

Research Article

Travel Time Reliability-Based Signal Timing Optimization for Urban Road Traffic Network Control

Zhengfeng Ma,^{1,2} Darong Huang¹,³ Changguang Li,⁴ and Jianhua Guo¹⁴

¹School of Traffic & Transportation, Chongqing Jiaotong University, Chongqing 400074, China

²School of Civil & Transportation Engineering, Qinghai Nationalities University, Xining 810007, China

³School of Information Science & Engineering, Chongqing Jiaotong University, Chongqing 400074, China

⁴Intelligent Transportation System Research Center, Southeast University, Nanjing 210096, China

Correspondence should be addressed to Darong Huang; drhuang@cqjtu.edu.cn and Jianhua Guo; gjh@seu.edu.cn

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Due to increasing traffic demand, many metropolitan areas are experiencing extensive traffic congestion, which demands for efficient traffic signal timing and optimization. However, conventional efficiency measure-based signal optimization cannot handle the ubiquitous uncertainty in the road networks, demanding for the incorporation of reliability measures into signal optimization, which is still in its early stage. Therefore, targeting this issue, based on the recent studies on recognizing travel time reliability (TTR) as an important reliability measure of road networks, a travel time reliability-based urban road traffic network signal timing optimization model is proposed in this paper, with the objective function to optimize a TTR measure, i.e., buffer time index. The proposed optimization model is solved using the heuristic particle swarm optimization approach. A case study is conducted using microscopic traffic simulation for a road network in the City of Nanjing, China. Results demonstrate that the proposed optimization model can improve travel time reliability of the road traffic network and the efficiency of the road traffic network as well. Future studies are recommended to expand the integration of travel time reliability into traffic signal timing optimization.

1. Introduction

Due to the increasing motorization and urbanization around the globe, congestion has become a pronounced phenomenon for many metropolitan areas (Huang et al. 2017) [1]. Consequently, many measures have been adopted to battle the worsening traffic congestion, with the traffic signal timing optimization as one of the most direct and effective strategies. However, due to many factors in the context of metropolitan areas, uncertainty is ubiquitous in urban transportation systems, and hence in addition to the conventional efficiency measures, the incorporation of reliability measures into traffic signal optimization to deal with traffic uncertainty is gaining increasing attention from different perspectives of the society.

Travel time reliability (TTR) is an important reliability measure, relating heavily to the variability of travel time. It is

an important indicator for measuring the reliability of traffic systems. Travel time reliability is in general defined as the probability of a vehicle reaching the destination from the origin within a specified time. It can also be defined as the maximum time a traveler needs to arrive at the destination on time with a certain probability. According to different objectives, travel time reliability can be measured in terms of road segment travel time reliability, path travel time reliability, or road network travel time reliability. In this end, road segment travel time reliability refers to the probability a traveler completes the travel on a given road segment within a given period of time, path travel time reliability takes into account all the road segment travel time reliability in the path, and road network travel time reliability will incorporate the reliability of travel time over all OD pairs.

Even though the importance of travel time reliability has been acknowledged by traffic signal control practitioners or

scholars, the incorporation of travel time reliability into urban traffic signal timing optimization and control is still in its infancy. Currently, few studies have paid attention to optimize traffic signal timing based on travel time reliability, both for isolated intersections or network level signal timing optimization. Therefore, the objective of this paper is to propose an urban road traffic network signal timing optimization model based on optimizing travel time reliability of the road network. The heuristic approach of particle swarm optimization is applied to solve the proposed model, and microscopic simulation is used in a case study to implement and validate the proposed model for a road network in the City of Nanjing, China, as an example.

The rest of the paper is organized as follows. First, Section 2 provides a brief review on travel time reliability measures and travel time reliability-based signal optimization studies. Then, Section 3 presents the proposed travel time reliability based signal timing optimization model, together with the solution approach based on particle swarm optimization. Afterwards, a case study is conducted to implement and validate the proposed model, together with a comparison of the proposed model with the conventional travel time-based optimization model. Finally, the paper concludes with summaries and recommendations on future research.

2. Literature Review

In this section, travel time reliability measures are summarized, together with a brief review on travel time reliability-based signal timing optimization studies.

2.1. Travel Time Reliability Measures. Many travel time reliability measures have been proposed in the literature. In this end, commonly used travel time reliability measures include in general probabilistic indicators (Asakura (1996) [2]; Lo et al. (1999) [3]; Levinson and Zhang (2001) [4]), statistical indicators (Booz-Allen (1998) [5]; Recker et al. (2005) [6]; Sisiopiku and Roushail (1994) [7]; Petty et al. (1998) [8]), buffer time indicators (Lomax et al. (2001) [9]; Chen et al. (2003) [10]; Lo (2002) [11]; Lo and Tung (2003) [12]; Lo and Luo (2004) [13]; Lo et al. (2006) [14]; Luo (2004) [15]; Siu and Lo (2008) [16]; Shao et al. (2006) [17]; Shao et al. (1985) [18]; Shao et al. (2008) [19]; Lam et al. (2008) [20]), and delay indicators (Lomax et al. (2003) [21]). In practice, probability indicators could be the distribution of travel time or percentile travel time, statistical indicators could be the average, median, or standard deviation of travel time, buffer time indicators could be buffer time or buffer time index of travel time, and delay indicators could be delay time or delay time index. As is clear from above descriptions, all these reliability indicators are helpful for transportation system managers to estimate the performance of the road network, and all these indicators can be tailored to accommodate the purpose of specific transportation applications.

