

## Research Article

# Traffic Congestion Evaluation and Signal Control Optimization Based on Wireless Sensor Networks: Model and Algorithms

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This paper presents the model and algorithms for traffic flow data monitoring and optimal traffic light control based on wireless sensor networks. Given the scenario that sensor nodes are sparsely deployed along the segments between signalized intersections, an analytical model is built using continuum traffic equation and develops the method to estimate traffic parameter with the scattered sensor data. Based on the traffic data and principle of traffic congestion formation, we introduce the congestion factor which can be used to evaluate the real-time traffic congestion status along the segment and to predict the subcritical state of traffic jams. The result is expected to support the timing phase optimization of traffic light control for the purpose of avoiding traffic congestion before its formation. We simulate the traffic monitoring based on the *Mobile Century* dataset and analyze the performance of traffic light control on VISSIM platform when congestion factor is introduced into the signal timing optimization model. The simulation result shows that this method can improve the spatial-temporal resolution of traffic data monitoring and evaluate traffic congestion status with high precision. It is helpful to remarkably alleviate urban traffic congestion and decrease the average traffic delays and maximum queue length.

## 1. Introduction

The traffic crowds seen in intersection of urban road networks are highly influential in both developed and developing nations worldwide [1]. Urban residents are suffering 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, vehicular collisions associated with traffic jams, higher emission, environmental pollution, and more. The idea that the improvements to transport infrastructure are the efficient way has been central to transport economic analysis, but in fact

this problem cannot be resolved with better roads [2–4]. Intelligent transportation systems (ITS) have been proven to be a scientific and efficient solution [5]. Comprehensive utilization of information technology, transportation engineering and behavioral sciences to reveal the principle of urban traffic, measuring the traffic flow in real time, and try to route vehicles around them to avoid traffic congestion before its formation promotes a prospective solution to resolve the urban traffic problem from the root [5–7].

Nowadays, in an information-rich era, the traditional traffic surveillance and control methods are confronted with great challenges [8, 9]. How to get meaningful information from large amounts of sensor data to support transportation applications becomes more and more significant [6, 10]. Modern traffic control and guidance systems are always networked in large scale which need real time, traffic data with higher spatial-temporal resolution that challenges the traditional traffic monitoring technologies such as inductive loop, video camera, microwave radar, infrared detector, UAV, satellite image, and GPS [11]. The state-of-the-art, intelligent, and networked sensors are emerging as a novel network paradigm of primary relevance, which provides an appealing alternative to traditional traffic surveillance approaches in near future [12], especially for proactively gathering monitoring information in urban environments under the grand prospective of cyber physical systems [13, 14]. Wireless sensors have many distinctive advantages such as low cost, small size, wireless communication, and distributed computation. Over the last decade, many researchers have endeavored to study traffic monitoring with novel technologies, and recent research shows that the tracking and identification of vehicles with wireless sensor networks for the purpose of traffic surveillance and control are widespread applications [15–19].

Traffic research currently still cannot fully express the intrinsic principle of traffic congestion formation and predict under which conditions traffic jam may suddenly occur. In the essentials, urban traffic is a typical self-driven many-particle huge system which is far from equilibrium state, where the traffic flow is a complicated nonlinear dynamic process, and the traffic congestion is the spatial-temporal conglomeration of traffic volume in finite time and space. In 2009, Flynn et al. have conducted some theoretical work to model traffic congestion with macroscopic traffic flow theory and obtained some basic results in congestion prediction [20], which are regarded as a creative solution of traffic equations proposed in 1950s and reported as a great step towards answering the key question that is how can the occurrence of traffic congestion be avoided. Based on current research, the congestion status of traffic flow is expected to be evaluated in real time and higher precision to support traffic control.

Traffic light control at urban intersection can be modeled as a multiobjective optimization problem (MOP). In UTCS (Urban Traffic Control System) such as SCOOT/SCATS/REHODES system, it always employs single loop sensor or double loops as vehicle detector deployed at upstream of the signalized intersections. Generally, in current traffic control strategies, optimization objectives include stop of vehicle, average delay, travel time, queuing length, traffic volume, vehicle speed, and even exhaust emission [21]. The traditional traffic detection is *Eulerian sensing* which collects data at predefined locations [22], and the sensors cannot be deployed in large amount as compared to the huge scale of urban road networks for sake of budget restriction and maintenance cost; as a result the data such as vehicle stops and delays of individual's vehicle is difficult to be achieved accurately. In the essentials, comparing to existing criteria mentioned above, the traffic congestion is a directly relevant factor and the root reason. Introducing a method to evaluate the degree of traffic congestion and proposing into the optimization model of traffic light control promote a feasible approach to improve traffic control performance.

