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This paper proposed the model and algorithms for traffic data monitoring and signal timing optimization based on continuum traffic model and wireless sensor networks. Given the scenario that sensor nodes are sparsely installed along the segment between signalized intersections, an analytical model is built based on continuum traffic equations, and an adaptive interpolation method is proposed to estimate traffic parameters with scattered sensor data. Based on the principle of traffic congestion formation, a congestion factor is introduced which can be used to evaluate the real-time status of traffic congestion along the segment, and to predict the subcritical state of traffic jams. The result is expected to support the signal timing optimization of traffic light control for the purpose to avoid traffic jams before its formation. We simulated the traffic monitoring based on Mobile Century dataset, and analyzed the performance of signal control on VISSIM platform when congestion factor is introduced into the phase optimization model. The simulation result shows that this method can improve the spatial-temporal resolution of traffic data monitoring, and it’s helpful to alleviate urban traffic congestion that remarkably decreases the average delays and maximum queue length.

Keywords: intelligent transportation system, traffic surveillance, wireless sensor networks, traffic congestion evaluation, congestion factor, cost function, traffic flow theory, scattered data fitting, timing phase optimization, multi-objective optimization

1. INTRODUCTION

Traffic crowds seen in intersection of urban road networks are highly influential in both developed and developing nations worldwide. Urban residents are suffered poor transport facilities, and meanwhile the considerable financial loss caused by traffic becomes a large and growing burden on the nation’s economy, including costs of productivity losses from traffic delays, traffic accidents, traffic jams, environmental pollution, and more [1, 2]. The idea that improvements to transport infrastructure is the efficient way has been central to transport economic analysis, but in fact this problem can’t be perfectly resolved with better roads [3, 4]. Intelligent transportation system (ITS) has...
been proven to be an efficient solution [5]. Comprehensive utilization of information technology, transport engineering and behavioral science to reveal the principle and dynamics of traffic flow, measuring traffic data and route vehicles to avoid traffic jam before its formation, promotes a prospective to resolve traffic problem from the root [6].

Nowadays, in an information-rich era, the traditional traffic surveillance and control methods are confronted with great challenges [7]. How to obtain meaningful information from large amounts of sensor data to support transportation applications becomes more and more significant [8]. Modern traffic control and guidance systems are always networked in large scale which needs real-time traffic data with higher spatial-temporal resolution, that challenges traditional traffic monitoring technologies such as inductive loop, video camera, microwave radar, infrared detector, UAV, satellite image, and GPS, etc. [9]. The state-of-the-art, intelligent and networked sensors are emerging as a novel network paradigm, which provides an appealing alternative to traditional traffic surveillance technologies in the near future [10], especially for proactively monitoring traffic data in urban environments under the grand prospective of cyber physical systems [11]. Many researchers have endeavored to traffic monitoring based on novel technologies, and recent research shows that wireless sensor networks for the purpose of traffic surveillance and control are widespread applications [8, 12-14].

However current research still cannot fully explain the intrinsic principle of traffic congestion formation and under what conditions traffic jam may suddenly occur. M.R. Flynn et al. studied traffic congestion modeling based on macro-scope traffic flow theory and obtained some basic results in congestion prediction [15], which is regarded as a great step towards answering the key question that how can the occurrence of traffic congestion be avoided. Signal timing optimization can be modeled as a multi-objective optimization problem (MOP), and current control strategies include fixed-time control, inductive control and adaptive control. In urban traffic control systems such as SCOOT, SCATS and REHODES, it always deploys single or double loops as vehicle detector. The traditional traffic detection is Eulerian sensing which collect data at predefined locations [16], and the loops can’t be deployed in large amount as comparing to the scale of road networks, as a result the traffic data is difficult to be achieved accurately [17].