2.2. TTR-Based Signal Timing Optimization. Currently, reliability-based traffic signal control is limited with insufficient applications. Heydecker modified the equation of

control delay to show the randomness of traffic, and the randomness of control effectiveness is reflected by the correction of delay equation [22]. Although the concept is relatively easy, the steady state at the intersection is difficult to achieve at each cycle at higher saturation level. Kamarajugadda and Park used delay variance and average delay as optimization objectives to consider reliability in traffic signal control optimization, while delay variance is obtained by assuming a given delay distribution and the selected normal distribution needs further justification [23]. Hong studied the reliability of signalized intersections and used the randomness of intersection traffic signal control to characterize its reliability [24]. Using the phase clearance reliability (PCR) as the starting point, single-layer and multi-layer signal control models are adopted. Simulation results show that, under low saturation level, PCR can be greatly improved by increasing the traffic signal control cycle. Lu and Niu proposed a signal timing optimization model based on PCR [25]. According to the definition of PCR and the stochastic characteristics of arrival rate, quantitative relationship between PCR and parameters at each intersection is studied, and the equation of cycle and green time under given PCR can be derived. Application results showed that the randomness of queuing length at an intersection has great influence on signal parameters. Lu and Niu studied the influence of traffic flow randomness on traffic signal timing optimization at the intersection level [26]. PCR is expressed by expected offset of each phase, and traffic signal timing optimization model is established with the goal of minimizing the sum of all expected offsets. Example studies showed that longer green time is required for larger phase variance at the intersection under a given reliability level.

2.3. Summary. In summary, the study on reliability-based urban traffic road network signal timing and control is still in its infancy. First, studies in this field mostly focus on the framework and definition of the concept with limited applicable models and methods. In addition, current studies are mostly directed at isolated intersection with limited studies on reliability of network traffic signal control. Therefore, this paper proposes a travel time reliability based signal timing optimization model for urban road network signal timing optimization and control.

3. Proposed TTR-Based Signal Timing Model

In this section, the selected travel time reliability measure is described, and the proposed TTR-based signal timing model is presented together with the solution approach based on particle swarm optimization.

3.1. Travel Time Reliability Measure Selection. Travel time reliability measure is fundamental in the field of transportation system reliability optimization. In this end, considering the importance of travel time in measuring the performance of transportation systems, buffer time is defined as the extra travel time within a reasonable range to ensure an on-time arrival at the destination under uncertain

traffic conditions. In this sense, buffer time measures the reliability of road network from the perspective of travelers and hence can effectively assist the travelers in making reasonable travel plans to tackle traffic uncertainty. In addition, since travel time is closely related to the traveling distance, in order to measure the reliability of travel time consistently across the road network, buffer time index is developed through normalizing the buffer time with respect to the traveling distance. Therefore, in this paper, the buffer time index is used as the reliability indicator with its calculation as follows:

$$\text{BTI} = \frac{T_{90} - \bar{T}}{\bar{T}}, \quad (1)$$

where T_{90} is the 90% percentile value of the travel time in the sample data and \bar{T} is the average travel time. It should be noted that there is a balance between the selected percentile value and the efficiency performance of the optimized signal control system. In general, it is conjectured that the higher percentile value will introduce higher network reliability with reduced efficiency performance. Therefore, in order to ensure a preferable integrated system performance in terms of reliability and efficiency, 90% percentile travel time is selected in this paper when calculating the buffer time index.

Buffer time has many ramifications in transportation field, relating to factors such as purpose of traveler, travel mode, and psychological factors of traveler. Buffer time can be used for the comparison of the same road segment at different times and different road segments at the same time as well. Buffer time can reflect the changes in the accessibility and convenience of travel at different stages, and smaller buffer time indicates higher level of travel convenience and accessibility. Buffer time can also be used to determine the level of sustainable urban transport development for further road network optimization.

3.2. Proposed TTR-Based Optimization Model. The performance of traffic signal control system manifests the state of traffic flow movement under the control of a certain timing plan. The essence of establishing a traffic signal control model is to use mathematical or analytical methods to simulate the traffic flow movement on the road network and study the influence of changes in signal timing parameters on the movement of traffic, so as to objectively develop an optimized signal timing plan. The traffic model should be able to reliably assess the traffic movement parameters under the control of different traffic timing schemes.

In the abovementioned signal optimization process, delay is conventionally selected as efficiency measure for signal timing optimization. Delay is closely related to travel time. However, vehicle travel time is a random variable, and average travel time cannot reflect the actual traffic condition. For example, for heavily uncertain traffic, average travel time cannot accurately reflect the reliability of road network. Therefore, as discussed previously, reliability measure should be incorporated into

signal optimization. As a typical travel time reliability measure, buffer time can be incorporated to develop a regional traffic signal timing optimization model. In this model, the average buffer time index of road segments in the road network can be minimized to improve road network reliability. In this end, the objective function of the model is defined as

$$y = \frac{1}{n} \sum_{i=1}^n \text{BTI}_i, \quad (2)$$

where n represents the number of station pairs in the road network, BTI_i represents the buffer time index of the road segment for the i^{th} station pair in the road network, and y represents the optimization objective function. It should be emphasized that station pairs are counted according to adjacent intersections and directions are considered. For example, a road section can be counted as two station pairs according to different directions, and the buffer time index should be calculated separately in the model.

Next, constraints are set for the major signal control parameters, including offset, green time, and signal cycle. First, effective green time cannot be negative. Therefore, following constraints are listed as

$$\begin{aligned} g_{i,k} &\geq 0, \\ g_{i,\min} &\leq g_{i,k} \leq g_{i,\max}, \end{aligned} \quad (3)$$

where i denotes the intersection number in the road network, k denotes the phase number of the intersection, $g_{i,k}$ denotes the effective green time of the k^{th} phase of the i^{th} intersection, $g_{i,\min}$ denotes the lower limit of effective green time for the i^{th} intersection, and $g_{i,\max}$ represents the upper limit of the effective green time for the i^{th} intersection.

Second, the traffic signal cycle of an intersection cannot be negative. Therefore, following constraints are listed as

$$\begin{aligned} \sum_{k=1}^m g_{i,k} + L_i &= C_i, \\ C_{i,\min} &\leq C_{i,k} \leq C_{i,\max}, \end{aligned} \quad (4)$$

where m denotes the total number of phases for the intersection, L_i denotes the total loss time in the signal cycle of the i^{th} intersection, C_i denotes the traffic signal control cycle of the i^{th} intersection, $C_{i,\min}$ indicates the lower limit of the cycle for the i^{th} intersection, and $C_{i,\max}$ represents the upper limit of the cycle for the i^{th} intersection.

