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An application of fuzzy graph in accidental prone zone to reduce the traffic congestion

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Abstract

The concept of a fuzzy graph model is a method of analyzing traffic congestions. This paper focuses on the usage of a fuzzy graph model in traffic congestion. Traffic congestions are due to increase of a number of vehicles flow in a city. It can be used to represent traffic networks in a city. In cities, there are different types of accident prone zone with the help of this concept accident prone zones can be regulated in better ways.

In this paper, a fuzzy graph model is useful to represent the traffic network system. The road structure design need to be investigated how to reduce the accident prone zone, such that, the total number of vehicles are moving in a particular time on the road and to minimized traffic congestions.

In order to minimize accidents, a classification of this type is very helpful. To avoid traffic jam in bigger cities, a development of fuzzy application can be used to prevent traffic jam.

Keywords

Fuzzy set, Fuzzy graphs, α-cuts, Traffic congestion's, Accident prone zone.

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Contents

1. Introduction

The concept of fuzzy logic was first introduced by Lofti, A. Zadeh in a suitable environment. There was ambiguity in certain situations because of the result of the concept of fuzzy graph where the motive of uncertainty and vagueness had evolved.

Many researchers have developed a real time scenario by using this fuzzy logic test. The fuzzy graph application involves the arc definition and the strength of connectedness between each arc. This paper has discussed the usage of the maximum strength.

Although several applications have studied, in that, some of the applications have represented graphically by using fuzzy graphs, which are useful in a real-time life situation.

The concept of strength of connectedness of arcs is based on classifications and effectiveness. In this paper is reviewed to ensure the effectiveness of these arcs in some real circumstances. The traffic level of cars in western countries is more. As a result, the rate of flow is slower on the roads and leads to traffic congestions. The concept of strong arcs is applied to identify the path which has the higher flow and sustains the congestion level to a minimum.

Traffic congestions are bigger problems in cities. Using the strength of connectedness of arcs connections such as α-strong arcs, β-strong arcs, and δ-strong arcs can be used to identify real problem in traffic congestions. These connections are helpful for problems of traffic congestion.

In modern cities, there is growth of a population keep on increasing every year for that new roads and high ways are constructed in order to accommodate the number of growing vehicles. This has resulted in the increase of time loss of traffic participants, traffic accidents and increasing noise pollution.

Traffic congestion is one of the main obstacles for development in western countries which is due to traffic condition.

These obstacles are continuing even after construction of new roads. Further this may improve the situation, but it is very costly in many cases the existing structures make it impossible. The best way to control the traffic flow in these situations is to use the current road network more efficiently.

2. Preliminaries

Definition 2.1. *A fuzzy relation on S is a fuzzy subset $S \times S$. A fuzzy relation μ on S is a fuzzy relation on the fuzzy subset σ if $\mu(x,y) \leq \sigma(x) \wedge \sigma(y)$ for all x,y in S, where $\wedge$ stands for minimum value. A fuzzy relation μ on S is symmetric if $\mu(x,y) = \mu(y,x)$ for all $x,y \in S$. A fuzzy relation on the fuzzy subset σ on S is said to be reflexive if $\mu(x,x) = \sigma(x)$ for all $x \in S$.*

Example 2.2. *See Fig. 1.*

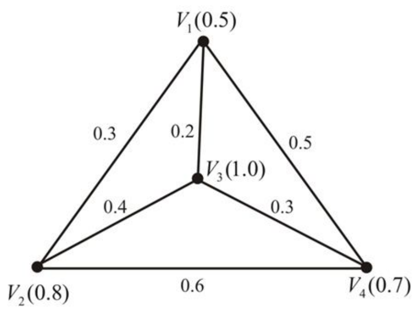

Figure 1. Fuzzy relation.