In this paper, we studied the intrinsic space-time properties of actual traffic flow, and build an observation model to estimate traffic parameters based on wireless sensor networks. We are interested in how to evaluate traffic congestion quantitatively and what the performance of signal control would be if take congestion factor as one of the objectives in timing optimization. The rest of the paper is organized as follows. Current research on traffic surveillance based on sensor networks is briefly reviewed in section 2. An observation model for traffic parameters estimation based on traffic flow theory is described in section 3. The traffic congestion evaluation model and congestion factor based signal timing optimization are studied in section 4. The performance is analyzed based on simulation in section 5. Finally, a conclusion and future works are given in section 6. Symbols will be used in this paper are listed in Table 1.

2. RELATED WORKS AND PROBLEM STATEMENT

Several research works on traffic monitoring with wireless sensor networks have been carried out in recent years [8]. In PATH program launched by UC Berkeley and
Caltrans, P. Varaiya et al. creatively applied wireless sensor networks in traffic surveillance and obtained high precision exceeding 95% [10]. Joint with Nokia, UC Berkeley launched a pilot traffic-monitoring system named Mobile Century to collect traffic data based on GPS sensors equipped in cellular phone [16]. M. L. Li et al. studied traffic data collection based on vehicular networks equipped with GPS sensors [18], and Y. Zheng et al. studied traffic pattern based on history GPS trajectories to reveal the cause of traffic jams [3]. In TIME program, researchers developed a data compress method using weekly spatial-temporal pattern of traffic data [19]. M. Babak et al. applied kinematic wave theory in traffic model and try to reconstruct vehicle trajectories based on fixed and probe sensor data [20]. But in current research there are something important out of consideration: (1) Few considerations are given to the intrinsic space-time properties of traffic flow and the principle of traffic congestion formation. (2) How to evaluate traffic congestion quantitatively with sufficient precision and real-time performance, and introduce it as an objective to support signal timing optimization? (3) How to combine sensor networks with traffic control system to analyze future traffic state under current timing strategies and try to avoid traffic jams before its formation.

Traffic flow theory has expanded significantly in recent decades [21]. The typical models include LWR continuum model [22] and Payne-Whitham higher model [23]. Vast majority of current research is focused on state-space methodology, and limited amount of work has been performed using space-time model [20, 24]. Y. Sugiyama et al. explained the formation of traffic congestion by experimental observations [25], and based on this, M. R. Flynn et al. built a congestion model, Jamitons, to explain and predict traffic congestion based on traveling wave solutions of continuum traffic models [15].

The goal of this paper is to estimate traffic parameters based on sparsely deployed sensor networks, evaluate the degree of traffic congestion to explain the spatiotemporal

