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Possibilistic Clustering Technique-Based Traffic Light Control for Handling Emergency Vehicle

F. Titouna, S. Benferhat, K. Aksa, and C. Titouna

Abstract**—**A traffic light gives security from traffic congestion, reducing the traffic jam, and organizing the traffic flow. Furthermore, increasing congestion level in public road networks is a growing problem in many countries. Using Intelligent Transportation Systems to provide emergency vehicles a green light at intersections can reduce driver confusion, reduce conflicts, and improve emergency response times. Nowadays, the technology of wireless sensor networks can solve many problems and can offer a good management of the crossroad. In this paper, we develop a new approach based on the technique of clustering and the graphical possibilistic fusion modeling. So, the proposed model is elaborated in three phases. The first one consists to decompose the environment into clusters, following by the fusion intra and inter clusters processes. Finally, we will show some experimental results by simulation that proves the efficiency of our proposed approach.

Keywords**—**Traffic light, Wireless sensor network, Controller, Possibilistic network/Bayesain network.

I. Introduction

TRANSPORTATION research has the goal to optimize transportation flow of people and goods. As the number of road users constantly increases, and resources provided by current infrastructures are limited, intelligent control of traffic will become a very important issue in the future. However, some limitations to the usage of intelligent traffic control exist. Avoiding traffic jams for example is thought to be beneficial to both environment and economy, but improved traffic-flow may also lead to an increase in demand [1].

Today, traffic roads in any city in the world are very much affected by traffic light controllers. When waiting for a traffic light, the driver looses time and the car uses fuel. Therefore, reducing waiting times before can reduce perfectly the economic fees and the road users receive information about how to drive through a city in order to minimize their waiting exploit the emergence of novel technologies such as wireless sensor networks, as well as the use of more sophisticated algorithms for setting traffic lights. The use of on-road sensors for collecting data is necessary for crossroad management. This would not only improve traffic management but would also help satisfy the growing demand of drivers who are willing to pay service providers as long as they have access to relevant real-time information: will there be any congestion on my usual route today? How to avoid it? If not, how long will it last? Etc. Such questions require traffic data to be accurate, reliable, timely and as complete as possible.

Traffic lights on major road corridors need to manage traffic flows at peak times and reduce vehicle delay and co_2 emissions, while providing opportunities for vehicles in side streets to enter or cross the major road. Improved traffic flow can be achieved if the green light at the next intersection on a major road is arranged to coincide with the arrival of traffic. To achieve this, traffic lights may be coordinated or linked. The conventional traffic light control methods include fix-time control, time of day control, vehicle actuated control, semi-actuated control, green wave control, area static control and area dynamic control. However, there is no system meeting the adaptive characteristic. This is because the traffic control system is non-linear, fuzzy and non deterministic.

The sudden appearance of an emergency vehicle on road can be extremely disruptive to nearby vehicles as individual drivers maneuver to get out of the way. Some drivers become confused and create conflicts that can cause emergency vehicle crashes or block lanes increasing response times. Using Intelligent Transportation Systems to provide emergency vehicles a green light at intersections can reduce driver confusion, reduce conflicts, and improve emergency response times. Emergency vehicle preemption operation and limitations must be a part of initial and recurring emergency vehicle driver training. In addition, signals near emergency facilities (i.e., hospitals, trauma centers, and fire/rescue) will be preempted more often than others and drivers may experience delays if multiple preemption events occur during a short period of time. Each of the sites indicated that the public accepted these delays and that a public awareness campaign highlighting the public safety benefits of preemption was a key factor in reducing preemption-related complaints [24].

Our work focuses on the use of the sensor-nodes to detect the presence of emergency vehicles such as fire engine, police vehicle…etc. Each sensor-node can offer several measures such as speed, weight, silhouette…etc. Indeed, the sensor network can be divided into four local clusters, where each cluster has a head-cluster. All the range measurements in a certain cluster are forwarded to the cluster-head where computation takes place. At this level, a possibilistic fusion method is applied to select and produce pertinent information which be routed directly to the final destination.

The remainder of this paper is organized as follows. In section II, we present related works for traffic light and clustering techniques. In section III, we present how to deal

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with emergency vehicle. Section IV is devoted to the presentation of our proposed approach. Simulation and evaluation of the developed model are presented in section V. Finally, we conclude in section VI by giving results reached through this work and some guided perspectives.