Let

$$\sigma(V_1) = 0.5, \sigma(V_2) = 0.8, \sigma(V_3) = 1, \sigma(V_4) = 0.7 \text{ and}$$
$$\mu(V_1,V_2) = 0.3, \quad \mu(V_2,V_3) = 0.4, \quad \mu(V_3,V_4) = 0.3,$$
$$\mu(V_2,V_3) = 0.4, \quad \mu(V_3,V_4) = 0.3,$$
$$\mu(V_1,V_4) = 0.5, \quad \mu(V_2,V_4) = 0.6, \quad \mu(V_1,V_3) = 0.2$$
$$\mu(V_1,V_2) \leq \sigma(V_1) \wedge \sigma(V_2) \text{ for all } V_1,V_2 \in V.$$

Let $\sigma = \{V_1/0.5, V_2/0.8, V_3/1, V_4/0.7\}$ and μ be a fuzzy relation defined on σ as follows:

Table 1. Fuzzy relation

μ	V_1	V_2	V_3	V_4
V_1	0.5	0.3	0.2	0.5
V_2	0.3	0.8	0.4	0.6
V_3	0.2	0.4	1	0.3
V_4	0.5	0.6	0.3	0.7

It is clear that μ is both reflexive and symmetric.

Definition 2.3. *A fuzzy graph is a pair $G : (\sigma, \mu)$ where σ is a fuzzy subset of S and μ is a symmetric fuzzy relation on σ. The elements of S are called the nodes or vertices of G and the pair of vertices as edges in G. Assume that S is finite and non-empty set, μ is reflexive and symmetric. Thus it $G : (\sigma, \mu)$ is a fuzzy graph, then $\sigma : S \to [0.1]$ and $\mu : S \times S \to [0.1]$ such that $\mu(u,v) \leq \sigma(u) \wedge \sigma(v)$ for all $u, v \in S$.*

Example 2.4. *See Fig. 2.*

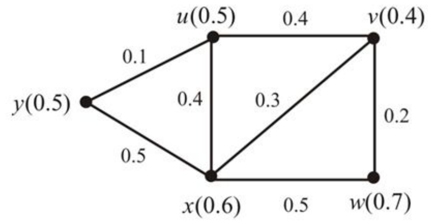

Figure 2. Fuzzy Graph $G : \sigma(\mu)$

$G : (\sigma, \mu)$ is a fuzzy graph with the underlying set $V : (u,v,w,x,y)$, where $\sigma : V \to [0.1], \mu : V \times V \to [0.1]$ are defined as $\sigma(u) = 0.5, \sigma(v) = 0.4, \ \sigma(w) = 0.7, \ \sigma(x) = 0.6, \ \sigma(y) = 0.5, \sigma(u,v) = 0.4, \mu(v,w) = 0.3, \mu(x,w) = 0.5, \mu(u,x) = 0.4, \ \mu(x,y) = 0.5, \ \mu(v,x) = 0.3, \ \mu(u,y) = 0.1$. Then G is a fuzzy graph. Since $\mu(uv) \leq \sigma(u) \wedge \sigma(v)$ for all $u, v \in S$.

Definition 2.5. *Let $G : (\sigma, \mu)$ be a fuzzy graph. The strength of connectedness between two nodes x and y is defined as the maximum of the strengths of all paths between x and y and is denoted by* $\mathrm{CONN}_G(x,y)$.

$x - y$ path P is called a strongest $x - y$ path if its strength equals $\mathrm{CONN}_G(x,y)$.

A fuzzy graph $G : (\sigma, \mu)$ is connected if for every x, y in σ^*, $CONN_G(x,y) > 0$.

Example 2.6. *See Fig. 3.*

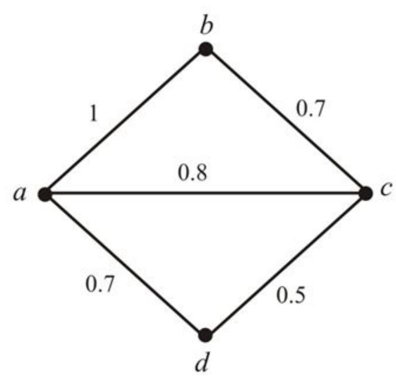

Figure 3. Strength of connectedness.

Let $G : (\sigma, \mu)$ be a fuzzy graph with $\sigma^* = \{a,b,c,d\}$. In this fuzzy graph, $\mu(a,b) = 1, \ \mu(b,c) = 0.7, \ \mu(d,a) = 0.7, \ \mu(a,c) = 0.8, \ \mu(c,d) = 0.5$.