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### Table 1. Nomenclature and symbols.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
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<tbody>
<tr>
<td>$x \in [0, L_x]$</td>
<td>Location in road segment</td>
</tr>
<tr>
<td>$t \in [0, +\infty)$</td>
<td>Observation time</td>
</tr>
<tr>
<td>$u(x, t)$</td>
<td>Traffic flow speed</td>
</tr>
<tr>
<td>$p(x, t)$</td>
<td>Traffic density</td>
</tr>
<tr>
<td>$x_i(t)$</td>
<td>Vehicle trajectory</td>
</tr>
<tr>
<td>$\hat{p}(x, t)$</td>
<td>Estimated traffic data</td>
</tr>
<tr>
<td>$\rho(x, t)$</td>
<td>Traffic density</td>
</tr>
<tr>
<td>$\rho_M$</td>
<td>Maximum traffic density</td>
</tr>
<tr>
<td>$\bar{u}$</td>
<td>Equilibrium speed</td>
</tr>
<tr>
<td>$u_f$</td>
<td>Free speed on empty road</td>
</tr>
<tr>
<td>$p(\rho)$</td>
<td>Traffic pressure</td>
</tr>
<tr>
<td>$s(x, t)$</td>
<td>Flow production rate</td>
</tr>
<tr>
<td>$s_k$</td>
<td>Speed of vehicle $m$ at sensor $k$</td>
</tr>
<tr>
<td>$\hat{p}(x, t)$</td>
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</tr>
<tr>
<td>$\rho_M$</td>
<td>Maximum traffic density</td>
</tr>
<tr>
<td>$\eta = (s-xt)/\tau$</td>
<td>Self-similar variable</td>
</tr>
<tr>
<td>$\lambda_i$</td>
<td>Congestion factor of lane $i$</td>
</tr>
<tr>
<td>$\gamma_i$</td>
<td>Effective green time</td>
</tr>
<tr>
<td>$J_m(k)$</td>
<td>Cost function on lane $m$</td>
</tr>
<tr>
<td>$q_j(k)$</td>
<td>Inflow in phase $j$</td>
</tr>
<tr>
<td>$d_j(k)$</td>
<td>Outflow in phase $j$</td>
</tr>
<tr>
<td>$q_{j_{in}}(k)$</td>
<td>Arrival traffic flow at stop line</td>
</tr>
<tr>
<td>$q_{j_{out}}(k)$</td>
<td>Exit flow in phase $j$</td>
</tr>
<tr>
<td>$S_{g_j}$</td>
<td>Saturation flow for green</td>
</tr>
<tr>
<td>$S_{y_j}$</td>
<td>Saturation flow for yellow</td>
</tr>
<tr>
<td>$\xi_i$</td>
<td>Existing phase state</td>
</tr>
</tbody>
</table>

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| $\Delta t, \Delta x$ | Temporal-spatial scales |
| $u^e m_k$ | Speed of vehicle $m$ at sensor $k$ |
| $\xi_i$ | Existing phase state |
| $l_{in}(k)$ | Queue length in phase $i$ |

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### Note
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properties of traffic flow, and introduce a congestion factor to the optimization model of signal timing. We use Lagrangian detection [26] to collect traffic data, in which not only to detect point data, but also to estimate the time-space properties along the road segment. The deployment of sensor networks is shown in Fig. 1, where \( p(x, t) \) denotes traffic data such as velocity and density.

![Deployment of wireless sensor networks for urban traffic surveillance.](image)

The urban road network can be modeled as a directed graph consisting of vehicles \( v \in V \) and edges \( e \in E \). Let \( L_e \) be the length of edge \( e \). The spatial and temporal variables are road segment \( x \in [0, L_e] \), and time \( t \in [0, +\infty) \) respectively. On a given road segment \( x_e \) and time \( t \), the traffic flow speed \( u(x, t) \) and density \( \rho(x, t) \) are distributed parameters in time and space. While vehicle labeled by \( i \in N \) travels along the road segment with trajectory \( x_i(t) \), the sensor measurements \( u(x_i(t), t) \) and \( \rho(x_i(t), t) \) are scattered values as showed in Eq. (1). Here \( k \) is the sensor node number. The problem of traffic data monitoring can be transformed to estimate traffic parameters in given spatial and temporal variables \( t \) with these discrete values.

\[
U_i = (u_1, \ldots, u_k), \quad P_i = (\rho_1, \ldots, \rho_k)^T (1)
\]

### 3. TRAFFIC MONITORING AND DATA ESTIMATION

#### 3.1 The Continuum Traffic Flow Theory and Theoretical Models

Lighthill and Whitham introduced the continuum model (LWR) [22] based on fluid dynamics. Payne introduced dynamics equations and proposed the second order model (Payne-Whitham) [23]. The Payne-Whitham model is defined by Eq. (2) and the acceleration Eq. (3), given in non-conservative form.

