, the case representation step is followed by the research of the most similar cases. This step is based on the computation of similarity degree between registered cases and the new problem. In the literature, several local and global similarity measures were proposed.

The choice of a similarity measure is based generally on the nature of collected data that will be compared. In this paper, we adopt symbolic local similarity measure to compare attributes of two cases:

$$sim(a,b) = \begin{cases} 1 & if\ a = b \\ 0 & if\ a \neq b \\ 0,5 & if\ a\ or\ b\ is\ not\ defined \end{cases}$$
$$(1)$$

Where a and b are two attributes of two different cases. Furthermore, as a global similarity, the weighted block-city measure is used to calculate the similarity between two cases A and B:

$$sim(A,B) = \sum_{i=1}^{n} w_i \times sim_i(a_i, b_i) \qquad (2)$$

where n is the number of attributes of a case, w_i is the weight of the ith attribute and sim_i is the local similarity degree of the ith attribute.

3.2.3   The modification base

The modification base contains rules that represent all adaptation or modification made by the regulator. As previously mentioned, the regulator can adapt the obtained regulation action (the regulation action part of the most similar case). This base is considered in the "search for the most similar cases" step to adapt automatically most similar cases. In this base, rules have the following form:

Regulation action $\Rightarrow$ Modified Regulation action

Where *Regulation action* is the result of "search for the most similar cases" step. As previously mentioned, the regulator can adapt the regulation action according to the actual traffic state (*Modified Regulation action*).

In the next paragraph, the considered regulation action in the proposed system are detailed.

3.2.4   The regulation actions

The developed system is constituted from 6 regulation actions: 4 for normal situations:

– *Protagonist*(i,j): This function defines lanes that cannot share a conflict zone. This action is called during the initialization of the the traffic

light as well as during every green light of the i_{th} lane of the jth road.

– *Initialization*(P): The initialization of the traffic lights changes according the period P. Indeed, during period $P1$, the traffic is considered as inactive. The twinkling yellow light is activated in all roads of the intersection.

– *StopProtagonist*(i, j): when the green light of the ith lanes of the jth road is activated, vehicles from lanes that share a conflict zone have to stop and other vehicles can cross the crossroads. For example, *StopProtagonist*($1, 1$) engender the stop of the 3rd lane of the 3rd road and the 2nd lane of the 4th road as well as the activation of the green light of the other lanes that don't share the conflict zone.

– *ActivateNextLight*(i, j): The goal of this function is to activates the next light of the ith lanes of the jth road. For example, it activate the yellow light after the red one.

In the proposed system, 2 other regulation actions are implemented for abnormal situation such as traffic jam or accidents:

– *SpeedRegulation*($i, j, Feu_{i,j}, Li, j, Si, j$): This action is activated when the possibly problem is due the average speed $S_{i,j}$ that is too low and that can cause a traffic jam.

– *QueueRegulation*($i, j, Feu_{i,j}, Li, j, Si, j$): This action is activated when the possibly problem is due the length $L_{i,j}$ that is too high and that can alse cause a traffic jam in a previous intersection.

Among these actions, the algorithm of three actions will be detailed here. The first one is *StopProtagonist*(i, j). Let us note that *LightDuration* is a function defined as:

$$LightDuration : Light \rightarrow R$$
$$l \mapsto LightDuration_{i,j}(l)$$

Where $LightDuration_{i,j}(red)$ is the duration of the red light associated to the lane j of the road i and *Protagonist* is a function defined as:

$$Protagonist : Lane \times road \rightarrow R$$
$$(i, j) \mapsto Protagonist(i, j)$$

The function *protagoniste*(i, j) identify all lanes that share a same conflict zone. Vehicles cannot enter to this zone to avoid problems such as traffic jam or accidents. The function *protagoniste*(i, j) gives, for a given lane, the list of all lanes which share a same conflict zone. Let us consider, as an example, the 1st lane of the 2nd road. *protagoniste*($1, 2$) gives all lanes that in a conflict with 1st lane of the 2nd road and that are the 3rd lanes of the 4th road and the 2nd lane of the 1st road (See figure 2).
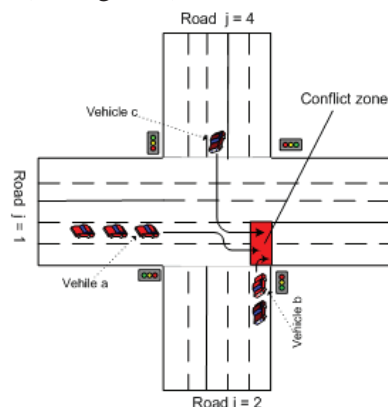

Figure 2. An example of conflict zone.

