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Smart Pedestrian Crossing Management at Traffic Light Junctions through a Fuzzy-Based Approach

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Abstract: In the last few years, numerous research efforts have been conducted to merge the Internet of Things (IoT) with smart city environments. The goal to make a city "smart" is arising as a possible solution to lessen the issues caused by the urban population growth and fast urbanization. Attention also has focused on the pedestrian crossings because they are one of the most dangerous places in the transport field. Information and Communications Technologies (ICT) can undoubtedly be an excellent support in developing infrastructures that can best manage pedestrian crossing. For this reason, this paper introduces a fuzzy logic-based solution able to manage dynamically the traffic lights' phases in signalized pedestrian crossings. The proposed approach provides the possibility to change the phases of the traffic light taking into account the time of the day and the number of pedestrians about to cross the road. The paper presents a thorough description of the fuzzy logic controller configuration, an in-depth analysis of the application scenario and simulative assessments obtained through Vissim simulations.

Keywords: fuzzy logic controller; pedestrian crossing; traffic light management; intelligent transportation systems; smart city

1. Introduction

The Internet of Things (IoT) idea has piqued much interest from the research and industry community in the last few years [1]. One of the main reasons for this hype towards the IoT is its supposed applicability to different domains [2], like smart environments [3], smart homes [4], Industry 4.0 [5] or e-health [6]. Nevertheless, there is an application domain of the IoT, i.e., smart cities [7,8], that is presumably standing out from the rest. A smart city is a mixed ecosystem distinguished by the exceptional administration of Information and Communications Technologies (ICT), with the aim to develop cities more appealing and more sustainable, i.e., unique areas for innovation and entrepreneurship [9,10]. The essential stakeholders involve application developers, service providers, citizens, government and public service providers, the research community and platform developers. Besides, it is clear that a smart city is composed of many ICT technologies, development platforms, solutions for maintenance and sustainability, apps for evolving citizens and technical, social, as well as economic key performance indicators. As a consequence, IoT schemes will represent a fundamental task in the deployment of large-scale heterogeneous infrastructures. IoT-based smart city applications can be classified by network type, flexibility, coverage, scalability, heterogeneity, repeatability and end-user involvements [11]. These applications can be arranged into personal and home, utilities, enterprises and mobile. For instance, mobile applications include Intelligent Transportation System (ITS) and logistics, traffic management, congestion control and waste management.

Numerous research efforts have been conducted to combine the IoT with smart city environments. For instance, the growth of communications grids and the development of innovative schemes for production systems are analyzed in [12]. The authors point out that smart cities have become the basis for urban competitiveness nowadays, and ICT undoubtedly plays a fundamental role. Several ICT solutions are investigated focusing on their influence on new social behaviors that mold the means of communication and the development of urban areas. The main aim of the authors is to judge the various technologies applied in smart cities by their usefulness and importance. The factors influencing citizens' approval and adoption of ICT-based services for smart cities to enhance their quality of life are investigated in [13]. The obtained results show that if an ICT-based solution is of high quality, involves innovative ideas and ensures personal privacy, generally, the citizens tend to accept it and are willing to use it. The authors of [14] propose an edge-based platform as a useful IoT tool for the implementation of distributed applications for smart cities. The proposed solution can hide the heterogeneity of the associated physical devices and protocols. After validating their platform, the authors provide a set of design guidelines that could yield valuable advantages in developing services for smart cities, such as system extensibility, fault tolerance, integration of systems and system maintenance.

The goal to make a city "smart" is rising as a possible solution to lessen the issues caused by the urban population growth and fast urbanization. In fact, academic research has examined this phenomenon [15]. For instance, the authors of [16] suggest a framework to understand the idea of smart cities to reduce the gap in the literature about them considering the increasing use of this concept. In fact, they recognize several critical characteristics concerning smart cities, such as organization and management, governance, technology, people and communities, policy context, economy, built infrastructure and natural environment. These factors establish the basis of the proposed framework that can be employed to investigate how local governments are envisioning initiatives for future smart cities. On the contrary, the authors of [17] highlight that the use of big data has the potential to achieve notable results for smart cities, simultaneously with innovative services and products, higher competitiveness and economic progress. Nevertheless, the exploitation of big data in transport is at a significantly lower level compared to other areas such as retail and healthcare.

Although numerous studies exist about IoT and smart cities, the convergence of these two areas needs further academic efforts for the thriving of IoT-based smart cities. Nevertheless, the application fields of IoT-based solutions are plentiful. For this reason, it is beneficial to develop approaches that are proper and smart to handle one of the many issues that concern ITS. Among them, it is worth noting that of the pedestrian crossing.

A pedestrian crossing (British English) or crosswalk (American English) is a part of the road painting and is designated for pedestrians to cross a road. Crosswalks are usually outlined to retain pedestrians together where motorists can see them and wherever they can pass most safely over the flow of vehicular traffic. Marked pedestrian crossings are usually located at intersections at grade, but may also be at other positions on bustling roads that, otherwise, would be too risky to cross without a support due to vehicle numbers, speed or road widths. Crosswalks are also usually situated where a considerable number of pedestrians is striving to cross, for instance near shopping areas, or where exposed road users (such as school children) frequently cross. It is clear that specific rules are needed for the use of the pedestrian crossings to ensure safety. For instance, in some areas, the pedestrian must be more than halfway across the crosswalk before the driver proceeds. Signalized pedestrian crossings are employed to divide traffic types, i.e., pedestrians or road vehicles, that use the road junction. On the contrary, un-signalized crossings habitually support pedestrians and usually prioritize them.

The pedestrian crossings are one of the most dangerous places in the transport field. In fact, most of the traffic accidents happen there. In urban areas, especially in inner cities, pedestrians crossing the road unquestionably affect the traffic flows. For this reason, several approaches have been developed for the detection of traffic and pedestrian flows at traffic lights [18–20]. Generally, for several reasons, the priority should be assigned to pedestrians. However, as highlighted in [21], the inclination to give pedestrians a high priority in crosswalks influences the road traffic capacity considerably. The authors have examined several distances between pedestrian crossings to determine their assessment; a non-constant inter-crosswalk spacing is also considered. The analysis carried out in [22] shows that more and more pedestrians use mobile phones in their daily activities. This action is a real distraction for pedestrians when they are going to cross the street, especially at un-signalized intersections. The authors of [23] show that, in the class of unsafe road users, the pedestrians are identified as those with the most significant chance to be influenced by severe or fatal casualties in road accidents. Nevertheless, there are several factors to be analyzed. First of all is the randomness of users' behavior. Moreover, sometimes, the inadequate attention of traffic light operation settings implies that the pedestrians are involved in road accidents, in particular in isolated signalized junctions. As a consequence, there is a clear need for new and intelligent systems to play a fundamental role in the improvement of pedestrian safety.

ICT-based solutions can undoubtedly be an excellent support in developing infrastructure that can best manage pedestrian crossing. For instance, a method for crosswalk marking detection by using laser-based applications for intelligent vehicles systems, as well as pedestrian security, is proposed in [24]. The approach introduced by the authors aims to recognize crosswalks and is based on the road marking material and the pattern produced by the reflection of the laser beam from the road surface. The obtained results prove a satisfying performance for real-time application since the average processing time is relatively low for the crosswalk marking detection. The authors of [25] present a robust method for crosswalk detection and location, based on Maximally-Stable Extremal Regions (MSER) and extended Random Sample Consensus (ERANSAC), in traffic surveillance scenes. Compared to several existing detection techniques, the proposed method can efficiently derive crosswalk areas under the various illumination conditions. In this way, it is possible to bypass the selection of thresholds according to the current environmental situation, and as a consequence, the system flexibility and robustness are significantly increased. On the contrary, other authors have concentrated on signalized crosswalks. For instance, an algorithm for the detection of traffic lights and crosswalks, which globally compose a framework, is proposed in [26]. The solution introduced by the authors is developed to run also in embedded devices with small computational resources in real time. The framework is based on image detection, and the achieved results show that the accuracy of the algorithms is relatively high, although inaccurate results can easily be produced based on the quality of the detected images. The authors of [27] present a high-resolution data system able to gather the location, speed and turn movement of each vehicle as it enters an intersection, together with the signal phase and pedestrian and bicycle movements. The proposed system is based on video monitoring. The authors highlight that the use of a high-resolution data system can be a valuable support for intersection performance and for improving mobility and safety. However, it is necessary to point out that their solution requires powerful hardware and quite high computational performance. A new pedestrian twice crossing pattern, capable of realigning the vehicle signal sequence, is introduced in [28] with the aim to fully employ the temporal-spatial resource of a road intersection, helping thus pedestrians' crossing, providing them more time. The obtained results, regarding the average travel time, average delay and intersection capacity, of the road junctions that apply different signal sequences and pedestrian crossing patterns show promising performance compared to other solutions.