\[
\frac{\partial \rho}{\partial t} + \frac{\partial (\rho u)}{\partial x} = s(x, t) (2)
\]

\[
\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} + \frac{1}{\rho} \frac{\partial p}{\partial x} = \frac{1}{\tau} (\ddot{u} - u) (3)
\]
Where $x$ and $t$ denote space and time, $u(x, t)$ and $\rho(x, t)$ are the traffic flow speed and density at the point $x$ and time $t$ respectively, $\rho$ is traffic density in unit of vehicles/length, $\tau$ is delay, $p$ is traffic pressure which is inspired from gas dynamics and typically assumed to be a smooth increasing function of the density only, i.e. $p = p(\rho)$. The parameter $\tilde{u}$ denotes the equilibrium speed that drivers try to adjust under a given traffic density $\rho$, which is a decreasing function of the density $\tilde{u} = \tilde{u}(\rho)$ with $0 < \tilde{u}(0) = u_f < \infty$ and $\tilde{u}(\rho_M) = 0$. Here $u_f$ is the desired speed of free flow, $\rho_M$ is the maximum traffic density in congestion state at which vehicles are bumper-to-bumper in the traffic jam. In Jamitons model [15], the relationship between $\tilde{u}$ and $\rho$ is denoted in Eq. (4).

$$
\tilde{u}(\rho) = \tilde{u}_f (1 - \frac{\rho}{\rho_M})^\gamma, u_f = \frac{\tilde{u}_f}{\rho}, \rho
$$

In Eq. (2), the $s(x, t)$ is flow production rate, and for road segment with no ramp $s(x, t) = 0$, for entrance ramp $s(x, t) < 0$, for exit ramp $s(x, t) > 0$. Assuming the velocity of vehicle traveling from the given intersection during green light interval is $v_i(t)$, and the intervals of green light phase is $T$, thus the flow production rate can be denoted as follows.

$$
s(x,t) = \int_0^T v_i(t)dt
$$

The continuum model is given by partial differential equations, and it is difficult to obtain exact solution in analytical form. Based on the LWR solver developed by A. M. Bayen et al. [27], we can obtain the approximate numerical solutions with given initial parameters. That means the future state of traffic flow and congestion can be predicted and analyzed in a system scale.

### 3.2 Signal Processing for Traffic Data Estimation Based on Sensor Networks

In this paper, we employ high sensitive magnetic sensor to detect vehicles, as shown in Fig. 2 (a). Given the detection radius is $R$, sensor node detects travelling vehicle based on ATDA algorithm [10], which detects vehicle based on an adaptive threshold, and estimates velocity with time difference and the lateral offset, as shown in Fig. 2 (b). Where $D$ is sensor separation, $s(t)$ is raw data, which will be sampled as sensor readings in discrete values $s(k)$, and transformed to $a(k)$ after noise filtering.
\[
\hat{v}_{m} = \text{avg}(\frac{D_{m} - t_{s,ap} - t_{s,down}}{t_{s,ap} - t_{s,down}})
\]  \hspace{1cm} (6)

The \( h(k) \) is an adaptive threshold at detection interval \( k \), and \( d(k) \) is detection flag. The instantaneous velocity can be estimated by Eq. (6). Here time \( t_{up} \) and \( t_{down} \) are the moment when sensor signals exceed the threshold continuously with count \( N \) and \( M \) respectively. In actual applications, sensor signals are usually error-prone, we use history data to eliminate errors from magnetic field self-interference and signal absence, as Eq. (7), where \( B(k) \) is baseline and \( \alpha \in [0, 1] \) is forgetting factor.

\[
B(k) = \begin{cases} 
B(k-1) \times (1 - \alpha) + a(k) \times \alpha, & \text{if } s(\tau) = 0 \forall \tau \in [(k - s_{out}) \ldots (k - 1)] \\
B(k-1), & \text{others}
\end{cases}
\]  \hspace{1cm} (7)

In actual application, there are tight temporal correlations among sensor readings. Assuming the temporal-spatial scales are \( \Delta t \) and \( \Delta x \), the vehicle trajectory \( r \) and observation time \( t \) are dispersed into \( L \) and \( T \) sections. Then the two-dimensional \( x \times t \) domain can be transformed to a grid mesh, as shown in Fig. 3, which can be denoted by Eq. (8).