There are three different paths from a to c namely,

$$P_1 = a - b - c$$
$$P_2 = a - d - c$$
$$P_3 = \mathrm{arc}(a,c)$$

Now,
Strength of $P_1 = \min\{1, 0.7\} = 0.7$
Strength of $P_2 = \min\{0.7, 0.5\} = 0.5$

Strength of $P_3 = 0.8$

$\therefore$ The strongest path joining a to c is the arc (a,c) with strength 0.8.

Hence,

$$\mathrm{CONN}_G(a,c) = 0.8$$

Similarly,

$$\mathrm{CONN}_G(a,b) = 1$$
$$\mathrm{CONN}_G(b,c) = 0.8$$
$$\mathrm{CONN}_G(a,c) = 0.8$$
$$\mathrm{CONN}_G(d,a) = 0.7$$
$$\mathrm{CONN}_G(c,d) = 0.7$$

Definition 2.7. *An arc of a fuzzy graph is called strong if its weight is at least as great as the connectedness of its end nodes when it is deleted, that is*

$$\mu(x,y) \geq \mathrm{CONN}_{G-(x,y)}(x,y),$$

where $G-(x,y)$ is the fuzzy sub graph of G obtained by deleting the arc (x,y). An $x-y$ path P is called a strong path if P contains only strong arcs.

Example 2.8. *See Fig. 4.*

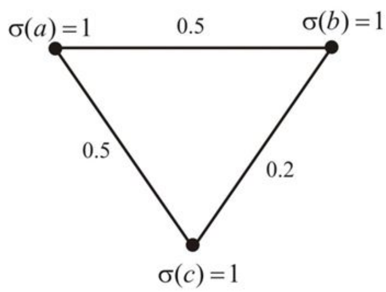

Figure 4. Strong Fuzzy Graph.

Let $G:(\sigma,\mu)$ be a fuzzy graph with $* = \{a,b,c\}\sigma(a) = \sigma(b) = \sigma(c) = 1, \sigma(a,b) = 0.5, \sigma(b,c) = 0.2, \sigma(c,a) = 0.5$.

Here,

$$\mathrm{CONN}_{G-(a,b)}(a,b) = 0.2$$
$$\mathrm{CONN}_{G-(b,c)}(b,c) = 0.5$$
$$\mathrm{CONN}_{G-(c,a)}(c,a) = 0.2$$

Then arcs (a,b) and (c,a) are strong arcs, while arc (b,c) is not strong as

$$\mu(b,c) = 0.2 > 0.5 = GONN_{G-(b,c)}(b,c).$$

Definition 2.9. *Let $G:(\sigma,\mu)$ be a fuzzy graph. The strong degree of a node $v \in \sigma^*$ is defined as the sum of membership values of all strong arcs incident at v. It is denoted by $d_s(v)$. Also if $N_s(v)$ denote the set of all strong neighbors of v, then*

$$d_s(v) = \sum_{\mu \in N_s(v)} \mu(u,v).$$

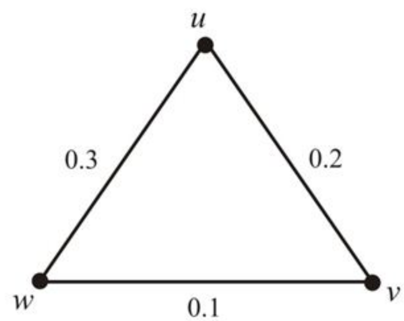

Figure 5. Fuzzy Graph with Strong Degree Node.

