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An ADAPTIVE TRAFFIC LIGHT CONTROL SCHEME AND ITS IMPLEMENTATIONIN WSN-BASED ITS

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Abstract- We investigate the problem of adaptive control of traffic lights using real-time traffic information collected by a wireless sensor network (WSN). Previous studies mainly focused on optimizing the intervals of green lights in a fixed sequence of traffic lights, and ignored some traffic flow's characteristics and special traffic circumstances. In this paper, an adaptive traffic light control scheme has been proposed, in which the sequence of traffic lights can be adjusted dynamically in accordance with the real time traffic detected, including traffic volume, waiting time and vehicle density. Subsequently, the optimal traffic light length can be determined according to the local traffic and predicted traffic data. Simulation results demonstrate that the proposed scheme can achieve much higher performance, in terms of throughput and average waiting time. We also implement proposed scheme into our WSN-based ITS project, iSensNet, and the result shows that our scheme is effective and practical.

Index terms: wireless sensor network, intelligent transportation system, adaptive traffic light control, real-time traffic data.

I. INTRODUCTION

Traffic congestion is a huge problem nowadays, due to the rapid increase in the demand for transportation and limited resources provided by traffic infrastructures. The result is longer vehicle travel times, increased energy consumption, growing environmental pollution, reduced traffic safety, and a decrease in the efficiency of transportation infrastructure. Hence, controlling traffic has become a very important issue under a growing pressure to relieve traffic congestion. Traffic control is an important component of Intelligent Transportation Systems (ITS). ITS refers to a system that integrates advanced communications, information, and electronics technologies into transportation infrastructure and vehicles, to relieve traffic congestion, improve safety, and reduce transportation times and fuel consumption. Controlling traffic lights plays a key role in increasing traffic throughputs and reducing delays. When scheduling traffic lights, current traffic conditions should be considered as they can significantly affect the control scheme. Hence, the collecting real-time traffic data is a very important issue.

Conventional methods of traffic data collection have limitations. These include limited coverage due to a sensor's fixed-location installations and the cable-based communication methods used to transmit the detected traffic information, which increases the costs of implementation and maintenance [1] [2]. Based on these drawbacks, it is necessary to search for another way to monitor traffic conditions. With the continuing development of Wireless Sensor Networks (WSNs), which use wireless sensor nodes for surveillance and communication, the possibility of overcoming these drawbacks is increasing. Because of flexibility in deployment and various functions, WSN has numerous potential applications. These typically include environmental monitoring, industrial monitoring, machine health monitoring, and tracking or controlling [3] [4][5] [6] [7] [8]. Under the guarantee that all of the traffic data in the whole network range can be measured, using sensor nodes can overcome the shortcomings mentioned above [1]. Therefore, we apply WSN into ITS to provide real-time traffic data and enhance traffic safety.

Traffic light control refers to a strategy to schedule the traffic lights to ensure traffic can move as smoothly and safely as possible. Different control strategies have different performances. The performance criteria include vehicle throughputs, waiting times, and so forth. An optimal control strategy can increase the utilization of infrastructure, improve traffic safety, and reduce energy consumption. Most current traffic light control approaches use one of three control types: fixed-time, actuated, or adaptive. Regarding the strategy to control traffic lights, a number of apparent difficulties should be taken into account [9]. They include the increasing size of the problem for a large traffic network, the limited coverage of traffic detection, and many unpredictable disturbances which are difficult to measure, such as traffic incidents and illegal parking. The combination of these difficulties makes it harder to design a traffic light control strategy with the purpose of achieving an optimal real-time schedule, especially when the traffic network is large enough, since the coordination between adjacent intersections also should be taken into account.

A large number of traffic light control approaches have been proposed in the past decades, most of them [10], [11], [12], [13], [14], [15] do not deal with the traffic lights sequence adjustment when scheduling traffic lights, which is also a challenging issue in adaptive traffic light control. The lights sequence adjustment can reduce average delays and improve throughput, especially in traffic fluctuation conditions. Most traffic light control approaches use a fixed sequence with optimization on the length of the traffic lights. Furthermore, some of them usually take minimum average waiting time and the number of stopped vehicles as objectives, while failing to consider throughput. In addition, many of the approaches [12] [16], [17], [18], [19], [20], [21] employ artificial intelligence, such as a neural network, and learning and genetic algorithms, to optimize the decision making of the traffic light control. Due to the number of iterations, more computation time is incurred. In addition, many existing works pay little attention to the characteristics of traffic flow, especially when dealing with the discontinuous traffic flow; and few works mention traffic light solutions for special traffic circumstances, such as ambulances, fire engines, or traffic accidents.

