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Chaos Theory in Urban Traffic Flow: Is Crowd Sensed Data Driving the Macro-traffic Behavior to Oscillation or Equilibrium?

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Abstract— **Stability theory tells us that a dynamic system will eventually converge to its stable state, in which the system's overall energy is at its minimum. On the other hand, chaos theory states that small perturbations of the system are able to drive itself from previously-stable state to another state. This phenomenon has been observed in many fields like cosmetology, physics, biology and chemistry. Our research question is whether chaos theory also applies to the transportation domain. Specifically, when we are given imperfect or delayed crowd-sensed data, will we observe the cyclic/oscillatory transition between different traffic states? This paper aims at investigating this chaotic phenomenon (oscillatory traffic behavior in this paper) on urban transportation with imperfect or delayed crowd-sensed information and delivering recommendations for crowdsensing-based traffic applications to avoid the undesirable oscillations.**

I. INTRODUCTION

Funds for transportation network investment have long failed to keep pace with the ever growing traffic volumes (from 980 million units in 2009 to 1.015 billion units in 2010, reported by [1]), hence traffic congestion occurs and has become one of the plagues of modern life in almost all the metropolitan cities.

In the 39 metropolitan areas in the United States with the population of one million or more, roughly one-third of all vehicular travels take place under congested conditions in which the travel speed averages half of the free-flow value. About half of this congested driving is on expressways, causing a delay of about six-tenths of a minute per kilometer of travel; the remaining half is on other urban networks, causing about 1.2 minutes delay per kilometer of travel [2].

Research has shown that the cost of driving is quantifiable. Through their actual choices, drivers have demonstrated a willingness to pay, on average, about $1.33 to save 10 minutes travel time, or $8.00 per hour. This figure does not include the costs of disruption from the unpredictability of traffic delays, or the costs of extra fuel, accidents and air pollution. Even without taking all of these additional factors into account, the annual cost of driving delays comes to $48 billion, or $640 per driver [2].

On the flip side of the coin, with the rapid development of data sensing and communication technologies, people can be granted with more and more real time traffic information for statistical analysis, prediction and recommendation. Pervasive networked sensing systems can provide traffic engineers with great opportunities to monitor and predict traffic flow and provide intelligent route guidance system (RGS) [3] and parking recommendation systems [4].

Since traffic congestion is created by a crowd of drivers, relying on the crowd itself to provide information service so as to avoid traffic jams seems to be a reasonable way. This essentially leads to *crowdsensing* techniques which fetch information from the crowd of participants and provide instructions to the drivers after processing the data. In the next section, we will provide a detailed review on crowdsensing applications to traffic related services.

However, if the crowdsensing application can significantly influence the crowd behavior, are we creating new traffic jams? Furthermore, if we are creating new traffic jams, and we rely on crowdsensing technique to, again, direct drivers away from the newly created traffic jam, will we see the flipping behavior of traffic flow? Let us take the following scenario as an example. Imagine there are two routes, namely, A and B. Currently, A is less congested. As a crowdsensing application detects it and sends a mass of cars through route A, in this case, B becomes less congested. The crowdsensing application will send many drivers to route B, which will make B crowded again and A less crowded. Over the course of a few minutes/hours, the crowdness of routes A and B will alternate with one another as the preferred routes.

This paper tries to investigate whether this kind of oscillatory crowd behavior will appear under crowdsensing applications, and gives out some general recommendations on how to avoid the meaningless oscillatory crowd behavior.

The paper structure is as follows: we lay down related literature of crowdsensing applications for transportation, and oscillation phenomenon in other research fields in Section II, followed by the modeling work in Section III. We perform simulation and analysis of the model, and give out recommendations to crowdsensing applications in Section IV. The paper ends with conclusion and future works in Section V.

II. RELATED WORK

In this section, we perform literature review in both traffic-related crowdsensing applications and oscillatory phenomenon in other research fields such as biology. We want to evaluate whether crowdsensing applications lead to similar oscillatory behaviors as what already exist in other domains.

A. Crowdsensing Applications in Transportation

The term "crowdsensing" refers to the process where a number of users equipped with sensing and computing devices share their individually sensed data, process and obtain meaningful information for an objective of interest

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[5]. The devices may include, for example, smartphones, sensor embedded gaming systems (XboX, Wii), and in-vehicle sensor devices. In this subsection, we review the main crowdsensing applications in traffic domain.