Similarly, phase offset in signal control cannot be negative, with the constraint listed as

$$\phi \geq 0, \quad (5)$$

where ϕ represents the phase offset between two intersections.

In summary, the travel time reliability-based urban road network traffic signal timing optimization model can be established as follows:

$$\begin{aligned} Z = \min y &= \min \frac{1}{n} \sum_{i=1}^n \text{BTI}_i \\ \text{s.t. } &\left\{ \begin{array}{l} g_{i,k} \geq 0, \\ g_{i,\min} \leq g_{i,k} \leq g_{i,\max}, \\ \sum_{k=1}^m g_{i,k} + L_i = C_i, \\ C_{i,\min} \leq C_{i,k} \leq C_{i,\max}, \\ \phi \geq 0, \end{array} \right. \end{aligned} \quad (6)$$

where $g_{i,\min}$ is set as 0 for both off-peak and peak hours, $g_{i,\max}$ is set as 50 seconds or 60 seconds for off-peak hours or peak hours, respectively, $C_{i,\min}$ is set as 0 for both off-peak and peak hours, and $C_{i,\max}$ is set as 150 seconds or 180 seconds for off-peak or peak hours, respectively.

3.3. Particle Swarm Optimization (PSO) Procedure. Particle swarm optimization (PSO) procedure is adopted in this paper to solve the proposed optimization model. Particle swarm algorithm originated from the foraging process of biological population or group. Each individual in the group is termed as a particle, and the space where the particle is located is termed as a D-dimensional space. The D-dimensional space represents the solution space of the optimization problem, and the position of each particle represents a solution. In order to move the particles in the

D-dimensional space, i.e., to search the solution space, each particle is given a certain initial flight speed. In order to evaluate the location of a particle, that is, to evaluate the solution in the solution space, a fitness function must be defined. For PSO, through a sharing mechanism, the search information is shared from a global scope, and each particle changes the direction of advancement according to its own moving experience so that the entire population moves toward the global optimum value. In addition, particle swarm optimization uses the uncertainty of random factors and inertia weight to expand the search space and ensures the global convergence of the optimization algorithm.

During the movement of each particle in the D-dimensional space, the fitness function of its position is calculated and the maximum value of the fitness function of the particle in its own flight path is recorded as the optimal fitness value. The particle position corresponding to the optimal fitness value is recorded as the individual optimal value. For the entire group, there is only one location that attracts all particles. The optimal fitness values of all particles are compared and the largest fitness value is regarded as the global optimum fitness value. The particle position corresponding to the global optimal fitness value is recorded as the global optimal value, i.e., the solution to the optimization problem.

The flying speed of each particle is not fixed. After each population movement, the flying speed of each particle is updated using the velocity equation. Clerc and Kennedy improved the basic particle swarm algorithm and introduced a shrinkage factor in the velocity equation as below to ensure the convergence of the optimization process [27]:

$$\begin{aligned} V_{id}^{t+1} &= K(V_{id}^t + c_1 \cdot \text{rand}_1 \cdot (pbest_{id}^t - V_{id}^t) + c_2 \cdot \text{rand}_2 (gbest_d^t - V_{id}^t)), \\ \theta &= c_1 + c_2, \\ K &= \frac{2}{|2 - \theta - \sqrt{\theta^2 - 4\theta}|}, \end{aligned} \quad (7)$$

where $pbest_{id}^t$ is the d^{th} dimensional element of the i^{th} particle in generation t ; $gbest_d^t$ is the best d^{th} dimensional element for all particles in generation t ; rand_1 and rand_2 are uniformly distributed random numbers within $[0, 1]$; V_{id}^t is the i^{th} dimensional element representing particle speed; c_1 and c_2 are the accelerating factors with $c_1 = c_2 = 2.005$; and K is the shrinking factor.

In summary, given proper design of the particle swarm optimization problem, the general flowchart of implementing the particle swarm optimization is shown in Figure 1.

3.4. Particle Swarm Optimization Design. To solve the regional signal timing optimization issue using the particle swarm optimization procedure, mainly two aspects should be designed first. The first aspect is the parameters setting of

the optimization algorithm, and the second aspect is determination of the fitness function.

3.4.1. Parameter Settings. According to the proposed optimization model, the traffic signal control parameters to be optimized include mainly intersection phase offset and green time of each phase. Therefore, each particle in the population must express green time for each phase and phase offset. Note that signal cycle for each intersection can be computed by summing up the green times for the corresponding signal phases. In summary, the structure of each particle is described in Figure 2, with the dimension of each particle set to 65.

In addition, the number of particle populations is set to 30. The corresponding velocity vector for each particle has a dimension of 65, and the total number of velocity vectors for all particles is 30. The maximum evolution generation is set to 100.

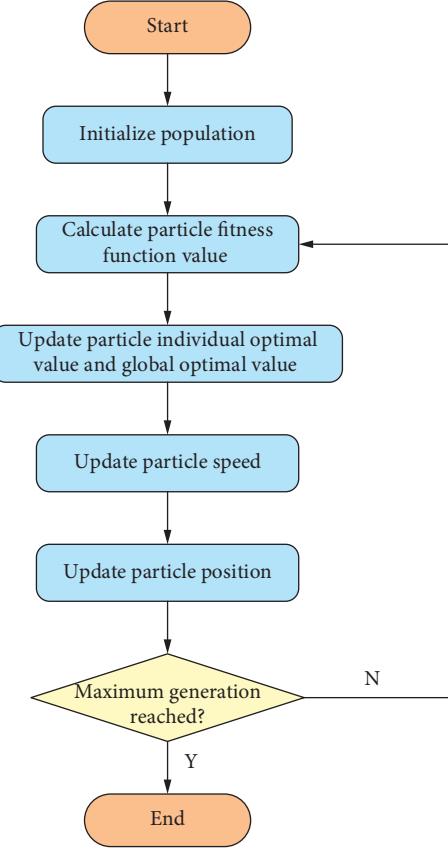


FIGURE 1: Flow chart of particle swarm algorithm optimization.