Taking advantage of real-time traffic data that is detected and transmitted through wireless communication technology, we propose an adaptive traffic light control scheme which can dynamically control traffic lights so that the green lights sequences and durations can be adapted to a dynamically changing traffic environment, while achieving more attractive performance in terms of network throughput, average waiting time compared with previous works. The proposed scheme can adjust both the sequence and length of the traffic lights in accordance with the real-time traffic detected. A number of traffic factors have been taken into consideration, such as traffic volume, waiting time, vehicle density, and others, to determine the green light sequence and the optimal green light length. We conduct simulations to evaluate the performance compared with previous solutions. Our extensive simulation results demonstrate that our scheme produces much higher throughputs and lower average waiting times for vehicles, compared with a fixed-time traffic light control and an actuated traffic light control [13]. Furthermore, we apply the proposed approach into our WSN-based ITS platform iSensNet, and define several traffic scenarios to evaluate the performance. A demonstration [22] with different types of traffic conditions shows that our approach is effective and can be practical in our platform.

The remainder of this paper is organized as follows. In Section II, we briefly discuss the previous works on traffic light control. In Section III, we model the problem and define some notations. In Section IV, we propose an adaptive traffic control scheme to detect traffic conditions, and then determine the sequence and length of the green lights. In Section V, we evaluate the performance of our scheme through simulations. We implement the proposed scheme to our WSN-based ITS project iSensNet in Section VI. In Section VII, we present our conclusions and discuss future works.

II. RELATED WORK

There has been considerable works on traffic light control optimization. In the past, there emerges a number of well-known traffic light control systems, SCOOT and SCAT are two most implemented systems worldwide. SCOOT [2], [18], [23] is a centralized traffic responsive system to coordinate traffic lights in a fixed green light sequence in urban areas as an automatic respond to traffic flow fluctuation. SCATS [12], [24] is another widely used system which can provide intelligent pre-defined traffic plans to schedule the traffic lights, which coverers various traffic situations such that can offers substantial reduction in vehicle delay and particularly in peak periods.

There are also a lot of studies using some techniques, such as fuzzy logic control, neural network, genetic algorithm and so forth. Fuzzy logic has been the pioneers to be applied in traffic control by Pappis and Mamdani [25]. They considered an un-saturated isolated intersection with simple one-way traffic control with green light length extension optimization. Chiu and Chand [22], [26] considered a two-way streets intersections, in which fuzzy rules were used to adjust cycle time, phase split and offset parameters independently based on local traffic condition.

The first known attempt to apply reinforcement learning in traffic light control problems was by Thorpe [11] [27]. They considered a single intersection with two phases, north-south permission and east-west permission. Thorpe used a neural network to predict the Q-values for each possible decision, based on the total waiting time of all vehicles and the time since the lights last changed. Thorpe also considered a simple traffic network with 16 one-lane four-direction intersections [28], in which SARSA was used to represent the current traffic state and train intersection controller.

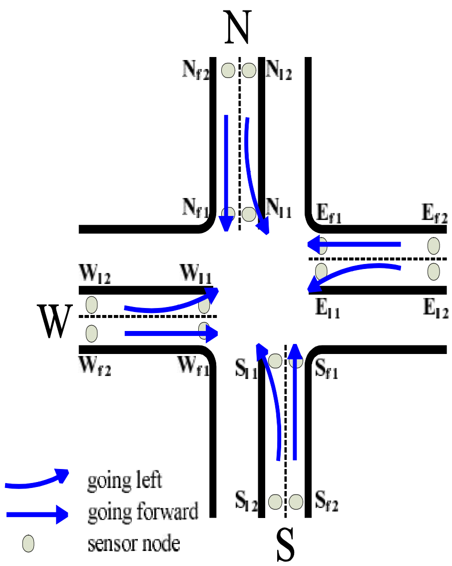
The first attempt of applying GA to traffic light control was by Foy et al. in [29], which considered a traffic network with four intersections with purpose to minimize the delay. Chen and Shi applied a real-coded genetic algorithm (RGA) to an isolated two-way intersection with multiple lanes [3], in which a traffic flow model was designed and then RGA was used to optimize the green times and cycle time in order to minimize the throughput.

Bingham [30] considered an isolated intersection with two one-way streets in which a fuzzy logic controller was designed to generate continuous action candidates to represent the possible extension duration of current green light. And then, a fully connected feed-forward neural network was designed to compute the value of each state, such that the candidate action with the greatest value can be selected as the decision.

Choy et al. [31], [32] proposed a distributed, cooperative approach to manage the real-time traffic in an arterial network by using a hybrid multi-agent system involving an effective traffic light control strategy. The authors also proposed another multi-agent system approach to real-time traffic light control problem in urban traffic network [28], with one more multi-agent system designed by integrating the simultaneous perturbation stochastic approximation theorem in fuzzy neural networks to update the weight of each neuron.

III. PROBLEM FORMULATION AND NOTATIONS

The common traffic network structure in real world consists of multiple inter-connected intersections. Here, an important factor should be taken into account, the distance between two adjacent intersections. When the distance is long, the influence would be small, and can be almost ignored under the real-time detection and advanced wireless communication technology. This situation can be treated as traffic light control in another type of isolated intersection. Hence, we investigate the high performance of adaptive traffic light control in this type traffic network.



