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Intelligent Traffic Light using Fuzzy Neural Network

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Abstract

In the past, when there were few vehicles on the road, the T.O.D.(Time of Day) traffic signal worked very well. The T.O.D. signal operates on a preset signal cycling which cycles on the basis of the average number of average passenger cars in the memory device of an electric signal unit. Today, with increasing traffic and congested roads, the conventional traffic light creates startup-delay time and end lag time so that thirty to forty-five percent efficiency in traffic handling is lost, as well as adding to fuel costs. To solve this problem, this paper proposes a new concept of optimal green time algorithm, which reduces average vehicle waiting time while improving average vehicle speed using fuzzy rules and neural networks. Through computer simulation, this method has been proven to be much more efficient than fixed time interval signals. Fuzzy Neural Network will consistantly improve average waiting time, vehicle speed, and fuel consumption.

Key words : Intelligent traffic light, Fuzzy Neural traffic light, spillback

1. Introduction

These days, the role of the traffic signal is very important when the volume of traffic can't be predicted. When there are a lot of running vehicles at an intersection, the signal cycle should be extended and when there are few running vehicles the signal cycle should be shortened. Most research has focused on low-saturated traffic conditions [1,2,3,4].

Only a few studies have investigated traffic control for high-saturated traffic conditions [6,7]. In order to produce traffic optimal signal cycle we must first check how many waiting cars are in the lower intersection. If there are a lot of cars between the two intersections there may not be enough space for cars to pass through the lower intersections. T.O.D. traffic signal systems simply repeat the fixed preset traffic signal cycle. Creating end lag time and start up lost time when queue length at the lower traffic intersection is bigger than the capacity of the upper traffic intersection.

Electro sensitive traffic systems can not consider passenger car unit. Because of this, it causes start up delay time and passenger waiting time. In this paper, it antecedently creates optimal traffic cycle of passenger car unit at the bottom traffic intersection. Mistakes can be made due to different can lengths, car speed ,and width of road. However, it continues to reduce the car waiting time and start-up delay time using fuzzy control of feed-back data.

Moreover, to prevent spillback, it can adapt control even though upper traffic intersection has a different vehicle length, road slope and road width. In this paper we used fuzzy membership function vary between 0 and 1 which estimate uncertain length of vehicle, vehicle speed and width of road. Fuzzy neural networks can accommodate uncertain traffic conditions very easily.

Therefore in this paper, we consider how to prevent spillback in high saturated traffic conditions, by introducing an optimal traffic signal using fuzzy control. An electro-sensitive traffic light system can extend the traffic cycle when many vehicles are on the road or it can reduce the traffic cycle when there are few vehicles. One drawback to just using an electro-sensitive traffic light system is that it doesn't consider vehicle length, so overflows may occur if the passing vehicle is long such as a bus or truck[10-12].

If we improve average traffic speed by 10-15%, It will save 2 million dollars per year. Since, traffic congestion has increased steadily in urban traffic networks, route guidance systems have been proposed to avoid traffic congestion links and inform the shortest travel time route of traffic networks. Moreover, cycle lengths and green time must be adaptively controlled according to the variation of incoming traffic volume, and change more drastically than actual measurement values. To solve this problem, this paper proposes a new concept of optimal green time using fuzzy neural network. Using computer simulation, we prove that the spillback phenomenon generated under highly saturated traffic condition is improved using fuzzy logic and neural networks. This paper is organized as follows: Section Ⅱ briefly explains the problems of conventional traffic lights. Section Ⅲ discusses the determination of optimal traffic cycles using a neural network and fuzzy logic computer simulation. Section Ⅳ describes simulation results. Finally, Section Ⅴ will give our conclusions.

2. Problems Using Conventional Traffic Light

Looking at Fig 1. there are 6 vehicles waiting at the lower traffic intersection. At the upper traffic intersection, the traffic condition is such that the degree of saturation is low thus all 6 vehicles can pass to the upper traffic intersection during the green time. Fig.1 with associated table 1 shows that the waiting automobiles consist of 4 small vehicles and 2 medium size vehicles. From the calculations, all 6 vehicles may pass to the upper traffic intersection during the green time, since the avaliable distance is 30 meters and only 28.5 meters are required to pass the traffic through. Fig. 2 with associated table 2 shows the waiting automobiles consist of 3 large vehicles and 3 medium sized vehicles. In this case only the first 3 vehicles may pass to the upper traffic intersection during the green time since the total distance required for 3 vehicles is 29 meters. If all 6 vehicles were to pass to the upper intersection, a spillback would be created, since a minimum distance of 48.5meters would be required to hold the vehicles. A detailed description is presented in Section Ⅲ. which describe how to prevent this spill back phenomenon from occurring.