In this paper, we studied the intrinsic space-time properties of actual traffic flow at the intersection and near segments and build an observation system to estimate and collect traffic parameters based on sparsely deployed wireless sensor networks. We are interested in understanding how to evaluate and express the degree of traffic congestion quantitatively and what the performance for traffic signal control would be if we take into account the traffic congestion factor as one of the objectives in timing optimization.

The rest of the paper is organized as follows. The current studies on traffic surveillance with wireless sensor networks are briefly reviewed in Section 2. The observation model based on traffic flow theory and traffic flow parameters estimation algorithm based on wireless sensor networks are described in detail in Section 3. The traffic congestion evaluation model and congestion factor based signal phrase optimization algorithms are discussed in Section 4. The performance is analyzed based on simulation and experimental results in Section 5. Finally, a conclusion and future works are given in Section 6.

## 2. Related Works and Problem Statement

Several research works on traffic monitoring with wireless sensor networks have been carried out in recent years. Most of them have focused on individual vehicle and point data detection, where the traffic spatial-temporal property is not an issue in these circumstances. Pravin et al. creatively applied the magnetic sensor networks to vehicle detection and classification in Berkeley PATH program from 2006 and obtained high precision beyond 95% [12, 23]. In 2008, UC Berkeley launched a pilot traffic-monitoring system named *Mobile Century* (successor project is known as *Mobile Millennium*) to collect traffic data based on the GPS sensor equipped in cellular phones [22]. They found that 2–5% point data provided by mobile sensors is sufficient to provide information for traffic light control, and their conclusion motivates the research to collect traffic data and control traffic flow via sparsely deployed sensor networks in this paper. Hull et al. studied the travel time estimation with Wi-Fi equipped mobile sensor networks [24, 25]. Bacon et al. developed an effective data compress and collection method based on sensor networks using the weekly spatial-temporal pattern of traffic flow data in TIME project [26]. But in current research there are some important aspects out of consideration. (1) Few considerations are given to the intrinsic space-time properties and operation regularity of actual traffic flow and traffic congestion formation. (2) How to evaluate traffic congestion quantitatively with sufficient precision and real-time performance and be introduced as an objective to support control optimization in traffic light control? (3) How to combine traffic surveillance sensor networks with traffic control system to analyze future traffic conditions under current timing strategies and try to avoid traffic congestion before its formation.

The discipline of transportation science has expanded significantly in recent decades, and particularly traffic flow theory plays a great role in intelligent transportation systems [27–29]. The typical models include LWR continuum model [30] and Payne-Whitham higher model [31]. From the physical view of traffic flow, the spatiotemporal behavior is the fundamental propriety in nature. In previous work, the vast majority of inductive techniques were focused on state-space methodology that forecasts short-term traffic flow based on historical data with relatively small number of measurement locations [32–34]. Limited amount of work has been performed using space-time model [35], and the resolution or precision is insufficient for the purpose of traffic light control. In 2008, Sugiyama et al. explained the formation process of traffic congestion by experimental observations [36], and

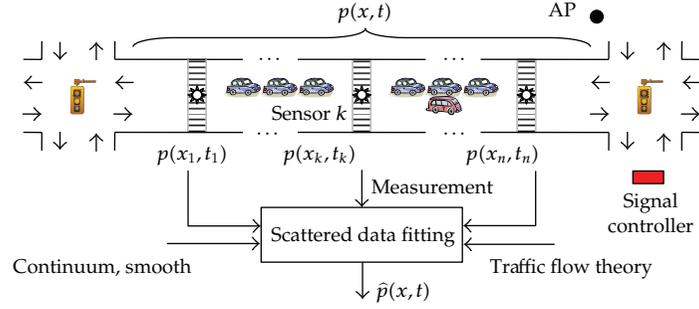


Figure 1: Deployment of wireless sensor networks for urban traffic surveillance.

based on this, Flynn et al. built a congestion model to explain and predict traffic congestion with macroscopic traffic flow theory in 2009 [20], which is regarded as a solution of traffic flow equations and a great step towards answering the key question that how can the occurrence of traffic congestion be avoided.

The goal of this paper is to estimate traffic parameters based on sparsely deployed sensor networks, evaluate the degree of traffic congestion, and obtain a quantitative factor to express the spatiotemporal properties of traffic flow in real time. Based on this, introduce the congestion factor to the optimization model of traffic light control. In this paper we use *Lagrangian* detection [37]. Not only detect point data via imperfect binary proximity sensor network [38], but also try to estimate the time-space properties along the road segment based on scattered sensor measurements. The deployment of sensor networks is shown in Figure 1, where  $p(x, t)$  denotes traffic data such as velocity and density. Based on this, the congestion status and evaluation criteria can be studied from the comprehensive scope. The sensor network is expected to monitor real-time traffic data, to predict the subcritical state, and to control traffic signal to avoid the traffic jams before its formation.