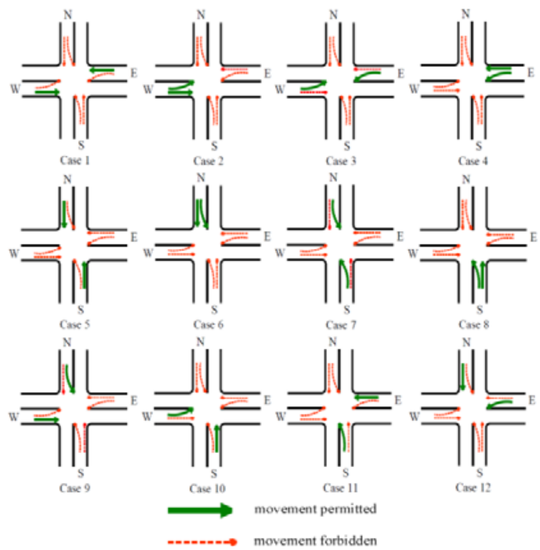


Figure 1: An Intersection ModelFigure 2: Twelve possible configurations of green lights

To model this problem, we use (see Fig. 1) a sensor-equipped intersection model [33], a total of sixteen sensor nodes are placed on the eight lanes to detect the flow of traffic. Each lane has two sensor nodes: one is installed at the intersection and the other at a given distance, called the *SensorDistance*, from the intersection. Each intersection has a maximum of twelve different possible cases of green lights (see Fig. 2) [33].

Table 1: Notations

$C = \{1,2,3,...,12\}$, $k \in C$	$R = \{1,2,3,...,8\}$, $r \in R$
I = {north, south, east, west}	J = {forward, left}
TP: total throughput	*AV GWT*: average waiting time
AR(k, t): number of arrival vehicles in case k at t.	
DP(k, t): number of departure vehicles in case k at t.	
RM(k, t): number of vehicles in case k at t.	
WT(k, t): sum of vehicles' waiting time in case k at t.	
*Xy*1: sensors installed at the intersection in lane y at direction X, $X \in I$, $y \in J$.	
*Xy*2: sensors installed with distance *SensorDistance* from the intersection in lane y at direction X, $X \in I$, $y \in J$.	

Therefore, in the face of a dynamically changing traffic environment, the problem is transformed into a decision on which case should obtain a green light next in each intersection and for how long the light should last. In order to maintain fairness for each case in each intersection, we define two upper bounds [33]: maximum vehicle waiting time and the upper bound of the hunger level.We define the notations in Table I, and assume that all vehicles have the same constant speed, and the sensor node used should be the same type.

IV. ADAPTIVE TRAFFIC LIGHT CONTROL SCHEME

The scheme contains three steps: real-time traffic detection, green light sequence determination and light length determination. Real-time traffic detection detects and calculates traffic information in real-time. Green light sequence determination uses the traffic information to determine the next green light to the case in the most need. Light length determination determines how long the green light will last for. At the beginning, we set a control cycle *Tcontrol* first, which is defined as an upper bound of light length. This value of *Tcontrol* is based on expert knowledge.

a. Real-time Traffic Detection

The first step is to detect the arrival and departure rate of vehicles in each lane, and then collect relevant data, with sensor nodes installed in each lane of the intersection. Sensor nodes detect the number of vehicles in each lane and each vehicle’s ID and type. Xy1 is responsible for detecting vehicles at the intersection; Xy2 is responsible for detecting vehicles from the intersection with the distance *SensorDistance* mentioned. *SensorDistance* is equal to $T_{control}$ times *speed* so that Xy1 will get the information on the vehicles that will reach the intersection after $T_{control}$ time in advance through the communication between Xy1 and Xy2.Using these detected data, the arrival rate and departure rate in each lane can be determined in real-time.

Because each vehicle has a length $L_{vehicle}$, we divide lane length L_{lane} into m intervals with the same length $L_{interval}$ equal to L_{lane}divided by m, shown as D_1, D_2, …, D_m. D_i is demonstrated as interval [d_{i1}, d_i]; d_i is defined as the distance to the intersection, which is equal to i times $L_{interval}$. $RM(D_i, t)$, $AR(D_i, t)$, $DP(D_i, t)$ are defined as the number of vehicles in, arriving in, and departing from D_i at time t, respectively. The arrival rate in D_i at time t is equal to the departure rate in D_{i+1}at time t1. $RM(D_i, t)$ can then be calculated (in equation 1 and equation 2). After that, $G(D_i)$ can be determined (in equation 3), which is defined as the density of the traffic flow in interval D_i.

The density of the traffic flow in lane VDDF(D_1, D_2, …, D_m) can then be demonstrated in equation 4.

$$AR(D_i, t) = DP(D_i + 1, t - 1) \quad (1)$$

$$RM(D_i, t) = \max\{ RM(D_i, t-1) + AR(D_i, t) - DP(D_i, t), 0 \} \quad (2)$$

$$G(D_i) = \frac{RM(D_i, t)}{L_{interval}} \quad (3)$$

$$VDDF(D_1, D_2, \dots, D_m) = f(G(D_1), G(D_2), \dots, G(D_m)) \quad (4)$$

This is a nonlinear function. Different intervals have different traffic flow densities, which mean a different number of vehicles. At some intervals, there exists a subinterval without any vehicle, and its length is larger than $L_{vehicle}$. Here, we define this subinterval as a blank. In order to accurately check blanks, $L_{interval}$ should be equal to 2.5 times $L_{vehicle}$. Then, if there exists a $G(D_i)$, whose value is lower than 0.4 and higher than 0.2, we can decide that there is a blank in Di and that the length of the blank *L(blank)* is equal to $L_{vehicle}$. If there exists a $G(D_i)$, whose value is lower than 0.2, we can decide that there is a blank in $G(D_i)$ and that the *L(blank)* is equal to $2\times L_{vehicle}$.