This paper introduces a fuzzy logic-based solution for coping with the dynamic management of traffic lights' phases in signalized pedestrian crossings. In the smart solution introduced in this paper, the traffic light is dynamically regulated, by a Fuzzy Logic Controller (FLC). In fact, the employment of rule-based FLCs helps the development of multi-criteria control procedures. Fuzzy logic is capable of performing real-time decisions, even with incomplete knowledge. More in detail, in recent years, various fuzzy-based strategies have been proposed to enhance the administration of traffic light junctions [29–31]. Since fuzzy logic schemes can naturally handle the linguistic rules, they are mainly suitable in different contexts, such as the dynamic management of traffic lights. Besides, fuzzy systems can be employed by mixing different parameters and rules, which may provide an optimal result.

For instance, the use of smart setting and tuning techniques for FLCs can improve several ITS-based solutions for smart cities. As a consequence, the FLCs, based on linguistic rules instead of rigid reasoning, can be the appropriate choice to represent a mechanism for the dynamic control of traffic light phases in pedestrian crossings. The proposed fuzzy-based solution provides the possibility to adjust the phases of the traffic light taking into account the time of the day and the number of pedestrians about to cross the road. In fact, the time of green can be extended, compared to that established statically, to enable a better disposal of the pedestrians accumulation.

This paper is organized as follows. The examination of the scenario analyzed in this paper, i.e., the traffic light junction that involves a pedestrian crossing, is carried out in Section 2. The proposed fuzzy-based system model is introduced in Section 3, where the configuration of the suggested smart FLC is presented. Section 4 assesses the performance obtained in simulation scenarios, and finally, Section 5 ends the paper.

2. The Analyzed Scenario

The proposed smart solution is applied on a signalized road intersection located in the urban area of Enna, an Italian town (Figure 1). In particular, the investigated scenario is associated with a four-arm intersection. It is composed of the main road (namely Viale Diaz), represented in Figure 1, with Arms 1 and 3, both two-way and one-lane roads, and a secondary one (namely Via Libertá), indicated in Figure 1 with Arms 2 and 4. In this case, Arm 2 is a two-lane one-way road, while the Arm 4 a two-way road with one lane in each direction. Several business activities are located around this area, such as bars and offices, overlooking Arms 2 and 3, while on the left side of the corner between Arms 1 and 4, there is a primary school ("De Amicis"). Other businesses, such as banks, wine bars and restaurants, are closed to the intersection, causing pedestrian movements.

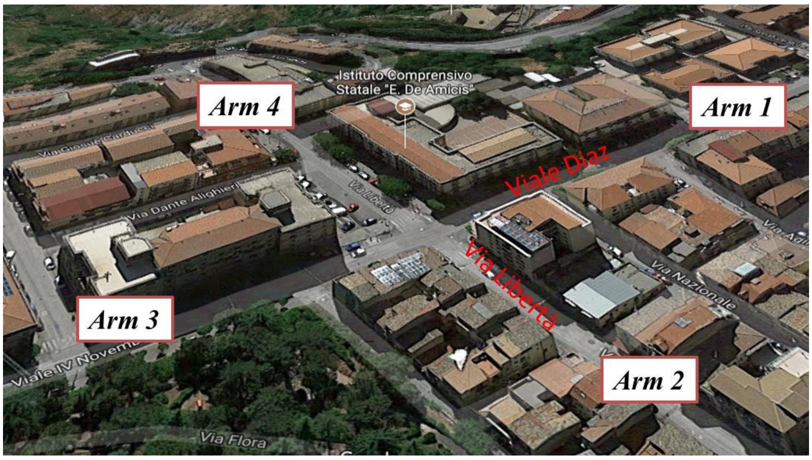


Figure 1. The analyzed signalized road intersection located in the urban area of Enna.

The peak of traffic flows, concerning vehicles and pedestrians, is associated with the entrance and exit times of business activities, mainly referring to schools and offices. Figure 2 shows the trend of traffic and pedestrian peak flows during a weekday. For instance, it is possible to note that the increase in vehicles is the highest on Tuesdays due to the open market (i.e., the 5th, 9th and 12th monitoring days).

It is valuable to estimate the percentage of vehicles and pedestrians that are involved in the various arms. Data shown in Table 1 are based on about 1000 veh/h, where each percentage of vehicles is related to the maneuvers on the investigated road intersection (Figure 3). The same analysis can be carried out regarding the pedestrians. In fact, the values in Table 2 refer to about 250 pedestrians/hour distributed in the two directions for each arm, considering the pedestrian flows during the peak hours (Figure 4).

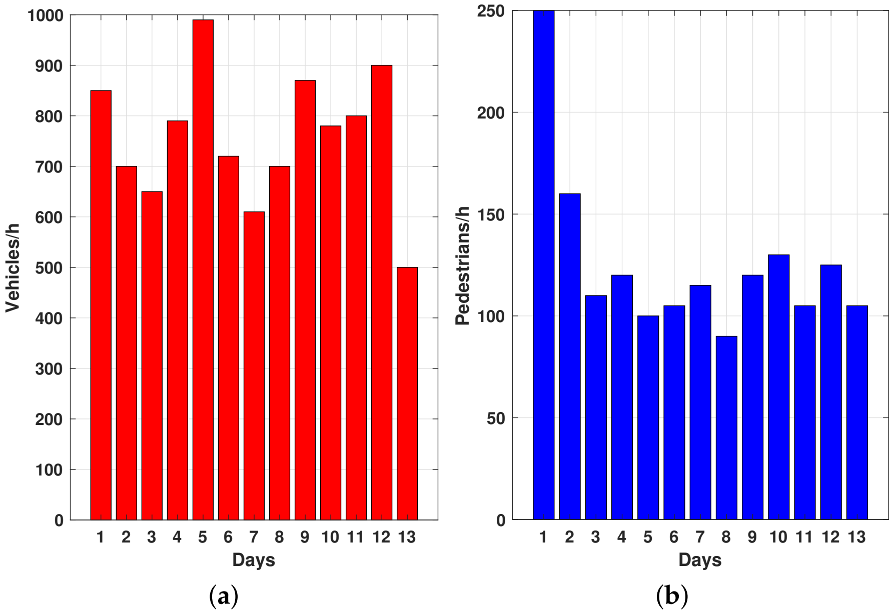


Figure 2. The peak of traffic flows: (**a**) vehicles; (**b**) pedestrians.

Table 1. Vehicle percentage in the various arms.

	Arm 1	Arm 2	Arm 3	Arm 4
Arm 1	0%	0%	40%	60%
Arm 2	60%	0%	14%	26%
Arm 3	60%	0%	0%	40%
Arm 4	30%	0%	70%	0%

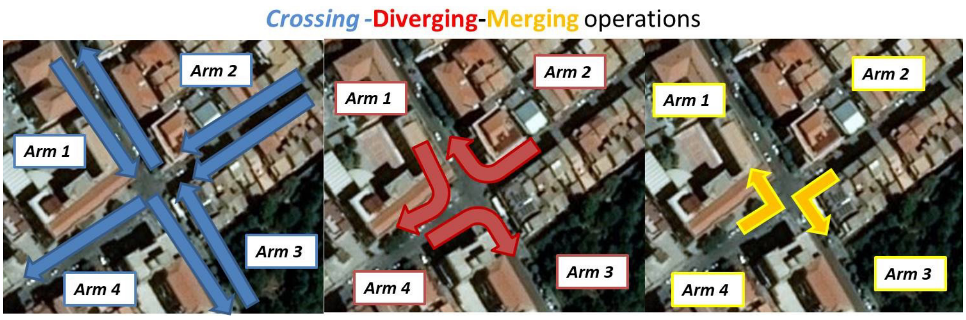


Figure 3. Maneuvers on the investigated road intersection: blue = crossing; red = diverging; yellow = merging.