II. Related work

A. Traffic Light Control

Findler and Stapp [11] describe a network of roads connected by traffic light-based expert systems. An *expert system* uses a set of given rules to decide upon the next action. In traffic light control, such an action can change some of the control parameters. The expert systems can communicate to allow for synchronization. Performance on the network depends on the rules that are used. For each traffic light controller, the set of rules can be optimized by analyzing how often each rule fires, and the success it has. The system could even learn new rules. Findler and Stapp showed that their system could improve performance, but they had to make some simplifying assumptions to avoid too much computation.

Taale [10] compare using *evolutionary algorithms* evolution strategy to evolve a traffic light controller for a single simulated intersection to using the common traffic light controller in the Netherlands. They did not try their system on multiple coupled intersections, since dynamics of such networks of traffic nodes are much more complex and learning or creating controllers for them could show additional interesting behaviors and research questions.

Reinforcement learning for traffic light control has first been studied by Thorpe [9]. He used a traffic light based value function, and we used a car based one. Thorpe used a neural network for the traffic light based value function which predicts the waiting time for all cars standing at the junction. A neural network is used to predict the Q values for each decision, based on the number of waiting cars and the time since the lights last changed. The goal state is the state in which there are no cars waiting. Thorpe trained only a single traffic light controller, and tested it by instantiating it on a grid of 4 X 4 traffic lights. The system outperformed both fixed and rule based controllers in a realistic simulation with varying speed.

Tan et al. describe a fuzzy logic controller for single junction Fuzzy rules are used to determine if the duration of the current state should be extended. In experiments the fuzzy logic controller showed to be more flexible than fixed controllers and vehicle actuated controllers, allowing traffic to flow more smoothly, and reducing waiting time. A disadvantage of the controller seems to be its dependence on the preset quantification values for the fuzzy variables. They might cause the system to fail if the total amount of traffic varies [12].

B. Clustering techniques

When network scalability and efficient communication is needed, hierarchical-based routing is the best match. It is also called cluster based routing. Hierarchical-based routing is energy efficient method in which high energy nodes are randomly selected for processing and sending data while low energy nodes are used for sensing and send information to the cluster heads. This property of hierarchical-based routing contributes greatly to the network scalability, lifetime and minimum energy. Another reason of energy efficiency is by performing data aggregation and fusion in order to decrease the number of transmitted messages to the Base Station [15]. Several hierarchical based routing protocols are proposed such as Hierarchical Power-Active Routing (HPAR), Threshold sensitive energy efficient sensor network protocol (TEEN), Power efficient gathering in Minimum energy communication network (MECN) [16], [17]. Most clustering schemes in the literature fall in three categories that are identifier-based clustering, topology-based clustering and energy-based clustering. In order to achieve the long term operation of WSNs, communication protocols based on clustering have been extensively studied such as LEACH, ACE and HEED. In [26], authors propose and evaluate a new distributed energy-efficient clustering scheme for heterogeneous wireless sensor networks, which is called DEEC. In DEEC, the cluster-heads are elected by a probability based on the ratio between residual energy of each node and the average energy of the network. In [27] authors propose two types of clustering methods for WSNs. The first type, which is based on centralized management, employs vector quantization (VQ) for effective clustering. The second type, which is performed in a distributed fashion, takes into account remaining battery level and node density. A rapid cluster formation algorithm using a thinning technique: rC-MHP(rapid Clustering inspired from Mateern Hard- Core Process) is proposed in [28]. In order to prove its performance, it is compared with a well known cluster formation heuristic Max-Min.

III. Handling Emergency Vehicle

In this section, we seek to develop a new approach for dealing with a specific vehicle that is emergency vehicle such as police vehicle, ambulance and fire vehicle. All these vehicles have a common characteristic. They emit a sound during their travel which means: “a vehicle executes an emergency mission”. So, we need to describe the environment where the scenarios of traffic happened.

A. Description of the Environment

Let us consider a crossroad. It has four paths leading to the road intersection and each path has two lanes to the incoming direction. In addition of inductive-loop detector fixed on each lane, we assumed that the environment is equipped of another specific sensor that is an acoustic sensor. These sensors are inexpensive and are able to collect dynamic information about vehicle movement on the roads. Systems using an acoustic sensor override the traffic signal when a specific pattern of tweets or wails from the siren of an emergency vehicle is picked up. Advantages of a system like this are that they are fairly inexpensive to integrate into existing traffic signals and the ability to use siren equipment already installed in emergency vehicles thus dispensing with the need for special equipment [5]. The sensors are wireless enabled, and communicate with a central server to convey the learnt information. In fact, sensors are not always efficient, so the information issued from them is often pervaded of uncertainty and imprecision. Sometimes theses sensors are improperly designed or poorly adjusted. So, they don't provide reliable and precise information. In this case, what happened and how the sensors can predict the value or the color of the traffic light to avoid congestion.