There have been numerous crowdsensing applications for routing guidance and parking recommendations. TrafficSense [6] collects users' travel related information such as travel mode, speed and acceleration, in the meanwhile provides route planning services to the user. Based on the fused crowdsensing information, TrafficSense is able to monitor the real time traffic information and therefore give smart recommendations. DoppelDriver [7] tries to answer the common question of "What would have happened, had I taken the alternative route?", through crowdsensing applications. The authors measure and compare the actual travel time of the current route with those on road segments corresponding to alternative routes, through crowdsensed traffic measurements (from other contributing users) and generate route recommendations. SmartRoad [8] is a crowdsensing application for the detection of traffic regulators (traffic lights, stop signs). With enough user penetration, SmartRoad is able to build a transportation with the geo-location of traffic regulators, hence provide safe recommendations when the user is approaching it without noticing the traffic light.

Crowdsensing for Parking has also seen a wide variety of products, see [4], [9], [10] as examples. ParkNet [9] is, to the best of our knowledge, the first to apply the idea of crowdsensing for Parking recommendations. It provides a mobile approach to collect road-side parking availability information, and the accuracy is reportedly over 95%. However, its reliance on extra sensors (such as ultrasonic range finder for parking availability detection) to be installed on ParkNet vehicles prohibits its extensive deployment to the market.

All in all, crowdsensing applications rely on a 'crowd' of users to build the traffic map (say travel-speed map, traffic light location map, parking availability/location map), then the application would use the map to provide services back to the crowd. While the idea is straightforward to implement, there is one underlying assumption: the crowdsensed map is not influenced by the 'crowdsensed recommendation'. This assumption may be true for crowdsensing applications with a small penetration of users, when the user penetration is large enough, the assumption is violated, and oscillatory behavior might appear. In the next subsection, we will give a review on the oscillation phenomenon in other areas without crowdsensing, then we consider crowdsensing and evaluate whether oscillation phenomenon occurs in crowdsensing applications with large enough user penetration rate.

B. Oscillation Phenomenon in Other Research Fields

Oscillation phenomenon has long been be observed in many domains, ranging from biology (Turing model), chemistry (BZ reaction), animal respiratory system (central pattern generation) to morphogenesis (gene regulatory networks) and cosmology (universe expansion contraction theory). This subsection provides a brief overview of the existing research works that are trying to explain the oscillation phenomenon in those domains.

In biology, the existence of oscillatory patterns is bountiful (see the periodical strip pattern on a zebra or a fish in Fig. 1 as examples). One of the fundamental questions in developmental biology is how the vast range of pattern and structure we observe in nature emerges from an almost uniformly homogeneous fertilized egg [11]. Turing proposes a computation model [12] which is able to generate periodical patterns out of an almost uniformly homogeneous fertilized egg. The study took the form

$$\frac{\partial \boldsymbol{u}}{\partial t} = \boldsymbol{D}\nabla^2 \boldsymbol{u} + \boldsymbol{f}(\boldsymbol{u}), \tag{1}$$

where $\boldsymbol{u}$ is a vector of chemical concentrations, $\boldsymbol{D}$ a matrix of constant diffusion coefficients (usually diagonal) and $f(u)$ the reaction kinetics (typically nonlinear).

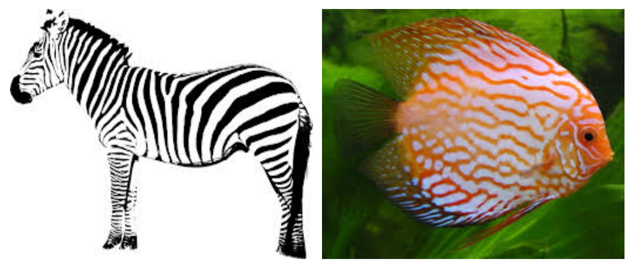


Fig. 1. Biological Oscillatory Pattern Example

In chemistry, the Belousov-Zhabotinsky system [13] exhibits similar oscillations as what exists as Turing patterns for animals. The chemical reactions among the injected elements are far from equilibrium and remain so for a significant length of time and evolve chaotically [13]. They provide an interesting chemical model of non-equilibrium biological phenomena, and several researchers have provided different (from simple to complex) mathematical models to explain the oscillatory behavior.