Table 2. Pedestrian percentage in the various arms.

	Arm 1	Arm 2	Arm 3	Arm 4
Arm 1	0%	20%	50%	30%
Arm 2	30%	0%	20%	50%
Arm 3	50%	30%	0%	20%
Arm 4	30%	0%	50%	20%

It is useful to note that in real case studies [23], it emerged that 10–13% of pedestrians do not take into account the red interval time of traffic lights. Furthermore, the variability of traffic light settings could produce an increased risk for pedestrians who are crossing on average with a reduced time to collision. The age groups that are subject to the higher risk are 15–30, and females behave more aggressively than males. Considering also other findings on the implication of Red Light Running (RLR) proneness when adaptive traffic light operations are employed [32], it is clear that while the daily variability of traffic light settings improves the disposal of vehicles, on the other hand, it has a detrimental effect on pedestrian safety.

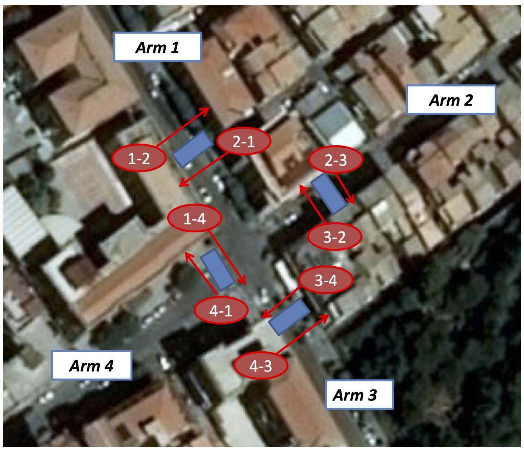


Figure 4. Pedestrian flows during the peak hours.

The variability of vehicle and pedestrian flows is related to the activities that take place in the areas around the traffic light junction throughout the day. In fact, some flows exceed 250 ped/h and 1000 veh/h in peak hours, while there are values of about 1/3 in other hours of the day. This variability is most noticed during the weekend. Therefore, to optimize the management of pedestrian/vehicle flows, the traffic light junction requires the implementation of a dynamic control infrastructure that can optimally handle the times of the traffic lights taking into account the number of pedestrians that are going to cross the road. Another peculiarity to consider is the time of day. In fact, as mentioned earlier, in some hours of the day, there may be copious flows of pedestrians and vehicles, while in others, the size decreases considerably. Consequently, the dynamic monitoring infrastructure of the traffic light cycle must also take into account whether it is at a critical time when evaluating the number of pedestrians and vehicles. The goal is to allow not only a modulation of flows consistent with the analyzed context (Figure 1), but also an increment of safety for pedestrians and motorists.

It is clear that to achieve these goals, an ICT infrastructure is needed. It must be able to detect the number of pedestrians and to handle the traffic lights' cycles dynamically. The approach proposed in this paper, based on a fuzzy logic controller, is presented in the following section.

3. The Proposed Fuzzy Logic Controller

A generalized representation of the fuzzy-based solution proposed in this work is depicted in Figure 5, which shows the inputs and the output of the FLC. It is helpful to note that the proposed FLC is applied to manage dynamically the phases of traffic lights located in pedestrian crossings, allowing the best disposal of pedestrians according to the time of day. The structure of the proposed FLC (Figure 5) is considerably simple because it allows not only a straightforward implementation on real devices, but notably, low computing needs. The smart system proposed in this paper requires small data transfers, as the data to be controlled by the FLC are the number of pedestrians waiting to cross the road and the time slot. Consequently, there is a lower computing need [29]. On the contrary, other techniques based on composite fuzzy controllers (such as Petri net or Type-2 fuzzy), other systems that use multiple controllers in parallel or other methods that are based on numerous parameters as input to the controller require higher computing needs. These advantages of the proposed FLC are presumed to be useful regarding lower data processing times and lower control actuation times.

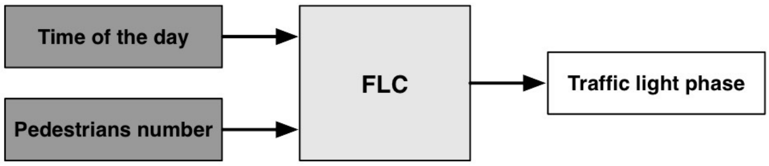


Figure 5. Proposed Fuzzy Logic Controller (FLC) Architecture.

As shown in Figure 5, an input parameter is represented by the number of pedestrians, standing in front of the traffic lights, who are preparing to cross the road. Several solutions can be utilized to identify and count groups of people, whether stationary or on the move. In the scenario analyzed in this paper, the group of people is represented by standing pedestrians waiting for the green of the traffic light. For this reason, to provide an input value to the FLC, in this paper, the pedestrians are counted through the technique proposed in [33], which is based on the use of cameras. It is based on a novel projection method to evaluate the area that represents each blob in real-world coordinates. This approach has been chosen because it decreases issues due to objects that are not similar to human height. Moreover, the contrasts between the projected area of people at various distances from the camera are also taken into account. Another original feature of the solution presented in [33], compared to other standard techniques, is the management of groups as single objects rather than treating individuals separately. However, this system has been extended in this work, with the aim of making it able to deal with stationary people in a scene, by including a different type of background segmentation, which is not based on motion.

From an implementation point of view, the approach proposed in [33] requires the use of a single camera to count groups of people in a reference area. At the intersection of Enna taken into account in this paper, eight cameras would be needed to calculate the groups of people in all pedestrian crossings. Regarding the computational power, the approach proposed in [33] does not require many hardware resources. The authors only state that it is appropriate to use a calibrated camera, i.e., able to adapt its characteristics to the conditions of the recording area. The cost of a video camera of this type ranges between about 100 € and 3000 € according to the features. As a result, it is possible to estimate the installation cost of the entire infrastructure proposed in this paper. The price could range between about 2000 € and 25,000 €.

Following the description of the proposed FLC scheme, it is relevant to concentrate on the fuzzy inference system that determines the phases of the traffic lights and, primarily, concisely specifying the membership functions applied in this paper. The proposed fuzzy logic controller employs three membership functions (*Low*, *Medium*, *High*)for the pedestrians number (input) and phases of the traffic light (output). These functions fuzzify the crisp inputs, while their range for pedestrians number (input) fluctuates from 0–200. On the contrary, for the phases of the traffic light (output), the values are related to the configuration of the traffic light regarding the green, yellow and red times.

The triangular membership functions of the pedestrians number are represented in Figure 6, where the degree of membership is realized by normalized values [0 ÷ 1]. Regarding the time of day, it is not possible to obtain a continuous numerical range as for the the pedestrian number. In fact, there may be hours where the traffic light junction is more crowded concerning vehicles and pedestrians, while in others, the situation may be somewhat more regular and almost linear. For this reason, considering the signalized road intersection located in the urban area of Enna, introduced in Section 2, the following time intervals, represented through the symbol ÷, have been labeled as "*Critical*":

- 07:00 a.m. ÷ 09:00 a.m.;
- 01:00 p.m. ÷ 02:00 p.m.;
- 05:00 p.m. ÷ 06:00 p.m.

i.e., for instance, the first interval extends between 07:00 a.m. and 09:00 a.m. On the contrary, the other hours of the day have been identified as "*Not Critical*".