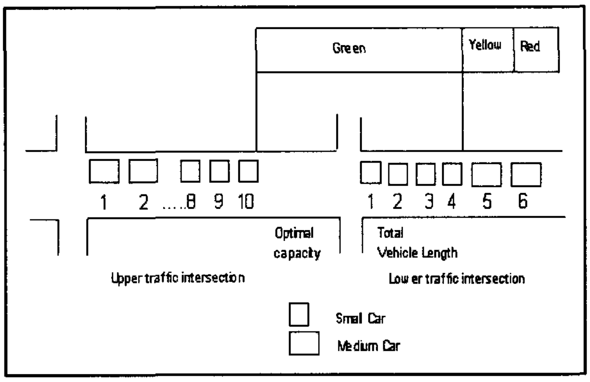

Fig.1 Greentime depending on waiting vehicle queue 1.

Table1. Waiting queue length consisting of small- medium vehicles at the lower traffic intersection

Passing Cars	Length	Passenger Car Unit
1(small)	4 meter	1.3
2(small)	4 meter	1.3
3(small)	4 meter	1.3
4(small)	3.5 meter	1.2
5(med)	6 meter	1.5
6(med)	7 meter	1.6

Optimal Capacity < *Upcap* – *Occv*
Occv : Total occupied distance at the upper intersection
*Occ*v equals 70 meter
$(4+4+4+3.5+6+7)=28.5$ METER < 30 METER

Optimal Capacity : $\sum_{n=1}^{n=6} wq(i)$

Upcap Maximum upper intersection capacity
Total waiting vehicles length
Upcap equals 100 meter
wq(i) : $(4+4+4+3.5+6+7)=28.5$ meter

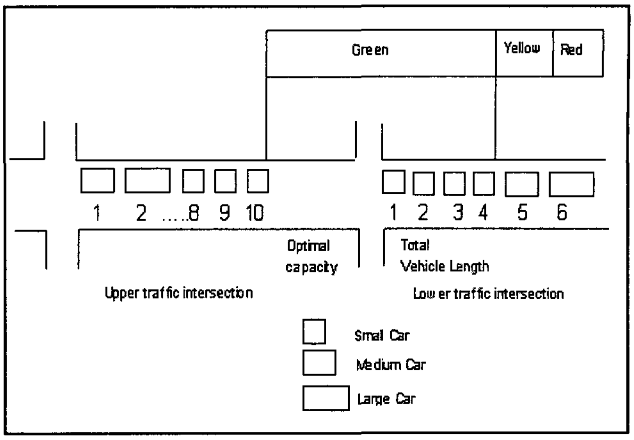

Fig. 2 Green time depending on vehicle waiting queue 2.

Table 2. Waiting queue length consisting of small- medium-large vehicles at the lower traffic intersectiion

Passing Cars	Length	Passenger Car Unit
1 (small)	4 meter	1.3
2 (med)	6.5 meter	1.5
3 (med)	6 meter	1.5
4 (med)	7 meter	1.6
5 (Large)	12 meter	1.7
6 (Large)	13 meter	1.8

Optimal Capacity < *Upcap* – *Occv*
Occv : Total occupied distance at the upper intersection
Occv equals 70 meter
$(4+6.5+6+7+12+13)=$ 48.5 METER > 30 METER

Optimal Capacity : $\sum_{n=1}^{n=6} wq(i)$

Upcap : Maximum upper intersection capacity
Total waiting vehicles length
Upcap equals 100 meter
wq(i) : $(4+6.5+6+7+12+13)=48.5$ METER

3. Design of fuzzy neural traffic light

In this section, we present a system for coordinating green time which controls 10 traffic intersections. For instance, if we have a baseball game at 8 pm today, traffic volume toward the baseball game will be increased 1 hour or 1 hour and 30 minutes before the baseball game. At that time we can not estimate optimal green time. Therefore, we used fuzzy neural network to estimate uncertain optimal green time and reduce vehicle waiting time. Fuzzy neural networks can accommodate uncertain traffic conditions very easily.