3.4.2. Fitness Function. Based on the proposed urban road network traffic signal timing optimization model, the average buffer time index of all road segments in the road network is used as the fitness function to evaluate the signal timing plan represented by each particle in the particle group. After running simulation, the buffer time index of all road segments in the road network can be calculated. Smaller average buffer time index shows that travelers do not need to reserve excessive extra time and the travel time of the road network is reliable. Therefore, the traffic signal timing plan can increase the reliability of the travel time of the road network. The equation for the fitness function is as follows:

$$\text{fitness}_2 = \frac{n}{\sum_{i=1}^n \text{BTI}_i}, \quad (8)$$

where n represents the number of station pairs in the road network and BTI_i represents the buffer time index of the segment along the i^{th} station pair of the road network.

4. Case Study

This paper proposed an urban road network traffic signal timing optimization model, which can be solved using the heuristic particle swarm optimization procedure. In this section, the proposed model is implemented and validated in a microscopic simulation environment for a real-world urban road network. Note that microscopic traffic

simulation software Paramics is selected in this study due to its flexible programming ability provided through abundant Application Programming Interfaces (APIs).

4.1. Study Area and Data Collection. The study area selected in this paper is a region in the city of Nanjing, China. For this road network, 22 radio frequency identification (RFID) base stations are installed, collecting individual vehicle passing records continuously. These base stations are in general located along Zhujiang Road, East Zhongshan Road, Ruijin Road, Middle Longpan Road, and Yu Dao Street. The selected road network and the locations of the RFID base stations are shown in Figure 3, and the overview of the intersections within this road network is shown in Table 1.

RFID is a noncontact automatic identification technology. Noncontact two-way radio communication is employed to automatically recognize target objects, and therefore, for each vehicle equipped with a RFID tag passing a certain RFID base station, a vehicle passing record will be generated, with collected information primarily including base station number, passing time, and vehicle license plate number. From these vehicle passing records, travel time between base station pairs can be obtained by matching the recorded information at the starting base station and the destination base station. The RFID base station pairs are listed in Table 2 for the selected road network. For more information on processing RFID data, readers can refer to [28].

In addition, for signal timing parameters of this road network, primarily the turning information and the phase setting information are collected manually for both peak hours and off-peak hours. For these intersections, 7 intersections have 5 phases, 2 intersections have 7 phases, and 1 intersection has 6 phases. The overview of the signal timing setting is shown in Tables 3 and 4 for peak hours and off-peak hours, respectively.

4.2. Comparison Models and Performance Measures. Three models will be implemented and compared in this case study, as listed in Table 5. Original_Plan indicates the current timing plan without optimization. TTR_Plan is the timing plan generated using the proposed travel time reliability based optimization model. TT_Plan is the timing plan generated using minimum mean travel time as the optimization objective with the objective function defined as

$$Z = \min \frac{1}{n} \sum_{i=1}^n \overline{\text{TT}}_i, \quad (9)$$

where $\overline{\text{TT}}_i$ is the average travel time of the road segment i in the road network. Note that TT_Plan is also solved using the particle swarm optimization technique, and the fitness function for PSO is as follows:

$$\text{fitness}_3 = \frac{n}{\sum_{i=1}^n \overline{\text{TT}}_i}. \quad (10)$$

Particle T_i	$t_{i,1}$	$t_{i,2}$	$t_{i,3}$	$t_{i,4}$	$t_{i,5}$	$t_{i,6}$	$t_{i,7}$	$t_{i,8}$	$t_{i,9}$	$t_{i,10}$	$t_{i,11}$	$t_{i,12}$	$t_{i,13}$	$t_{i,14}$	$t_{i,15}$	$t_{i,16}$	$t_{i,17}$	$t_{i,18}$	$t_{i,19}$	$t_{i,20}$	$t_{i,21}$	$t_{i,22}$	
	φ_1	g_{1-1}	g_{1-2}	g_{1-3}	g_{1-4}	g_{1-5}	φ_2	g_{2-1}	g_{2-2}	g_{2-3}	g_{2-4}	g_{2-5}	φ_3	g_{3-1}	g_{3-2}	g_{3-3}	g_{3-4}	g_{3-5}	φ_4	g_{4-1}	g_{4-2}	g_{4-3}	...

FIGURE 2: Particle structure.