Example 2.10. *See Fig. 5.*

Let $G:(\sigma,\mu)$ be an fuzzy graph with $\sigma^* = \{u,v,w\}$, $\mu(u,v) = 0.2$, $\mu(v,w) = 0.1$ and $\mu(w,u) = 0.3$. Then arcs (u,v) and (w,u) are strong arcs. In this fuzzy graph,

$$d_s(u) = 0.3$$
$$d_s(v) = 0.2$$
$$d_s(w) = 0.3$$

Definition 2.11. *The minimum strong degree of G is, $\delta s(G) = \wedge\{d_s(v)/v \in \sigma^*\}$ and maximum strong degree of G is $\Delta_s(G) = V\{d_s(v), v \in \sigma^*\}$.*

Example 2.12. *See Fig. 6.*

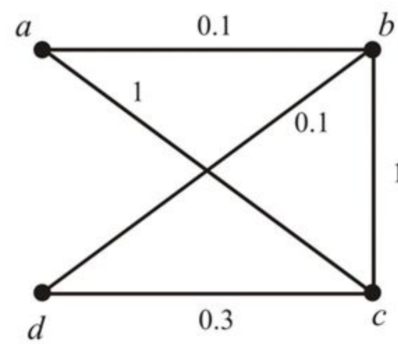

Figure 6. Strong degree in a fuzzy graph.

Let $G:(\sigma,\mu)$ be with $\sigma^* = \{a,b,c,d\}$ and $\mu(a,b) = 0.1, \mu(b,c) = 1$, $\mu(c,d) = 0.3$, $\mu(a,c) = 1$, $\mu(b,d) = 0.1$. Here, $(b,c),(a,c),(c,d)$ these arcs are strong. Thus $d_s(a) = 1$, $d_s(b) = 1$, $d_s(c) = 2.3$ and $d_s(d) = 0.3$. Hence, $\delta s(G) = 0.3$ and $\Delta s(G) = 2.3$.

Definition 2.13. *An arc (x,y) in G is called α-strong, if*

$$\mu(x,y) > \mathrm{CONN}_{G-(x,y)}(x,y)$$

An arc (x,y) in G is called β-strong, if

$$\mu(x,y) > \mathrm{CONN}_{G-(x,y)}(x,y)$$

An arc (x,y) *in G is called* δ*-strong, if*

$$\mu(x,y) > \mathrm{CONN}_{G-(x,y)}(x,y)$$

A δ *-arc* (x,y) *is called a* δ^**-arc, if*

$$\mu(x,y) > \mu(u,v)$$

where (u,v) *is a weakest arc of G.*

Example 2.14. *See Fig. 7.*

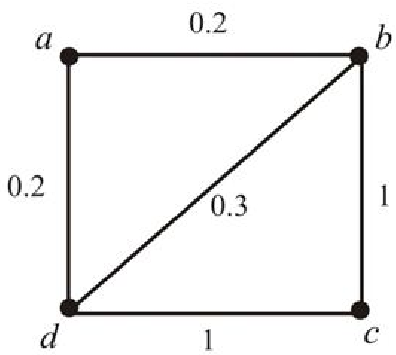

Figure 7. Strong arc in a Fuzzy Graph.

Let $G:(\sigma,\mu)$ be with $\sigma^* = \{a,b,c,d\}$, $\mu(a,b) = 0.2$, $\mu(b,c) = 1$, $\mu(c,d) = 1$, $\mu(d,a) = 0.2$, $\mu(b,d) = 0.3$.

$$\begin{aligned}
\mu(a,b) =& 0.2, \mathrm{CONN}_G(a,b) = 0.2, \mathrm{CONN}_{G-(a,b)}(a,b) = 0.2\\
\mu(b,c) =& 1, \mathrm{CONN}_G(b,c) = 1, \mathrm{CONN}_{G-(b,c)}(b,c) = 0.3\\
\mu(c,d) =& 1, \mathrm{CONN}_G(c,d) = 1, CONN_{G-(c,d)}(c,d) = 0.3\\
\mu(d,a) =& 0.2, \mathrm{CONN}_G(d,a) = 0.2, CONN_{G-(d,a)}(d,a) = 0.2\\
\mu(b,d) =& 0.3, \mathrm{CONN}_G(b,d) = 1, \mathrm{CONN}_{G-(b,d)}(b,d) = 1
\end{aligned}$$

Therefore (b,c) and (c,d) are α-strong arcs. (a,b) and (d,a) are β-strong arcs. (b,d) is a δ-arc.

Also (b,d) is a δ^*- arc, since $\mu(b,d) > \mu(a,b)$, where (a,b) is a weakest arc of G.