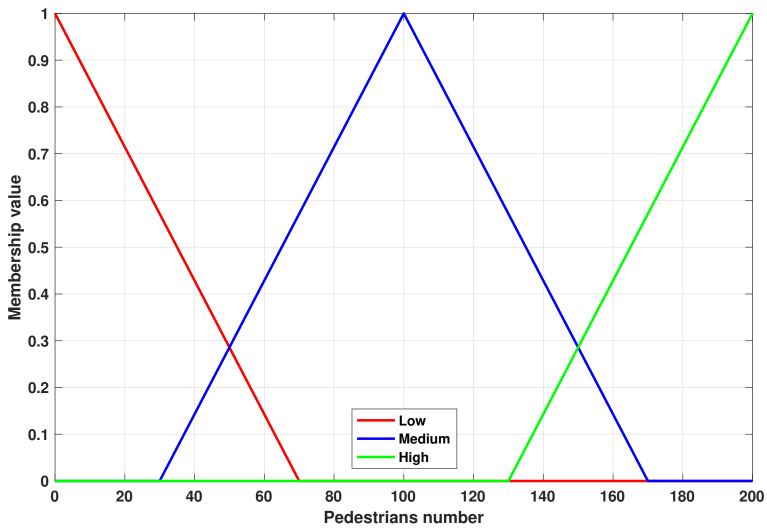


Figure 6. Membership functions of the pedestrian number.

The traffic-light cycle considered in the proposed approach is related to two phases along the two roads (Figure 1). The set for the overall traffic light cycle can be 84 s (i.e., 30 for green, 49 for red and 5 for yellow) or 94 s (i.e., 25 for green, 64 for red and 5 for yellow). This cycle of 84 or 94 s is related only to the traffic light and does not represent an input/output parameter of the FLC. The output of the FLC defines the variation of this set by increasing or decreasing green and red times. Concerning the phases of traffic lights for pedestrians, the values of green, yellow and red times, updated dynamically based on the membership function (*Low*, *Medium*, *High*), are shown in Table 3. In detail, for instance, considering the 84-s cycle, the standard values of green, yellow and red times (i.e., *Low* membership function) are 30, 5 and 49 s. When the value of the membership function falls in the *Medium* range, then the green time will have an increase of about 33%, while in the *High* range, the improvement is about 66%. Consequently, the red time is reduced. The same mechanism is implemented for the 94-s cycle.

Table 3. Variation of the traffic light set.

Membership Function	Green Time (s)	Yellow Time (s)	Red Time (s)
	84 s cycle		
Low	30	5	49
Medium	40 (i.e., about +33%)	5	39
High	50 (i.e., about +66%)	5	29
	94 s cycle		
Low	20	5	64
Medium	45 (i.e., about +125%)	5	44
High	55 (i.e., about +170%)	5	34

As depicted in Table 4, the output value of the FLC is specified through six fuzzy rules based on the *IF-THEN*statement of traditional programming languages. For instance, considering Rule 1, if *Time of the day*is *Critical* and *Pedestrians number* is *Low*, the *Traffic light phase* will be *Medium*. As is recognized, in an inference mechanism, the outputs are fuzzy variables. For this reason, the fuzzy logic controller needs to convert its internal fuzzy output variables into crisp values, by the defuzzification method, so that the actual system can handle them. For instance, taking into account the cycle of the traffic light (84 or 94 s), if the output of the defuzzification process (i.e., a numerical value and not a linguistic variable) falls in the Mediumrange, the direct result of Rule 1 (Table 4), previously analyzed, is related to the values shown in Table 3. In this case, the values of green, yellow and red times will be 40, 5 and 39 s for the 84 s cycle, while they will be 45, 5 and 44 for the 94-s cycle.

Table 4. Inference rules.

Rule	Time of the Day	Pedestrians Number	Traffic Light Phase
1	Critical	Low	Medium
2	Critical	Medium	Medium
3	Critical	High	High
4	Not Critical	Low	Low
5	Not Critical	Medium	Medium
6	Not Critical	High	High

4. Performance Evaluation

4.1. Simulation Model

The traffic light junction has been implemented through the use of Vissim micro-simulation software [34], which is based on the car model defined by Wiedemann [35]. In the first phase, the geometric road diagram has been implemented by inserting strings and nodes that are part of a transport graph. In general, the nodes of a road network are identified by the intersection of the roads constituting the system to be analyzed. The analysis of supply/demand has further been implemented by considering the Origin/Destination (O/D) attributes with particular reference to the percentages of maneuvers made from one node to another. The graph nodes match at the origin or destination of the displacement. Of them, the source/destination centroids corresponding to the beginning/end maneuver for each intersection arm have been highlighted. In the case of pedestrian flow, they correspond to the beginning/end of crossing for each arm of the urban road intersection. The arcs of the graph are characterized by a principal direction, corresponding to Direction 1–3, and a secondary one, corresponding to Lines 2–4, as noted above.

Any network can be described as a matrix with rows as the set of origins and the columns as the set of destinations. The number of rows and columns would match the number of nodes in the network. Conventionally, the horizontal rows of a matrix are recognized as a set of origin nodes, and the vertical columns of the matrix are specified as a set of destination nodes. Every cell entry in the matrix can be utilized to register data on the connection between a pair of nodes. Every single node is well connected to other nodes in a network and, as a consequence, can be accessed. However, this evaluation is not reasonable in a more complex network involving a more significant number of nodes and also alternative routes.

More in detail, given a graph-oriented $G(N, A)$, with $|N| = n$ and $|A| = m$, G is a matrix M of size $n \times m$ composed of $(0, 1, -1)$ as follows. Each row is associated with a node of N, while each column is associated with an arc of A. Specifically, the M column associated with the arc $uv \in A$ will have exactly a value of -1 at the line associated with the node u, while it will have $+1$ at the line associated with node v, and 0 in all other rows. M is called incidence matrix (arcs-nodes) of G.

The incidence matrix associated with the analyzed nodes/arcs, referring to possible maneuvers, is shown in Table 5. The cells of the matrix have a value of one if the node is a departure in the arc; on the contrary, it is -1 if it is the destination, and zero if the node does not exist in the arc.

Table 5. Incidence matrix associated with the analyzed nodes/arcs.

O/D		Arcs								
		1-3	**1-4**	**2-1**	**2-3**	**2-4**	**3-1**	**3-4**	**4-1**	**4-1**
Nodes	*1*	1	1	−1	0	0	−1	0	−1	0
	2	0	0	1	1	1	0	0	0	0
	3	−1	0	0	−1	0	1	1	0	−1
	4	0	−1	0	0	−1	0	−1	1	1

The mathematical investigation of traffic-related phenomena is based on code theory. Traffic is then modeled as a stochastic process. For instance, a process defines the arrival times of vehicles entering a specific passage, and another defines the time taken to make a route. The qualitative classification of congestion is usually carried out on a six-letter scale (from A–F) referring to Levels Of Service (LOS), as defined in the Highway Capacity Manual [36]. These levels are used in transport engineering as a quick way to describe traffic levels on roads or crossroads. Since collisions between pedestrians and vehicles have a much higher potential for mortality than other types of accidents, in the last few years, a growing sensitivity in understanding and predicting the causes of these types of accidents is spreading. It is necessary to consider specific global parameters or for a single arm to study a road intersection concerning capacity and flows. These parameters, described in Tables 6 and 7, must be evaluated both regarding their maximum and average values.

To correctly evaluate the acceptable time gap for the pedestrian crossing to be safe, it is necessary to focus the analysis on the pedestrian's point of view. The pedestrian population must be treated very differently from the vehicular one. Pedestrians do not have rigidly channeled paths. Their speed may vary according to age and physical conditions. Moreover, they can cross-track their trajectories randomly and have almost instantaneous acceleration/deceleration profiles. Consequently, it is necessary to evaluate the heterogeneous nature of the pedestrian population preliminarily. Furthermore, it is natural to think that a pedestrian will modify his/her attitude if he/she is in a hurry compared to when he/she is relaxed, varying his/her speed. For instance, concerning pedestrians, in [36], a walking speed of 3.9 ft/s (i.e., 1.2 m/s) is recommended, with the speed reduced to 3.1 ft/s (i.e., 1 m/s) if the percentage of elderly pedestrians exceeds 30%. Moreover, pedestrian speeds at crosswalks on intersections and on-road trunks have been studied in [37]. The results show that there are slower average speeds at road trunks. In [38], it is suggested to lower the walking speed of the pedestrian to 3.5 ft/s (i.e., 1.1 m/s). Nonetheless, it is also stated that speeds even lower may be appropriate in some instances. In fact, the variability of the speed of the pedestrian is a determining factor when it comes to problems related to crossing because it is directly proportional to the time required to overcome a certain distance.

Table 6. Descriptive parameters of vehicular flows.