Where \((x_i, t_j)\) is grid point, and \( h \) and \( k \) are spatiotemporal scales that can be denoted as \( h = \Delta x \) and \( k = \Delta t \).

\[
x_i = ih, t_j = jk, i \in [0, L], j \in [0, T]
\]  \hspace{1cm} (8)

The total number of sensor node is \( K \). Sensor reading \( u(x_i, t_j) \) in grid cell \( g(i, j) \), may be considered as a detection unit on location \( [i, i + 1] \cdot \Delta x \), and there is a single sensor node which take effect in time interval \( [j, j + 1] \cdot \Delta t \). Define \( v_{m} \) the actual speed of the \( m \)th vehicle travelling from the \( k \)th sensor in grid \( g(i, j) \), \( \hat{v}_{m} \) is the estimated speed calculated from sensor measures, \( u_k \) is the average speed, \( m \) and \( m' \) are the first and last vehicle in detection interval respectively, and \( u(x, t) \) is the theoretical speed based on the continuous traffic flow model. The actual and estimated traffic flow speed can be denoted by following equations.

\[
u_i = \frac{1}{m' - m} \sum_{m} v_{m}, \hat{u}_i = \frac{1}{m' - m} \sum_{m} \hat{v}_{m}
\]  \hspace{1cm} (9)
If the space-time scale is small enough, it could be inferred that the traffic flow speed keep unchanged in the unit grid, and consequently the partial differential Eqs. (2)-(5) can be rewritten in an approximated way, as Eq. (10). Here the subscripts \(i\) and \(j\) indicate space and time respectively.

\[
\left[ \frac{\partial u}{\partial x} \right]_i = \frac{u_{i+1}^j - u_{i-1}^j}{h}
\] (10)

With the scattered measurements as boundary initial values, the traffic data can be estimated by numerical interpolation, as shown in Fig. 4. For instance of traffic flow speed detection, denote \(\hat{u}_{k}^m\) and \(u_{k}^m\) the estimated and actual velocity of \(m\)th \((m \in [1, M])\) vehicle on sensor \(k\) \((k \in [1, K])\), respectively. The estimation error is \(e_{k}^m\), which can be formulated as:

\[e_{k}^m = \hat{u}_{k}^m - u_{k}^m.\] (11)

We use the same objective function as that in [28], which is defined by Eq. (12). Here \(\hat{E}\) is objective function, \(\hat{E}_k\) is mean square error (MSE) of traffic parameter estimation for all \(M\) vehicles on sensor \(k\). The purpose of optimization is to minimize the total MSEs of all sensors

\[\hat{E} = \sum_{k=1}^{K} \sum_{m=1}^{M} (e_{k}^m)^2 / M = \sum_{k=1}^{K} \hat{E}_k.\] (12)

Assume \(K\) point data \(\hat{u}(x_i, t)\) obtained in detection area \(g(i, j)\), and \(u(x_i, t)\) is the corresponding value given by traffic equations. The noise root-mean-square error \(\sigma_{\text{rms}}\) between model outputs and measured data can be defined as Eq. (13), which is a two-dimensional random field, and we assume it is unbiased.

\[\frac{1}{K} \sum_{i=1}^{K} \left[ \frac{\hat{u}(x_i, t) - u(x_i, t)}{\hat{u}(x_i, t)} \right]^2 = \sigma_{\text{rms}}^2\] (13)

The velocity change in real traffic flow \(u(x, t)\) is continuous. To eliminate noise, we introduce a smoothing factor based on the minimum sum of squares of the second derivative, as shown in Eq. (14). Where \(\Omega\) denotes two-dimensional square detection area. To solve the conditional extremum problem based on Eqs. (13) and (14), we can use the similar method in [29] based on finite elements method.

\[\omega_{\text{min}} = \min \int \sum_{x} \left( \frac{\partial^2 u(x, t)}{\partial x^2} \right)^2 d\Omega\] (14)