Definition 2.15. *We consider a very common traffic flow problem shown in Figure.8. Let us assume that intersection of two divided zones where all left and right turns are permitted. The arrows indicate the traffic flow along to each line. It is also assumed that all the direction is equally heavy. This traffic flow can be modeled as a graph where each traffic flow is represented as vertex. Two vertices are adjacent if the corresponding traffic flows cross each other.*

For example, a cross-sectional road has a traffic flow system. It has represented graphically. It is shown below.

Example 2.16. *See Fig. 8. and Fig. 9.*

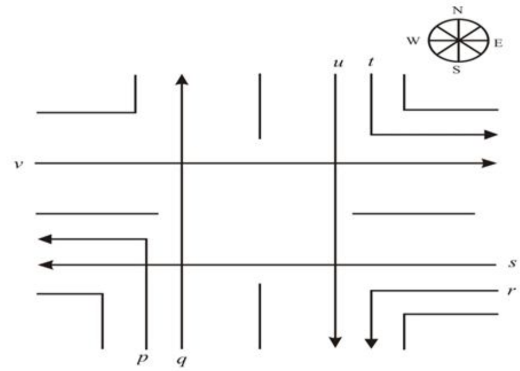

Figure 8. Traffic flows with the directions shown.

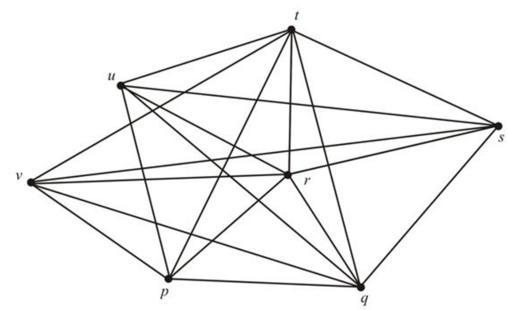

Figure 9. Compatible Fuzzy Graph of Fig.8

3. Proposed method for strong arcs in roundabout

The concept of strong arcs using fuzzy graph is analyzed for a better solution of the problem of roundabout traffic condition in Western countries.

3.1 Interpretation of Cross Roads

For example, the roundabout is considered to be the flow of traffic at the crossroads city of Keene, exactly on Winchester street of United Sates – the main street of Krif road.

Figure 10. The Main Street of Krif road (United States)

A roundabout is a complete fuzzy graph in structure with nine nodes namely,

$\sigma(V_1), \sigma(V_2), \sigma(V_3), \sigma(V_4), \sigma(V_5), \sigma(V_6), \sigma(V_7), \sigma(V_8), \sigma(V_9)$

which has two way roads to all four directions.

The fuzzy graph problem has represented below is the traffic flows, which is considering in the figure-11.

Each arrow shows the path of vehicles take from one direction to another. The numbers of vehicles in the different paths are unequal. As a result this is considered as a fuzzy graph with membership value depending on the level of car flow in each side as a vertex membership value (in percentage) for each node. The edge membership value (in percentage) of the fuzzy graph is the way in which each vehicle flows.

Depending on every-side of the flow of the cars α -strong, β -strong and δ -strong arcs identified the nature of the arc. The arc classification shows that there is a heavy congestion with an α -strong arcs, a medium flow in β -strong arcs and a normal flow in δ – arcs.

3.2 A graphical model of Traffic Problem at the Cross-roads

Consider a complete fuzzy graph that consists of 9 vertices and 27 edges respectively. We have seen 9 directional flows which are labeled by,

$\sigma(V_1), \sigma(V_2), \sigma(V_3), \sigma(V_4), \sigma(V_5), \sigma(V_6), \sigma(V_7), \sigma(V_8), \sigma(V_9)$

The following figure shows the direction of traffic flows.