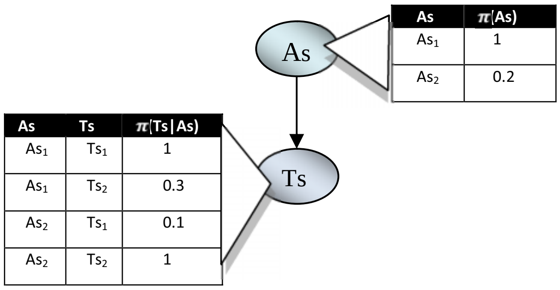
B. Possibilistic Graphical Modeling

The basic idea of the work consists to adapt the switching traffic signal according to the type of vehicle at different moment of the day. The model developed uses road-side acoustic sensors which are able to identify the emergency vehicle and adjusts the color light dynamically. The main objective of this technique is to set the traffic signal duration in an efficient and dynamic manner so that we try to minimize the average queue length and the average waiting time. The possibilistic model elaborated introduces a data structure called possibilistic network similar to the Bayesian network [20]. It is an important tool proposed for an efficient representation and analysis of uncertain information modeled in the framework of possibility theory [22]. Possibilistic network is a graphical structure known as a directed acyclic graph (DAG) which is often considered as the "qualitative" part of the model, one needs to specify the "quantitative" parameters of the model. The parameters are described in a manner which is consistent with a Markovian property, where the conditional possibility distribution (CPD) at each node depends only on its parents. For discrete random variables, this conditional possibility is often represented by a table, listing the local possibility that a child node takes on each of the feasible values for each combination of values of its parents. The joint distribution of a collection of variables can be determined uniquely by these local conditional possibility tables (CPTs). In particular, each node in the graph represents a random variable, while the edges between the nodes represent possibilistic dependencies among the corresponding random variables. These conditional dependencies in the graph are often estimated by using known statistical and computational methods. Hence, BNs combine principles from graph theory, possibility theory, computer science, and statistics [6]. A possibilistic network [19] provides a complete description of the domain defined by a set of variables $X_1,\dots,X_n$. The joint possibility distribution is a conjunction of particular assignments to each variable, such as $\pi(X_1=x_1,\dots,X_n=x_n)$. Thus, the joint possibility distribution is defined using the chain rule given by the following equation:

$$\pi(X_1,\dots,X_n) = \prod_{i=1}^{n} \Pi(X_i|par_{Xi}) \quad (1)$$

Where par_{Xi} represents the parents associated with the variable X_i.

Now consider the following network which will represent the graphical structure of our model. It is composed of two nodes. Variables *traffic signal* and *Acoustic sensor* are denoted by "Ts" and "As" respectively.



As	π(As)
As_1	1
As_2	0.2

As	Ts	π(Ts|As)
As_1	Ts_1	1
As_1	Ts_2	0.3
As_2	Ts_1	0.1
As_2	Ts_2	1

Fig. 1 A Simple possibilistic network

The conditional possibility distributions associated with the previous network are given by the tables (CPT). The value of each instance vi of a variable belongs to the unit interval [0, 1] and $max_i vi = 1$ (normalization condition). We assumed that the variable defined in the graph is binary. Each value assigned to a node reflects the current state of the node. The posterior possibility distribution is computed under the given evidence. For example let's compute the possibility that is the color of traffic signal is green given the acoustic sensor is detecting an emergency vehicle.

$$\Pi(A_S = ev|T_S = g) = \frac{\pi(Ts=g,As=ev)}{\Pi(Ts=g)} \quad (2)$$

Using the marginal possibility distribution i.e. maximizing out over irrelevant variables, we obtain:

$$\Pi(A_S = ev|T_S = g) = \frac{\pi(Ts=g,As=ev)}{max_{As}\pi(Ts=g,As=ev)} \quad (3)$$

*Example*1:

Consider the topology given in the Figure 1. The quantitative component associated with the possibilistic network is given by the conditional possibility tables (CPTs). The CPT associated with the variable *Acoustic sensor* means that the sensor does not detect the emergency vehicle with a low possibility degree (0.2). While the CPT associated with the variable *Traffic signal (in the third row)* means that it is less possible that the traffic signal is switch on green when the sensor doesn't detect the emergency vehicle. Now, consider the case where we have evidence from more than one source.