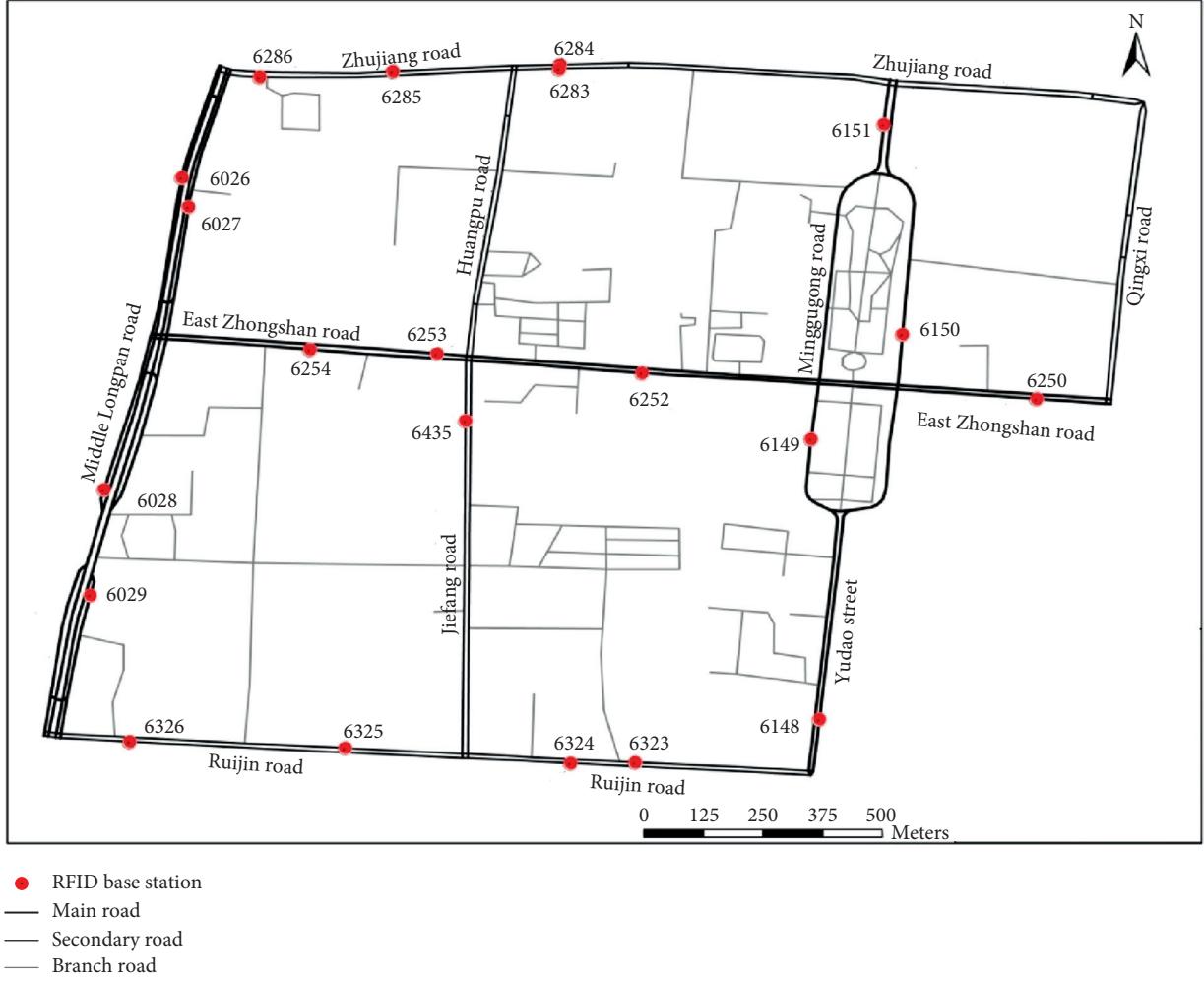


FIGURE 3: Selected road network.

In order to compare these three models, four performance measures are selected, including travel time of road network (NTT), buffer time index (BTI), queue length at the intersection (QL), and delay of the road (DR). Note that these performance measures are calculated for the simulated road network, which can provide detailed traffic network condition data for computing these measures.

4.3. Simulation Model Calibration. Before model validation and comparison, it is necessary to calibrate the simulated

road network in the simulation software, i.e., to adjust the traffic volume for each OD pair in the simulated network, so that the simulated road network will reflect truthfully the real world road network. For this purpose, the particle swarm optimization technique is used for simulation model calibration, as presented below.

4.3.1. Parameter Settings of OD Calibration Algorithm. In the road network, there are 144 OD pairs to be calibrated. Therefore, each particle in the defined particle group will

TABLE 1: Road network intersection overview.

No.	Intersection location
J_1	Zhujiang rd./Middle longpan rd.
J_2	Huangpu rd./Zhujiang road rd.
J_3	Zhujiang rd./Beianmen bridge rd
J_4	Middle longpan rd./East Zhongshan rd.
J_5	East Zhongshan rd./Huangpu rd.
J_6	East Zhongshan rd./Minggugong rd.
J_7	East Zhongshan rd./Minggugong rd.
J_8	Middle longpan rd./Ruijin rd.
J_9	Ruijin rd./Jiefang rd.
J_{10}	Ruijin rd./Yudao st.

TABLE 2: RFID base station pair overview.

No.	Start station	End station
1	6148	6251
2	6150	6283
3	6151	6250
4	6026	6254
5	6028	6326
6	6251	6435
7	6252	6150
8	6253	6028
9	6283	6435
10	6285	6026
11	6324	6148
12	6435	6324
13	6148	6250
14	6149	6323
15	6151	6251
16	6027	6286
17	6029	6254
18	6252	6149
19	6253	6027
20	6254	6435
21	6284	6151
22	6286	6435
23	6325	6029
24	6435	6325
25	6286	6284
26	6283	6285
27	6026	6028
28	6029	6027
29	6254	6252
30	6252	6250
31	6251	6253
32	6326	6324
33	6323	6325
34	6148	6150
35	6151	6149

have 144 elements, each of which corresponds to a volume of an OD pair, with the structure of the particle shown in Figure 4.

In addition to the structure design of the particle, the number of particles is set to 30. The corresponding velocity vector of each particle has a dimension of 144, and there are 30 particle velocity vectors. The maximal evolution generation is set to 100.

TABLE 3: Original signal timing parameters for peak hours (unit: second).

Timing parameter	J_1	J_2	J_3	J_4	J_5	J_6	J_7	J_8	J_9	J_{10}
G_{i-1}	48	15	13	15	16	20	20	13	55	21
G_{i-2}	40	25	28	40	17	33	35	11	20	33
G_{i-3}	12	35	34	20	48	58	56	20	25	21
G_{i-4}	21	30	20	22	15	20	20	40	12	24
G_{i-5}	44	20	40	10	19	24	24	10	23	40
G_{i-6}	—	—	—	—	—	—	—	—	—	13
G_{i-7}	—	—	—	—	—	—	—	25	—	—
Y_i	3	3	3	3	3	3	3	3	3	3
C_i	180	140	150	155	130	170	170	170	150	170

TABLE 4: Original signal timing parameters for off-peak hours (unit: second).