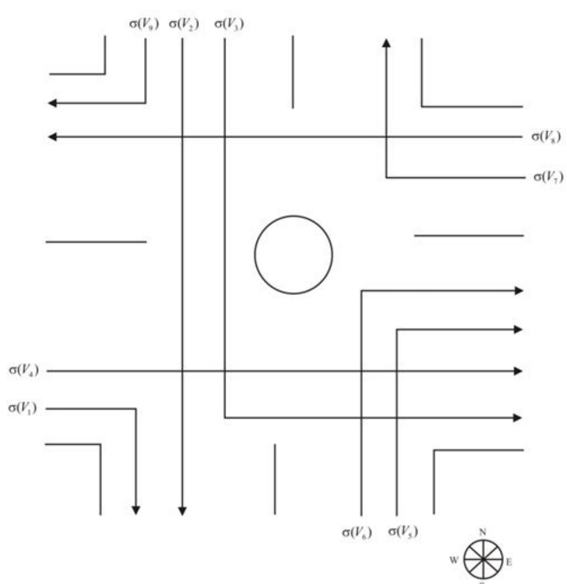

Figure 11. The main street of Keene city road and the direction of movements.

The fuzzy graph problem has represented below is the traffic flows, which is Considering in the fig.11. Each arrow shows the path of vehicles take from one direction to another.

The flows are compatible which can be seen in the following:

1. $\sigma(V_1)$ movement is compatible with the flows
   $\sigma(V_2), \sigma(V_3), \sigma(V_4), \sigma(V_5), \sigma(V_6), \sigma(V_7), \sigma(V_8), \sigma(V_9)$.
2. $\sigma(V_2)$ movement is compatible with the flows
   $\sigma(V_1), \sigma(V_3), \sigma(V_5), \sigma(V_6), \sigma(V_7), \sigma(V_9)$
3. $\sigma(V_3)$ movement is compatible with the flows
   $\sigma(V_1), \sigma(V_2), \sigma(V_7), \sigma(V_9)$
4. $\sigma(V_4)$ movement is compatible with the flows
   $\sigma(V_1), \sigma(V_7), \sigma(V_8), \sigma(V_9)$
5. $\sigma(V_5)$ movement is compatible with the flows
   $\sigma(V_1), \sigma(V_2), \sigma(V_6), \sigma(V_7), \sigma(V_8), \sigma(V_9)$
6. $\sigma(V_6)$ movement is compatible with the flows
   $\sigma(V_1), \sigma(V_2), \sigma(V_5), \sigma(V_7), \sigma(V_8), \sigma(V_9)$
7. $\sigma(V_7)$ movement is compatible with the flows
   $\sigma(V_1), \sigma(V_2), \sigma(V_3), \sigma(V_4), \sigma(V_5), \sigma(V_6), \sigma(V_9)$
8. $\sigma(V_8)$ movement is compatible with the flows
   $\sigma(V_1), \sigma(V_4), \sigma(V_5), \sigma(V_6), \sigma(V_9)$
9. $\sigma(V_9)$ movement is compatible with the flows
   $\sigma(V_1), \sigma(V_2), \sigma(V_3), \sigma(V_4), \sigma(V_5), \sigma(V_6), \sigma(V_7), \sigma(V_8)$

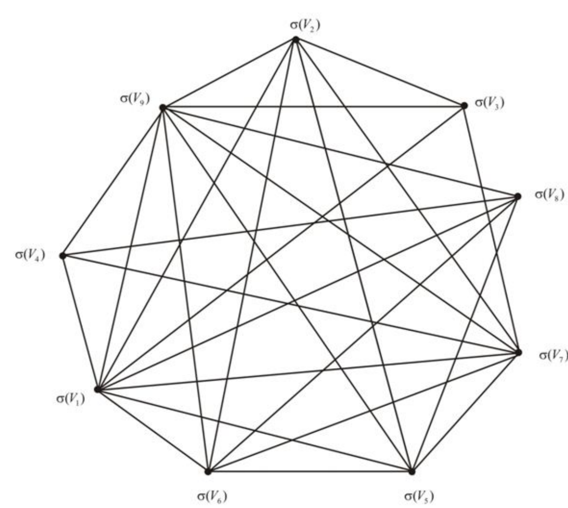

Figure 12. Compatible Graph.

Table 1. Volume Data.