C. Possibilistic Merging

One of the important aims of merging uncertain information issued from different sources, is to exploit complementarities between the sources in order to get a complete, precise and global point of view on a given problem. In possibility theory, there is a well-known (and used) combination mode that is based on the product operator. This mode is generally applied when all sources agree and are considered as reliable.

Furthermore, it expresses a reinforcement effect which means, if all the sources agree that a value $A_s = v$ is not fully possible, then this value will receive a possibility degree strictly smaller than $\min_{i=1,n} \pi_i(v)$, i.e., the lack of complete possibility is reinforced, a necessary condition for choosing such an operation is the independence of the sources. This assumption is more adapted to sensor fusion problems.

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In addition, the main characteristic of the product operator is the fact it is a majority operator (see [23]). Namely, if some event is accepted by some possibility distributions, then repeating this possibility distribution enough time guarantee that this belief will be accepted in the result of merging.

Since this operator is symmetric and associative, merging n possibility distributions is done recursively. Given a set of possibility distributions π_i's. The result of combination mode considered here is the product of possibility distributions, namely:

$$\forall\omega,\ \pi_*(\omega) = \prod_{i=1}^{n} \pi_i(\omega) \quad (4)$$

IV. Detection and Decision Model

In this approach, we develop an adaptive traffic light system based on the clustering technique. We use intelligent sensors suitable for traffic. These sensors are able to measure some parameters to detect the emergency vehicle such as sound and speed. Generally, we know that the emergency vehicle has a specific sound which is emitted during its travel. This sound is particular and it is continuous so, we can differentiate it easily from other sounds in the traffic. The speed is another way to take in consideration this kind of vehicle. During the travel, the emergency vehicle often moves rapidly. Now, we explain the procedure of our approach. First, a variety of sensors nodes are randomly deployed in the field of interest. Then, we divide the environment in four regions (each region corresponds to a path of the considered intersection) called clusters (see Figure 2). Each of them must contain a subset of neighboring sensors such that each node is assigned to one and only one cluster. Nodes can communicate locally within the same cluster, and different clusters communicate through a cluster head specified within each cluster. Each cluster can sense the environment independently and generates series of observations which consists of mixtures of the source signals generated by the sensors nodes. So, possibilistic detection-decision algorithms are performed on the observations from each cluster, and the posterior possibility for each hypothesis is established. These possibility degrees are then sent to a fusion center where a decision regarding the source number hypothesis is made. The process of detection-decision is performed in three steps. First, we begin by creation the four clusters, and then we apply the fusion intra-cluster algorithm. Finally, a decision is made after applying the fusion inter-cluster (see Figure 3 and Figure 5).

Although sensors are often not reliable or accurate, their small size and low cost have enabled applications to network hundreds and thousands of these micro-sensors to achieve greater performance [25].

It is noted that, to maintain a reliable information delivery, data aggregation and information fusion that is necessary for efficient and effective communication between these sensor nodes. Only processed and concise information should be delivered to the sinks or 'actuators' to reduce communications energy and to prolong the effective network lifetime.

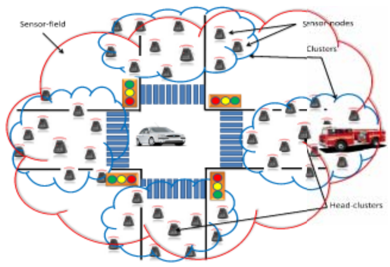

Fig. 2 Decomposition of sensor field into four clusters

A. Clusters Creation Phase

In this phase, we assume that the model elaborated is composed of four clusters according with four paths defined in the previous section. Each cluster contains a set of heterogeneous nodes. This variety of nodes is principally due to the need of sensing different parameters in the road. The Algorithm1 shows how to create four clusters. First we assume that the selection of the starting nodes is depending on whether a sensor node belongs or not to the considered path. Then, a set of closest sensors are determined such that two clusters are mutually exclusive. Finally, we elect the cluster head among the sensor nodes within the same cluster. This sensor must have the greatest global energy (internal energy + processing energy) and has the minimal distance separating the concerned sensor node and the controller (which plays the role of the base station in this case). Moreover, this processing is achieved by propagating, inside the cluster, a message containing the identifier of the cluster head, to inform the remaining nodes.