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 parameter system 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 discrete and instant values, as shown in (2.1), and here  $k$  is the sensor node number. The problem of traffic flow information monitoring can be transformed to estimate traffic parameters in given spatial and temporal variables  $t$  with these discrete values (Nomenclature and symbols are available in Table 1):

$$U_t = (u_1, \dots, u_k)^T, \quad P_t = (\rho_1, \dots, \rho_k)^T. \quad (2.1)$$

### 3. Traffic Monitoring and Data Estimation

In this section, we firstly describe the intrinsic characteristic of traffic flow and then propose a method to estimate traffic parameters based on scattered data collected by sparsely deployed sensor networks.

**Table 1:** Nomenclature and symbols.

$x \in [0, L_e]$	Location in road segment
$u(x, t)$	Traffic flow speed
$x_i(t)$	Vehicle trajectory
$\hat{P}(x, t)$	Estimated traffic data
$\tilde{u}$	Equilibrium speed
$p(\rho)$	Traffic pressure
$S(k)$	Sensor readings at time $k$
$t_{\text{up}}, t_{\text{down}}$	Time signals exceed threshold
$\Delta t, \Delta x$	Temporal-spatial scales
$e_k^m$	Error from sensor $k$ of vehicle $m$
$\eta = (s - xt)/\tau$	Self-similar variable
$g_i^l, g_i^u$	Min/max green time
$J_m(k)$	Cost function on lane $m$
$q_{\text{out}}^j(k)$	Outflow in phase $j$
$d_i(k)$	Demand flow in phase $j$
$S_{ni}^g$	Saturation flow for green
$\xi_{ni}(k)$	Existing phase state
$t \in [0, +\infty)$	Observation time
$\rho(x, t)$	Traffic density
$p(x, t)$	Traffic data
$\rho_M$	Maximum traffic density
$u_f$	Free speed on empty road
$s(x, t)$	Flow production rate
$h(k)$	Vehicle detection threshold
$d(k)$	Detection flag
$u_k^m$	Speed of vehicle $m$ at sensor $k$
$\hat{E}_k$	Mean square error (MSE)
$C_{cf}^i(t)$	Congestion factor of lane $i$
$G_i$	Effective green time
$q_{\text{in}}^j(k)$	Inflow in phase $j$
$q_s^i(k)$	Arrival traffic flow at stop line
$s_j(k)$	Exit flow in phase $j$
$S_{nj}^y$	Saturation flow for yellow
$l_{ni}(k)$	Queue length in phase $i$

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

The continuum model is excellent to describe the macroscopic traffic properties such as traffic congestion state. In 1955, Lighthill and Whitham introduced the continuum model (LWR model) [30] based on fluid dynamics, which builds the continuous function between traffic density and speed to capture the characteristics such as traffic congestion formation. In 1971, Payne introduced dynamics equations based on the continuum model and proposed the second-order model (Payne-Whitham model) [31]. Consider the

Payne-Whitham model defined by (3.1) (conservation of mass) and the acceleration equation, written in nonconservative form as (3.2):

$$\frac{\partial \rho}{\partial t} + \frac{\partial(\rho u)}{\partial x} = s(x, t), \quad (3.1)$$

$$\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} + \frac{1}{\rho} \frac{\partial p}{\partial x} = \frac{1}{\tau} (\tilde{u} - u), \quad (3.2)$$

where  $x$  and  $t$  denote the space and time, respectively,  $u(x, t)$  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, and  $p$  is traffic pressure which is inspired from gas dynamics and typically assumed to be a smooth increasing function of the density only, that is,  $p = p(\rho)$ . 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 on empty road, and  $\rho_M$  is the maximum traffic density at which vehicles are bumper-to-bumper in the traffic jam. In MIT model of self-sustained nonlinear traffic waves, the relationship between  $\tilde{u}$  and  $\rho$  denotes as the following. Here  $u_f$  denotes free flow speed, and  $\rho_M$  is the traffic flow density in congestion state:

$$\tilde{u}(\rho) = \tilde{u}_0 \left(1 - \frac{\rho}{\rho_M}\right)^n, \quad u(\rho) = u_f - \frac{u_f}{\rho_M} \rho. \quad (3.3)$$

In (3.1), the  $s(x, t)$  is flow production rate, and for road segment with no ramp  $s(x, t) = 0$ , for entrance ramp  $s(x, t) < 0$ , and for exit ramp  $s(x, t) > 0$ . Assume the velocity of vehicle traveling from the given intersection during the green light interval is  $v_x(t)$ , and the intervals of green light phase are  $T$ ; thus the flow production rate can be denoted as follows:

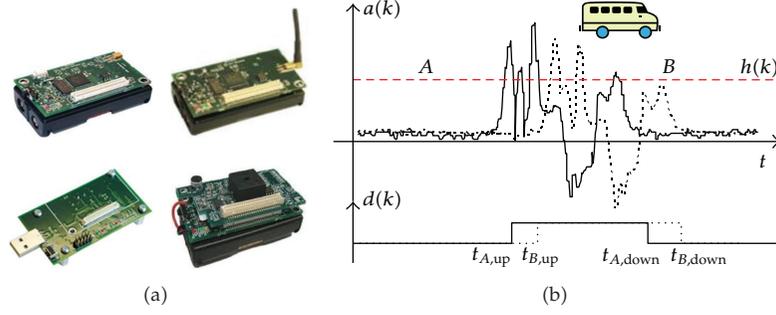
$$s(x, t) = \int_0^T v_x(t) dt. \quad (3.4)$$

Based on the exact LWR solver developed by Berkeley [39], we can obtain the solutions of traffic equations with given initial parameters. That means the operation status and future parameters of the traffic flow can be predicted and analyzed on a system scale.

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

In this paper, we employ high sensitive magnetic sensor, as shown in Figure 2(a), to detect vehicles. Given that the detection radius is  $R$ , sensor node detects travelling vehicle with the ATDA algorithm developed by UC Berkeley [12], which detects vehicle presence based on an adaptive threshold, and estimates vehicle velocity with the time difference of up/down thresholds and the lateral offset [12, 23], as shown in Figure 2(b).

Where  $D$  is sensor separation,  $s(t)$  is the raw data, which will be sampled as sensor readings in discrete values  $s(k)$  and transformed to  $a(k)$  after noise filtering.  $h(k)$  is the threshold at detection interval  $k$ , and  $d(k)$  is the corresponding detection flag. The instantaneous velocity can be estimated by (3.5). Here time  $t_{\text{up}}$  and  $t_{\text{down}}$  are the moments



**Figure 2:** (a) Magnetic sensor node and gateway. (b) Presence and velocity detection based on ATDA.

when magnetic disturbance signals exceed the threshold continuously with count  $N$  and  $M$ , respectively:

$$\hat{v}_{mk} = \text{avg} \left( \frac{D_{AB}}{t_{B,up} - t_{A,up}}, \frac{D_{AB}}{t_{B,down} - t_{A,down}} \right). \quad (3.5)$$

In actual applications, for sake of cost, the sensor node number is expected as few as possible [40], so there need a tradeoff between sensor number and measurement precision. In this paper we try to improve the traffic detection exactness based on the spatial and temporal relations of sampled data. The main idea is to estimate the lost traffic information based on the limited sensor readings with traffic flow model and numerical interpolation. 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, respectively. Consequently the two-dimensional  $x - t$  domain is transformed to a grid mesh, as shown in Figure 3, which can be denoted by (3.6) for an arbitrary location and detection time. Where  $(x_i, t_j)$  is grid point and the  $h$  and  $k$  are spatiotemporal scales that can be denoted as  $h \equiv \Delta x$  and  $k \equiv \Delta t$ ,

$$x_i = ih, \quad t_j = jk, \quad i \in [0, L], \quad j \in [0, T]. \quad (3.6)$$

For 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 takes effect in time interval  $[j, j + 1] \cdot \Delta t$ . To take into account the disconnected vehicle queue under unsaturated state, here the sensed traffic flow speed is defined as the average velocity of all vehicles that pass the detection point in predefined interval. In actual applications, the traffic data is typically collected in 20 s, 30 s, 1 min, or 2 mins.

The sensor network is sparsely deployed, and the total number of sensor node is  $K$ . We denote by  $v_{mk}$  the actual speed of the  $m$ th vehicle travelling from the  $k$ th sensor in the detection grid  $g(i, j)$ ,  $\hat{v}_{mk}$  is the estimated speed calculated from sensor measures,  $u_k$  is the average speed in detection grid,  $m$  and  $m'$  are the first and last vehicles in detection interval,

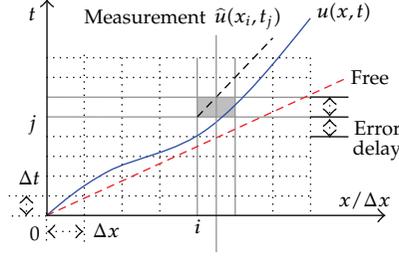


Figure 3: The detection grid in  $x-t$  space.

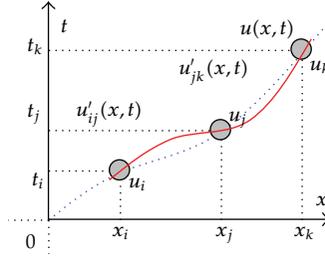


Figure 4: Scattered data fitting with proximity points.

