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Traffic Signal Phase Scheduling Based on Device-to-Device Communication

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ABSTRACT Device-to-device communications enable direct communications among mobile entities, which brings new revolutions to existing cellular networks. Many use cases which can benefit from D2D are introduced such as vehicles to vehicles communication, vehicles to infrastructure communication, machine to machine communication and so on. With the help of these information communication techniques, we propose a real-time traffic signal control approach to relieve traffic problems in this paper. Currently, a series of traffic problems, such as traffic congestion, traffic accidents, vehicle exhaust emission, is increasingly inconveniencing city residents, especially in rush hours. One of the most dominating approaches to relieve the traffic congest is to determine the phase timing of traffic signals. However, a major shortcoming of the existing phase timing related control strategies is of highly computational complexity, which causes, to some extent, a response delay. The approach based on device-to-device communication in this paper on one hand can collect data of various types via sensors and actuators and on the other hand can reduce the response time as much as possible. Specifically, considering an intersection with four legs, we encoded the corresponding set of signal lights of each leg using genetic algorithm. To evaluate the efficiency of phase timing plan in this paper, we have conducted extensive simulations and the results show that our approach can respond to the considered traffic flow within one second. Compared to other traffic signal control systems, the performance is improved almost by 67% with regards to the queue length waiting at the intersections during traffic signal light cycle(s).

INDEX TERMS Device-to-device, phase timing, real-time, signal control, traffic congestion, genetic algorithm

I. INTRODUCTION

Device-to-device (D2D) communication enables direct communications between two mobile entities, which brings new revolutions to existing cellular networks [1]. This kind of communication does not have to require the infrastructure (e.g., base stations) act as the relay node to disseminate the information or data packets. Therefore, it improves the robustness of the short-range wireless networks when the central node such as base station breaks down. Some use cases which can benefit from D2D communications are introduced increasingly by researchers such as vehicles to vehicles (V2V) communication, vehicles to infrastructure (V2I) communication, machine to machine (M2M) communication and so on. One of the typical application scenario is the traffic data collection and processing, which aims to better cater for the stochastic nature of traffic flow and further design reasonable traffic signal phase timings for each signalized intersection.

Nowadays, the quantity of vehicles rapidly increases as a result of economic development, which results in a series of traffic problems, such as traffic congestion, traffic accidents, vehicle exhaust emission. These problems then greatly cause inconvenience to the city residents, especially in rush hours. Several countermeasures have been taken by governments to overcome the traffic problems. For instance, the number of lanes in each road is increased, and the elevated roads are built. However, both countermeasures require enormous fiscal expenditures. Hence, conversely, traffic signal control, as the most popular measure to ease the traffic congestion, has also been evolving very fast in the past few decades.

Three primary traffic signal control systems exist nowadays, which are fixed-time, actuated and adaptive signal control systems, respectively. In fixed-time signal control systems, the phase sequence is unchangeable, and the phase lengths are preset according to the historical traffic flow during different times of a day. However, the arrival of vehicles at the intersection cannot be predicted, and thus the stochastic nature of the traffic flow cannot be fully reflected in the fixed-time signal control systems. With the help of loop detectors deployed underneath the road near the intersections to detect the number of the approaching vehicles, actuated signal control systems can cope with the stochasticity of the vehicle arrival by extending the green time or optimizing the phase timings once the vehicles enter the detecting scope. However, the actuated signal control system can only respond to the instantaneous behaviors of vehicles (e.g., passing over the detectors), regardless of the direct metrics about vehicles themselves such as speed and acceleration. In adaptive signal control systems, similar sensors such as loop detectors, video detectors or radar are employed to collect the traffic flow information to predict the stochasticity of the arrival of the vehicles and further optimize the signal timing based on a predefined objective function.

Aside from the aforementioned traffic signal control systems, D2D communication makes the equipped vehicles communicate with each other and the third party (e.g., the infrastructure or even the users) via the vehicles to vehicles (V2V) and vehicles to infrastructure (V2I) communication techniques [2, 3], which provides a much richer traffic flow information while taking into account security and privacy issues [4], thus enabling a real-time traffic signal control. Artificial Intelligence based algorithm, such as Reinforcement Learning (RL) [5, 6], is becoming a dominating approach in real-time signal control. Other approaches such as Binary Mixed Integer Linear Program (BMILP) [7, 8], genetic algorithms (GA)[9-13] are also adopted by researchers to optimize the traffic signal phase sequences and phase timing.