Parameter	Units of Measurement
Vehicle flow	veh/h
Queue length	m
Delay	s
Speed variation	m/s or km/h
Acceleration variation	m/s^2 or km/h^2
Stop number	unit

Table 7. Descriptive parameters of pedestrian flows.

Parameter		Description	Units of Measurement
Pedestrian number variation	PEDENT(ALL)	Pedestrians inserted in the network	ped/s
	PEDARR(ALL)	Pedestrians have arrived at their destination before the end of the simulation	ped/s
	PEDACT(ALL)	Pedestrians within the network once the simulation is over. Pedestrians that have not arrived (PEDARR)	ped/s
	DENSAVG(ALL)	Average pedestrian density	Ratio of all pedestrians in the network to pedestrians in pedestrian areas
Pedestrian flow	FLOWAVG(ALL)	Average flow given by the product between the average current speed on all pedestrians and the current density	ped/s
	FLOWTODESTAVG(ALL)	Flow in the direction of the average destination given by the product between the current velocity and the total current density taking into account the static potential in the position of each pedestrian	ped/m
	TRAVTMAVG(ALL)	Average travel time of pedestrians who are in the network or have already been removed from the network	s
Speed	SPEEDTODESTAVG(ALL)	Speed in the direction of the destination	km/h
	NORMSPEEDAVG(ALL)	Average normalized speed given by the ratio between the actual speed and the desired speed averaged between all pedestrians and time steps	km/h
	SPEEDAVG(ALL)	Average speed	km/h
Stops	STOPSAVG(ALL)	Average number of stops per pedestrian	Ratio between the total number of stops and the sum between the number of pedestrians in the network and the number of pedestrians that have arrived
	STOPTMAVG(ALL)	Average duration of the stop	s

This indicator has been used and developed to assign the frequency and severity of critical events between vehicles and pedestrians when crossing the road. The study of this indicator is based on the fact that critical times and distance intervals are identified as a function of vehicle speed. As a consequence, it has been evaluated, experimentally, that many drivers do not adapt their speed to the limit imposed and do not consider pedestrians who are near a potential danger. Moreover, it has been observed that out of four drivers, only one stops or slows down to let the crossing of the pedestrian who is forced, in many cases, to perform this action very quickly. Post-Encroachment Time (PET) [39] is conventionally defined as the time between the first road user leaving the common spatial zone (in a two-road user encounter) and the second road user arriving at it. The Time To Collision (TTC) [40] is defined as the time to collision of two road users if they keep their directions and velocities. In the performance evaluation of the solution introduced in this paper, the minimum TTC during the pedestrian-vehicle conflicts is used as one of the surrogate safety measures. Three related safety measures for data analyses are used in this paper, and they are defined as follows:

- dm (m/s^2): the maximum deceleration during the pedestrian-vehicle conflict period;
- PET (s): post-encroachment time for the pedestrian-vehicle conflict;
- TTCmin (s): the minimum time to collision during the pedestrian-vehicle conflict period.

In general, for the case of conflicts between pedestrians and vehicles, the time to collision (TTCp) is defined as follows:

$$TTCp = Dxi(v) - Dxi(p)/Vp \tag{1}$$

where $TTCp$ is the time that a pedestrian takes to reach the conflict zone; $Dxi(v)$ is the transverse position of the vehicle; $Dxi(p)$ is the transverse position of the pedestrian; and Vp is the speed of the pedestrian.

4.2. Simulation Results

The matrices of vehicle and pedestrian traffic flows have been acquired through different simulations, statically setting the cycle of the traffic light at 84 and 94 s, respectively. Furthermore, the installation of the cameras has been simulated to apply the fuzzy logic controller through the external interface module provided by Vissim, where the operating code has been written. Even in this case, the fuzzy-based approach proposed in this paper has been applied with cycles of 84 and 94 s that, nevertheless, have been dynamically changed. Precisely, micro-simulations have been performed in the following time frames:

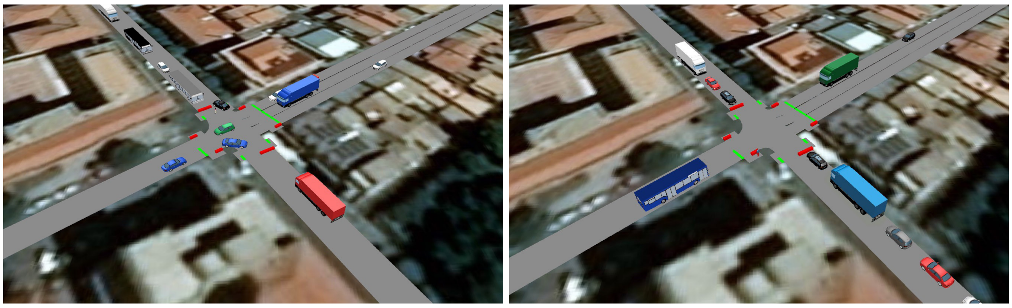
- 07:00 a.m. ÷ 09:00 a.m.;
- 01:00 p.m. ÷ 02:00 p.m.;
- 05:00 p.m. ÷ 06:00 p.m.

These time slots correspond to vehicular flow and pedestrian peaks corresponding to the entry/exit of influential offices and schools in the investigated area.

The measured values for the distribution of flows, shown in Table 8, according to the significant pedestrian crossings ad maneuvers, have allowed evaluating the different types of maneuvers. The obtained values, in terms of number of vehicles (*VEHS*), average queue length (*QLEN AVG*), max queue length (*QLEN MAX*) and number of stops (*STOPS*), show that the change in the overall traffic light cycle, with an increase from 84–94 s, raises the length of the stop queue, and this involves a higher propensity of the infrastructure to the congestion. This situation leads to lower levels of LOS and reduces the comfort and safety of pedestrians and passengers. Figure 7 shows how the output of the Vissim software allows evaluating the occurrence of a more significant congestion in the arms by switching from a traffic light cycle of 84–94 s, without employing the fuzzy-based approach introduced in this paper. On the contrary, as shown in Table 9, applying the FLC proposed in this paper, concretely better results can be achieved. In fact, the measured values are almost lower than the those depicted in Table 8.

Table 8. Obtained distribution of flows without the proposed fuzzy-based solution.

	Traffic Light Cycle 84 s				**Traffic Light Cycle 94 s**			
Arcs	***VEHS***	***QLEN AVG***	***QLEN MAX***	***STOPS***	***VEHS***	***QLEN AVG***	***QLEN MAX***	***STOPS***
1-3	100	14.14	104.82	0.73	100	24.19	109.24	0.91
1-4	151	14.14	104.82	0.75	152	24.19	109.24	0.96
2-1	145	3.39	59.38	0.52	145	2.32	55.00	0.39
2-4	63	1.21	28.96	0.41	63	0.78	28.99	0.29
2-3	36	0.91	23.61	1.23	35	0.68	24.55	0.96
3-1	144	44.78	111.48	1.54	92	86.50	111.62	2.86
3-4	98	44.78	111.48	2.28	62	86.50	111.62	4.11
4-1	72	7.15	90.15	0.84	71	4.73	82.26	0.61
4-3	172	7.15	90.15	0.56	171	4.73	82.26	0.42
Total for intersection	981	15.29	111.48	0.98	891	26.07	111.62	1.28



(**a**) (**b**)

Figure 7. Queue length in the arms with the static traffic light cycle: (**a**) 84 s; (**b**) 94 s.

Table 9. Obtained distribution of flows with the proposed fuzzy-based solution.