Because CHs often transmit data over longer distances, they lose more energy compared to member nodes. The network may be clustered again periodically in order to select energy-abundant nodes to serve as CHs, thus distributing the load uniformly on all the nodes. Besides achieving energy efficiency, clustering reduces channel contention and packet collisions, resulting in better network throughput under high load. Indeed, after every elapsed time Δt (defined initially), we check the state of the cluster head. If its energy exceeds a predetermined threshold then we should to apply again the selection step of the cluster head presented in the Algorithm1.

The methods developed in the following sections are applied in order to determine how an emergency vehicle approaching a give-way sign can cross without lost waiting time. In other terms, we assign a high priority to an emergency vehicle than other vehicles moving on the road.

The basic idea behind detection-decision model is that sensor nodes are deployed within an area and the clusters (groups of nodes) determine whether or not a target (emergency vehicle) has entered or is presently within the area. Sensors usually determine if a target is present by detecting a change in some sort of signal, whether it is acoustic, light, temperature or some other type. Since the strength of this signal will scatter throughout the sensor network the nodes need to collaboratively work together in order to determine if the target has been detected or not.

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We see in the following sections, the detection and decision model design as a two-stage fusion process. Based on the graphical possibilistic [30] structure the fusion approach models our problem in an easily and interesting manner.

***Algorithm1**: Creation of clusters*

Input: A set of sensors $S_{i,i=1,n}$, 4 distinct paths U_i, Controller X
Output: Four clusters C_1,C_2,C_3,C_4
Begin
Choice four initial sensors (S_1,S_2,S_3,S_4) such that each $S_i \equiv U_i$
$Adj_{Si} \leftarrow \emptyset$
for *each sensor node* $S_{j,j\neq i}$ do
    $d_j \leftarrow$ distance(S_i, S_j)
    if $d_j < r_i$ then // r_i *denotes the transmission range of the node* S_i
        $Adj_{Si} \leftarrow Adj_{Si} \cup S_j$
    endif
endfor
$C_i \leftarrow Adj_{Si}$
Let $I_m = C_i \cap C_j$ // *C_i and C_j two distinct clusters; m: number of nodes contained into the intersection*
if $I_m \neq \emptyset$ then
    Remove sensors from two clusters
    Let be $C_i \leftarrow C_i \setminus I_{1..m/2+/1}$; $C_j \leftarrow C_j \setminus I_{m/2+/1,..,m}$ // *if m is odd*
    Let be $C_i \leftarrow C_i \setminus I_{1..m/2}$; $C_j \leftarrow C_j \setminus I_{m/2,..,m}$ // *if m is even*
endif
//Election of the cluster head
for *each* C_i *and each* $S_j \in C_i$ do
    $e_{ij} \leftarrow$ *compute (global energy of* S_j)
    $d_j \leftarrow dist_E(S_j, X)$ // *$dist_E$ denotes the Euclidian distance*
    $CH_i \leftarrow S_k(\min_j d_j, \max e_{ij})$
    Broadcast(S_j, CH_i)\\ *Inform all the nodes S_j that CH_i is the cluster Head.*
endfor
End

B. Intra-cluster Fusion Phase

Before starting the fusion process performed during this phase, it is more preferable to select first the cluster having the small size (in terms of number of sensor nodes). That is implying less computations and consequently less time spending. The cluster head behavior decision is modeled as a local possibilistic computing (see Figure 3) that is based on a series of independent causal networks (A causal network refers to a Bayesian network where the arcs denote cause-effect relationships). Their success is due to their simplicity and their capacity of representing and handling independence relationships which are important for an efficient management of uncertain pieces of information.

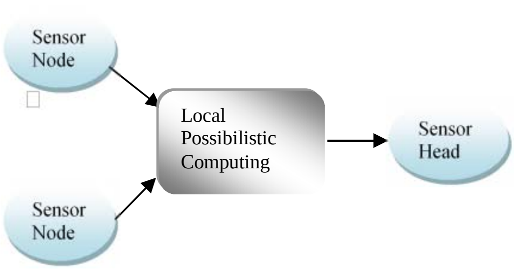

Fig.3 Intra-cluster fusion

These different graphs are the result of several observations obtained from different sensors within the same cluster. The principle role of each sensor of the network consists to collect data from traffic road at different moment of the day. However, a sensor node takes into account some relevant parameters according to its type and its characteristics in order to explicitly control the traffic light dynamically. We see in the Figure 4, an example of the behavior's sensor node described through a Direct Acyclic Graph (DAG).