Timing parameter	J_1	J_2	J_3	J_4	J_5	J_6	J_7	J_8	J_9	J_{10}
G_{i-1}	38	12	10	12	15	18	23	12	40	15
G_{i-2}	33	20	20	28	12	30	27	10	15	22
G_{i-3}	12	28	25	15	38	45	42	18	20	20
G_{i-4}	22	25	20	17	10	15	18	27	10	18
G_{i-5}	30	15	30	12	15	22	15	10	20	27
G_{i-6}	—	—	—	15	—	—	—	22	—	10
G_{i-7}	—	—	—	10	—	—	—	20	—	—
Y_i	3	3	3	3	3	3	3	3	3	3
C_i	150	115	120	130	105	145	140	140	120	130

TABLE 5: Comparative models.

Model abbreviations	Description
Original_Plan	Original timing plan
TTR_Plan	Optimized plan based on maximum TTR
TT_Plan	Optimized plan based on minimum TT

4.3.2. Fitness Function. According to the positions of RFID base stations in the road network, vehicle detectors are set in the simulated road network, counting number of vehicles passing the detectors during the simulation. Note that the difference between simulated traffic volume and real world traffic volume indicates the closeness of the simulated network to the real world network. Consequently, this difference is used to build the fitness function of the particle swarm optimization algorithm, as follows:

$$\text{fitness}_1 = \frac{1}{(\sum(|\text{rfid}_i - \text{vde}_i|)/22) + 1}, \quad (11)$$

where rfid_i denotes the real world traffic volume detected by the i^{th} RFID base station and vde_i denotes the simulated traffic volume detected by the i^{th} vehicle detector.

4.3.3. Calibration Result. Using the designed particle swarm optimization algorithm, the simulated road network was calibrated for both peak hours and off-peak hours, with the pattern of the fitness function values shown in Figures 5 and 6, respectively. Clearly, with the progress of optimization,

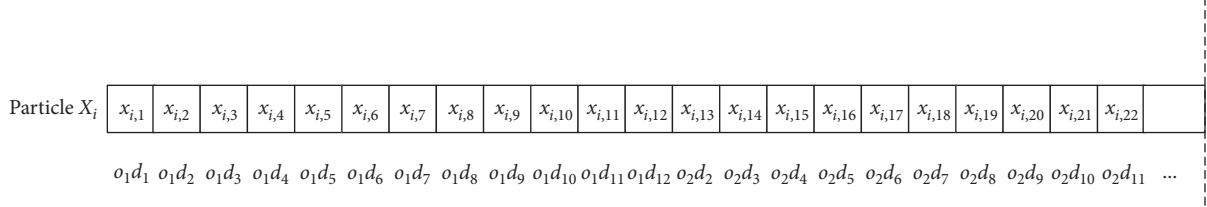


FIGURE 4: Structure of OD pair volume particles.

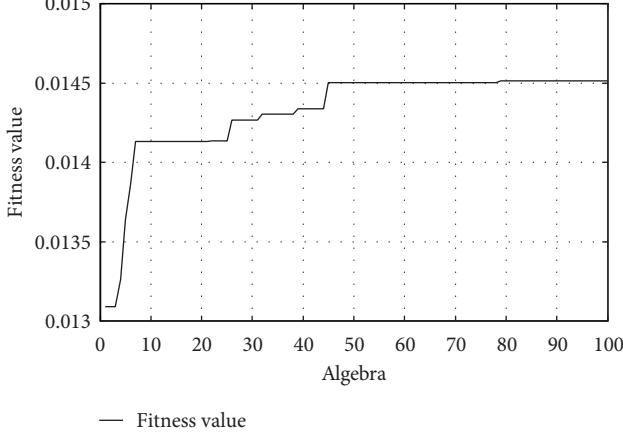


FIGURE 5: Calibration fitness function pattern for peak hours.

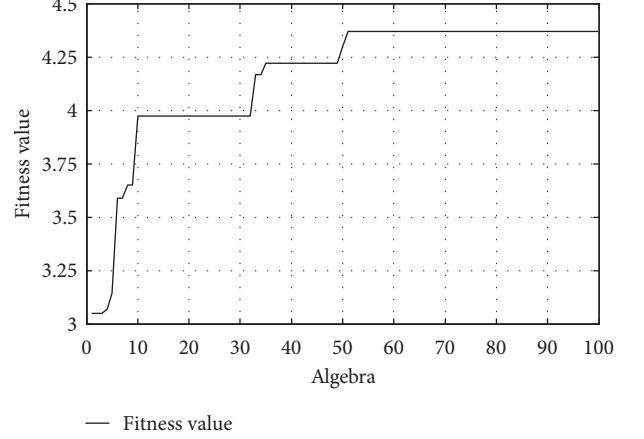


FIGURE 7: TTR_Plan fitness function pattern for peak hours.

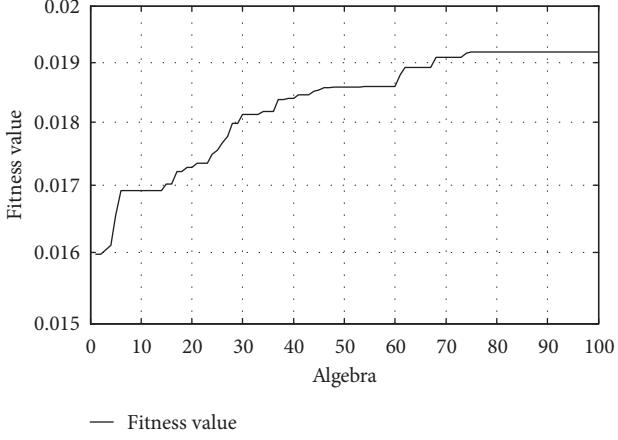


FIGURE 6: Calibration fitness function pattern for off-peak hours.