	Traffic Light Cycle 84 s				Traffic Light Cycle 94 s			
Arcs	*VEHS*	*QLEN AVG*	*QLEN MAX*	*STOPS*	*VEHS*	*QLEN AVG*	*QLEN MAX*	*STOPS*
1-3	100	12.04	95.16	0.67	100	22.18	67.21	0.41
1-4	151	14.02	88.11	0.43	152	16.37	88.64	0.68
2-1	145	1.99	60.12	0.32	145	1.05	42.13	0.43
2-4	63	1.05	20.24	0.39	63	0.57	21.87	0.25
2-3	36	0.66	12.15	0.71	35	0.69	21.34	0.74
3-1	144	39.73	89.59	0.87	92	45.38	87.15	1.59
3-4	98	35.05	100.32	1.54	62	71.25	88.84	2.98
4-1	72	4.02	75.17	0.81	71	3.56	81.23	0.66
4-3	172	6.08	80.76	0.58	171	2.09	66.76	0.55
Total for intersection	981	12.73	100.32	0.70	891	18.13	88.84	0.92

The same analysis has been carried out from a pedestrian point of view, through Viswalk, a tool provided by Vissim, and the results are shown in Tables 10 and 11. Even in this case, the application of the FLC implies an improvement in performance since the values presented in Table 11 are almost lower than those in Table 10 concerning the average queue length and stops. A better understanding of the average queue length can be obtained by analyzing the values shown in Figure 8. The variation in green and red times for the two traffic light cycles is more efficiently managed with the use of the fuzzy-based solution introduced in this paper. In fact, the values of the average queues are lower.

Table 10. Obtained distribution of pedestrians without the proposed fuzzy-based solution.

	Traffic Light Cycle 84 s				Traffic Light Cycle 94 s			
Arcs	*Speed ped* (m/s)	dm (m/s^2)	*QLEN AVG*	*STOPS*	*Speed ped* (m/s)	dm (m/s^2)	*QLEN AVG*	*STOPS*
1-3	1.1	6.3	1.4	0.73	1.01	6.1	2.19	0.91
1-4	1.51	5.9	1.67	0.75	1.02	5.4	2.19	0.96
2-1	1.05	6.1	2.01	0.52	1.05	5.9	2.32	0.39
2-3	2.36	5.2	1.91	1.23	1.3	5	1.68	0.96
2-4	1.63	6.7	1.01	0.41	1.3	6.3	1.78	0.29
3-1	1.44	5.6	4.78	1.54	1.2	5	6.5	2.86
3-4	0.98	5.9	1.78	2.28	0.62	5.6	1.5	4.11
4-1	0.72	6	1.15	0.84	0.71	6	1.73	0.61
4-3	1.72	5.7	1.15	0.56	1.01	5.1	1.73	0.42
Total for intersection	1.39	5.93	1.87	0.98	1.02	5.60	2.40	1.28

Table 11. Obtained distribution of pedestrians with the proposed fuzzy-based solution.

	Traffic Light Cycle 84 s				Traffic Light Cycle 94 s			
Arcs	***Speed ped*** **(m/s)**	**dm** **(m/s^2)**	***QLEN AVG***	***STOPS***	***Speed ped*** **(m/s)**	**dm** **(m/s^2)**	***QLEN AVG***	***STOPS***
1-3	1.1	6.3	1.11	0.41	1.01	6.1	1.17	0.43
1-4	1.51	5.9	1.02	0.81	1.02	5.4	1.21	0.62
2-1	1.05	6.1	1.04	0.45	1.05	5.9	1.51	0.38
2-3	2.36	5.2	1.88	1.01	1.3	5	1.07	0.81
2-4	1.63	6.7	1.12	0.33	1.3	6.3	1.08	0.31
3-1	1.44	5.6	2.83	1.08	1.2	5	3.34	1.15
3-4	0.98	5.9	1.22	1.06	0.62	5.6	1.11	2.27
4-1	0.72	6	1.03	0.53	0.71	6	1.73	0.52
4-3	1.72	5.7	1.08	0.52	1.01	5.1	1.81	0.39
Total for intersection	1.39	5.93	1.37	0.69	1.02	5.60	1.56	0.76

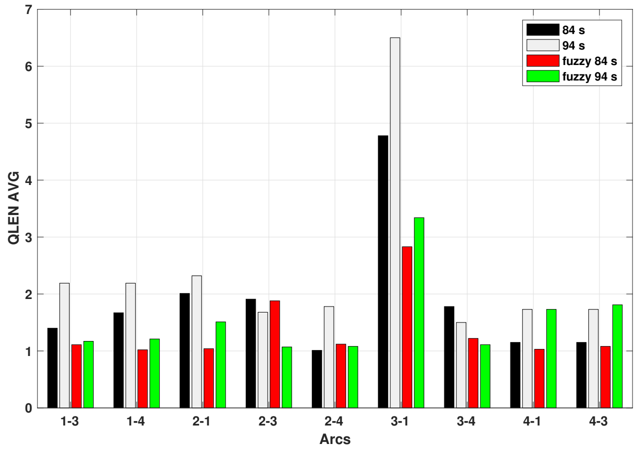


Figure 8. Average queue length of pedestrians.

The pedestrian flow has been analyzed in the various traffic light cycles through the variation of the parameters described in Table 7. Precisely, a similar variation of the stops and average stops for the two cycles analyzed has been measured, as shown in Figure 9. Furthermore, as shown in Figure 10, there is a similarity in the values of NORMSPEEDAVG, an increase of less than 5% of the parameter SPEEDTODESTAVGand an increase of 8–10% of the parameter SPEEDAVGduring the traffic cycle from 84 s to that of 94 s. These values arise from the pedestrian green times, i.e., 49 s for the cycle of 84 s and 64 s for that of 94 s respectively. The results obtained through the application of the fuzzy-based approach are almost similar to those with the static management of the traffic light cycle. In fact, the goal of the FLC is not to significantly increase the speed of pedestrians, but to dispose of their influx through a smart management of the traffic light phases.

An analysis has been made regarding the density of pedestrian flows. More in detail, the average flow in the direction of the destination, obtained from the product between the current speed and the total current density, has been evaluated, taking into account the static potential in the position of each pedestrian. Besides, the average pedestrian density parameter, i.e., the ratio of all pedestrians in the network to pedestrians in pedestrian areas, has also been measured. The values depicted in Figure 11 highlight an overall similarity of the two results when the traffic light cycle changes.

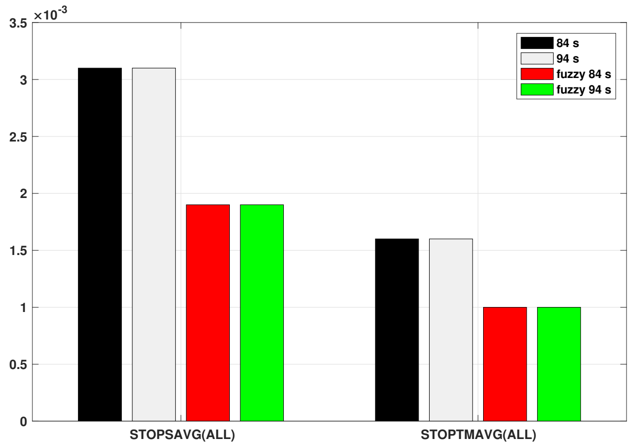


Figure 9. Variation of the stops and average stops of pedestrians.

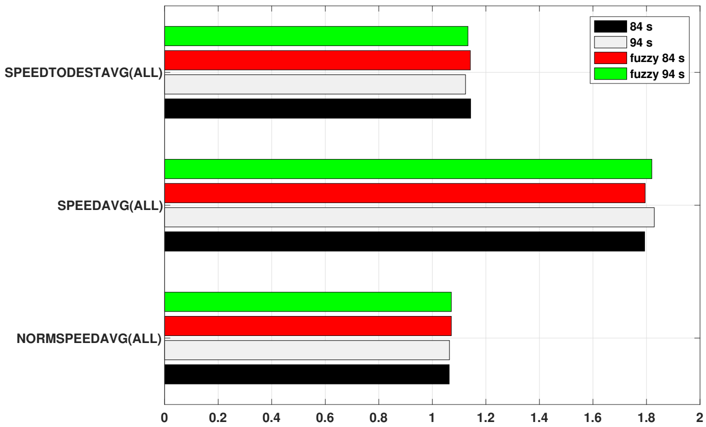


Figure 10. Speed of pedestrians.