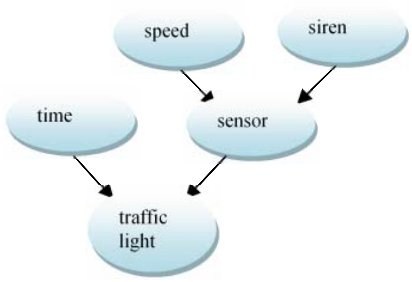

Fig. 4 Example of a DAG describing the sensor' model

We assume that each node of the graph has two states. The variable *speed* describes the speed of the target that is emergency vehicle. The speed of such a vehicle is often fairly high compared to conventional vehicles. Two states (present and absent) of the *siren* variable characterize well the emergency vehicle. While the variable *time* expresses the delay time expanded for the duration of the traffic light. So, the possibility that the *sensor* perceives the target depends directly from the possibility degrees associated with each of variables *speed* and *siren*. For example, if an acoustic sensor detects the sound of the *siren's* target with a degree 0.8 then it perceives the target with a possibility degree 0.9, despite the fact that the *sensor* has detected the *speed* with 0.33 degree. Also, the variable traffic-light is turn-on green with a 0.95 degree when the sensor perceives the target with 0.8 degree and the maximum delay has not yet reached with 0.7 degree. In this case, one may evaluate the posterior possibility distribution of the variable *sensor* given evidence or new event observed (delay of *time* is elapsed) on the network. This is done using the marginal possibility distribution as follows:

$$\Pi(se|ti = e_1) = max_{sp,si,tl}\pi(sp, si, se, tl, ti = e_1) \quad (5)$$

Where sp, *si*, *se*, *ti*, *tl* denote the variables *speed*, *siren*, *sensor*, *time* and *traffic_light* respectively. e_1 denotes the value of the evidence.

Our approach to merging possibilistic networks are appropriate when available pieces of information involve a large number of variables, It can be explicitly stated by compact representation such as possibilistic networks.

Now, we develop in the Algorithm 2 the required steps to fuse possibilistic networks. These networks express the information provided from independent sensors. We assume in this case that the possibilistic networks are similar in the same cluster and all variables are binary and propositional (either true or false). The result of fusing is a possibilistic network having the same graphical structure (qualitative component) that means the nodes and the links in the fused graph are identical to the initial ones. Only the conditional possibilitic distributions (quantitative component) in the fused graph change. These values are computed by applying the product operation on the initial possibilistic distributions (for more details see [29]). The obtained result indicates the reinforcement effect since the possibility degrees associated with the fused network are lower than the initial ones. So, each variable of the fused network occurs with a high degree of certainty (Possibility theory uses two concepts, the possibility Π and the necessity N of the event ϕ. The necessity measure is defined by: $\mathrm{N}(\phi) = 1 - \Pi(\phi'))$. For example, if we have two possibilistic networks built according to the DAG of the Figure 4 and we are interested to compute the possibility degree of the variable *sensor* in the fused network. First, we assume that the variable *sensor* perceives the target with 0.5 degree in the first network while in the second its possibility degree is 0.3. So, the possibility that the sensor perceives the target is 0.15. The degree is less than the one determined by each sources separately, which increases the certainty degree that the target is perceived. At last, each cluster head sends the result of processing to the controller.

C. Inter-clusters Fusion Phase

The fusion process continues during this phase. Once the controller receives information from different clusters, it proceeds to elaborate the final result (see Figure 5). Indeed, we assume that the possibilistic networks obtained from clusters head are not similar (in terms of edges and links).

Algorithm2: Intra-cluster fusion

Input: Four clusters (C_1,C_2,C_3,C_4)
Output: Local estimation ψ_L
Begin
Δt ← initial_ time
Δp ← processing_time
Broadcast(Ch_i, query, S_i)
\\ *Building causal network* $\aleph_i$
Repeat
for *each* $\mathbf{S_i} \in C_j$ do
Generate a graphical structure which will be dented by G_i *as illustrated in Figure* 4
Attribute a local possibility distribution π_i *at each variable* v_i *of* G_i *given its parents* μ_i .
endfor
\\ *Merging the same graphical structure*
$G_* = G_1 = \cdots = G_n$ \\ *n denotes the size of the causal network associated with each sensor node* S_i
\\ *Merging quantification structures*
for *each root variable* A do
$\forall a_i \in X_A,\ \pi_*(a_i) = \pi(a_i) * \cdots * \pi(a_i)$
for *each variable A having one or more than one parent* do
$\forall a_i \in X_A, \forall \mu_{ai} \in X_{\mu A}, \pi_*(a_i|\mu_{ai}) = \pi_1(a_i|\mu_{ai}) * \cdots * \pi_n(a_i|\mu_{ai})$
\\ X_A and $X_{\mu A}$ denote all the states of the variable A and its parents respectively
\\ Preservation of the semantic of the merging causal network
$\forall \omega \in \Omega,\ \pi_*^J(\omega) = \pi_1^J(\omega) * \cdots * \pi_n^J(\omega)$
Until $\Delta t > \Delta p$
\\ *Send the merging result to the specified cluster head*
Send ($\aleph_L^i$, Ch_i , Ψ_L^i).
End