-	V_1 0.22)	V_2 (0.05)	V_3 (0.21)	V_4 (0.35)	V_5 (0.28)	V_6 (0.41)	V_7 (0.39)	V_8 (0.02)	V_9 (0.24)
V_1 (0.22)	-	0.22	0.27	0.40	0.28	0.31	0.41	0.29	0.28
V_2 (0.05)	0.22	-	0.27	-	0.14	0.47	0.39	-	0.19
V_3 (0.21)	0.27	0.27	-	-	-	-	0.39	-	0.41
V_4 (0.35)	0.40	-	-	-	-	-	0.46	0.35	0.41
V_5 (0.28)	0.28	0.14	-	-	-	0.04	0.39	0.29	0.33
V_6 (0.41)	0.31	0.47	-	-	0.04	-	0.44	0.41	0.42
V_7 (0.39)	0.41	0.39	0.39	0.46	0.39	0.44	-	-	0.48
V_8 (0.02)	0.29	-	-	0.35	0.29	0.41	-	-	0.41
V_9 (0.24)	0.28	0.19	0.41	0.41	0.33	0.42	0.48	0.41	-

Table 2.

S. No.	Origin to destination	Weight of the edge of the path	Strength of the vertex of the path	Strong arc.
1 .	$\sigma(V_1)-\sigma(V_2)$	0.22	0.22	β-strong
	$\sigma(V_1)-\sigma(V_3)$	0.27	0.22	α-strong
	$\sigma(V_1)-\sigma(V_4)$	0.40	0.35	α-strong
	$\sigma(V_1)-\sigma(V_5)$	0.28	0.28	β-strong
	$\sigma(V_1)-\sigma(V_6)$	0.31	0.41	δ-strong
	$\sigma(V_1)-\sigma(V_7)$	0.41	0.39	α-strong
	$\sigma(V_1)-\sigma(V_8)$	0.29	0.22	α-strong
	$\sigma(V_1)-\sigma(V_9)$	0.28	0.24	α-strong
2 .	$\sigma(V_2)-\sigma(V_3)$	0.27	0.22	α-strong
	$\sigma(V_2)-\sigma(V_5)$	0.14	0.28	δ-strong
	$\sigma(V_2)-\sigma(V_6)$	0.47	0.41	α-strong
	$\sigma(V_2)-\sigma(V_7)$	0.39	0.39	β-strong
	$\sigma(V_2)-\sigma(V_9)$	0.19	0.11	α-strong
3 .	$\sigma(V_3)-\sigma(V_7)$	0.39	0.39	β-strong
	$\sigma(V_3)-\sigma(V_9)$	0.41	0.21	α-strong
4 .	$\sigma(V_4)-\sigma(V_7)$	0.46	0.39	α-strong
	$\sigma(V_4)-\sigma(V_8)$	0.35	0.35	β-strong
	$\sigma(V_4)-\sigma(V_9)$	0.41	0.35	α-strong
5 .	$\sigma(V_5)-\sigma(V_6)$	0.04	0.41	α-strong
	$\sigma(V_5)-\sigma(V_7)$	0.39	0.39	β-strong
	$\sigma(V_5)-\sigma(V_8)$	0.29	0.28	α-strong
	$\sigma(V_5)-\sigma(V_9)$	0.33	0.28	α-strong
6 .	$\sigma(V_6)-\sigma(V_7)$	0.44	0.41	α-strong
	$\sigma(V_6)-\sigma(V_8)$	0.41	0.41	β-strong
	$\sigma(V_6)-\sigma(V_9)$	0.42	0.41	α-strong
7 .	$\sigma(V_7)-\sigma(V_9)$	0.48	0.39	α-strong
8 .	$\sigma(V_8)-\sigma(V_9)$	0.41	0.24	α-strong

An observation of the crossroads forms are assumptions, as follows.

- The flow does not follow the light when turning to the left $\sigma(V_1)$, indicating that the flow can increase at any time under the waiting time of 0 (zero).
- The flow of the main street turning left from north $\sigma(V_2)$ is not directly related to the intersection of the left-turn lane before the intersection.
- For other flows, move the current to the left $\sigma(V_4), \sigma(V_5)$, $\sigma(V_6)$ to follow the light.
- There is just one flow turn left $\sigma(V_3)$.

The number of vehicles are passing through each cross road on the Krif road (in percentage)

4. Result and discussion

Table 3.