In this paper, it antecedently creates an optimal traffic cycle of passenger car units at the bottom traffic intersection. Mistakes are possible due to different car lengths, car speed, and length of intersection. Therefore, it consequently reduces the car waiting time and start-up delay time using fuzzy control of feed-back data..

Moreover, to prevent spillback, it can adapt control even though upper traffic intersection has a different vehicle length, road slope and road width. Figure 3 shows a block diagram of an optimal traffic cycle light, using fuzzy neural network.

The diagram reinterates the network's ability to reduce vehicle waiting time and to determine optimal green time, adapting to any different type of traffic intersection.

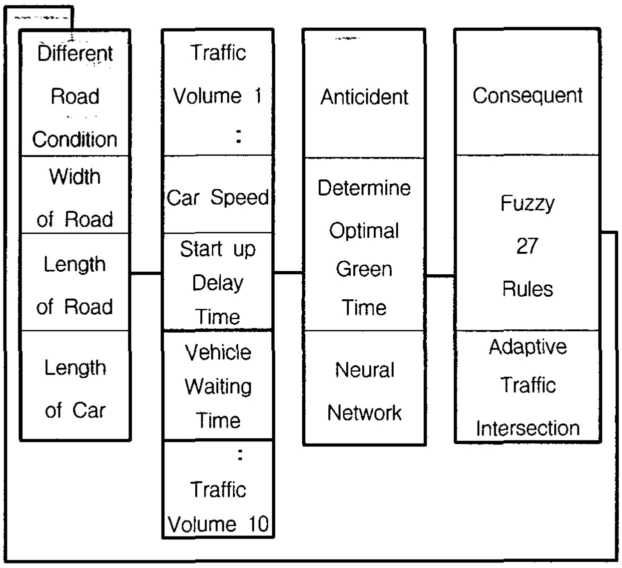

Fig 3. Block diagram of optimal traffic cycle light using fuzzy neural network

In order to solve spillback problems, we must determine which car is big or small. However, traffic intersection length, width of lane and number of lanes in the intersection is different. It adapts to the different traffic intersection types and sizes, while using the fuzzy 27 rules.

In this paper, the neural network consist of one input layer, one hidden layer, and one output layer. We use supervised learning process which adjust weights to reduce the error between desired output and real output for green time. This is depicted as follows.

(1) Initialize Weights and Offset

(2) Establishment of training pattern

(3) Compute the error between target pattern output layer neural cell(t_j) and output layer neural cell(a_j)

$$e_j = t_j - a_j \qquad (1)$$

(4) calculate weights between input neural cell(i, j) by the following equation

$$W(new)_{ij} = W(old)_{ij} + a e_{iaj} \qquad (2)$$

$$e_j = t_j - a_j \qquad (3)$$

(5) Repeat the process from number (2) above. The process is repeated until optimal green time is calculated.

Optimal Traffic		Optimal Traffic	Optimal Traffic			Optimal Traffic		Optimal Traffic
Cycle K		Cycle K+1	CycleK+2			Cycle K+3		Cycle K+4
Traffic I.D. 01	Traffic I.D. 02	Traffic I.D. 03	Vehicle Speed ...	...Delay ...Time ...		Traffic I.D. 08	Traffic I.D. 09	Traffic I.D. 10
Volume	Volume	Volume	....			Volume	Volume	Volume

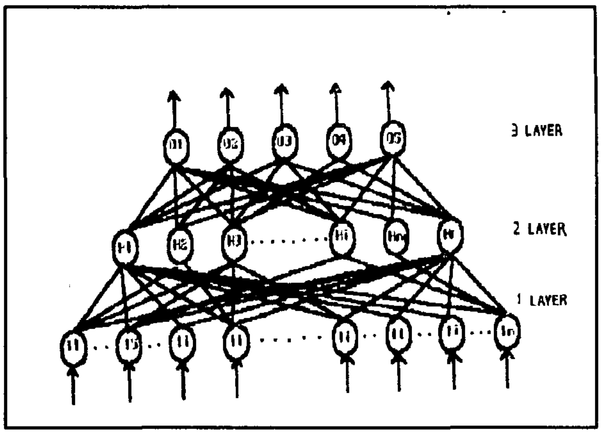

FIg. 4 Simulation of neural fuzzy traffic light

Figure 4. shows neural network to estimate uncertain optimal green time and reduce vehicle waiting time.