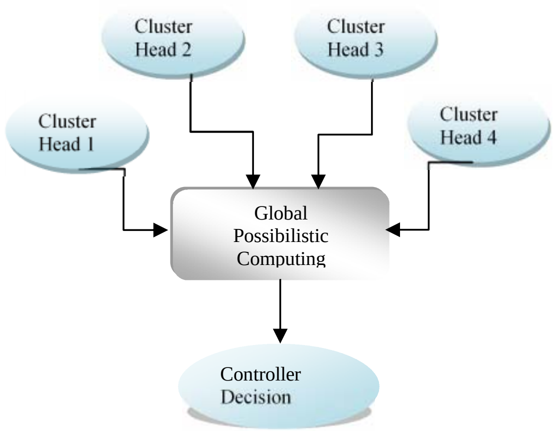

Fig. 5 Inter-clusters fusion

That means sensors in different clusters model the captured information flow in several ways. The fusion process applied here consists first to extend each initial network to a common structure by adding the necessary links and variables to each input network. Then, we apply the procedure of fusion networks of the same networks described in the Algorithm 2. The process of fusion inter-clusters is clarified in the Algorithm3. Once the fused graph is obtained, one can apply propagation algorithms, such as the one proposed in [31], to answer queries. For instance, if we are interested to compute the possibility degree of the variable *traffic_light* in the fused network, then the use of the Algorithm3 gives:

$$\pi_*(tl = r) = 1 \text{ and } \pi_*(tl = g) = 0.12.$$

Since, from one source, the possibility degree associated with the variable *traffic_light* is $\pi_1(tl = r) = 1 \text{ and } \pi_1(tl = g) = 0.3$.While another source provides the following degrees:

$$\pi_2(tl = r) = 1 \text{ and } \pi_2(tl = g) = 0.4.$$

Algorithm3: Inter-clusters fusion

Input: Clusters: C1,C2,C3,C4; $\aleph_i(G_i, \psi^i_L)$ \ i=1,..4,Controller X
Output: Global decision estimation ψ_G.
Begin
Broadcast (Ch_i, query, X).
Δt_m ← maximum_time_light_control.
\\ Merging process
i← 1
While i ≤ n and $\Delta t_m > 0$ do \\ n denotes the number of clusters, here n is 4.
Let G_i and G_{i+1} be two graphs within different structures.
Transform G_i and G_{i+1} to the same one :
- add new variables/ let A be the new one such that its possibility distribution is the uniform distribution π(A)=1.
- add new edges /let (A→C) be the new edge such that π(C|A)= π(C).

Apply the merging procedure defined in Algorithm2
end
\\ Compute the possibility distribution of interest variable
Compute ($\aleph_G$, X , Ψ_G)
Trigger (traffic_light, Ψ_G).
End

The degree is less than the individual sources which increases the certainty degree that the traffic light is green.

V. Simulation and Results

In this section, the effectiveness of the proposed methods is demonstrated by numerical simulation. In the simulation, N sensor nodes are randomly distributed in the square region of size 100 m ×100 m and the base station is 50 meters away from the center of a side. The simulation is performed for N = 100, 200 and 400. We test our approach using Matlab and we use the BNT toolbox to perform the detection-decision model based principally on the clustering technique and the fusion of possibilistic networks. Indeed, we have thought that it is interesting to evaluate our approach by comparing the possibilistic clustering model proposed with the conventional one (the control of traffic light is performed with predetermined time).So, we use some parameters to test our model. So, the method developed in this paper is the result of collaboration between the different sensors deployed in the environment that is an intersection. According to the previsions performed by the sensor nodes, the controller should take as inputs the sensor signals on the road that detect whether a target (emergency vehicle) is present and should have as outputs the colors of the various signals. We implement the traffic light controller for a standard four-way intersection.