What needs to be considered with blanks is dealing with the problem that arises when a blank reaches the intersection and the current green light is for its lane, which leads to a waste of a green light. This means that, within the a period of time equal to the length of this blank *L(blank)*, the number of vehicles passing through the intersection is not as large as supposed, so that there is an increase in the total waiting time of vehicles in other lanes. Therefore, we try to release the blank by making the blank reach the intersection with the red light for that certain lane.

b. Green Light Sequence Determination

The second step is to make a decision to determine the sequence of green lights, using real-time traffic data. In order to make this decision, we define GLD(k, t) to indicate case *k*'s green light demand at time t, so that the case with the most urgent demand should get the next green light. Since our objectives are to maximize the throughput and minimize the average waiting time, the number of vehicles detected in each lane, their corresponding waiting times, and the blank circumstance are influential factors. To guarantee that each case will not wait too long, it is also necessary to take the hunger level into account in determining the sequence of green lights.

Furthermore, special circumstances and the effect from adjacent intersections can also play a role. Equation 5 demonstrates all of the factors of GLD(k, t).

$$\mathrm{GLD(k,t)} = a_1 \times \mathrm{TV\ (k,t)} + a_2 \times \mathrm{WT\ (k,t)} + a_3 \times \mathrm{HL\ (k,t)} + a_4 \times \mathrm{BC\ (k,t)} + a_5 \times \mathrm{SC\ (k,t)} + a_6 \times \mathrm{Neibor\ (k,t)} \tag{5}$$

Here, TV(k, t), WT(k, t), HL(k, t), BC(k, t), SC(k, t), Neibor(k, t) are defined as the weight of the traffic volume, average waiting time, hunger level, blank circumstance, special circumstance, and influence from neighboring intersections of case k at time t, respectively, and a_i is defined as the coefficient of these parameters to demonstrate their priorities, *i* = 1, 2, 3, 4, 5, 6. In our problem, since the distance between two intersections is longer than *SensorDistance*, Neibor(k, t) can be ignored in this problem. Therefore, we discuss the five main factors sequentially.

(1) Traffic Volume

After the *VDDF(d, RM(t))* calculation, we can calculate the weight of the traffic volume of each case. To calculate *TV(k, t)*, we first need to obtain *TraVol(i, t)*, which is defined as the total number of vehicles in lane *i*, from time t to following *Tcontrol* time. FV(i, t) is defined as the number of vehicles that would reach the intersection at time t in lane i, i ∈ R. Equation 6 shows TraVol(i, t) in lane i with the green light at time t, and equation 7 shows TraVol(i, t) in lane i with the red light at time t. Thus, traffic volume case k can be obtained (in equation 8), and u, v are two lanes of case k. Then, the traffic volume weight can be calculated (in equation 9). A higher TV has more influence in decision-making.

$$TraVol(i,t) = \sum_{j=1}^{Tcontrol} \Big(\big(FV(i,t+j) - DP(i,t+j)\big) + \sum L(blank)\Big) + RM(i,t) \tag{6}$$

$$TraVol(i,t) = RM(i,t) + \sum_{j=1}^{Tcontrol} \big(FV(i,t+j)\big) \tag{7}$$

$$TraVol(k,t) = TraVol(u,t) + TraVol(v,t) \tag{8}$$

$$TV(k,t) = \frac{TraVol\ (k,t)}{\sum_{k \in C} TraVol\ (k,t)} \tag{9}$$

(2)Waiting time

To calculate WT(k, t), we need to obtain AVGTwait (i, t) first, which is defined as the average waiting time in lane i, from time t to following Tcontrol time. Equation 10 shows AVGTwait (i, t) in lane i with the green light at time t, and equation 11 shows AVGTwait (i, t) in lane i with the red light at time t. Thus, the average waiting time in case k can be obtained (in equation 12), and u, v are two lanes of case k. Then, the weight of the average waiting time can be calculated (in equation 13). A longer WT has more influence in decision-making.

$$AVGT_{wait}\,(i,t) = 0 \tag{10}$$

$$AVGT_{wait}\,(i,t) = \frac{RM(i,t) \times Tcontrol\ + \sum_{j=1}^{Tcontrol}\ (FV(i,t+j) \times Tcontrol\ - j)}{TraVol\ (i,t)} \tag{11}$$

$$AVGT_{wait}\,(k,t) = \frac{AVGT_{wait}\ (u,t) + AVGT_{wait}\ (v,t)}{2} \tag{12}$$

$$WT(k,t) = \frac{AVGT_{wait}\ (k,t)}{\sum_{k \in C} AVGT_{wait}\ (k,t)} \tag{13}$$