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 the following equations:

$$u_k = \frac{1}{m' - m} \sum_{i=m}^{m'} v_{ik}, \quad \hat{u}_k = \frac{1}{m' - m} \sum_{i=m}^{m'} \hat{v}_{ik}. \quad (3.7)$$

Assume that we have trajectories of a certain number of vehicles  $M$  in an observation interval. If the scale is small enough, it could be inferred that the traffic flow speed keeps unchanged in the unit grid. And consequently the partial differential equations (3.1)–(3.4) can be rewritten in an approximated way, such as (3.8). Here the subscripts  $i$  and  $j$  indicate space and time, respectively:

$$\left[ \frac{\partial u}{\partial x} \right]_i^j = \frac{u_i^j - u_{i-1}^j}{h}. \quad (3.8)$$

With the scattered measurements as boundary initial values, the traffic data can be estimated by numerical interpolation based on the approximated traffic equations, as shown in Figure 4. For instance of traffic flow speed detection, denote by  $\hat{u}_k^m$  and  $u_k^m$  the estimated and actual velocities 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

$$e_k^m = \hat{u}_k^m - u_k^m. \quad (3.9)$$

There are many evaluation criteria for error optimization; we use the same objective function as that in [41], which has the expression of (3.10) as follows. Here  $\hat{E}$  is the objective function, and  $\hat{E}_k$  is the mean square error (MSE) of traffic parameter estimation for all  $M$  vehicles on sensor  $k$ . And the purpose of optimal estimate algorithm is to minimize the total MSEs of all sensors:

$$\hat{E} = \frac{\sum_{k=1}^K \sum_{m=1}^M (e_k^m)^2}{M} = \sum_{k=1}^K \hat{E}_k \quad \text{where } \hat{E}_k = \frac{\sum_{m=1}^M (e_k^m)^2}{M}. \quad (3.10)$$

Assume  $K$  point data  $\hat{u}(x_i, t_i)$  is obtained in detection area  $g(i, j)$ , and  $u(x_i, t_i)$  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 denoted as (3.11), which is a two-dimensional random field, and we assume it is unbiased:

$$\frac{1}{K} \sum_{i=1}^K \left[ \frac{\hat{u}(x_i, t_i) - u(x_i, t_i)}{\hat{u}(x_i, t_i)} \right]^2 = \sigma_{\text{rms}}^2. \quad (3.11)$$

The velocity change in real traffic flow  $u(x, t)$  is continuous. To eliminate noise, we introduce the smoothing factor with the minimum sum of squares of the second derivative, as shown in (3.12). Where  $\Omega$  denotes two-dimensional square detection area,

$$\omega_{\min} = \min \int_{\Omega} \sum_x \sum_t \left( \frac{\partial^2 u(x, t)}{\partial x \partial t} \right)^2 d\Omega. \quad (3.12)$$

The traffic data estimation can be transformed to a two-dimensional data fitting problem with time-space constraints based on scattered measurements. To solve the conditional extremum problem based on (3.11) and (3.12), we can use the similar method in [42] based on Lagrange multiplier and finite elements method.

## 4. Congestion Factor Based Signal Optimization

In this section, we focus on traffic congestion evaluation and signal optimization. Based on traffic flow theory, the traffic flow near signalized intersections and connecting links can be modeled as entrance and exit ramps. The traffic light control algorithm will generate a shock wave at the stop line of the lanes, from the beginning of red signal phase, which will affect the traffic state in future. We introduce congestion factor to evaluate the degree of traffic congestion, and cost function to represent the influence of current timing phase on next phase. The result is helpful to optimize signal control.

### 4.1. Traffic Congestion Evaluation and Congestion Factor

The traffic congestion without external disturbance is an unsolved mystery. Knowing that traffic on a certain road is congested is actually not very helpful to traffic control system, and the information about how congested it is and the process it formed is more useful. There

is much novel research about traffic congestion prediction and evaluation in last decades [43, 44]. Flynn et al. studied these phenomena and introduced the traffic congestion model named *Jamitons* [20], in which the traffic congestion is modeled as traveling wave. Based on the traffic model described in (3.1)-(3.2), the traffic congestion can be expressed and denoted in a theoretical way. Assuming the speed of traveling wave is  $s$ , with introducing the self-similar variable defined by  $\eta = (s - xt)/\tau$ , the traffic equations in Section 3.1 can be rewritten, and (4.1) holds:

$$\frac{du}{d\eta} = \frac{(u - s)(\tilde{u} - u)}{(u - s)^2 - c^2}, \quad (4.1)$$

where  $s$  is the speed of the traveling shock wave, and traffic flow density and speed can be denoted as function of  $\mu$ ,  $\rho = \rho(\eta)$ ,  $u = u(\eta)$ . The subcritical state can be predicted by (4.1), where  $c = \sqrt{p\rho} > 0$  denotes the subcritical condition. To solve these equations, we select the shallow water equations [45] denoted as (4.2) to simplify the problem:

$$p = \frac{1}{2}\beta\rho^2. \quad (4.2)$$

Applying this assumption to (4.1) and the LWR model denoted by (3.1) and (3.2), (4.1) can be rewritten as (4.3). Here  $m$  is a constant denoting the mass flux of vehicles in the wave frame of reference:

$$\frac{du}{d\eta} = \frac{(u - s)\{\tilde{u}_0(1 - (m/\rho_M(u - s))) - u\}}{(u - s)^2 - (\beta m/(u - s))}. \quad (4.3)$$