Algorithm 1 *StopProtagonist*(i, j)
  for i_0=1 to *nbRoads* **do**
    for j_0=1 to *nbLanes* **do**
      if $(i_0, j_0) \in protagonist(i, j)$ **then**
        $Light_{i_0,j_0}$ = red during $LightDuration_{i_0,j_0}(red)$;
      else
        $Light_{i_0,j_0}$ = green during $LightDuration_{i_0,j_0}(green)$;
      end if
    end for
  end for

The second action that is detailed here is the QueueRegulation (i,j, $Feu_{i,j}, L_{i,j}, S_{i,j}$).

As mentioned above, this action is activated when the problem is caused by the length of the queue of vehicles of the ith lanes of the jth road. Besides, this algorithm is called in two situations. The first one is when the length of the queue of vehicles tends to reach a critical length L_{max} and the actual light is the red. This critical length is defined by the regulator and depends on several data such as the distance which separates two intersec-

tions. In this situation, the lane is blocked. Such situation may be the origin of a problem in a previous intersection. To resolve this problem, the action *QueueRegulation* evacuates the blocked lane to minimize the length of the queue. Therefore, the light associated to this lane is switched to the green.

The second situation that require the activation of this action is when the light of a lane is green and the length of the vehicles queue of the lane reaches a critical threshold whereas the average speed of the flow is acceptable. The number of arriving vehicles is higher than those exiting the lane. In this case, the system increases the duration of the green light in order to allow to pass more vehicles.

Algorithm 2 $QueueRegulation(i, j, Feu_{i,j}, Li, j, Si, j)$

{The first situation};
if $((Feu_{i,j} = red$ AND $L_{i,j} \simeq L_{max})$ OR $((Feu_{i,j} = red$ AND $L_{i,j} = L_{max})$ **then**
  $Feu_{i,j} = green$ during $LightDuration_{i,j}(green)$;
end if
{The second situation};
if $((Feu_{i,j} = green)$ AND $(L_{i,j} \simeq L_{max})$ AND $(S_{i,j} > 0)$ AND $(S_{i,j} > V_{min})$ **then**
  $LightDuration_{i,j}(green) = 2 *$
  $LightDuration_{i,j}(green)$;
end if

The third action is *SpeedRegulation* and that is generally activated if the problem is caused by the low average speed $S_{i,j}$ and the actual light is the green. This means that there is a problem in this lane (for example an accident). So, this action begins by switch the light to the red in order to evacuate the intersection.

Algorithm 3 $SpeedRegulation(i, j, Feu_{i,j}, Li, j, Si, j)$

  $Light_{i,j} = red$ during $LightDuration_{i,j}(red)$;
  $StopProtagonist(i, j)$.

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4 Integration of imprecise data

In a previous work [21], the attributes of a case, such as $L_{i,j}$ and $S_{i,j}$, were considered as crisp value. However, some variables can have imprecise values and in particular linguistic values. For that reason, the fuzzy set theory can be used to integrate imprecise data and the attributes of stored case will have fuzzy (or linguistic) values. In this work, fuzzy set theory is used in case representation to provide a

characterization of imprecise and uncertain information. Consequently, the stored rules will have the following form:

if P is P_1 AND $L_{i,j}$ is L_k and $Light_{i,j}$ is red and $S_{i,j}$ is S_k then The action is A

Where L_k and S_k are linguistic values.

Accordingly, a fuzzy sets-based approach is proposed in this paper ensuring the better representation of linguistic variables. Moreover, Zadeh [23] noted that the use of linguistic variables is a better approximation of the human thought process. Fuzzy sets are the best adapted formalism to integrate the imperfection aspects to such variables by integrating measures of uncertainty and variability in such parameters. Linguistic variables will be defined in this paper as triangular fuzzy numbers.

A fuzzy number is defined by its support and a fuzzy membership function that has a peak value of 1. The membership function indicates the degree of possibility of an element, but it does not represent the probability of the element in the whole set. More formally, the definition of a fuzzy set is: If X is a collection of objects denoted generically by x then a fuzzy set A in X is a set of ordered pairs:

$$A = \{(x, \mu_A(x)) | x \in X\} \qquad (3)$$

Let us remember that a fuzzy set A is called triangular fuzzy number with peak (or centre) a, left width $\alpha > 0$ and right width $\beta > 0$ if its membership function has the following form:

$$A(x) = \begin{cases} 1 - \frac{a-x}{\alpha} & if \ a - \alpha \leq x \leq a \\ 1 - \frac{x-a}{\beta} & if \ a \leq x \leq a + \beta \\ 0 & otherwise \end{cases} \qquad (4)$$

The triangular fuzzy number, that will be noted in this paper by $A = (a, \alpha, \beta)$, is graphically represented as shown in figure 3.
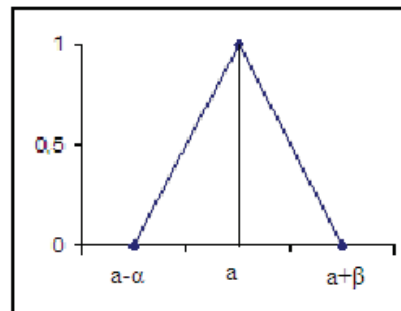

Figure 3. A triangular fuzzy number.