(3) Hunger Level

The hunger level HL(k, t) is defined to guarantee fairness. It can be determined by the number of times case k has a green light, which is represented by N(k, t), k $\in$ C, in equation 14. The more times the case previously got green lights, the lower its current hunger level; the fewer times the case previously got green lights, the higher its current hunger level.

$$HL(k,t) = \frac{N(k,t)}{\sum_{k \in C} N(k,t)} \tag{14}$$

(4)Blank Circumstance

Blanks play an important role in calculating GLD(k, t). We try to minimize the frequency of the circumstance in which there is a blank at the intersection with the green light for a certain lane. In order to maximize the throughput and minimize the average waiting time, we calculate how many blanks there are in each lane, and the length of each blank.Within a T(blank) time, if a sensor node cannot detect a vehicle passing through, we decide there is a blank of length L(blank). T(blank) should be larger than *Lvehicle* divided *speed* , and L(blank) = T(blank) × *speed*.

In the detection of blanks, there are three possible circumstances: where every case has a blank, or some cases have a blank, or none of them has a blank. Different circumstances have different solutions. When every case has at least one blank, we would like to give a green light with high priority to the case in which the first detected blank has the farthest distance to the intersection. In this way, a green light would be provided to let more vehicles leave. When some cases have a blank, we would decide to give a red light for these cases next. When none of them has a blank, we treat them with the same level of priority. How to determine blank length has been mentioned before.

(5)Special Circumstance

Special circumstance refers to some situations where a green or red light must be activated urgently. For example, a green light must urgently be given for the lanes having ambulances or fire engines; a red light should be given for the lanes in which a traffic accident has occurred. Hence, we define SC(k, t) to demonstrate these green light demands; *SC(k, t)* is a signum function (equation 15) with only three values, 1, 0, and -1.

$$SC(k,t) = \begin{cases} 1 \text{ if high green light priority vehicle detected} \\ -1 \text{ if high red light priority vehicle detected} \\ 0 \text{ otherwise} \end{cases} \tag{15}$$

(6)Coefficient Determination

Finally, we need to determine the coefficient of each factor, which is treated as a priority. Priority for a green or red light should be assigned to these factors. Differentprioritiesaregiventodifferentfactors,sortedfromhightolowasspecialcircumstance,blankcircumstance,hungerlevel,trafficvolume, and waitingtime,asshowninTable II.Based onthevalueof*GLD*,thecasewiththelargestvalue canget a greenlightnext.

Table 2: Green Light Sequence Determination

Green Light Sequence Determination in Isolated Intersection

Input:VDDF(d,RM(t)), the case *i* holding green light.

Output: decision which case should obtain green light.

begin

1. Check special circumstance.
2. **if** there exists a case *k* with green light priority **then**
3. Assign green light to case *k*
4. **else**
5. **if** there exists a case *j* with red light priority **then**
6. Assign red light to case *j*
7. **else**check blank
8. **if** all case have blank **then**
9. Find the case k has the farthest blank
10. Assign green light to case k
11. **else**
12. **if** at least one case have blank **then**
13. Assign red lights to these cases
14. **else** computer *TV(k,t), WT(k,t)*,*HL(k,t)*
15. **if** there exists a case *k* with *HL(k,t)* larger than threshold **then**
16. Assign green light to case *k*
17. **else**
18. **if** maximum *WT* is larger than *WT(i,t)***then**
19. Assign green light to the case with maximum *WT*
20. **else**
21. **if** maximum *TV* is larger than *TV(i,t)***then**
22. Assign green light to the case with maximum *TV*
23. **else** Assign green light to current case *i*.

end

c. Light Length Determination

The third step is to determine the length of the green light – that is, how long the green light should last for. Gnext is defined as the length of the next green light. It is equal to the time for vehicles in lanes having the next green light to go through the intersection (in equation 16), in which i, j are two lanes of the case with the next green light. If the value of Gnext is larger than Tcontrol, Gnext should be equal to Tcontrol. Then, after Gnext time, we would calculate the current traffic environment and again determine the sequence and length of the green lights.

$$G_{next} = \frac{\max\{TraVol\ (i,t), TraVol\ (j,t)\}}{speed} \quad (16)$$

V. PERFORMANCE EVALUATION

We define *volume-to-capacity* to indicate the busy degree of each lane. Here, *capacity* is defined as how many vehicles can be in the lane at the same time, equals to $L_{lane}/L_{vehicle}$. We use the proposed scheme compared with the optimal fixed-time traffic control (FTC) and actuated traffic control (ATC) [13], which are based on the same random arrival rate of each lane, *Tcontrol* , *speed*, *Lvehicle* and *Llane* and same traffic structure. The performance metrics include throughput-to-volume and average waiting time. Throughput-to-volume is defined as the percentage of passing vehicles in total traffic volume.