In order to improve vehicle waiting time, we used a 3 input fuzzy membership function and 2 output fuzzy membership function. The following is the Fuzzy Logic Control of the Traffic Signal Light. On the basis of 'RULE BASE' of 'FUZZY MEMBERSHIP' function under each condition, we use the MAX-MIN deduction method and the center of gravity method as defuzzification method.

High saturation rate (Upper Traffic intersection)

IF PA is Low
and PS is MED
and WT is High
then
Op is HIGH
Os is Low

PA is Degree of saturation rate
PS is Passing vehicle speed
WT is Length of vehicle vehicle
OP is Expecting Traffic signal cycle
OS is Expecting strtup delayTime

Optimal traffic cycle = Expecting car speed(OS) * Number of cars * Expecting passenger car unit(op)

Table 3 explains the adaption of optimal green time control, even though the upper traffic intersection has a different vehicle length, road slope and road width.

Real traffic conditions include different vehicle speed, length, and width of lane. Therefore, we use 27 fuzzy rules for improving optimal green time of the 10 intersections used, when the vehicle speed falls to a minimum of 5 km/hr, or increases to a maximum of 50 kn/hr, or if the length of vehicle is above 12 meter and there is a different length of traffic intersection from 50 meter to 250 meter.

Table 3 Adapting fuzzy rule for length of vehicle and width of road

Car \ Road Cond.	RWDH	RWDM	RWDS
PCUH	M	B	PB
PCUM	S	M	B
PCUS	S	S	M

RWDH : width of road is high
PCUB:Vehicle length is high
RWDM: width of road is medium
PCUM:Vehicle length is medium
RWDS:width of road is small
PCUS:Vehicle length is small

To determine passenger car unit in this paper it used loop detector, weight sensor and pressure sensor The passenger car unit is taken from the loop detector and placed on the road 25 meters before the traffic light, 3 fuzzy input membership function and 27 fuzzy logic control rules are used to adapt to every intersection.

The first fuzzy input membership function for length of vehicle is illustrated in Fig.5. as Short, Medium, and Big. It is very important to prevent the spillback as mentioned before in Section Ⅱ.

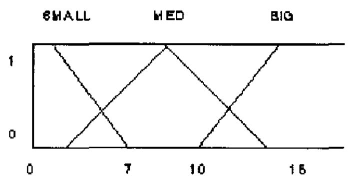

Fig. 5 Input fuzzy membership function for length of vehicle

Length of small vehicle is 4-6 meter
.... membership function is SMALL
Length of medium vehicle is 9-15 meter.
.... membership function is MED
Length of large vehicle is 9-15 meter.
.... membership function is BIG
Length of traffic intersection is 50-100 meter
.... membership function is SMALL
Length of traffic intersection is 101-150 meter.
.... membership function is MEDIUM
Length of traffic intersection is 151-200 meter
.... membership function is BIG.
Length of traffic intersection is 201-250 meter
.... membership function is VERY BIG.

The output of the fuzzy traffic controller estimates the size of the passenger car unit and it's expecting vehicle speed. This will adapt to the green time at every different traffic intersection. Conditions are shown in fig. 6. Finally, computer simulation proved the fuzzy neural network work control every traffic intersection, even though different length, slope and width. Table 4 explains the advantages of neural fuzzy traffic light.