However, we notice that a major shortcoming of theses existing real-time control strategies is of highly computational complexity, which causes, to some extent, a delayed response. Other factors such as limited bandwidth and transmission latency also delay the response in traffic signal control. To tackle the aforementioned shortcomings, we propose a real-time traffic signal control approach based on genetic algorithms. Several heuristic rules are adopted to avoid the individual enumeration in the total population space and further speed up the execution of the traffic signal control approach in real time.

The rest of paper is organized as follows. In Section II, we review some related works on the traffic signal light optimization. Section III addresses some notations and formulates our optimization problem. Then we presents our phase timing optimization in Section IV. Next, extensive experiments are conducted to evaluate our phase scheduling approach in section V. Finally, we conclude our work and plan the future works in Section VI.

II. RELATED WORKS

There are numbers of works which aim to realize the real-time traffic signal control by means of approaches and strategies, including the aforementioned approaches such as RL, GA and BMILP. Most metrics and optimization objectives focus on minimizing vehicle travel time, the number of total stops, traffic delay, and the vehicle length waiting at the intersections. In addition, some traffic signal controlling strategies aim to optimize customized metrics such as prioritizing the emergency vehicles. However, to design an efficient traffic controlling strategy is not straightforward, for the reason that there are numbers of issues which need to be addressed, e.g., the unpredictability of traffic flow, the heterogeneity of vehicles and the communication via V2X techniques and fusion of traffic data under the backgrounds of Internet of Things (IoT) [14-17] and so on. In this section, we will review some existing literature about the real-time traffic signal control. Currently, most of these researches focus on the optimization of the traffic signal light configuration such as the phase sequences and the phase timing plans, under assumption of a variety of conditions. Many researchers optimize the intelligent signal light scheduling by leveraging the real-time traffic flows. The optimization of the traffic signal mainly falls into two categories, i.e., the evolutionary algorithms based approaches and the RL related approaches.

An architecture on searching out the optimal traffic light cycles in a traffic network is presented in [18], in which the genetic algorithm is applied to solving the optimization problem. Turky et al present an intelligent traffic light controlling approach using the genetic algorithm [9], which describes both the vehicle traffic flow and the pedestrian crossing. In order to simulating the driving rules of vehicles, the cellular automata (CA) is leveraged. However, the model of the algorithm is simple, and the pedestrian crossing is not considered in the representation of the chromosome. The experimental results show that the traffic light controlling approach does not achieve real-time performance.

Some researchers combine the evolutionary algorithms with other techniques such as fuzzy logic, machine learning and so on to optimize the traffic signal light scheduling. A hybrid algorithm which integrates fuzzy logic controller (FLC) and genetic algorithms for the traffic light system is proposed in [19], which aims to adopt the rules of FLCs to achieve a better performance compared to the conventional FLC-based control. The evaluation shows that the hybrid algorithm presents a big improvement than the conventional traffic controller and traditional logic FLC controller. Zhao et al introduce an algorithm to enhance the capacities of the traffic control, which combines genetic algorithm and machine learning algorithm [20]. The method allocates the light phases via the genetic algorithm, while taking into account the next phases of traffic flow at intersections by machine learning algorithm. A traffic control algorithm which is integrated into SUMO [21] is presented in [22] to measure the queue length at each intersection and further attempt to minimize the queue length at the intersection.

The advancement of IoT will enable much richer means of monitoring and collecting the traffic flow data. Many researchers leverage these new communication techniques such as V2V and V2I to realize a better traffic control at the intersection under assumption of certain market penetration. For instance, to reduce the waiting time and the queue length at the intersection, Maslekar et al try to solve this traffic problem based on V2V communications [23].

Priemer et al utilize V2I communication techniques to gather the vehicle data such as speed, heading, and acceleration, with the purpose of improving the efficiency of the traffic control by minimizing the waiting delay time of the vehicles at the intersections based on the phase-based strategy algorithm [24]. Feng et al present a real-time adaptive signal phase allocation algorithm using V2I/V2V communication techniques, in which two objective functions are taken into account, e.g., minimization of the total delay and minimization of the queue length of vehicles waiting at the intersections [25]. The experimental results show that the approach outperforms other approaches in a high penetration rate. Other works such as [26-29] also belong to this kind of category.