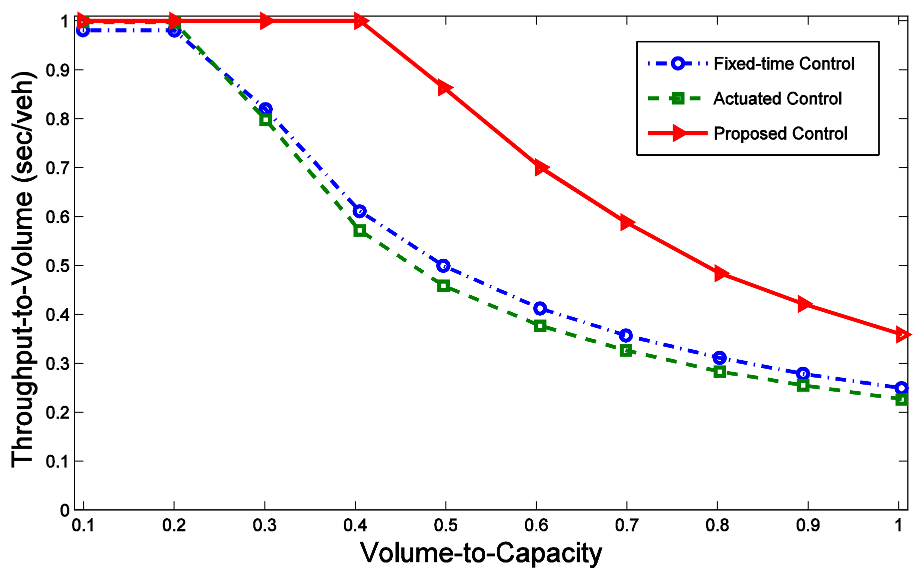


Figure 3: Throughput-to-volume comparison

Fig. 3 compares the throughput-to-volume when using a fixed-time control, an actuated control and our proposed scheme. Our scheme can achieve the best throughput. When *volume-to-capacity* is in interval [0.2, 0.4], our scheme as well obtains the best performance, while the difference with the other two control schemes and ours become larger. When *volume-to-capacity* is in [0.4, 1], the throughput of ours is almost 1.6 times as the other two.

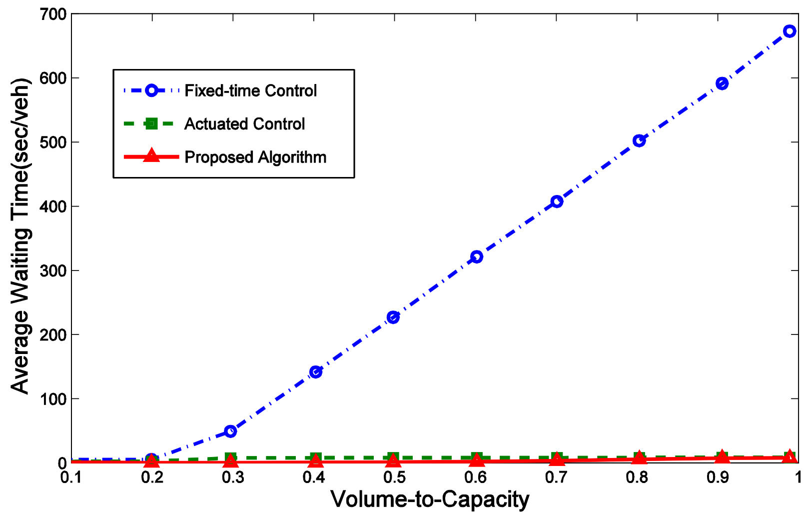


Figure 4: Average waiting time comparisonbetween fixed, actuated and adaptive control

Fig. 4 compares the average waiting time of the three schemes.Our approach can always achieve lower average waiting time. With *volume-to-capacity* increasing, average waiting time in FTC increase rapidly, much faster than the other two, whose average waiting time stay in interval [0, 10].

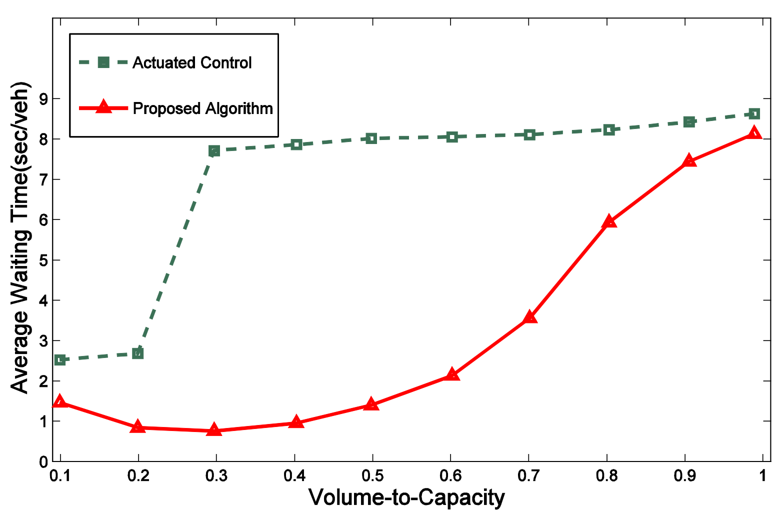


Figure 5: Average waiting time comparisonbetween actuated and adaptivecontrol

Since it is hard to distinguish the difference between ATC and our scheme in Fig. 4, we enlarge the two solutions performance in Fig.5. Our approach obtains less average waiting time than ATC, especially when *volume-to- capacity* is 0.3.