Respiratory system itself is an oscillatory (or even periodic) system. Animals inhale and exhale in a certain rhythm. Neurologists propose several kinds of neural networks, called central pattern generators (CPGs) [14] explaining the underlying mechanism that generate the oscillatory(cyclic) behavior. CPGs have also been used as controllers for robot's oscillatory/cyclic movement such as crawling, waling and running [15].

Oscillatory phenomena have also been be observed in both microscopic world and macroscopic world, which attracts researchers from totally different domains to hypothetically propose dynamic models for explanations to similar phenomena. Recent discoveries inside molecules reveal that the gene expression levels are also exhibiting oscillatory behavior [16]. However, since the underlying coupled relationship among genes are still a mystery to human beings, researchers often use offline evolutionary algorithm to explore the gene regulatory relationship and hence explain the oscillatory phenomenon in gene expression levels [17]. In the ultra macroscopic world, the universe also exhibits some kind of oscillatory behavior [18]. Scientists have proposed different computation models to explain the phenomenon. For example, Einstein has postulated a universe expansion-and-contraction theory as probed explanations to the cyclic universe behavior (which has been translated and revisited by [19] recently).

This paper tries to pioneer in research on whether the oscillatory phenomenon will occur in traffic under crowdsensing applications. Like researchers in other domains, we are also trying to build a reasonable mathematical model for the influence of crowdsensing applications to traffic behavior. Then, we will evaluate whether and under which condition, the oscillatory behavior is likely to occur, and we will give out recommendations to avoid this unnecessary oscillations.

III. The Dynamic Models for Crowdsensing Traffic Applications

In this section, we will lay down two reasonable models which, on the one hand are reasonable for a crowdsensing application, on the other hand, do (in some cases) generate oscillating traffic behaviors. We take route recommendation as the crowdsensing application scenario, and we argue that it can be generalized to almost all the other traffic related crowdsensing applications. In this specific crowdsensing-based route recommendation system, drivers' travel speed is gathered, and after the travel speed map has been built up, the fastest route as route recommendation will be delivered to the crowdsensing application users. It is worth noting that we propose two *separate* models which consider the effect of information delay and information quality, respectively. Unifying the two separate models and evaluating the co-effects are left for future works.

A. Relationship Between Velocity and Traffic Density

It has long been discovered that the route's velocity is roughly inversely proportional to the route's traffic density [20], see Fig. 2 as an example. When there are very few vehicles on the road, vehicles are traveling in the free-flow state, and the travel speed is at the route's maximally allowed speed. As the vehicle density increases, drivers have to drive carefully to avoid clashing with each other, and hence the travel speed decreases gradually. When the vehicle density grows into a certain size, traffic jam occurs, and the travel speed is decreased to almost zero.

Throughout this paper, we use a simple negative sigmoid function to approximate the relationship between a route's average travel speed and the route's traffic density. The quantitative relationship is shown in Eq. 2:

$$v = 2 \cdot V_f(1 - f(x)), \tag{2}$$

where v is the driving speed of the route, V_f is a constant number which is equal to the free flow speed of that route, x is the traffic density of the route, and $f(.)$ is a sigmoid function which is defined in Eq. 3:

$$f(x) = \frac{1}{1 + e^{-kx}} \tag{3}$$

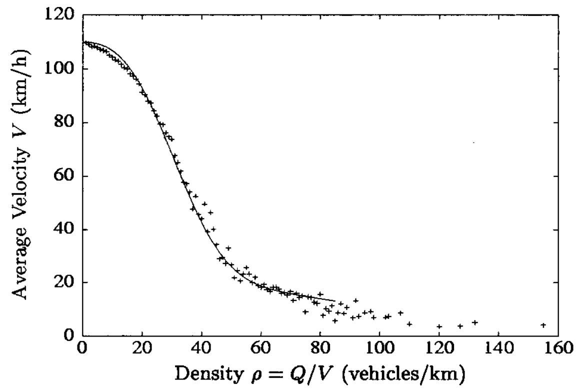


Fig. 2. Empirical relationship between velocity and vehicle density.

where k is a constant positive number determining the slope of the sigmoid function.