Our phase scheduling approach in this paper distinguishes the aforementioned works in that we encode the set of signal lights on each leg at the intersection and reduce the length of the chromosome as much as possible based on the observations. With incorporation of V2V data, we present the potential of our proposed GABPR approach which can achieve better performance while maintaining real-time execution.

III. PROBLEM FORMULATION

A. ASSUMPTIONS

Although V2V and V2I communication techniques are not fully applied in practice, we can envision a promising prospect in the near future. We assume that V2X techniques are available with certain market penetration in the equipped vehicles in this paper and we further combine these communication techniques with the common loop detectors to provider more accurate services. Moreover, other assumptions have also been made as follows:

- The length of the traffic light cycle is unchangeable.
  - This assumption is in line with most works about the traffic signal phase timing optimization.
- The sequence of signal phases does not change.
  - The change of sequence of signal phases sometimes can cause confusion and further result in traffic congestion. Therefore, we currently make this assumption to only focus on the optimization of signal timing for each phase to alleviate the traffic congestion in real time.
- The distance between the front of two adjacent vehicles is fixed.
  - While other works assume that the entering vehicles usually have the identical length, we just assume that vehicles have regular patterns when they stop and wait for light at the intersections. Also, we disregard the driving habits of drivers, because metrics, such as the total delay, total number of stops, are difficulty to be estimated, if the driving habits of drivers are taken into account, especially for newly licensed drivers.
- The stopped vehicles start with a constant acceleration and then keep a uniform speed passing through the intersection when traffic signal turns green.
  - This assumption is reasonable, for the reason that a slow speed renders traffic congestion while a fast speed tends to cause traffic accidents, especially at the intersections with many pedestrians.

An intersection with four legs and corresponding four phases are shown in the traffic control system, which is shown in Fig.1, where the right turn on each leg is unrestricted.

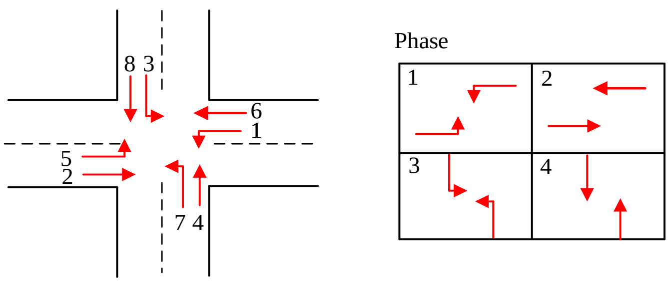

Figure 1. An intersection with four legs and corresponding four phases

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B. OBJECTIVE FUNCTION

Currently, most of real-time signal control strategies concentrate on optimizing the phase timings (i.e., phase duration) to ease the traffic congestion. Metrics, such as total or average delay, number of stops, queue length, number of vehicles passing through the intersections during signal cycle(s) and so on, are introduced as the performance indicators of the signalized intersections or optimization objectives. Specifically, we in this paper focus on minimizing the queue length of vehicles waiting at the intersection, e.g., by maximizing the number of vehicles passing through a single intersection during one or several cycles. In the traffic signal scenario proposed in this paper, the vehicles queue up for the signal light turning green. When the signal light turns green, the vehicles in sequence start and speed up with the fixed acceleration until the speed reaches the specified maximal speed , and then the vehicles bear off the intersection at this constant speed. Note that this theoretical scenario does not take the traffic accidents at the intersection into consideration, and assumes the pedestrians waiting on the opposite legs obey the traffic regulations.

The traffic flow data collected by loop detectors and V2X techniques are leveraged to make decisions about the signal timing plan. For example, during one signal light cycle, we minimize the queue length by maximizing the number of vehicles which succeed in crossing intersection based on the queue lengths on each lane. Intuitively, the fewer the number of vehicles remain in the queue after one cycle, the better the traffic signal controlling strategy. When the decision is made, the traffic signal controller re-allocates the phase duration by extending or reducing the green time of corresponding phases without violating the constraints. Thus, the traffic congestion can be alleviated for the intersections.