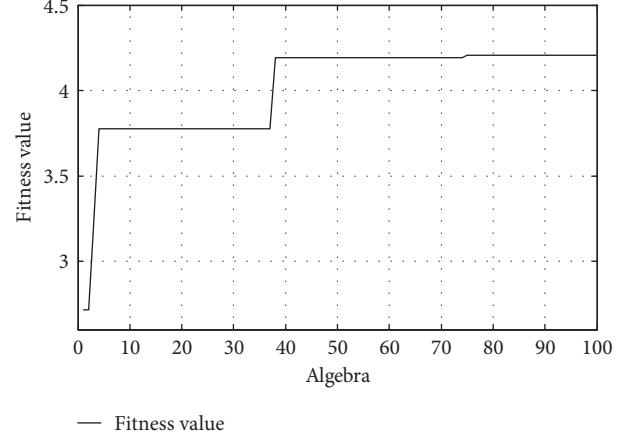


FIGURE 8: TTR_Plan fitness function pattern for off-peak hours.

the difference between the simulated and real world traffic volumes decreases continuously, and to the end of the optimization, the differences remain stable, indicating the convergence of the calibration process, for both peak hours and off-peak hours.

4.4. TTR_Plan Result. Using the calibrated road network, TTR_Plan was implemented. Figures 7 and 8 show the pattern of fitness function values of TTR_Plan during peak and off-peak hours, respectively. It can be seen that for both peak hours and off-peak hours, the fitness function value gradually increases as the optimization iteration proceeds,

indicating a continuous decrease of average buffer time index of the road network, i.e., a continuous improvement of the reliability of travel time in the road network.

The optimized signal timing settings are shown in Tables 6 and 7 for peak hours and off-peak hours, respectively. Clearly, the proposed model adjusted the signal timing settings for all the intersections, compared with the signal timing settings in Original_Plan.

4.5. TT_Plan Result. Using the calibrated road network, TT_Plan was implemented. Figures 9 and 10 show the pattern of fitness function values of TT_Plan during peak and off-peak hours, respectively. It can be seen that TT_Plan

TABLE 6: TTR_Plan signal timing parameters for peak hours (unit: second).

Timing parameters	J_1	J_2	J_3	J_4	J_5	J_6	J_7	J_8	J_9	J_{10}
G_{i-1}	28	9	21	30	30	53	42	11	24	16
G_{i-2}	25	38	33	33	34	16	28	8	32	28
G_{i-3}	40	58	27	1	51	4	34	21	42	46
G_{i-4}	40	30	24	51	30	47	37	16	14	23
G_{i-5}	32	30	60	4	20	45	23	26	53	30
G_{i-6}	—	—	—	8	—	—	29	—	18	—
G_{i-7}	—	—	—	32	—	—	47	—	—	—
φ_i	70	123	64	91	117	31	65	59	110	49
Y_i	3	3	3	3	3	3	3	3	3	3
C_i	180	180	180	180	180	179	179	180	179	179

TABLE 7: TTR_Plan signal timing parameters for off-peak hours (unit: second).

Timing parameters	J_1	J_2	J_3	J_4	J_5	J_6	J_7	J_8	J_9	J_{10}
G_{i-1}	44	20	35	23	16	24	28	20	36	23
G_{i-2}	29	18	37	14	13	20	28	26	42	13
G_{i-3}	16	9	32	12	50	30	38	23	21	13
G_{i-4}	19	43	16	13	11	38	25	17	27	28
G_{i-5}	27	44	15	22	16	23	16	15	9	24
G_{i-6}	—	—	—	13	—	—	14	—	30	—
G_{i-7}	—	—	—	32	—	—	14	—	—	—
φ_i	41	50	62	14	77	90	23	80	87	90
Y_i	3	3	3	3	3	3	3	3	3	3
C_i	150	149	150	150	121	150	150	150	150	149

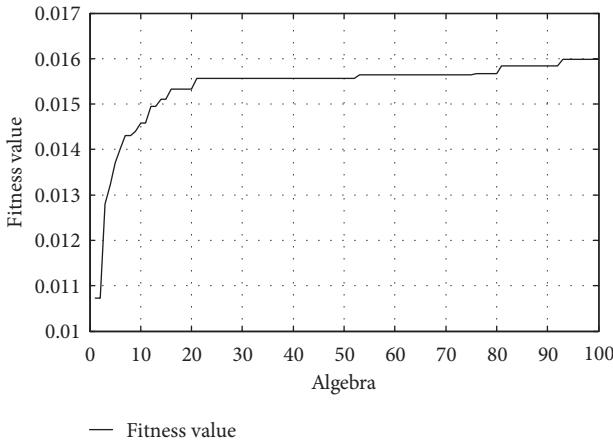


FIGURE 9: TT_Plan fitness function pattern for peak hours.

shows the same pattern as TTR_Plan, for both peak hours and off-peak hours. This indicates that TT_Plan improves network performance in terms of average travel time. However, no inference on the reliability of travel time can be drawn as travel time reliability measure is not incorporated in the optimization process.

Similarly, the optimized signal timing settings are shown in Tables 8 and 9 for peak hours and off-peak hours, respectively. Clearly, TT_Plan also adjusted differently the

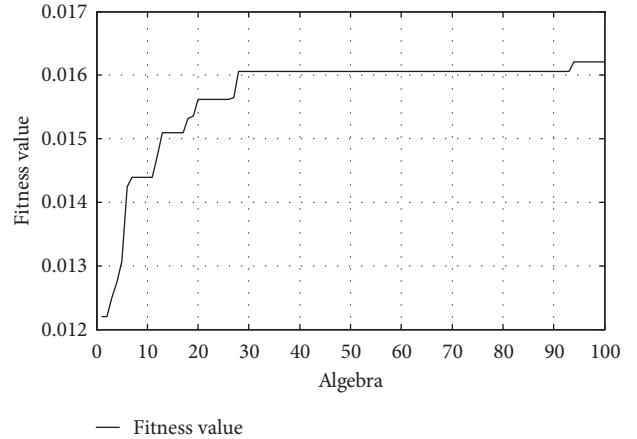


FIGURE 10: TT_Plan fitness function pattern for off-peak hours.

TABLE 8: TT_Plan signal timing parameters for peak hours (unit: second).