The fuzzy values of $L_{i,j}$ and $S_{i,j}$ are summarized in the table 2.

Table 2. Linguistic values of $L_{i,j}$ and $S_{i,j}$

Linguistic value	$L_{i,j}$	$S_{i,j}$
Very weak	(0,0,15)	(0,0,15)
weak	(5,20,30)	(10,25,40)
Moderate	(25,40,50)	(35,50,65)
Strong	(45,60,70)	(60,75,90)
Very strong	(65,80,80)	(85,100,110)

The fuzzy number $L_{i,j}$ is characterized by the membership function $\mu_{L_{i,j}}(x)$ associating to each element x a value in the interval [0 , 1], where x is one of possible linguistic values (see table 2). For instance, these numbers are modeled by triangular membership functions (see figure 3) but any kind of membership functions can be selected.

As some variables are defined as linguistic variables, the local similarity degree $sim(a,b)$, that had in previous work a crisp value 0, or 0,5 or 1, can have also linguistics values. We therefore propose the use of fuzzy sets. Consequently, the used fuzzy similarity measure is calculated using the triangular norm:

$$sim(a,b) = \top_{(a,b)} = min_{(a,b)} \qquad (5)$$

The global fuzzy similarity is calculated using the equation 2 and the addition is the the fuzzy addition. The case with the best similarity will be selected. Hence, some ranking methods become necessary for ranking the global fuzzy similarity. In this paper, we adopt the following ranking method for triangular fuzzy numbers [24]. In this ranking method, the criterion for dominance is given below:

$$C(\widetilde{A}) = \frac{(a-\alpha)+2*a+(a+\beta)}{4} \qquad (6)$$

where $\widetilde{A}$ is a triangular fuzzy number noted as $(a, a-\alpha, a+\beta)$.

5   Simulation and results

This paragraph will be devoted to the description of implemented system and the obtained results with a developed urban traffic simulator. The

case based system as well as the simulator are implemented using Java as programming language and MYSQL as a Database Management System (DBMS).

The simulated intersection is constituted by 4 roads with 1 lane for each one. In this example, the case base contain initially 42 cases. Although the type of the simulated intersection is not complicated, the use of the approach as well as the simulator remains always valid. The duration of the simulation is 10 min. In this scenario, the initial queue length of al lanes is 110 meters with an average speed of $40 m/min$. Also, let's note that during the simulation, the flow of arriving vehicles for each road is one vehicle per minute. The durations of green and red light are 2 seconds in four roads while the duration of the yellow light is equal to 0.5 second. Finally, the period of the simulated scenario is the day ($P = P2$) and the critical threshold is 120 meters.

In this paper, only two simulations were made. In the first one, no regulation action is considered. In other words, the durations of lights are considered as unchanged and the developed system is not connected to the intersection. The obtained results, after defuzzification, are illustrated in the figure 4. We notice that the length of the vehicles queue all roads does not stop increasing and reach unacceptable values (280 meters). This is due to the high number of arriving vehicles and the low duration of green and red light. Indeed, the durations of lights are always static and the dynamic state of the intersection is not considered.