TABLE I
NOTATIONS IN TRAFFIC SIGNAL CONTROL

Symbol	Description
C	Cycle length
P	Set of phases
λ_p	Vehicle arrival rate during phase *p*
g_{pk}^{min}	Minimal green time for phase *p* during cycle *k*
g_{pk}^{max}	Maximal green time for phase *p* during cycle *k*
g_{pk}	Green time for phase *p* during cycle *k*
g_{pk}^{exd}	Extending time of green signal for phase *p* during cycle *k*
g_{pk}^{rdc}	Reducing time of green signal for phase *p* during cycle *k*
g_{p}^{exd}	Maximal extending time of green signal for phase *p*
g_{p}^{rdc}	Maximal reducing time of green signal for phase *p*
a	Accelerated speed for vehicles when started at the intersection
V_{max}	Specified maximal speed which vehicles are accelerated to
D	Distance between the front of two adjacent vehicles
N_{pk}	Number of queuing vehicles for phase *p* during cycle *k*
WN_{pk}	Number of queuing vehicles for phase *p* for the last *k* cycles

Following the notation defined in Table 1 and the laws of physics, the objective function during one signal light cycle can be modeled as follows:

$$Minimize\ \ (Q):\sum_{p=1}^{P}\max\{0, N_{pk}+\lambda_p\cdot g_{pk}-\left\lceil\frac{\frac{1}{2}\cdot\frac{(V_{max})^2}{a}+V_{max}\cdot(g_{pk}-\frac{V_{max}}{a})}{D}\right\rceil\}$$

s.t.

$$\sum_{p=1}^{P} g_{pk}=C \tag{1}$$

$$g_{pk}^{min}\le g_{pk}\le g_{pk}^{max} \qquad 1\le p\le P,\forall k \tag{2}$$

$$g_{pk}+g_{pk}^{exd}\le g_{pk}^{max} \qquad 1\le p\le P,\forall k \tag{3}$$

$$g_{pk}-g_{pk}^{rdc}\ge g_{pk}^{min} \qquad 1\le p\le P,\forall k \tag{4}$$

$$g_{pk}^{exd}\le g_{p}^{exd} \qquad 1\le p\le P,\forall k \tag{5}$$

$$g_{pk}^{rdc}\le g_{p}^{rdc} \qquad 1\le p\le P,\forall k \tag{6}$$

Constraint (1) ensures that the total green times of phases equal the cycle length as shown in Fig.1. The green times of each phase are usually initialized based on the historical traffic flow data collected by kinds of sensors, which usually fall into a reasonable interval. Constraint (2) represents this kind of restricted relationship, and g_{pk}^{min} and g_{pk}^{max} can be set by historical experience. Constraints (3)-(6) indicate that even if the phase timings are updated according to the traffic signal controlling approach, e.g., the green time is extended or reduced, the constraints should still be satisfied.

IV. PHASE RE-ALLOCATION APPROACH

For an intersection with four legs, each leg corresponds to a set of traffic signal lights: left turning, right turning and straight moving, respectively. Thus, one intersection with four legs usually corresponds to four sets of traffic signal lights. To minimize the objective function Q, we in this section propose a genetic algorithm based phase re-allocation approach (GABPR). Genetic algorithm (GA) search solutions over the huge potential solution space iteratively. Four sets of traffic signal lights can be modeled as an individual in GABPR. In the following, we will discuss the implementation details on the genetic algorithm for real-time traffic signal controlling strategy.