### 4. CONGESTION FACTOR BASED SIGNAL OPTIMIZATION

#### 4.1 Traffic Congestion Evaluation and Congestion Factor

There much research about traffic congestion prediction and evaluation in last decades [30, 31]. In Jamitons model proposed by M.R. Flynn et al., the traffic congestion is
modeled as traveling wave [15]. Based on LWR continuum traffic models present in Eqs. (2)-(3), define a self-similar variable $\eta = (s - xt)/\tau$, Eq. (15) holds.

$$\frac{du}{d\eta} = \frac{(u-s)(\bar{u} - u)}{(u-s)^2 - c^2}$$  \hspace{1cm} (15)

Where $s$ is the speed of traveling shock wave, and traffic flow density and speed can be denoted as function of $\mu$, viz: $\rho = \rho(\eta), \ u = u(\eta)$. The subcritical state can be predicted by Eq. (15), where $c = \sqrt{\rho_p} > 0$ denotes the subcritical condition. To solve these equations, we select the shallow water equations [15] denoted as Eq. (16) to simplify the problem.

$$p = \beta \rho^2/2$$ \hspace{1cm} (16)

Then Eq. (15) can be rewritten as Eq. (17). Here $m$ is a constant denoting the mass flux of vehicles in the wave frame of reference.

$$\frac{du}{d\eta} = (u-s) \left\{ \bar{u}_i \left( 1 - \frac{m}{\rho_i(u-s)} \right) - u \right\} / \left\{ (u-s)^2 - \frac{\beta m}{(u-s)} \right\}$$  \hspace{1cm} (17)

The subcritical condition is therefore denoted as Eq. (18). If this equation is satisfied, the traffic congestion is inevitable to occur. The density will reach $\rho_\mu$ immediately when traffic conditions exceed the subcritical state.

$$u_c = s + (\beta m)^{1/3}$$ \hspace{1cm} (18)

The road can be regarded as share resource for vehicles and traffic flow links, and according to Jain’s fairness index for shared computer systems, the quantitative congestion factor can be defined as Eq. (19). Here $i$ indicates the lane number, $x$ is the locations coordinate with origin starting from stop line, and the traffic density is sampled from $n$ discrete values with fixed frequency. The congestion factor indicates the general congestion state on whole road segment, which is a number between 0 and 1, and larger value means more crowded.

$$C_{ij}(t) = \left( \frac{\sum_{m=1}^{n} \rho(x_m))^2}{n} \right) / \left( \frac{\sum_{m=1}^{n} (\rho(x_m))^2}{n} \right)$$  \hspace{1cm} (19)

Considering an intersection with four phases numbered $A$, $B$, $C$ and $D$, as shown in Fig. 5, the phase timing can be denoted as Eq. (20). Here $g_{i}^l$ and $g_{i}^u$ represent the minimum and maximum green time respectively, and $G_i$ is the effective green time of phase $i$.

$$G = \{G_A, G_B, G_C, G_D\}, \ G_i \in [g_{i}^l, g_{i}^u]$$  \hspace{1cm} (20)

Fig. 5. Four phases of traffic control.
Under the scenario that traffic flow stops by red signal, for instance of lane $m$ during signal phase $i$, the traffic flow from west to east will be blocked from the beginning of phase $A$, and the interval is $G_A$. The corresponding cost function on lane $m$ is denoted as Eq. (21). Here $\Delta T$ is timing adjustment step length, $C_{cf}^m(k)$ and $C_{cf}^m(k')$ represent congestion factor on lane $m$ of traffic flow under blocking status and normal condition under green phase respectively. The normal condition can be simulated based on Eqs. (2) and (3) with initial values detected by sensor networks at time $t$, where $s(t) = 0$. And traffic parameters can be predicted by resolving traffic equations.

$$J_n(k) = \sum_{i=0}^{K} [C_{cf}^m(k) - C_{cf}^m(k')] \Delta T \in [0, K], K = G_A / \Delta T$$

With the implementation of LWR solver [27], we can build a virtual simulator for traffic flow scheduling to analyze the traffic state, congestion factor and cost function in a theoretical way based on given initial parameters. For traffic flow of a straight lane, consider two scenarios that traffic flow run continuously and blocked by red signal at time $t$, the congestion factor and cost function can be simulated. The result is shown in Fig. 6. The congestion factor can denote the congestion extent of road segment.