The subcritical condition is therefore denoted as (4.4). If this equation is satisfied, the traffic congestion is inevitable to occur. The density will reach  $\rho_M$  immediately when traffic conditions exceed the subcritical state:

$$u_c = s + (\beta m)^{1/3}. \quad (4.4)$$

The road can be regarded as share resource for vehicle and traffic flow link, and according to Jain's fairness index for shared computer systems, the quantitative congestion factor can be defined based on the traffic congestion model, as (4.5). Here  $i$  indicates the lane number,  $x$  is the locations coordinate with origin starting from stop line, and the traffic density is sampled in  $n$  discrete values with fixed frequency. The congestion factor indicates the general congestion state on the whole road segment, which is a number between 0 and 1, and larger value means more crowded:

$$C_{cf}^i(t) = \frac{(\sum_{m=1}^n \rho(x_m))^2}{n \sum_{m=1}^n (\rho(x_m))^2}. \quad (4.5)$$

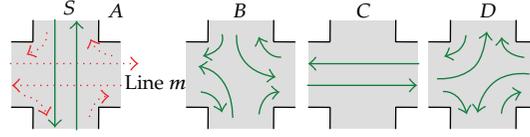


Figure 5: Four phases of traffic control.

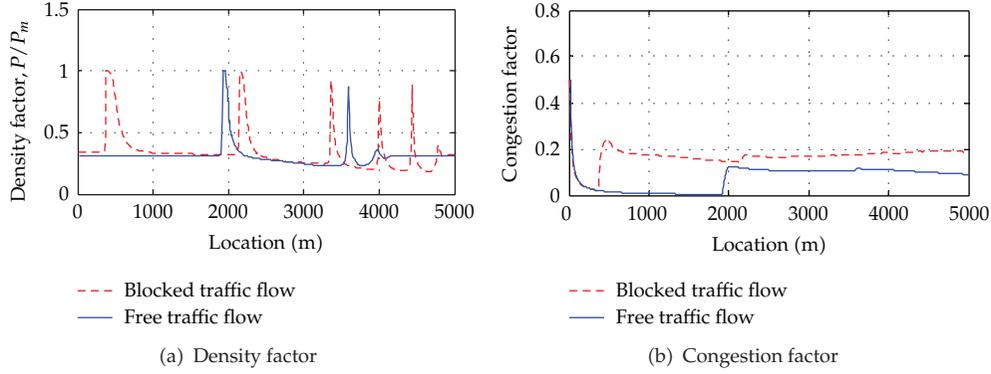


Figure 6: Traffic congestion factor at observation point  $x$ .

Considering an intersection with four phases numbered  $A$ ,  $B$ ,  $C$ , and  $D$ , as shown in Figure 5, the phase timing can be denoted as (4.6). Here  $g_i^l$  and  $g_i^u$  represent the minimum and maximum green times, respectively, and  $G_i$  is the effective green time of phase  $i$ :

$$G = \{G_A, G_B, G_C, G_D\}, \quad G_i \in [g_i^l, g_i^u]. \quad (4.6)$$

Under the scenario of 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 (4.7). Here  $\Delta T$  is timing adjustment step length, and  $C_{cf}^m(k)$  and  $C_{cf}^m(k)$  represent congestion factor on lane  $m$  of traffic flow under blocking status by signal and normal condition with green light, respectively. The normal condition can be simulated based on (3.1) and (3.2) with initial values detected by sensor networks at time  $t$ , where  $s(t) \equiv 0$ . And traffic parameters can be predicted by resolving the traffic equations:

$$J_m(k) = \sum_{i=0}^K |C_{cf}^m(k) - C_{cf}^m(k)|, \quad k \in [0, K], \quad K = \frac{G_A}{\Delta T}. \quad (4.7)$$

With the Matlab implementation of an exact LWR solver [39], we can build a virtual simulator of traffic flow scheduling to analyze the traffic equations, congestion factor, and cost function in a theoretical way, based on given initial conditions. For traffic flow of a straight lane, consider two scenarios that traffic flow runs continuously and blocked by red signal at time  $t$ , the congestion factor and cost function can be simulated. The result is shown in Figure 6.

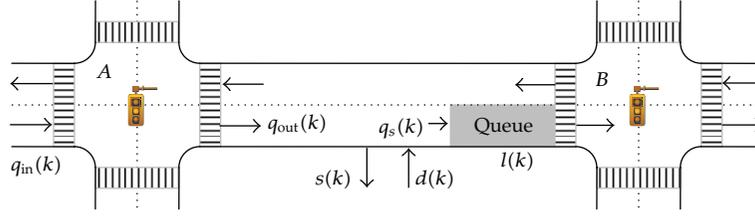


Figure 7: Urban intersection and road link model for traffic signal control.