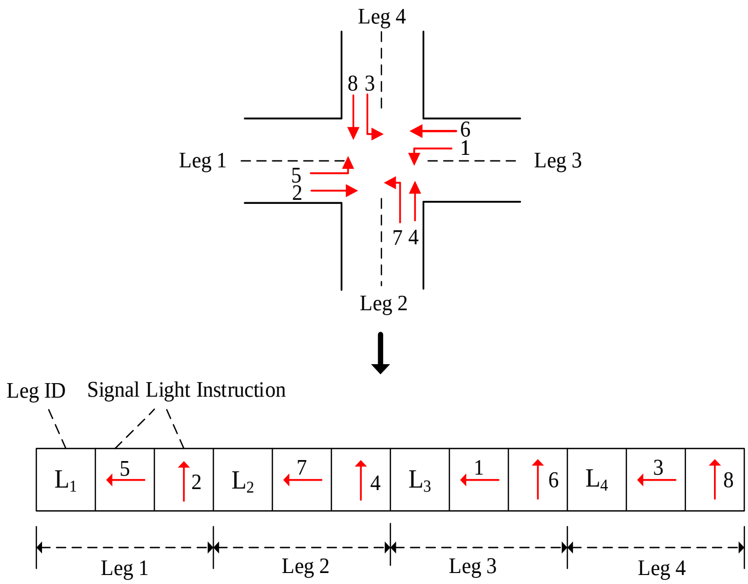

Figure 2. Corresponding set of traffic lights for each road leg

A. ENCODING AND INITIALIZATION

We in this paper only consider one type of road intersection, i.e., the intersection with four legs as shown in Fig.1. The corresponding relationships between road legs and the set of traffic signal lights are shown in Fig.2. For each leg at an intersection, there are usually two signal lights that indicate the traffic flow either in the rightward or straightforward directions. Note that we assume that the right turn is not restricted in this traffic scenario. For the initialization of the population in GA, we first define the chromosome. An intersection corresponds to four sets of traffic signal lights, of which each serves one leg as shown in Fig.2. Intuitively, each chromosome can be composed by four segments of genes, with each segment representing one set of traffic signal lights. However, in order to reduce the length of chromosome, the chromosome can be composed by only two segments of genes, for the reason that the signal light indications in Leg 1 (resp. Leg2) are the same as those in Leg 3 (resp. Leg4) in the traffic model with four phases adopted in this paper. The green time of each leg is encoded into genes by binary 0 or 1 and the gene length can be decided based on g_{pk}^{min} and g_{pk}^{max} . Thus, an example of representation of a chromosome is shown in Fig.3.

The initial population consists of *Num* individuals which are generated randomly. Note that *Num* is a constant through the generations, which however can also be tuned for different evaluation purposes.

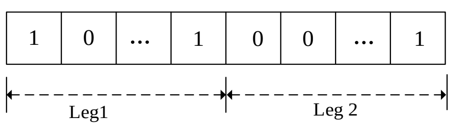

Figure 3.Representation of chromosome

B. FITNESS FUNCTION

As the quantitative metrics of the ability to adapt to the

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environments, fitness function is used to decide which individuals are reserved and which individuals are abandoned. The survived individuals are responsible for generating the offspring. Accordingly, fitness function design is very important to the genetic algorithm, which denotes the intention of the optimization objective and affects the speed on finding out the best solution to the optimization problem.

We focus on minimizing the queue length of vehicles waiting at the intersections in this paper. Accordingly, the fitness function is designed as the same to the objective function Q. Given the representation of the chromosome, e.g., (1, 0,..., 1), the green time of each phase g_{pk} can be calculated. Note that the chromosome consists of four gene segments of equal length and each segment denotes the green time of corresponding phase, thus g_{pk} is calculated as follows: $g_{pk} = \sum_{i=0}^{segment(p)} 2^i,\ 1 \le p \le 4$. Then the fitness function can be calculated by objective function.

C. SELECTION OPERATOR

Selection operation is to select parts of individuals from the current population to generate the next generation. Intuitively, the stronger the ability to adapt to the environments, the larger probability the individuals tend to be selected. To this end, many strategies, e.g., the roulette-wheel approach, do the selection operation based on the values of fitness functions, with an assumption that the probability that an individual is selected is proportional to its corresponding fitness value. Similarly, we also adopt the roulette-wheel approach to do the selection operation.

Algorithm 1: Multi-point crossover Operation

Input:
    Parents *A* and *B*, gene length *L*.
Output:
    The new generated offspring *a* and *b*.
1: Generate randomly a binary string *S* of 0 and 1;
2: **For** $i = 0: L$ **do**
3:   **If** $S[i] = 0$ **then**
4:     The value of the i^{th} location in *a* equals that in *A*;
5:     The value of the i^{th} location in *b* equals that in *B*;
6:   **Else**
7:     The value of the i^{th} location in *a* equals that in *B*;
8:     The value of the i^{th} location in *b* equals that in *A*;
9:   **Endif**
10: **Endfor**
11: **Output**: *a* and *b*.

Algorithm 1. **Multi-point crossover operation**

D. MULTI-POINT CROSSOVER OPERATOR

The crossover operation is to produce new offspring by exchanging gene segments of two parents. The pseudo code of crossover operation adopted in this paper is shown in Algorithm 1. We in this paper adopt multi-point crossover in which a binary string *S* with values 0 and 1 is generated randomly, and then the crossover operation is performed based on *S*. An example of multi-point crossover operation is shown in Fig.4.