Fig. 6. Traffic flow density and congestion factor at observation time $t$.

Fig. 7. Urban intersection and road link model for traffic signal control.

4.2 The Multi-Objective Optimization Model for Signal Control

The signal timing problem can be formulated as a mathematical programming to minimize multi-objective constraints [32]. Given two signaled intersections, the variables on intersection and connecting links of phase $j$ are shown in Fig. 7. We define $q_{in}(k)$ and $q_{out}(k)$ to be the inflow and outflow respectively, and define $d(k)$ and $s(k)$ to be the de-
mand flow and exit flow during the phase $j$ in an interval $[k\Delta T, (k + 1)\Delta T]$, where $\Delta T$ is the timing adjustment step, and $k$ is a discrete index. Define $S_{g}^{j}_n$ and $S_{y}^{j}_n$ as the saturation flow for green and yellow time of phase $j$ at intersection $n$. $u_{r}^g(k)$ indicates the signal, and $u_{r}^r(k) = 1$ means red light.

To simply the problem we just optimize the phase time, with assumption that phase order is unchanged, four phases as shown in Fig. 5, transfer in the presupposed order A, B, C and D. Based on the dynamics of traffic flow, the control objective of the dynamic model is to minimize the total delay and traffic congestion factor. To minimize:

\[
\text{Delay } TD = \Delta T \sum_{n=1}^{N} \sum_{k=1}^{K} I_{n}(k) \tag{22}
\]

\[
\text{Congestion factor } CF = \sum_{n=1}^{M} \sum_{k=1}^{K} C_{n}(k) \tag{23}
\]

\[
\text{Cost factor } J = \sum_{n=1}^{M} \sum_{k=1}^{K} J_{n}(k) \tag{24}
\]

With constraints subject to:

\[
g_{l}^{'} \leq G_{i} \leq g_{r}^{'} \tag{25}
\]

\[
l_{m}(k) \geq 0, \ k \in K; l_{m}(k) = l_{m}(k-1) + (q_{m}(k) - q_{m}^{i}(k))\Delta T \tag{26}
\]

\[
q_{m}^{i}(k) = \sum_{i} b_{i} q_{m}^{i}(k) \tag{27}
\]

\[
q_{m}^{d}(k) = (1 - u_{m}(k))(S_{g}^{m}(1 - \xi_{m}(k)) + S_{y}^{m} \times \xi_{m}(k) + S_{r}^{m} \times \xi_{m}(k)) \times u_{m}(k) \tag{28}
\]

For a given time window $T$, based on constraints of Eq. (24), the timing problem can be separated into $h (1 \leq h \leq Tg^{'} - 1)$ sub-problems. We can solve these $h$ problems and obtain $h$ non-inferiority set of optimal solutions, and then merge them to get a new non-inferiority set of optimal solutions, which is the solution of the original problem. In this paper we use MOPSO-CD (Multi-objective Particle Swarm Optimization Algorithm using crowding distance) to find the optimal timing phases.