Arc	α-strong	$\sigma(V_1)-\sigma(V_3)$	$\mathrm{CONN}(V_1,V_3)=0.22$
		$\sigma(V_1)-\sigma(V_4)$	$\mathrm{CONN}(V_1,V_4)=0.35$
		$\sigma(V_1)-\sigma(V_7)$	$\mathrm{CONN}(V_1,V_7)=0.39$
		$\sigma(V_1)-\sigma(V_8)$	$\mathrm{CONN}(V_1,V_8)=0.22$
		$\sigma(V_1)-\sigma(V_9)$	$\mathrm{CONN}(V_1,V_9)=0.24$
		$\sigma(V_2)-\sigma(V_3)$	$\mathrm{CONN}(V_2,V_3)=0.22$
		$\sigma(V_2)-\sigma(V_6)$	$\mathrm{CONN}(V_2,V_6)=0.41$
		$\sigma(V_2)-\sigma(V_9)$	$\mathrm{CONN}(V_2,V_9)=0.11$
		$\sigma(V_3)-\sigma(V_9)$	$\mathrm{CONN}(V_3,V_9)=0.21$
		$\sigma(V_4)-\sigma(V_7)$	$\mathrm{CONN}(V_4,V_7)=0.39$
		$\sigma(V_4)-\sigma(V_9)$	$\mathrm{CONN}(V_4,V_9)=0.35$
		$\sigma(V_5)-\sigma(V_8)$	$\mathrm{CONN}(V_5,V_8)=0.28$
		$\sigma(V_5)-\sigma(V_9)$	$\mathrm{CONN}(V_5,V_9)=0.28$
		$\sigma(V_6)-\sigma(V_7)$	$\mathrm{CONN}(V_6,V_7)=0.41$
		$\sigma(V_6)-\sigma(V_9)$	$\mathrm{CONN}(V_6,V_9)=0.41$
		$\sigma(V_7)-\sigma(V_9)$	$\mathrm{CONN}(V_7,V_9)=0.39$
		$\sigma(V_8)-\sigma(V_9)$	$\mathrm{CONN}(V_8,V_9)=0.24$
Arc	β-Strong	$\sigma(V_1)-\sigma(V_2)$	$\mathrm{CONN}(V_1,V_2)=0.22$
		$\sigma(V_1)-\sigma(V_5)$	$\mathrm{CONN}(V_1,V_5)=0.28$
		$\sigma(V_2)-\sigma(V_7)$	$\mathrm{CONN}(V_2,V_7)=0.39$
		$\sigma(V_3)-\sigma(V_7)$	$\mathrm{CONN}(V_3,V_7)=0.39$
		$\sigma(V_4)-\sigma(V_8)$	$\mathrm{CONN}(V_4,V_8)=0.35$
		$\sigma(V_5)-\sigma(V_7)$	$\mathrm{CONN}(V_5,V_7)=0.39$
		$\sigma(V_6)-\sigma(V_8)$	$\mathrm{CONN}(V_6,V_8)=0.41$
Arc	δ-Strong	$\sigma(V_1)-\sigma(V_6)$	$\mathrm{CONN}(V_1,V_6)=0.41$
		$\sigma(V_2)-\sigma(V_5)$	$\mathrm{CONN}(V_2,V_5)=0.28$
		$\sigma(V_5)-\sigma(V_6)$	$\mathrm{CONN}(V_5,V_6)=0.41$

The rules of strong arcs are classified as each link of the nodes. The classification shows a heavy congestion with an α-strong arcs, a medium flow in β-strong arcs and a normal flow in δ-arc.

The lanes with high traffic are represented by α-strong arcs. More number of vehicles will pass through the same lanes represented by α-strong arcs. Traffic congestion could be reduced in the roundabouts by diverting these lanes to other lanes, that is, β-strong, δ-arc with normal or medium flow.

5. Conclusion

The traffic jam of a road will be reduced an accidents minimized by this method. A better solution for roundabout traffic problem has been studied with the concept of strong arcs using fuzzy graph.

Long weights of junctions and congestion can be avoided more efficiently. The knowledge of strong arcs in fuzzy graph is very important in any real time application. The rate of traffic flow in peak time is moderate and congestions have avoided in roundabouts by the application of strong arcs in traffic flow problems.

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