A	1	0	1	1	0	0	0	1	1	1
B	0	0	0	1	1	0	1	1	0	0
S	0	0	0	1	1	0	1	1	0	0
a	1	0	1	1	1	0	1	1	1	1
b	0	0	0	1	0	0	0	1	0	0

Figure 4. **Multi-point crossover**

E. MULTI-POINT MUTATION OPERATOR

The mutation operation usually alters a gene randomly in the chromosome so as to generate a better offspring with regards to the fitness values. To cover more potential solution space, we in this paper adopt multi-point mutation operation. The pseudo code of mutation operation adopted in this paper is shown in Algorithm 2. Specifically, if the real number which is generated randomly is not smaller than the mutation probability, we will perform the mutation operation on the current chromosome, i.e., two genes are randomly selected from the chromosome and the corresponding values are reversed.

Algorithm 2: Multi-point Mutation Operation

Input:
    Individual *a*, Mutation probability *p*.
Output:
    The new generated offspring *b*.
1: Generate randomly a real number *r* between 0 and 1;
2: **If** *r* is not smaller than *p* **do**
3:   Randomly select two genes from *a*;
4:   Reverse the corresponding values of the genes;
5: **Endif**
6: **Output**: *b*.

Algorithm 2. **Multi-point mutation operation**

The pseudo code of GABPR is presented in Algorithm 3 based on the aforementioned crossover and mutation operations. A random function *fRandom*() (line 9 and 13) is utilized to generate a real number between 0 and 1 each time, so as to control the frequencies of the crossover and mutation operations. With regards to the selection operation, the best half of current population is selected first, and then the crossover and mutation operation are performed over the remaining half of population. Lastly, the newly generated child chromosomes combined with the previous best half population compose the next generation. When the algorithm reaches the maximal iterations, we find out the best individual with regards to fitness values. Finally, the chromosome is decoded to output the optimal phase timing plan.

F. IMPROVEMENT

Algorithm 3 can search out the best individual with regards to the fitness values given the predefined iterations, but we note that for each resulting chromosome, Algorithm 3 will check whether it satisfies the constraints or not, which on another hand will cause a longer response delay or even worse render the program in an infinite loop sometimes. The population size is set based on the historical experience, in which each individual represents a kind of phase timing plan. However, due to the constraint conditions, there is a probability that the number of individuals which satisfy the constraints is much less than the predefined population size. Thus, the verification of each individual immediately after the new child chromosomes are generated may prune numbers of chromosomes, which renders that the time taken to reach the population size in the while loop is much longer. Hence, to improve the efficiency of Algorithm 3, we place the verification of each individual after the next generation is generated (line 24). If the individual does not satisfy the constraints, we omit it from the current population. When the number of generations reaches the maximal iterations, we search out the best individual with regards to the fitness value and decode the chromosome to the corresponding phase timing plan.

Algorithm 3: GA Based Phase Re-allocation Algorithm (GABPR)

```
Notations: Num: Size of population; N^gen: Number of iterations;
           cp: Crossover probability; mp: Mutation probability.
Input:
      Parameters for genetic algorithm;
      Parameters for traffic signal controlling problem.
Output:
      The optimal phase timing plan.
1:  Generate an initial population of chromosomes;
2:  count=1;
3:  While (count<=N^gen) do
4:    Calculate the fitness values of current individuals in the population;
5:    Select the half of the current population, denoted by p1;
6:    p=0;
7:    While (p<=Num/2) do
8:      Select randomly two chromosomes m and n from the remaining chromosomes;
9:      If (fRandom()>cp) then
10:       Perform crossover operations on m and n to form child chromosomes;
11:       If The resulting chromosomes satisfy the constraints then
12:         p=p+2;
13:       Else if only one chromosome satisfies the constraints then
14:         p=p+1;
15:       Endif
16:     Endif
17:     If (fRandom()>mp) then
18:       Perform mutation operation on m or n to form new child chromosome;
19:       If the resulting chromosome satisfies the constraint then
20:         p=p+1;
21:       Endif
22:     Endif
23:   Endwhile
24:   Combine the resulting child chromosomes with p1 to form the next generations;
25:   count=1;
26: Endwhile
27: Find out the best individual in the current population;
28: Partition the chromosome into segments and calculate the optimal phase timing.
```

Algorithm 3. **GA based phase re-allocation algorithm (GABPR)**

V. SIMULATION AND RESULTS ANALYSIS

To evaluate the approach of phase timing scheduling, we in this section have conducted extensive simulation. First, the basic experimental setups are illustrated, and then the experimental results and analysis are given.