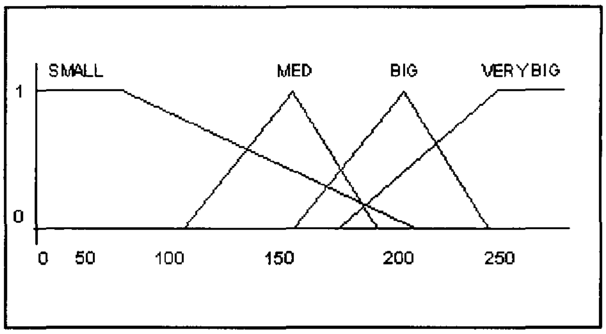

Fig. 6 Output fuzzy membership function for expecting optimal green time

Table.4 Simulation Result of neural fuzzy traffic light and Conventional method

Saturation Rate	Vehicle Speed	Passenger Car Unit		Conventional Method			Fuzzy Traffic Light	
%	km/ hour	Big	Medium	Small	T.O.D.	waiting time	WALK	waiting time
83	17	3	1	2	30	07 sec	20	3 sec
71	12	2	2	1	30	11 sec	20	9 sec
85	18	2	0	4	30	10 sec	20	8 sec
62	08	1	2	3	30	4 sec	20	6 sec
55	36	1	1	4	30	6 sec	20	4 sec
34	32	2	2	3	30	12 sec	20	15 sec
38	27	1	2	2	30	17 sec	20	14 sec

Finally, the proposed A.I. traffic simulation controller system has been implemented using look up table method and tested with various types of traffic condition as shown in fig. 7 and fig. 8.

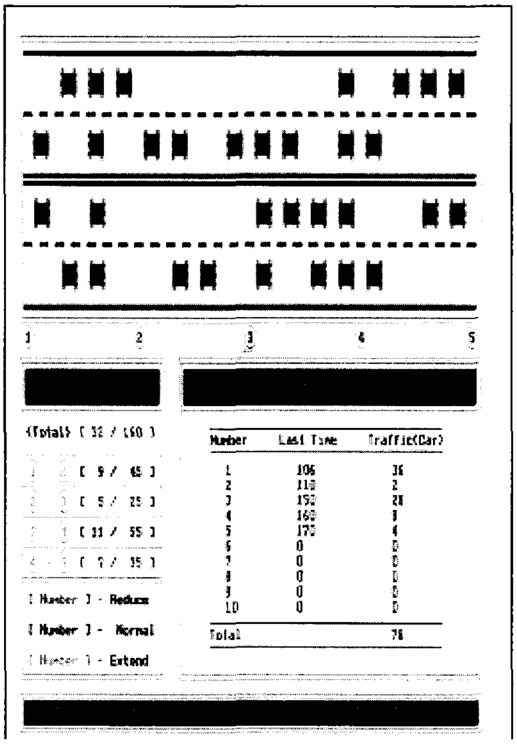

Fig. 7 Computer simulation of fuzzy neural traffic light using shortest path algorithm

Fig. 8 Implementation of fuzzy neural traffic light

4. Simulation Results

We saw that a fuzzy neural network analyzes the number of passing vehicles to predict the P.C.U. and to determine the optimal traffic cycle. This means that it can extend or reduce the traffic signal cycle depending on the number of vehicles present. It can also prevent the spill back phenomenon when there are multiple intersections close by. Fuzzy neural networks alone can accurately predict the optimal traffic cycle using the Shortest path algorithm. Moreover, the 27 Fuzzy rules are applied to adapt to different traffic intersection conditions.

Once the data is accurately analyzed, green time is adjusted according to the length and slope of the traffic intersection which makes for a much smoother flow of traffic.

5. Conclusion

With traffic constantly increasing at lighted intersections neural networks in conjunction with fuzzy logic will fit extremely well into today's traffic conditions. Remember that the T.O.D. method mentioned relies solely on a predetermined cycling time which remains constant This means that the T.O.D. system can not adjust the green time to the current traffic conditions for optimal traffic flow. An electro-sensitive traffic light system was shown to extend the traffic cycle when there are many vehicles passings on the road or reduce the cycle if there are few vehicles. However, it can not determine which vehicle is long or short. When this happens overflows or the spill back phenomenon occur and waiting time is increased. On the other hand, we saw that a fuzzy neural network analyzes the number of passing vehicles to predict the P.C.U. and to determine the optimal traffic cycle.

The conventional method was shown to produce a much longer waiting time as well as create spill back since it can not adjust for traffic conditions. In summary, not only will neural networks with fuzzy logic dramatically reduce vehicle waiting time and increase overall traffic efficiency, but it will also make a dramatic dent in decreasing energy costs.

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