Finally, from the simulation results, we can find that our proposed approach can achieve higher throughput and lower average delay compared with the optimal fix-time traffic control and an actuated traffic control.

VI. IMPLEMENTATION

In order to approach to real world application, we implement our proposed approach into our WSN-based ITS testbed, iSensNet (Intelligent Services with Wireless Sensor Network) platform, as shown in Fig.6.

a. A Simplified Intersection Model in iSensNet

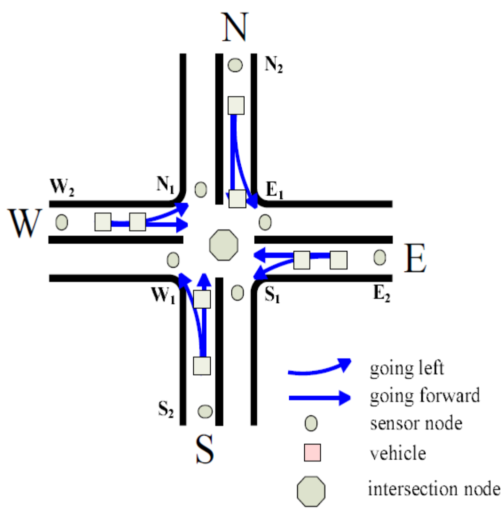


Figure 6: iSensNet testbedFigure 7: A Simplified Intersection Model in iSensNet

Due to the physical constraint existed in our platform, we have a simplified intersection model (see Fig. 7). At this model, there are four approaches, east, south, west, and north; each approach has only one lane with goring forward and left turning are permitted.In this scenario, we install three categories sensor nodes due to the different functionalities as follows:

- Detection Sensor Nodes (DSN), which installed under the two ends of each lane, are responsible to detect whether the vehicles in the lanes passing through these locations equipped, and then the number of vehicles in the lane can be calculated real-timely . Currently, we use IC card.

- Vehicle Nodes (VN), which are installed in each vehicle, can communicate with each other and other sensor nodes. So that vehicles can know current traffic conditions around to avoid possible traffic congestion.
- Roadside Unit (RN), which installed at the intersection to control the traffic lights, can communicate with other. RN has two functions in this implementation. Firstly, it is responsible to help vehicle to register and inform them the current traffic light information to guarantee the reliability of the wireless communication. Secondly, it can make traffic light scheduling decision based on our proposed approaches.

b. Work Flow

Under consideration to maximize number of vehicles through the intersection and avoid any traffic congestion at intersection, there exist two different traffic green lights combinations, which is different with our previous research work. Another difference is in this model, vehicle runs at left way; while in research, we assume all vehicles run at right way. Hence, there are only two cases, the corresponding traffic green lights configurations, as shown in Fig. 8.

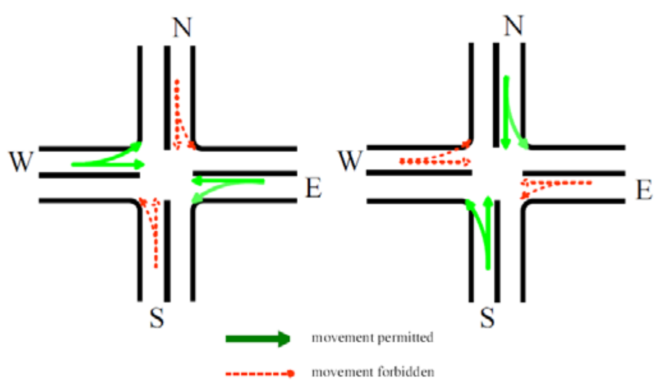


Figure 8: All Possible Cases of intersection in iSensNet

Hence, our task is to schedule the timings and periods of the traffic lights adaptively to maximize the intersection throughput and minimize the average delay in dynamic traffic environment. Similarly, there also exist two constraints, maximum vehicle waiting time at the intersection and hunger level of all cases, which could be considered as system fairness.

The working process is designed like this:

1) When a vehicle passes through DSN installed below, the VN can identify the certain current location. And then, VN would broadcast a packet to all one-hop neighbors; the packet contains its own VN id and the DSN id.

2) If the vehicle is in the approaching lane of the intersection, the corresponding RN can receive the packet, and help the VN to register for its arrival. Meanwhile, the RN would send the current traffic lights information to the vehicles such that vehicles should know whether they should stop at the intersection or can pass through the intersection.

3) At the same time, RN can process the information to calculate the number of vehicles in the four approaching lanes currently. And then, the RN makes control decision by using our proposed approach. Based on the real-time traffic volume, we can compute the two case's respective green light demand as the same principle proposed in section IV. Next, RN makes control decision approaching to objective under the satisfactory of constraints. After that, RN would schedule the traffic lights subsequently.