Timing parameter	J_1	J_2	J_3	J_4	J_5	J_6	J_7	J_8	J_9	J_{10}
G_{i-1}	9	31	20	25	16	38	34	34	34	36
G_{i-2}	52	28	21	22	17	22	24	6	32	21
G_{i-3}	30	50	43	22	60	37	36	22	23	25
G_{i-4}	43	30	23	15	15	32	34	30	30	35
G_{i-5}	31	26	57	16	19	36	37	12	46	27
G_{i-6}	—	—	—	30	—	—	—	37	—	17
G_{i-7}	—	—	—	28	—	—	—	17	—	—
φ_i	57	107	102	126	51	95	49	75	52	85
Y_i	3	3	3	3	3	3	3	3	3	3
C_i	180	180	179	179	142	180	180	179	180	179

TABLE 9: TT_Plan signal timing parameters for off-peak hours (unit: second).

Timing parameter	J_1	J_2	J_3	J_4	J_5	J_6	J_7	J_8	J_9	J_{10}
G_{i-1}	47	4	29	8	16	18	30	30	25	20
G_{i-2}	24	26	30	32	12	33	38	3	36	23
G_{i-3}	15	39	30	26	50	27	14	11	6	3
G_{i-4}	20	31	34	20	11	29	19	24	32	39
G_{i-5}	30	35	12	6	16	28	35	22	36	27
G_{i-6}	—	—	—	21	—	—	—	14	—	20
G_{i-7}	—	—	—	14	—	—	—	24	—	—
φ_i	51	47	93	64	69	64	60	50	61	64
Y_i	3	3	3	3	3	3	3	3	3	3
C_i	151	150	150	148	120	150	151	149	150	150

signal timing settings for all the intersections, compared with the signal timing settings in Original_Plan.

4.6. Performance Comparisons. Using optimized timing plans given above for TTR_Plan and TT_Plan, the performances of the three models can be compared quantitatively in terms of four performance measures, i.e., travel time of road network (NTT), buffer time index (BTI), queue length at the intersection (QL), and delay of the road (DR).

TABLE 10: Performance comparison for peak hours.

Timing plan	NTT (s)	QL (m)	DR (s)	BTI
Original_Plan	440.89	64.63	75.76	0.5245
TTR_Plan	437.67 (-0.73%)	48.18 (-25.45%)	28.39 (-62.53%)	0.2336 (-55.46%)
TT_Plan	357.22 (-18.98%)	41.13 (-36.36%)	45.99 (-39.30%)	0.3733 (-28.83%)

TABLE 11: Performance comparison for off-peak hour.

Timing plan	NTT (s)	QL (m)	DR (s)	BTI
Original_Plan	362.22	49.58	56.12	0.5269
TTR_Plan	318.44 (-12.09%)	36.93 (-25.51%)	28.39 (-49.41%)	0.3495 (-33.67%)
TT_Plan	345.67 (-4.57%)	39.93 (-19.46%)	41.09 (-26.78%)	0.4583 (-13.02%)

Table 10 lists the performance measures of the three models for peak hours. On observing Table 10, first, it can be seen that compared with Original_Plan, both TTR_Plan and TT_Plan show significant improvement in terms of all the measures. This indicates a significant margin of improving the original timing through applying optimization technique. Second, TTR_Plan outperforms TT_Plan in terms of BTI, while TT_Plan outperforms TTR_Plan in terms of NTT, which is in alignment with the optimization objective of these two models. Third, in terms of QL and DR, the performances of TTR_Plan and TT_Plan are mixed, indicating comparable performance of TTR_Plan and TT_Plan. In summary, both signal timing optimization plans can improve the network performance over the original timing plans, while the two optimization plans show comparable performances. On reflection, this might be caused by high traffic level where there might be less room left for optimization.

Table 11 lists the performance measures of the three models for off-peak hours. On observing Table 11, first, it is clear that both TTR_Plan and TT_Plan outperform significantly the Originial_Plan, which indicates that optimization technique can improve the performance of signal timing for off-peak hours. Second, different from the results for peak hours, for all the four performance measures, TTR_Plan consistently outperforms TT_Plan. This is an interesting finding, indicating that minimizing travel time reliability might at the same time minimize travel time for off-peak hours. On reflection, this might be caused by the existence of excessive room left for off-peak traffic levels to first balance travel time and then reduce the level of average travel time before reaching the minimized average buffer time index.

In summary, it is clear that for both peak hours and off-peak hours, the proposed travel time reliability-based signal optimization model can improve the performance of urban road network, in terms of both efficiency and reliability. In particular, for off-peak hours, the proposed model shows a consistent improvement of network efficiency and network reliability over models of minimizing average travel time only.

5. Conclusions

Recently, travel time reliability has become an important performance measure of the urban traffic network. However,

in urban traffic signal control systems, travel time reliability has not been sufficiently investigated. Therefore, more research is needed to understand the performance of network traffic signal control with the objective to optimize travel time reliability. To this end, an urban traffic network signal timing optimization model is proposed in this paper to optimize the average buffer time index of all road segments in the network. Particle swarm algorithm is adopted to solve the optimization models for both peak and off-peak hours. A case study is conducted for a road network in Nanjing city. The results show that the proposed travel time reliability-based signal timing optimization model can significantly improve the reliability of traffic network and efficiency as well, in particular for off-peak hours when excessive room is available for traffic signal optimization.

Considering the importance of incorporating reliability measures into real-world traffic management and control, future research is recommended as follows. First, more travel time reliability measures can be investigated in urban traffic network signal timing optimization. In particular, the effect of travel time percentile can be further investigated to show its effect on the reliability of the optimized system. Second, studies should be conducted to relate travel time reliability measures to the traffic condition uncertainty models as developed by Guo et al. (2008, 2012, 2014) [29–31] and Shi et al. [32], so that signal timing could be directly related to uncertain traffic conditions. Third, more advanced traffic signal optimization methods such as reinforced learning approach could be investigated together with the reliability measures. Finally, and most importantly, online methods are expected to be developed to meet the real world requirement of urban traffic signal optimization and control.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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