During the second simulation, the developed system is connected to the simulator to improve the situation. The obtained results are then illustrated in figure 4. The figure 4.a shows the evolution of the length of the queue before and after the activation of the regulation action. At the end of the simulation, the queue length in all roads is stabilized around 100 meters. It is necessary to underline that the length is stabilized at this value because of the dynamic duration of the light. This explains the evolution of the queue length in the other roads (figure 4.b, 4.c and 4.d). Indeed, the duration of the green light increases and at the same time, the duration of the green light of the other roads decreases and this to allow to more vehicles to cross the intersection. Finally, let us remember that the critical
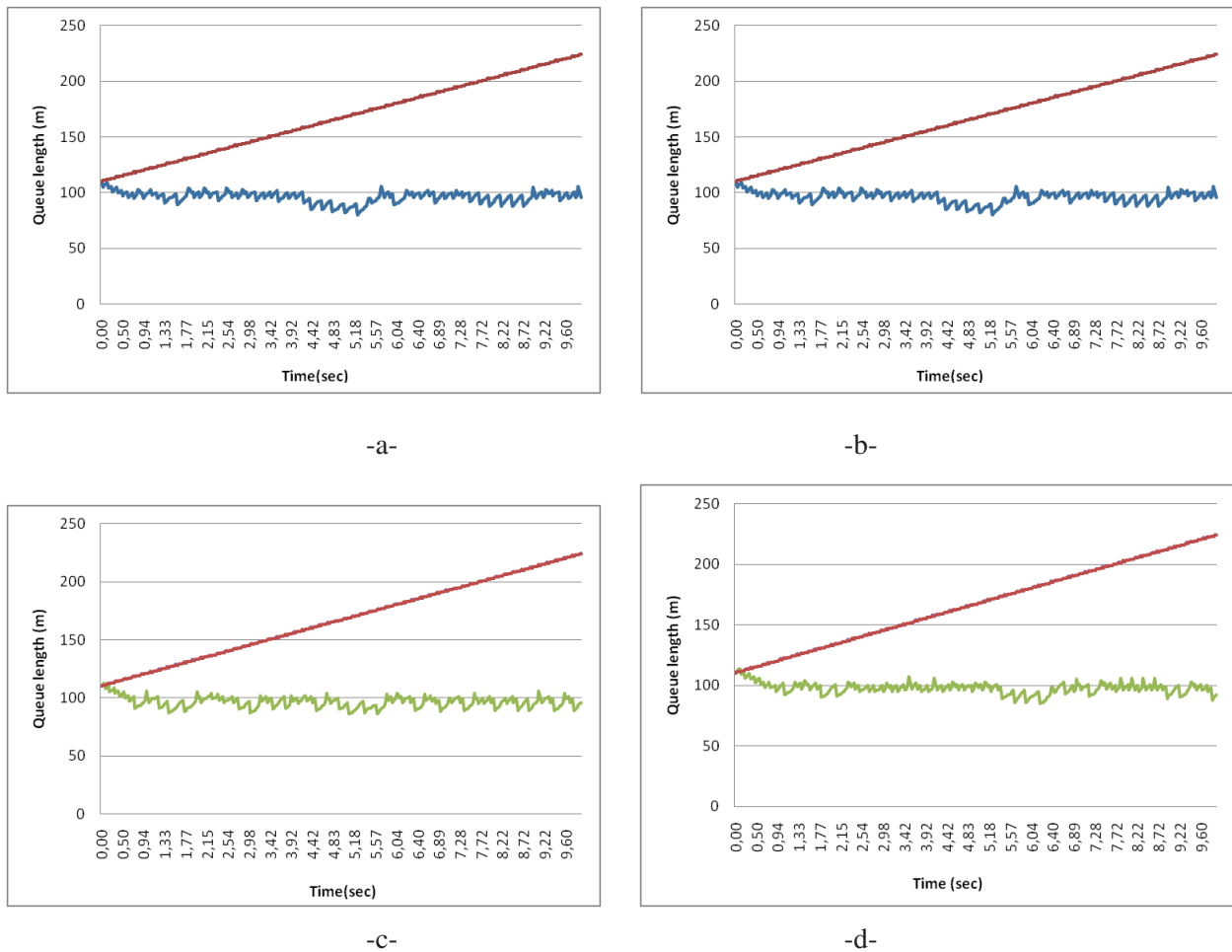
-a-

-b-

-c-

-d-

Figure 4. Results after and before the regulation actions

queue length L_{max} in this scenario is 120 meters and it is for that reason that the system react as soon as the length approaches this value.

Conclusion

This paper tried to highlight the importance of integrating the real traffic conditions to generate timing schedules. The consideration of the dynamic state of the traffic have an important impact on its fluidity. Nevertheless, some of existing systems neglect several dynamic constraints associated to the traffic conditions such as accidents, jam or other problems.

The aim of the study described in this paper is to propose a traffic light control system to improve the fluidity in some intersections. The developed system is based on CBR approach that is coupled

with fuzzy set theory where each case is associated to a regulation action. In this work, 6 actions are proposed that act on the duration of traffic lights. In this paper, two scenarios are simulated and the obtained results demonstrate that such system can resolve some traffic problems.

To improve this system, several directions must be explored. First, other constraints can be considered such as the heterogeneity of the traffic with the presence of public transportation that can have a higher level of priority than personal vehicles. The second perspective is to extend the system to control more than one intersection. As a solution, The Multi-Agent System (MAS) can be coupled with the CBR system to develop a distributed system.

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