A. EXPERIMENTAL SETUP

Firstly, a desktop with Microsoft Win7 OS is utilized to run the experiments. The scheduling algorithms are implemented by Python. Then the scheduling strategy is evaluated under different parameter settings. The involved parameters are listed in Table 2 with the value ranges and default values, respectively. Note that there are four phases at the intersection and for each phase, the corresponding number of queuing vehicles varies based on the experimental settings. The baseline we compare to in this paper is the fixed-time signal controlling approach. In each set of experiments, two methods to allocate the green time for each phase are adopted in this paper. One is to split the cycle length equally, and the other is to allocate the green time based on the number of vehicles on each phase, which will be illustrated as follows. The historical traffic flow based fixed-time signal control utilizes current traffic information to predict the next stage of traffic information and further decide the corresponding phase timings. Suppose that the cycle length is $C = 120$ seconds and during the last 100 cycles, the total number of vehicles waiting at the intersection for each phase $WN_{p,100}$ can be represented by the vector (100, 200, 300, 400). Then the green time for each phase for the next specified (e.g., 100) cycles, denoted by a vector ($g_{1,100}, g_{2,100}, g_{3,100}, g_{4,100}$), can be calculated by the equation $g_{i,100} = \frac{WP_{i,100}}{\sum_{j=1}^{4} g_{j,100}} \cdot C$, and hence the corresponding green time for each phase $g_{p,100}$ $(p = 1,2,3,4)$ is 12, 24, 36 and 48, respectively. Note that an extreme case may happen, for example, during the last k cycles for phase p, there are no vehicles waiting at the intersection. In such case, we reallocate the green time for phase p by g_{pk}^{min}, and the green time for other phases can be calculated as above. In this section, we denote the aforementioned two fixed-time methods by Normal_fixed and Weight_fixed, respectively.

TABLE II
PARAMETER SETTINGS

Name	Value	Default value
Population size	[100,1000]	500
Crossover probability	[0.3,0.8]	0.4
Mutation probability	[0.01,0.1]	0.02
Chromosome length	[10,30]	20
N^{gen}	[20,300]	100
V_{max}	[10,40]	20
C	[80,120]	90
λ_p	[1,5]	2
g_{pk}^{min}	[10,15]	10
g_{pk}^{max}	[30,45]	30
a	[3,6]	4
D	[5.5,7.5]	6
N_{pk}	[0,30]	15

B. EXPERIMENTAL RESULTS AND ANALYSIS

We first investigate the impact of generations of GA on the fitness values. The experimental results are shown in Fig.5, where the number of generations varies from 20 to 300. For each data set, i.e., the number of vehicles waiting at the intersection on eight lanes, we run it by GABPR with different generations, and then repeat this process 100 times to get the mean value of the fitness values. We can observe that as the number of generations increases, the fitness values are decreasing. Note that the smaller the fitness value, the better the performance in the experiment. When the number of generations reaches about 100, the fitness value almost achieve the best performance, for the reason that the fitness value almost keeps the same with the number of generations increasing.

Since the fitness value decreases by about 0.6% when the number of generations varies from 20 to 300, even if we the number of generations is to 20 in the experiment, the results are still acceptable. Fig6 shows the response time to retrieve the best individual under different generations.