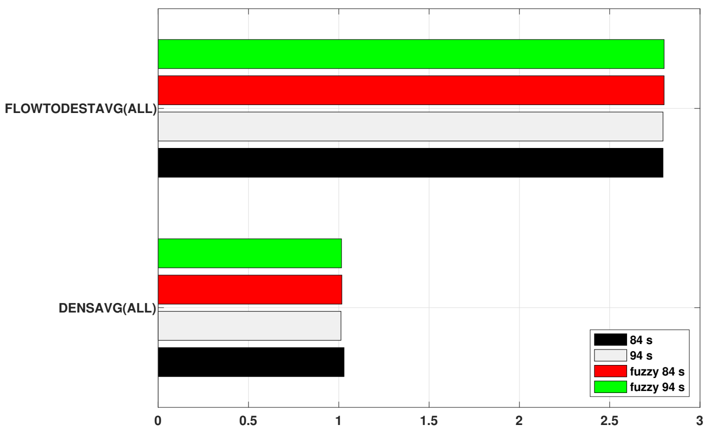


Figure 11. Density of pedestrians.

Further analysis has been carried out regarding the safety of the pedestrians at the traffic light crossing. To this end, the Time To Collision (TTC) and Post-Encroachment Time (PET) values have been evaluated. In fact, in research on traffic conflict techniques, TTC has been demonstrated to be a sound measure for traffic conflicts' severity. TTC is specified as the time to collision if two vehicles continue to drive at the same speed and in the same direction without any evasion behavior. The maximum value is infinite, and the minimum is 0 s (at the time the collision happens). The potential site of collision is first determined when Vehicle 1 occupies a precise position at a specific time. PET is defined as the time taken for Vehicle 2 to reach the identified site. The lower value of the TTCmin is associated with the higher risk of a collision. On the other hand, when TTC is high, but PET is small, there is no risk of rear-end collision. However, even a slight change in the motion characteristics may lead to a rear-end collision. The main difference between PET and TTC is the absence of the collision course criterion in PET. As shown in [41], since there is no requirement for the existence of collision course, PET is more useful in measuring transversal conflicts. The obtained values of TTC and PET are depicted in Figure 12. As is possible to note, even in this case, applying the FLC, the best performances are obtained compared to the use of the fixed traffic light cycle since the collision time lapse between the pedestrian and the vehicle and the pedestrian crossing compared to the one waiting to cross is increased. In general, only conflicts with a minimum TTC of less than 1.5 s are considered critical observers. Nevertheless, as can be noted in Figure 12, the TTC values exceed the value of 1.5 s through the fuzzy implementation, thus reducing the probability of accidents.

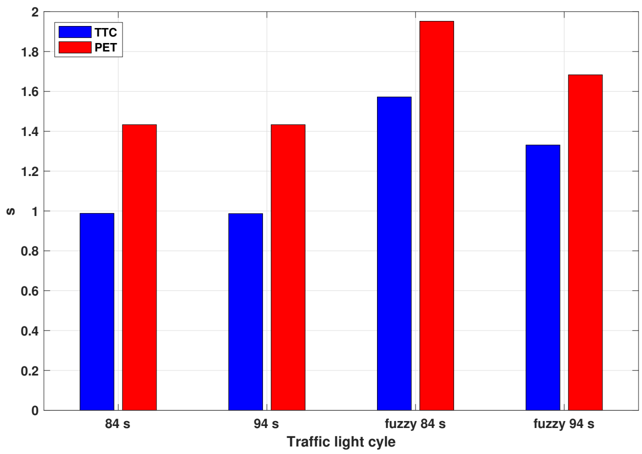


Figure 12. Time To Collision (TTC) and Post-Encroachment Time (PET) values.

Other parameters valuable for the evaluation of pedestrian safety during crossing are related to the possible types of accidents at the road infrastructure. The types of accidents examined in this paper are the following:

- Read end;
- Crossing;
- Changing lanes.

These types of collisions can be assessed through the Surrogate Safety Assessment Model (SSAM) tool [42] that employs some particular Vissim outputs to estimate the trajectories of vehicles and, consequently, their propensity to accidents. In Figure 13, an assessment of the various accidents before and after the application of the fuzzy logic is presented. It is possible to notice how the 84-s traffic light cycle leads to an increase in rear end accidents compared to the others. In particular, the increase in the 94-s cycle and a change in red/green times drives toward more than 1000 possible collisions, as in the 84-s cycle. On the other hand, the types of crossing and lane change accidents are comparable in value to the change of the traffic light cycle and green/red times. In detail, with the increase of the overall traffic cycle, there is an increment in the possible vehicle/pedestrian collisions during the crossing phase. Anyhow, the use of the FLC provides benefits even in this case, as the values relating to accidents are undoubtedly lower in both traffic light cycles.

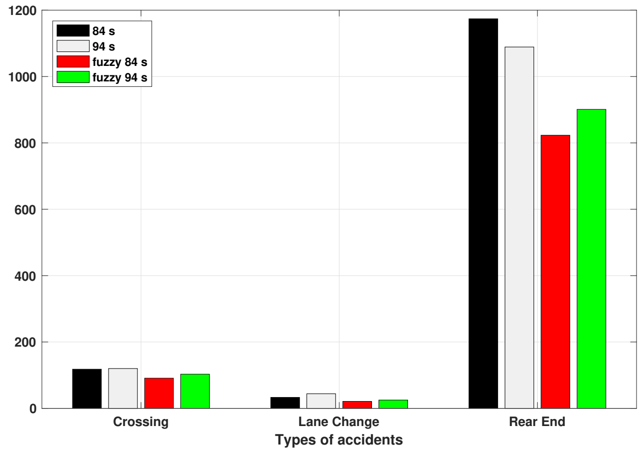


Figure 13. Types of accident values.

5. Conclusions

In this paper, a fuzzy-based approach to deal with the dynamic management of traffic lights in pedestrian crossing has been presented. The suggested solution provides the possibility to change the phases of the traffic light taking into account the time of the day and the number of pedestrians about to cross the road. In fact, the time of green can be increased compared to that defined statically to allow a better disposal of the pedestrians' accumulation. The paper offered an in-depth analysis of the FLC configuration and the application scenario. The paper also provided extensive simulative assessments, performed through Vissim, regarding the distribution of vehicles and pedestrians' flow, the queues at the traffic lights, the number of stops, and several parameters for the evaluation of pedestrian safety.

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References

1. Perera, C.; Liu, C.H.; Jayawardena, S. The Emerging Internet of Things Marketplace from an Industrial Perspective: A Survey. *IEEE Trans. Emerg. Top. Comput.* **2015**, *3*, 585–598.
2. Al-Fuqaha, A.; Guizani, M.; Mohammadi, M.; Aledhari, M.; Ayyash, M. Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications. *IEEE Commun. Surv. Tutor.* **2015**, *17*, 2347–2376.
3. Alnahdi, A.; Liu, S.H. Mobile Internet of Things (MIoT) and Its Applications for Smart Environments: A Positional Overview. In Proceedings of the 2017 IEEE International Congress on Internet of Things (ICIOT), Honolulu, HI, USA, 25–30 June 2017; pp. 151–154.
4. Park, E.; Cho, Y.; Han, J.; Kwon, S.J. Comprehensive Approaches to User Acceptance of Internet of Things in a Smart Home Environment. *IEEE Internet Things J.* **2017**, *4*, 2342–2350.
5. Wollschlaeger, M.; Sauter, T.; Jasperneite, J. The Future of Industrial Communication: Automation Networks in the Era of the Internet of Things and Industry 4.0. *IEEE Ind. Electron. Mag.* **2017**, *11*, 17–27.
6. Laplante, P.A.; Laplante, N. The Internet of Things in Healthcare: Potential Applications and Challenges. *IT Prof.* **2016**, *18*, 2–4.