### 4.3 Traffic Flow Detection and Control Algorithms

Based on above model and computational method, the overall block diagram of traffic data detection and control algorithm is shown in Fig. 8. It employs magnetic sensor and detects magnetic signature based on ATDA. The individual vehicle data is collected in time window $W$ and traffic flow speed is monitored at regular intervals. The scattered point data $U_i$, $P_i$ contains all sensor readings will be used to approximate the traffic equation and numerical approximation $u^i(\text{ih}, jk)$ obtained. Finally we can get the traffic data $u(x, t)$ and $\rho(x, t)$, which is expected to provide data to traffic control and evaluate traffic congestion.
The traffic congestion state can be evaluated based on Eq. (19) and we can obtain the congestion factor in every segment near the intersection. At the same time, a cost function in next control phase can be calculated with a traffic scheduling simulator which is based on traffic equations and LWR solver. When we give priority to different possible directions and block traffic flow on other directions, the overall delay cost from alternative timing strategies will be involved into a multi-objective optimization model before making the final signal. Finally, the traffic controller will choose the optimal timing scheme. This process operates in a circulation and in an adaptive way.

5. SIMULATION RESULT AND PERFORMANCE ANALYSIS

The model and algorithms are simulated based on VISSIM platform. The traffic flow data is generated with the Mobile Century field test dataset [16, 33] and LWR solver [27]. VISSIM is a microscope, time interval and driving behavior based traffic simulation toolkit. It supports external signal control strategies by providing API, in which an interface Calculate will be invoked with presupposed frequency. And user can obtain the signal control data from this interface. We designed a software/hardware in the loop simulation platform based on VISSIM, as shown in Fig. 9.

Fig. 9. Diagram of traffic flow detection and adaptive control model based on sensor network.

Fig. 8. Diagram of traffic flow detection and adaptive control model based on sensor network.

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Fig. 9. Diagram of traffic flow detection and adaptive control model based on sensor network.

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The traffic data for simulation is based on Mobile Century data-set. Traffic data near three intersections is used to simulate traffic data collection and timing phase opti-
mization. The traffic network is shown in Fig. 10. We select a fixed coordinate without sensor, and try to estimate traffic parameters with the method proposed in this paper based on proximity sensor readings. The estimation precision under different smooth factor $\omega$ is shown in Fig. 11. The performance is better than traffic prediction based on BP neural network [34].

In the signal timing simulation, we analyzed the performance by four scenarios: fixed-time control, inductive control, adaptive control, and congestion factor constrained control which combining delay with traffic congestion factor together as the optimization objective, and compare the performance in average delay and queue length. On the same traffic flow dataset, the performance is illustrated in Figs. 12 and 13. The criteria include average delay and the maximum queue length. The result shows that congestion factor based control optimization can increase the performance with lower average waiting time and shorter queue length.
Fig. 13 shows minimum total queue length under different traffic volume that denotes capacity of congestion dispersing under different traffic control strategies. Under peak flow 1000veh/h, comparing to fixed-time control, inductive control and adaptive control, congestion factor constrained control decrease queue length with 58%, 57% and 39% respectively, and under peak flow 2000veh/h, these values are 84%, 59% and 27% respectively. Result shows that congestion factor constrained control has obvious advantages in congestion dispersing.

6. CONCLUSION

In this paper we studied the traffic flow monitoring, congestion evaluation and congestion factor based control method based on wireless sensor networks. Taking into consideration the intrinsic properties of traffic flow and the model of traffic congestion, try to obtain optimal phase timing with better performance. The main idea is to study congestion state and its influence on future traffic flow, and combine traffic equations with optimization function. Based on the numerical solution of traffic equations via approximate method, traffic data is refined with data fitting and correlation between sensor readings. The model and algorithms are simulated based on VISSIM platform and Mobile Century dataset. The result shows better performance and it’s helpful to decrease average delay and maximum queue length.

Current research is limited to simple segments with continuous traffic flow. Future research should focus on complex segments and even road network, such as ramp, long road with multi-intersections. And the traffic control strategy, road capability and dy-
Dynamics caused by incidents need to take into consideration in actual applications. Furthermore, complex traffic flow pattern simulation and traffic control strategies on a networked scale among multi-intersections and arbitrary connecting segments in road network is also an important aspect in next step.

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