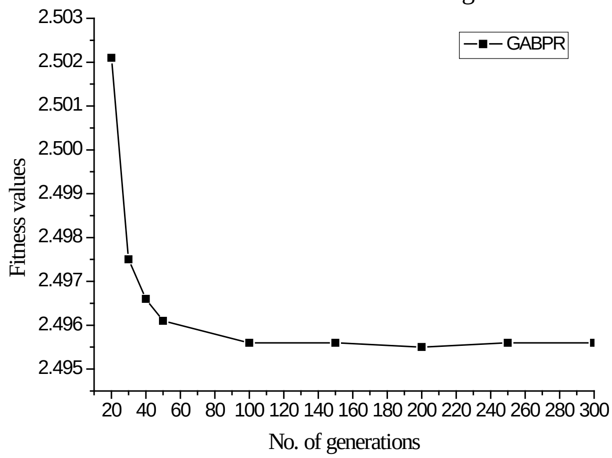

Figure 5. **Performance vs. generations**

It is obvious that the response time grows almost linearly with the number of generations increasing. When the number of generations is 200, the response time is about 1.56. It has taken twice as long as the time with the number of generations being 100, but the corresponding performance is almost the same. Therefore, the phase reallocation strategy proposed in this paper does not achieve the real-time performance when the number of generations is set to 200 or even higher. As a result, we set the number of generations to 100 as the default value, taking into account the tradeoff between the performance and the response time. For other parameters involved in the genetic algorithm such as crossover probability, mutation probability and population size, we also conducted a series of experiments to investigate the impact of them over the phase timing reallocation approach in this section, and the most suitable values of these parameters are set to default values as denoted in Table 2, respectively.

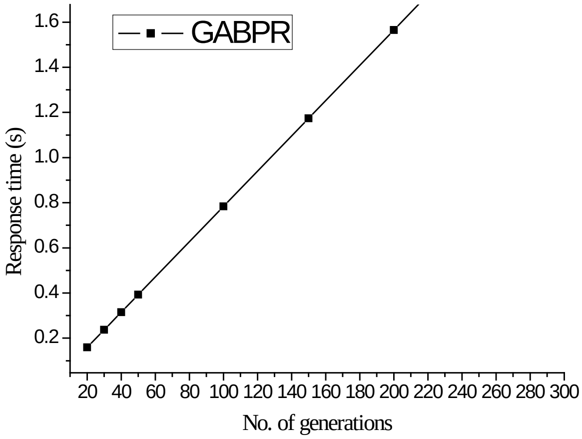

Figure 6. **Response time vs. generations**

We run a total of 500 data sets of the number of vehicles waiting for the traffic lights on eight lanes. Then we randomly select 10 sets of traffic information from the results and run the three algorithms on them, and the corresponding fitness values are shown in Fig.7. It is noticeable that the algorithm proposed in this paper (i.e., GABPR) is much better than two other approaches. Weight_fixed approach is totally better than Normal_fixed approach. The average performance of GABPR outperforms Normal_fixed and Weight_fixed by about 67% and 52%, respectively. The results strongly indicate the potential of our proposed GABPR approach which can achieve better performance while maintaining real-time execution.

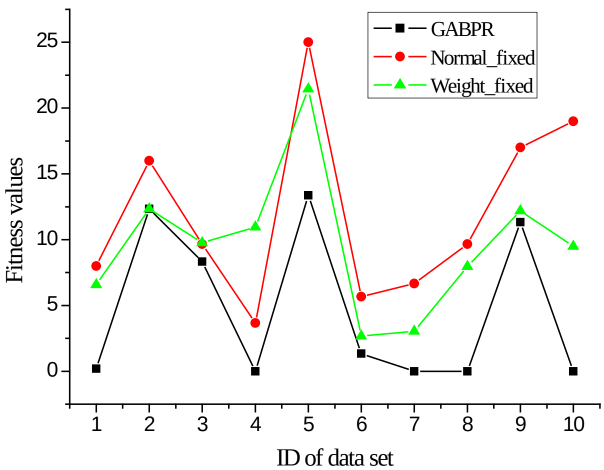

Figure 7. **Performance comparison among three approaches**

VI. CONCLUSION

One purpose of introducing D2D communication into traffic signal control systems is to efficiently collect traffic flow data of various types, e.g., by V2V and V2I techniques. These traffic data collected in real time fashion can help design the optimal signal phase timing with regards to specified metrics or evaluation function. In addition, a major shortcoming of the existing real-time control strategies is of highly computational complexity, which causes a response delay to some extent. In this paper, we proposed a real-time traffic signal control approach, which leverages the genetic algorithm to allocate the phase timing with the incorporation of V2V data. Specifically, an intersection with four legs are considered, and the corresponding set of signal lights of each leg is further encoded. The experimental results show that our GA-based traffic signal control approach significantly outperforms traditional approaches while maintaining real-time execution.

For future work, we plan to utilize the distributed genetic algorithm to solve the traffic signal control, so that the computational complexity can be further reduced.

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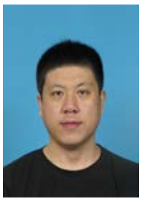

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