In the following two subsections, we will introduce two models which, in some cases, will generate oscillatory traffic behaviors. The first model mainly investigates the impact of information delay to the potential oscillatory traffic behavior, while the second model explores whether the quality of crowdsensing information will lead to oscillatory behavior. Before introducing the two models, we would like to clarify the parameters that are going to be used:

1) $x_i(t)$: the (true) vehicle density at route i at time t;
2) $x_{i,d}$: the default vehicle density at route i, which cannot be influenced by the crowdsensing application;
3) $x_{i,c}$: the crowdsensing vehicle density at route i, which can be influenced by the crowdsensing application;
4) $v_i(t)$: the velocity of route i at time t;
5) m: the total number of routes in the simulation;
6) τ: information delay of the crowdsensing system, which will be further explained in Model I;
7) q_i: information quality of route i, which will be further explained in Model II;
8) k_{q_i}: the relative weight of information quality over the velocity in Model II;
9) p: penetration rate of the crowdsensing application, i.e., the number of users that are influenced by the crowdsensing application over the total number of users;

The inherent relationship between the parameters are: $x_{i,d}(t) + x_{i,c}(t) = x_i(t)$ and $p = \sum_{i=1}^{m} x_{ic} / \sum_{i=1}^{m} x_i$.

B. Model I: Information Delay Effect

The information flow process of the crowdsensing system is: (1) the system gathers traffic information from the users, (2) it processes the information and reach a traffic map, (3) it delivers route guidance recommendation to the crowdsensing users. A natural consequence of the information flow is that there is a time delay between the crowdsensed traffic map and the real time traffic map. We conjecture that the delayed information might lead to oscillatory traffic behavior. We note the delay time step as τ.

The underlying rationale for crowdsensing route recommendation is that the crowdsensing application always makes decisions based on an 'old' traffic map, and hence influence the users accordingly. Eq. 4 describes the dynamics of vehicle densities along different routes:

$$\begin{aligned}\frac{dx_{i,c}}{dt} =& -\left(x_{i,c}(t-\tau) - \frac{1}{m}\sum_{j=1}^{m} x_{j,c}(t-\tau)\right) \\ &+ \left(v_i(t-\tau) - \frac{1}{m}\sum_{j=1}^{m} v_j(t-\tau)\right) + u_i(t),\end{aligned} \tag{4}$$

where $u_i(t)$ refers to the difference between incoming vehicles and leaving vehicles from outside the system at time t. In the following simulation section, we just set $u_i(t)$ to be zero for simplicity, since whatever outside input will not influence whether there are oscillations. All the other related parameters are pre-listed in the previous subsection.

The explanation of the design of Eq. 4 is as follows: (1) the information gathering has a time delay of τ; (2) if the detected vehicle density of route i ($x_{i,c}(t-\tau)$) is larger than the detected average vehicle density ($\frac{1}{m}\sum_{j=1}^{m} x_{j,c}(t-\tau)$), route i's density tends to decrease, because this route is more congested in terms of vehicle densities and users tend to leave this route for other routes based on the crowdsensed information; (3) if the detected velocity is higher than average, that route's density tends to increase, because drivers would like to come from other slower routes to the faster routes. Point (2) explains the first term of the right hand side (RHS) of Eq. 4, and Point (3) explains the second term.

From the dynamic equation as described in Eq. 4, we can see that the change of the crowdsensing vehicle density at route i depends on the relative velocity difference between the current route (route i) and the mean values of all the routes (but with the delayed information of τ).

The information delay τ will (in some cases) have the oscillation effect. Let us imagine a simple scenario in the following: there are only two routes (Route A and Route B), and the time delay is 5 minutes, which means that the crowdsensing users' decision making is always based on the crowdsensed information 5 minutes ago. Suppose that Route A is faster than Route B, the crowdsensed drivers will go to Route A, and it will make Route A slower than Route B. However, since there is an information delay of 5 minutes, the crowdsensed drivers are still continuously going to Route A, until the crowdsensing application finally finds that Route A is slower than Route B, which, in fact, happened 5 minutes ago. The effect has already been overshooting for 5 minutes, and then drivers start to alternate and change to Route B, which will again overshoot for 5 minutes, thus this flipping route behavior will continue. In Section IV, we will perform extensive simulation to test under which cases the oscillatory behavior happens and to what extent it can influence the overall traffic dynamics.