#### 4.2. The Multiobjective Optimization Model for Signal Control

The problem of traffic timing optimization for an urban intersection in a crowded city has been previously approached in much research [46, 47], and the existing traffic signal optimization formulations usually do not take traffic flow models in consideration. The variables on a signalized intersection and connecting links of phase  $j$  are shown in Figure 7. We define  $q_{in}^j(k)$  and  $q_{out}^j(k)$  to be the inflow and outflow, respectively, and define  $d_j(k)$  and  $s_j(k)$  to be the demand 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  $S_{nj}^g$  and  $S_{nj}^y$  as the saturation flow for green and yellow times of phase  $j$  at intersection  $n$ .  $u_{ni}^k(k)$  indicates the signal, and  $u_{ni}^k(k) = 0$  means green light and  $u_{ni}^k(k) = 1$  means red light. To simplify the problem we just optimize the phase timing, with assumption that phase order is kept unchanged, four phases, as shown in Figure 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,

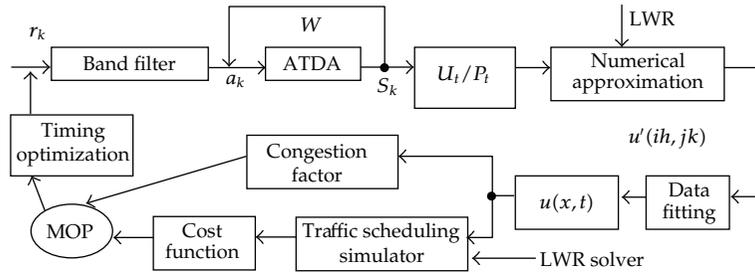
$$\text{Delay } TD = \Delta T \sum_{n=1}^N \sum_{i \in I_n} \sum_{k=1}^K l_{ni}(k), \quad (4.8)$$

$$\text{Congestion factor } CF = \sum_{m=1}^M \sum_{k=1}^K C_{cf}^m(k), \quad (4.9)$$

$$\text{Cost function } J = \sum_{m=1}^M \sum_{k=1}^K J_m(k). \quad (4.10)$$

With constraints subject to

$$\begin{aligned} g_i^l &\leq G_i \leq g_i^u, \\ l_{ni}(k) &\geq 0, \quad k \in K; \quad l_{ni}(k) \geq_{ni}(k-1) + (q_s^i(k) - q_{out}^i(k))\Delta T, \\ q_{in}^j(k) &= \sum_i b_{ij} q_{out}^i(k), \\ q_{out}^i(k) &= (1 - u_{ni}(k)) \left[ S_{ni}^g (1 - \xi_{ni}(k)) + S_{ni}^y \times \xi_{ni}(k) \right] + S_{ni}^g \times \xi_{ni}(k) \times u_{ni}(k). \end{aligned} \quad (4.11)$$



**Figure 8:** Flow diagram of traffic flow detection and adaptive control model based on sensor network.

For a given time window  $T$ , based on constraints of (4.10), the timing problem can be separated into  $h$  ( $1 \leq h \leq T/g^l - 1$ ) subproblems. We can solve these  $h$  problems and obtain  $h$  noninferiority set of optimal solutions and then merge them to get a new noninferiority set of optimal solutions, which is the solution of the original problem. In this paper we use MOPSO-CD (*Multiobjective Particle Swarm Optimization Algorithm using crowding distance*) to find the optimal timing.

### 4.3. Traffic Flow Detection and Control Algorithms

Based on the above model and computational method, the overall block diagram of traffic data detection and control algorithm is shown in Figure 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  $U_t, P_t$  contains all sensor readings that will be used to approximate the traffic equation and numerical approximation  $w(ih, jk)$  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 (3.9), 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 strategy will be taken into consideration before making the final signal, and the optimal timing can be obtained by solving a MOP. 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 [22, 48] and LWR solver [39]. VISSIM is a microscope, time interval, and driving behavior based traffic simulation tool kit. It supports external signal control strategies by providing API with DLL. The simulation tool will invoke the *Calculate* interface with presupposed frequency. And user can obtain the signal control related data in this interface.

With the DLL and COM interfaces, we designed a software/hardware in the loop simulation platform based on VISSIM, as shown in Figure 9.