7. Hernández-Muñoz, J.M.; Vercher, J.B.; Muñoz, L.; Galache, J.A.; Presser, M.; Hernández Gómez, L.A.; Pettersson, J. Smart Cities at the Forefront of the Future Internet. In *The Future Internet: Future Internet Assembly 2011: Achievements and Technological Promises*; Springer: Berlin/Heidelberg, Germany, 2011; pp. 447–462.
8. Zanella, A.; Bui, N.; Castellani, A.; Vangelista, L.; Zorzi, M. Internet of Things for Smart Cities. *IEEE Internet Things J.* **2014**, *1*, 22–32.
9. Gubbi, J.; Buyya, R.; Marusic, S.; Palaniswami, M. Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Gener. Comput. Syst.* **2013**, *29*, 1645–1660.
10. Carrino, F.; Mugellini, E.; Abou Khaled, O.; Ouerhani, N.; Ehrensberger, J. iNUIT: Internet of Things for Urban Innovation. *Future Internet* **2016**, *8*, 18, doi:10.3390/fi8020018.
11. Ray, P. A survey on Internet of Things architectures. *J. King Saud Univ. Comput. Inf. Sci.* **2016**, doi:10.1016/j.jksuci.2016.10.003.
12. Branchi, P.E.; Fernandez-Valdivielso, C.; Matias, I.R. Analysis Matrix for Smart Cities. *Future Internet* **2014**, *6*, 61–75.
13. Yeh, H. The effects of successful ICT-based smart city services: From citizens' perspectives. *Gov. Inf. Q.* **2017**, *34*, 556–565.
14. Cicirelli, F.; Guerrieri, A.; Spezzano, G.; Vinci, A. An edge-based platform for dynamic Smart City applications. *Future Gener. Comput. Syst.* **2017**, *76*, 106–118.
15. Ghannem, A.; Hamdi, M.S.; Abdelmoez, W.; Ammar, H.H. A context model development process for smart city operations. In Proceedings of the 2015 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), Hammamet, Tunisia, 15–17 November 2015; pp. 122–127.
16. Chourabi, H.; Nam, T.; Walker, S.; Gil-Garcia, J.R.; Mellouli, S.; Nahon, K.; Pardo, T.A.; Scholl, H.J. Understanding Smart Cities: An Integrative Framework. In Proceedings of the 2012 45th Hawaii International Conference on System Sciences, Maui, HI, USA, 4–7 January 2012; pp. 2289–2297.
17. Hill, N.; Gibson, G.; Guidorzi, E.; Amaral, S.; Parlikad, A.K.; Jin, Y. *Scoping Study into Deriving Transport Benefits from Big Data and the Internet of Things in Smart Cities*; Technical Report; Department for Transport, University of Cambridge: Cambridge, UK, 2017.
18. Ho, T.J.; Chung, M.J. Information-Aided Smart Schemes for Vehicle Flow Detection Enhancements of Traffic Microwave Radar Detectors. *Appl. Sci.* **2016**, *6*, 196, doi:10.3390/app6070196.
19. Zhang, Z.; Jia, L.; Qin, Y. Level-of-Service Based Hierarchical Feedback Control Method of Network-Wide Pedestrian Flow. *Math. Probl. Eng.* **2016**, *2016*, 14, doi:10.1155/2016/9617890.
20. Salvo, G.; Caruso, L.; Scordo, A.; Guido, G.; Vitale, A. Traffic data acquirement by unmanned aerial vehicle. *Eur. J. Remote Sens.* **2017**, *50*, 343–351.
21. Knoop, V.; Daganzo, C. The Effect of Pedestrian Crossings on Traffic Flow. In Proceedings of the 96th Annual Meeting Transportation Research Board, Washington, DC, USA, 7–11 January 2017.
22. Zhang, H.; Zhang, C.; Wei, Y.; Chen, F. The effects of mobile phone use on pedestrian crossing behavior and safety at unsignalized intersections. In Proceedings of the 4th International Conference on Transportation Information and Safety (ICTIS), Banff, AB, Canada, 8–10 August 2017; pp. 280–285.
23. Giuffre, T.; Campisi, T.; Tesoriere, G. Implications of Adaptive Traffic Light Operations on Pedestrian Safety. *IOSR J. Mech. Civ. Eng.* **2017**, *13*, 58–63.
24. Hernandez, D.C.; Filonenko, A.; Seo, D.; Jo, K.H. Crosswalk detection based on laser scanning from moving vehicle. In Proceedings of the IEEE 13th International Conference on Industrial Informatics (INDIN), Cambridge, UK, 22–24 July 2015; pp. 1515–1519.
25. Zhai, Y.; Cui, G.; Gu, Q.; Kong, L. Crosswalk Detection Based on MSER and ERANSAC. In Proceedings of the 2015 IEEE 18th International Conference on Intelligent Transportation Systems, Las Palmas, Spain, 15–18 September 2015; pp. 2770–2775.
26. Choi, J.; Ahn, B.T.; Kweon, I.S. Crosswalk and traffic light detection via integral framework. In Proceedings of the 19th Korea-Japan Joint Workshop on Frontiers of Computer Vision, Incheon, Korea, 30 January–1 February 2013; pp. 309–312.
27. Muralidharan, A.; Coogan, S.; Flores, C.; Varaiya, P. Management of intersections with multi-modal high-resolution data. *Transp. Res. Part C Emerg. Technol.* **2016**, *68*, 101–112.
28. Song, C.; Kim, I.; Xiang, Q. Evaluation of Large Signalized Intersection with New Pedestrians Twice Crossing. *Procedia Comput. Sci.* **2017**, *109*, 132–139.

29. Collotta, M.; Bello, L.L.; Pau, G. A novel approach for dynamic traffic lights management based on Wireless Sensor Networks and multiple fuzzy logic controllers. *Expert Syst. Appl.* **2015**, *42*, 5403–5415.
30. Odeh, S.M. Hybrid algorithm: Fuzzy Logic-Genetic Algorithm on traffic light intelligent system. In Proceedings of the 2015 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Istanbul, Turkey, 2–5 August 2015; pp. 1–7.
31. Moghaddam, M.J.; Hosseini, M.; Safabakhsh, R. Traffic light control based on fuzzy Q-leaming. In Proceedings of the 2015 International Symposium on Artificial Intelligence and Signal Processing (AISP), Mashhad, Iran, 3–5 March 2015; pp. 124–128.
32. Galatioto, F.; Giuffre, T.; Bell, M.; Tesoriere, G.; Campisi, T. Traffic Microsimulation Model to Predict Variability of Red-Light Running Influenced by Traffic Light Operations in Urban Area. *Procedia Soc. Behav. Sci.* **2012**, *53*, 871–879.
33. Kilambi, P.; Ribnick, E.; Joshi, A.J.; Masoud, O.; Papanikolopoulos, N. Estimating pedestrian counts in groups. *Comput. Vis. Image Underst.* **2008**, *110*, 43–59.
34. Planung Transport Verkehr AG. *VISSIM 5.40 User Manual*; PTV AG: Karlsruhe, Germany, 2012.
35. Aghabayk, K.; Sarvi, M.; Young, W. A State-of-the-Art Review of Car-Following Models with Particular Considerations of Heavy Vehicles. *Transp. Rev.* **2015**, *35*, 82–105.
36. Transportation Research Board. *Highway Capacity Manual*; Transportation Research Board, National Research Council: Washington, DC, USA, 2000.
37. Bennett, S.; Felton, A.; Akçelik, R. Pedestrian movement characteristics at signalised intersections. In Proceedings of the XXIII Australian Institutes of Transport Research, Melbourne, Australia, 10–12 December 2001.
38. Fitzpatrick, K.; Turner, S.; Brewer, M.; Carlson, P.; Ullman, B.; Trout, N.; Park, E.; Whitacre, J.; Lalani, N.; Lord, D. *Improving Pedestrian Safety at Unsignalized Crossings*; Nchrp Report 562; Transportation Research Board: Washington, DC, USA, 2006.
39. Allen, B.; Shin, B.; Cooper, D. Analysis of traffic conflicts and collision. *Transp. Res. Rec.* **1978**, *667*, 67–74.
40. Hayward, J. *Near Miss Determination through Use of a Scale of Danger*; Number No. 7115 in Near Miss Determination through Use of a Scale of Danger; Pennsylvania Transportation and Traffic Safety Center, The Pennsylvania State University: State College, PA, USA, 1972.
41. Archer, J. Indicators for Traffic Safety Assessment and Prediction and Their Application in Micro-Simulation Modelling: A Study of Urban and Suburban Intersections. Ph.D. Thesis, KTHKTH, Traffic and Logistics, Centre for Traffic Research, CTR, Royal Institute of Technology, Stockholm, Sweden, 2005.
42. Gettman, D.; Pu, L.; Sayed, T.; Shelby, S.G. *Surrogate Safety Assessment Model and Validation: Final Report*; Report fhwa hrt 08-051; Federal Highway Administration: Washington, DC, USA, 2008.