C. Model II: Information Quality Effect

Another factor that might cause oscillatory behavior out of crowdsensing applications is the information quality. Since the crowdsensed traffic map is built out of the crowdsensing users, the penetration rate of users will determine the quality of the traffic map. The underlying rationale is that when we have a large penetration rate of crowdsensing users, the information quality is high, however, since the penetration is high, it will most probably mean that the velocity along the route is low (congested). While for another route with lower penetration rate, the velocity is high, but the information quality is also low.

Let us take the two routes example again. Route A has a lot of users, thus information quality is high, but the velocity is low; on the other hand, Route B has fewer users, which makes information quality low, but the velocity high. If the velocity in Route A is 'bearable', users will stay there, because the information quality is high. However, as more and more users switch to Route A, the velocity becomes too slow, and users in Route A will take a chance to go to Route B. This will make Route B's information quality increase, and users will find that Route B is *really* faster than Route A. Now more users switch to Route B, and Route B's information quality increases, however, its velocity decreases. At some point, the crowdsensing users find that Route A is faster than Route B, and start to come back to Route A. The oscillation will continue like this. We will give out detailed experiments in Section IV. Now, we represent this scenario's density dynamics per route as follows:

$$\frac{dx_{i,c}}{dt} = k_{q_i} q_i(x_i) + v_i(x_i) - \frac{1}{m}\sum_{j=1}^{m}\left(k_{q_j}(x_j) q_j + v_j(x_j)\right) \tag{5}$$

Here, we model the value of k_{q_i} as two values which corresponds to high velocity and low velocity respectively. For high velocity, users care more about quality (i.e, whether the reported high velocity is accurate), while for low velocity, users care more about the value of velocity (because the velocity is too slow). In other words, k_{q_i} is a function of velocity, which takes two values, namely $k_{q_i,h}$ and $k_{q_i,l}$.

$$k_{q_i} = \begin{cases} k_{q_i,h}, & \text{if } v_i \geq V_{th} \\ k_{q_i,l}, & \text{otherwise.} \end{cases}$$

The quality of the route (q_i in Eq. 5) is defined as:

$$q = f_q(x) = \frac{1 - e^{-k_1 x}}{1 + e^{-k_1 x}} \tag{6}$$

where the quality of the information $q \in (0, 1)$. Here, as the user density increases, the quality of the information should increase. In the meanwhile, information quality has an upper limit as well as a lower limit. Hence $f_q(x)$ is defined an increasing function with saturation in both sides. The velocity-density relation model is expressed in Eq. 7:

$$v = g_v(x) = 2V_f(1 - \frac{1}{1 + e^{-k_2 x}}), \tag{7}$$

where $g_v(x)$ is a decreasing function with saturation.

In the next section, we perform experiments to evaluate whether and under which condition the dynamic equations as described in Eq. 5 generate oscillatory traffic behaviors.

IV. Simulation, Evaluation and Analysis

This section provides simulation results over the dynamic equations as presented in Model I and Model II, and the corresponding analysis. Recommendations are given in the end.

A. Penetration Rate

Before evaluating each of the proposed models, we would like to quantify the overall influential ability of the crowdsensing application to the overall traffic dynamics. Suppose the penetration rate of the crowdsensing application is p (Here, $p = n_c/n$ where n_c is the number of drivers that can be influenced by the crowdsensing application and n is the total number of drivers in the system), how much influence do we have if we can direct the paths of those n_c users? Here, the term 'influence' is defined as the velocity increase percentage over free flow state if we can direct p of the vehicles away, i.e, $influence = \frac{V_{crowdsensing} - V_{default}}{V_f}$, where $V_{default}$ is the route's velocity without crowdsensing inference, V_f is the route's free flow velocity (Note that$V_{default}$ is usually much smaller than V_f, since the default travel speed might be very low, i.e, traffic jam velocity).