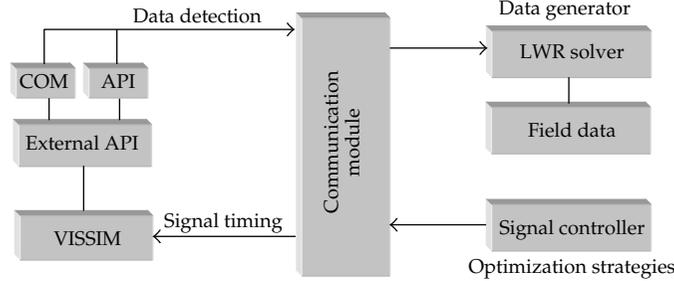


Figure 9: Software/hardware in the loop simulation based on VISSIM.

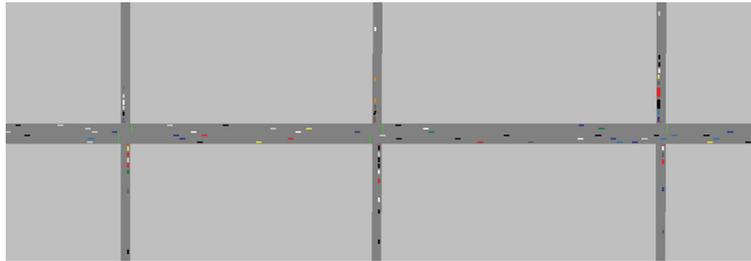


Figure 10: Traffic networks for timing optimization simulation.

The traffic data for simulation is based on Mobile Century dataset. Traffic data near three intersections is used to simulate traffic data collection and timing phase optimization. The traffic network is shown in Figure 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 Figure 11. The performance is better when compared to traffic prediction based on BP neural network.

In the control simulation, we analyzed the performance by two scenarios: control with delay constraint only and combining delay with traffic congestion factor together as the optimization objective, and compare the performance with fixed time control. On the same traffic flow dataset, the performance is illustrated in Figure 12. 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.

## 6. Conclusion and Future Research

In this paper we study the traffic flow congestion evaluation and congestion factor based control method using sparsely deployed wireless sensor network. Taking into consideration the traffic flow intrinsic properties and traffic congestion model, try to obtain optimal phase timing with as few sensor node as possible. The main idea is to study the congestion and its influence on future traffic flow, combine traffic equations with the optimization function, to obtain the numerical solution of the traffic equations via approximate method, and finally to refine traffic sensor data based on data fitting. The model and algorithms are simulated based

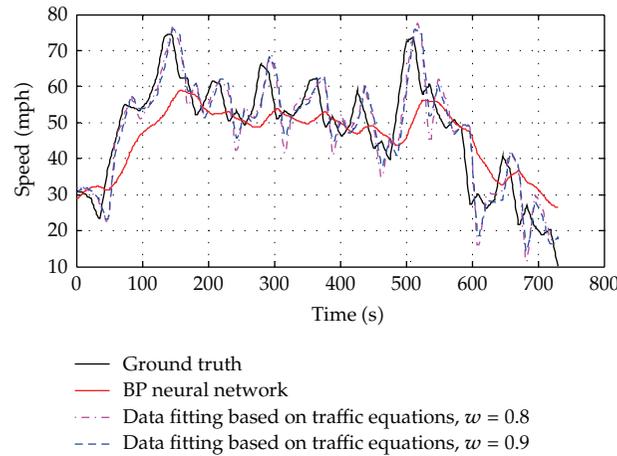


Figure 11: Performance of traffic data estimation based on traffic equations.

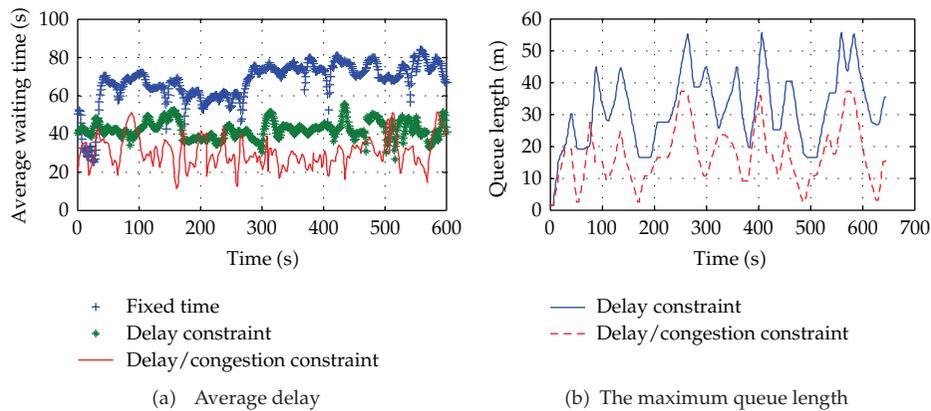


Figure 12: Performance analysis of traffic control based on congestion factor.

on VISSIM platform and *Mobile Century* dataset. The result shows better performance, and it is helpful to decrease average delay and the maximum queue length at the intersection.

Current research is limited to single intersection and 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 dynamics caused by incidents need to be taken 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 are also an important aspect in next step.

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