First, we generate randomly different DAGs (in terms of size) and then, we evaluate the three steps of fusion process (intra-cluster and inter-clusters). We show in Figure 6, as the number of sensor node increases as the degree of possibility decreases. In fact, the degree of certainty, of detecting the target, increases when the number of sensors is important (not exceeding a certain threshold since the fusion process becomes less reliable if the nodes are greater than 400 nodes). This case happens rarely since in clustering technique, we always try to restrict the size of clusters.

The Figure 7 shows the comparison established between two methods for traffic light control. In the predetermined time method, cars spend considerable time in traffic while in proposed model is less important. The combination of different opinions issues from different sources affects the global decision. Another important issue in this experiment consists to compute the average waiting time during periods of the day. We test our model at different moment of the day. Then, we show in Figure 8 that the model proposed is better than the classical one. The time that an emergency vehicle lost in traffic, especially during peak hour, is reduced. We note that the density of flow affects the detection of the target and then the decision taken by the controller is not reliable and not accurate. Moreover, an emergency vehicle is hardly detected when the number of present vehicles in the path is important. This is due to the existence of noise, klaxon and others sounds, all these parameters affect the decision of the controller (see Figure 9).

Our simulation results show that our detection–decision model is more suitable for larger than smaller numbers of sensor nodes since we know that the clustering technique reduces the number of nodes in a cluster, reduces the consumed energy of sensor nodes, and prolongs the lifetime of the sensor network. Also, the possibilistic fusion process allows a global decision when the information provides from the sensors is uncertain and imprecise.

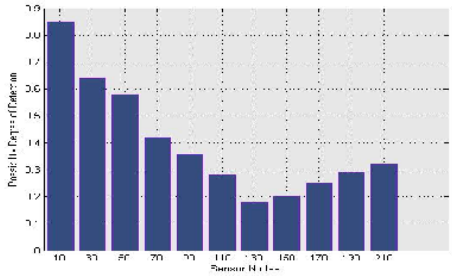

Fig. 6 Distribution showing number of sensors with possibility measures increase

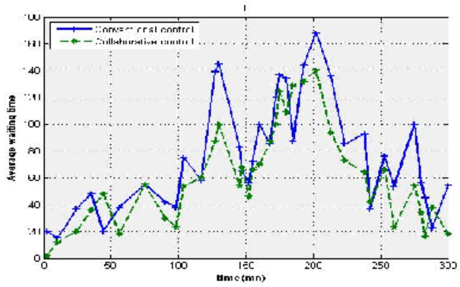

Fig. 7 Average waiting time computed within two methods

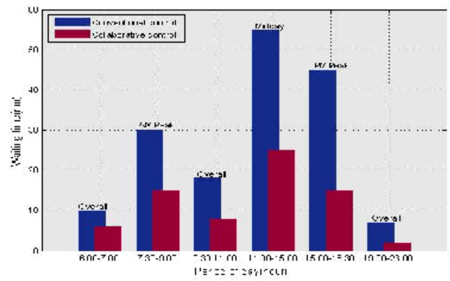

Fig. 8 Distribution showing period of day with target waiting time

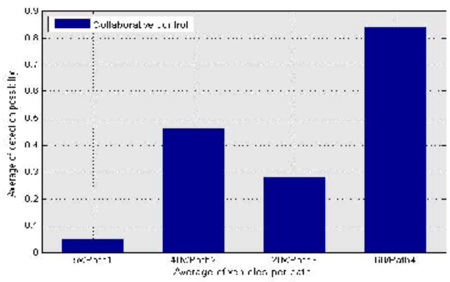

Fig. 9 Average time when a target is detected in a specific path

VI. Conclusion

During a traffic jam, the emergency vehicle spends a long time. This happen when the traffic flow is managed with a conventional method of fixed time light. In order to reduce the waiting time, we have proposed a new approach in the area of intelligent transportation system.

In this work, we present a hybrid approach for modeling traffic light control based on a set of specific sensors. Indeed, we adopt a simple model crossroad and we show how the use of sensors may affect the traffic management. So, we propose a possibility prediction technique to deal with the emergency vehicle. This approach is based principally on the structure of possibilistic causal network and the technique of clustering. A fusion approach is elaborated at level of clusters heads in the first step and at level of the controller in the second step.

All this information allows decreasing the jam in the crossroads and therefore reducing the pollution of the environment. In addition, some simulation results are presented. In the future work, we can extend the control of traffic light in more than one intersection, manage and coordinate not only crossroads but also controllers in real time. Another and important extended work consists to deal with different kinds of emergency vehicles. So, when these vehicles are present at the same moment in different paths of the intersection, how to affect the priority to coordinate between them.

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