Looking at Eq. 2 and Fig. 2, we can see that velocity is roughly inversely proportional to the vehicle densities. As we increase the overall vehicle densities, the predicted velocity goes down (will eventually go to zero, which corresponds to traffic jam occurrence). On the other hand, as we reduce the overall vehicle densities, the predicted velocity increases (will eventually go to free flow status). As we have already noted, n is the total vehicle density and p is the penetration rate, we re-write Eq. 2 into the following form:

$$v = 2 \cdot V_f (1 - \frac{1}{1 + e^{-k(1-p)n}}), \qquad (8)$$

We set $k = 0.1$, and perform simulation to evaluate to which extent our crowdsensing application can influence the overall traffic state. Fig. 3 shows the evaluation results. In the figure, we evaluate the effect of the penetration rate under three conditions: (1) n is small which makes $V_{default}$ the same as free flow speed, (2)n is medium which makes $V_{default}$ a bit smaller than free flow speed, (3) n is high which makes $V_{default}$ equal to traffic jam speed.

In Fig. 3, we can see that as we increase p, the crowdsensing influence increases. As long as the default traffic state is not in free flow state, we can have a big enough influence of velocities when $p > 0.05$. (Here, suppose the free flow velocity (V_f) is 120 km/h, an increase of 8% already means a velocity increase of $9.6 km/h$, and we deem it ($9.6 km/h$) as a big enough number which will influence the overall traffic dynamics, since users will deem the other route as much faster than the current route.)

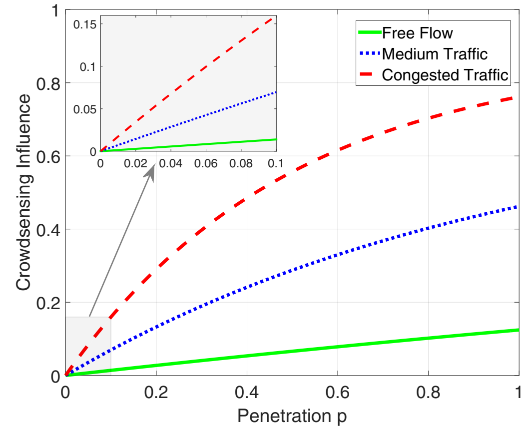
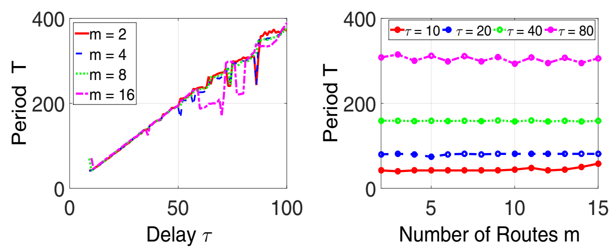


Fig. 3. Crowdsensing Effect VS. Penetration Rate



(a) Crowdsensing Effect VS. Time Delay τ (b) Crowdsensing Effect VS. The Number of Routes m

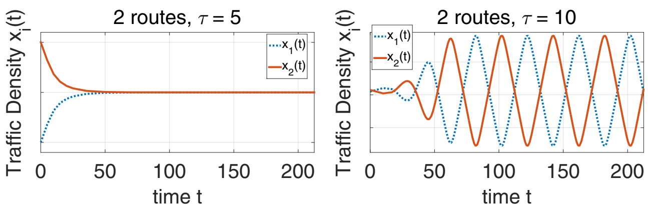
Fig. 4. Crowdsensing Effects VS. the Two Parameters

The discussion in this subsection shows that if we have a penetration of less than 0.05, we do not need to worry about the effect of the crowdsensing application to the overall traffic state. We can just go ahead with the recommendation. However, if we surpass that threshold, we have to consider the effect of the crowdsensing application itself. In the next two subsections, we assume that we already have a large-enough penetration rate (we set the penetration rate to be 0.3), and evaluate other parameter's impact on the oscillatory behavior.

B. Evaluation on Model I: Time Delay Effect

Besides the penetration rate p, which has already been discussed in the previous subsection, we have two other important parameters in Model I, namely time delay τ and the total number of routes m. This subsection will evaluate the effect of τ and m on the oscillatory traffic effect.