With the working process repeating, it is practical for the traffic light control system to run properly and adaptively using our proposed approaches.

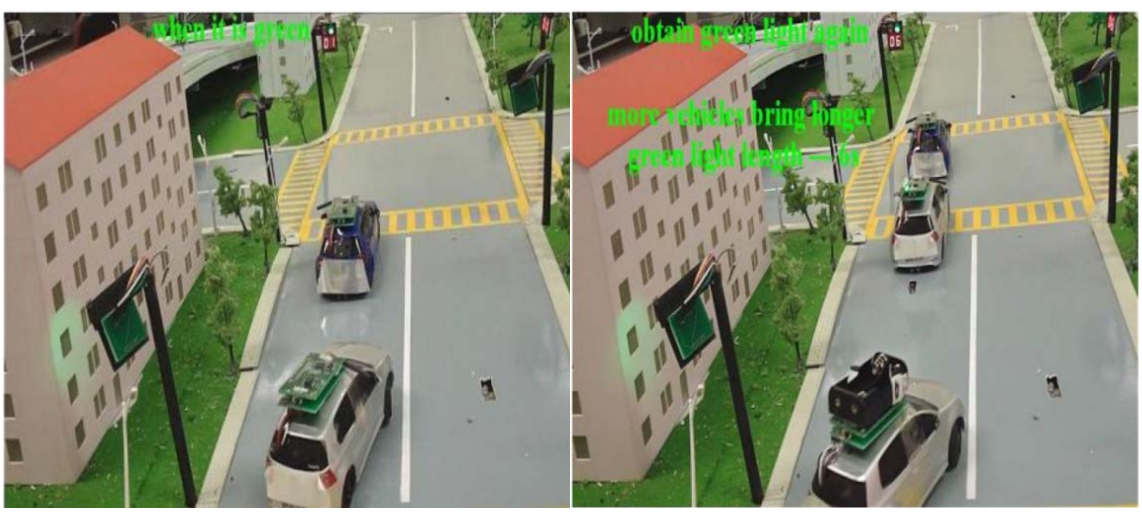
c. Demonstration

From Fig. 9, we can observe the case sequence adjustment. Fig. 9(a) shows the traffic condition before the light changes. There is only vehicle in this approaching lane and need the green light, while the other approaching lane does not be occupied by any vehicle with green lights. Under this kind of traffic situation, RN makes control decision to assign the green light for the case that admits the vehicle to pass through. Fig. 9(b) presents that the green light assigned to the certain case with duration of 5 seconds which is defined initially as the minimum green light length.

(a) before light changes (b) after light changes

Figure 9: Sequence Adjustment

From Fig. 10, we can observe the case duration adjustment. Fig. 10(a) shows the traffic condition before the light changes. There are two vehicles in this approaching lane and need the green light again, while the other approaching lane does not be occupied by any vehicle. Under this kind of traffic situation, RN makes control decision to assign the green light for the case again with longer green light length that admits the vehicles to pass through. Fig. 10(b) presents that the green light assigned to the certain case with duration of 6 seconds which is different with initial value to let more vehicles pass.Duration of 5 seconds which is defined initially as the minimum green light length.



(a) before light changes (b) after light changes

Figure 10: Length Adjustment

From Fig. 11 we can observe both the case sequence and case duration adjustments. Fig. 11(a) shows the traffic condition before the light changes. There are two vehicles in this approaching lane and need the green light, while the other approaching lane does not be occupied by any vehicle with green lights. Under this kind of traffic situation, RN makes control decision to assign the green light for the certain case with longer green light duration for the vehicles passing. Fig. 11(b) presents that the green light assigned to the certain case with duration of 6 seconds which is different with initial value to let current two vehicles leave.

(a) before light changes (b)after light changes

Figure 11: Both Sequence& Length Adjustments

Except the above three scenarios, we also define more complex traffic situations to evaluate the performance. A demonstration [22] with different types of traffic situations shows that our approach is effective and can be practical in our platform.

VII. CONCLUSIONS AND FUTURE WORK

In this paper, we have addressed how to design adaptive traffic light control approach for WSN-based ITS. Extensive evaluations, including simulations and implementations, have been conducted to examine the performance of our proposed approach. The results show that our objectives are well fulfilled, and can outperform the previous approaches in terms of throughput and average delay.

It remains as our future work to improve the proposed approaches and to investigate related research directions.One issue that deserves further study is to change the constant speed assumption. In our current models, the speed of all vehicles could be treated as the same which is not realistic that cannot reveal the traffic condition in real world. The changing speed consideration would make our models more dynamic and complicated, and increase the complexity of our approach design. How to achieve an adaptive and real-time traffic light control for vehicles with dynamic speed is worth investigation.We also would like to take into account the pedestrian in traffic light control. In this paper, we only take vehicles into consideration. However, most of the urban traffic network includes the pedestrian traffic which cannot be ignored in in real world. Hence, traffic light control combined the vehicle traffic and the pedestrian traffic should be studied further.

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