Fig. 4(a) shows the relationship between the oscillation period (T) and time delay (τ), if there is no oscillatory behavior, we simply leave the area with blank. In the figure, we can see that, for different m, as we decrease τ, all the oscillation period decreases. When the time delay (τ) is reduced below a certain threshold (9 in our simulation), the oscillation effect disappears (which is corresponding to system equilibrium state). On the other hand, as we can see from Fig. 4(b), if we have a fixed τ, as we increase the number of routes m, the oscillation period will almost not change. This reveals that regardless of the number of



(a) Equilibrium Example (b) Oscillation Example

Fig. 5. Example of Oscillation and Equilibrium

routes(m), the oscillatory behavior (oscillation period) stays the same. However, if m is too large (15 in our simulation), the oscillation period will change a little. The two subfigures in Fig. 5 illustrate the convergence and oscillatory effects of crowdsensing application to overall traffic.

C. Evaluation on Model II: Information Quality Effect

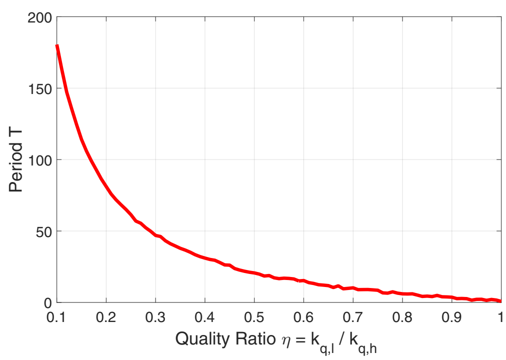


Fig. 6. Crowdsensing Effect VS. η

There are two key parameters that need to be evaluated for Model II, namely the quality ratio, η ($\eta = \frac{k_{q,l}}{k_{q,h}}$) and the number of routes, m. As we have already evaluated the effect of m in Model I, and due to page limits, we only evaluate the effect of η in Model II to the oscillatory behavior. Fig. 6 shows the relationship between the leading oscillation period and η (m is set to be 2). From the figure, we can see that, as we increase η, the oscillatory effect (oscillation period (T)) becomes smaller and smaller, until the end, there is no oscillation when $\eta > 0.9$. This phenomenon is explainable. If in the extreme case, k_q does not change at all ($\eta = 1$), it means that the users will always weigh the information quality and velocity at a fixed value, the state dynamics as described in Eq. 6 is differential equations with constant coefficients, and will converge to the equilibrium. On the other hand, as we widen the disparity between $k_{q,l}$ and $k_{q,h}$, the jump behavior will come into play, and the system will oscillate. The illustrative example of oscillation as well as equilibrium behavior over the macroscopic traffic system is quite similar to Fig. 5, and hence is omitted here.

D. Recommendations

This paper has investigated the impact of crowdsensing applications to the macroscopic traffic behavior. Based on the proposed models and simulation results, we offer the following recommendations to crowdsensing system developers.

If the crowdsensing system can only influence a relatively small portion of people (i.e, user penetration rate is less than 5%), the application will not influence the overall macroscopic dynamics. On the other hand, if the crowdsensing application has a large penetration rate, the oscillatory behavior might occur due to two specific factors, namely, time delay, and information quality. In order to avoid the overall oscillatory behavior, the crowdsensing system needs to be real time enough (with a small enough τ). If this feature is not attainable, we suggest that the application incorporate an inherent prediction mechanism and then deliver traffic-related recommendations. For information quality, currently it is assumed that the crowdsensing application delivers both the velocity and the quality of the information to the users, and users switch the weight between information quality and information goodness (high velocity in our case study). In this case, oscillatory traffic behavior might happen. It is suggested that the crowdsensing application delivers a constant weighted combination of the two information metrics as the final suggestion to the crowdsensing users without giving out the liberty of letting the user decide the weight.

V. Conclusion and Future Works

This paper presents some initial work on modeling the effects of crowdsensing applications with large user penetration rate on overall traffic dynamics. Two dynamic models, involving information delay effect and information quality effect respectively, are proposed and results are presented and analyzed. Simulation results show that when the crowdsensing traffic application has a relatively large user penetration rate, the application itself might create oscillatory behavior under various kinds of circumstances, i.e, information delay, information quality variation. Overall recommendations to avoid such phenomenon are given.

Our current work has proposed two separate dynamic models, then we evaluated the effect of information delay and information quality independently. One near future work is to unify the two proposed models to see whether and under which condition the overall oscillatory behavior happens. In the next phase, we would like to bring the research into practice by cooperating with crowdsensing application developers, so that we can validate our proposed models, and deliver more concrete recommendations to avoid this kind of oscillatory traffic phenomenon.

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