

Monte Carlo

A general overview of methods, theory and practice

Alexandros Sopasakis
Department of Mathematics
UNC Charlotte

Lectures

- Lecture 1- Background and theoretical/analytical development of the Monte Carlo method
- Lecture 2- Numerical simulation practices and common techniques used in modern modeling applications
- **Lecture 3- A research project perspective: application to traffic flow**

Outline

- The traffic model: properties and dynamics
- Calibration and parameter estimation
- Simulations and comparisons (one-lane highway)
- Deterministic closures and macroscopic models
- Multi-lane extensions
- Conclusions & References

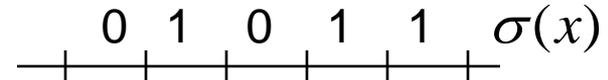
Proposed Traffic Model Properties/Attributes

- Asymmetric Simple Exclusion Process (ASEP)
- Arrhenius microscopic stochastic dynamics
- One directional flow
- Look-ahead interaction potential
- Retarded acceleration
- Timely braking
- Conservation of vehicles (assuming no entrances or exits)
- Numerical simulations via Kinetic Monte Carlo (KMC)
- Extensions to macroscopic traffic flow models and PDEs

Main Statistical Mechanics Concepts

We let Λ denote a **lattice** of N cells.

We also denote by $\sigma(x)$ the **spin configuration at x** .



We introduce the microscopic stochastic Ising process $\{\sigma_t\}_{t \geq 0}$

A spin configuration σ is an element of the configuration space $\Sigma = \{0,1\}^\Lambda$ and we write

$$\sigma = \{\sigma(x) : x \in \Lambda\}$$

The stochastic process $\{\sigma_t\}_{t \geq 0}$ is a **continuous time jump Markov** process on $L^\infty(\Sigma, \mathbb{R})$ with **generator**

$$Mf(\sigma) = \sum_{\substack{x \in \Lambda \\ y \neq x}} c(\sigma) [f(\sigma^*) - f(\sigma)]$$

The corresponding energy Hamiltonian is

$$H(\sigma) = \frac{1}{2} \sum_{x \in \Lambda} U(x) \sigma(x)$$

where the interaction potential is given by

$$U(x) = \sum_{\substack{z \neq x \\ z \in \Lambda}} J(x, z) \sigma(z) - h$$

where J denotes the local interaction potential

$$J(x, y) = \gamma V(\gamma |x - y|)$$

Here $\gamma = 1/(2L+1)$ and L denotes the interaction radius.

Equilibrium states of the stochastic model are described by the Gibbs measure $\mu_{\beta,N}$ at the prescribed temperature T ,

$$\mu_{\beta,N}(d\sigma) = \frac{1}{Z} e^{-\beta H(\sigma)} P_N(d\sigma)$$

where $\beta = \frac{1}{kT}$ and $P_N(d\sigma) = \prod_{x \in \Lambda} \rho(d\sigma(x))$

and $\rho(\sigma(x) = 0) = \frac{1}{2}$, $\rho(\sigma(x) = 1) = \frac{1}{2}$

The Mathematical Model

$$\frac{d}{dx} Ef(\sigma) = EMf(\sigma)$$

where $Mf(\sigma) = \sum_{x \in \Lambda} c(\sigma)[f(\sigma^*) - f(\sigma)]$

and σ^* denotes a new lattice configuration

Microscopic Arrhenius Spin-Exchange Dynamics

The Arrhenius spin-exchange rate $c(x,y,\sigma)$

$$c(x, y, \sigma) = \begin{cases} c_d e^{-U(x)}, & \text{if } \sigma(x) = 1, \text{ and } \sigma(y) = 0, \\ c_d e^{-U(y)}, & \text{if } \sigma(x) = 0, \text{ and } \sigma(y) = 1, \\ 0 & \text{, otherwise} \end{cases}$$

With exchange rate constant, $c_d = \frac{1}{\tau_0}$

Here τ_0 denotes the characteristic time of the stochastic process.

Again recall that $U(x) = \sum_{\substack{z \neq x \\ z \in \Lambda}} J(x, z) \sigma(z)$

The Arrhenius spin-flip rate $c(x, \sigma)$ at lattice site x and spin configuration σ is given by

$$c(x, \sigma) = \begin{cases} c_d e^{-U(x)}, & \text{when } \sigma(x) = 0 \\ c_a & \text{when } \sigma(x) = 1 \end{cases}$$

With adsorption/desorption constants, $c_a = c_d = \frac{1}{\tau_I}$

Here τ_I denotes the characteristic time of the stochastic process.

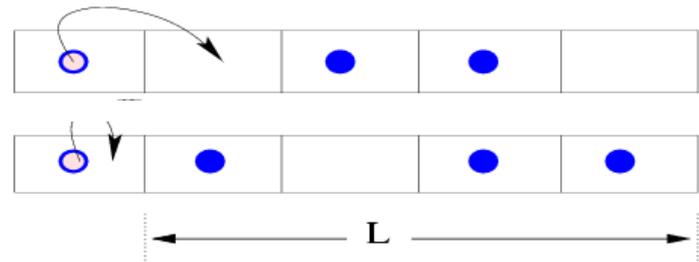
We consider **short vehicle** potential **interactions** J ,

$$J(x, y) = V(\gamma(x - y)), \quad x, y \in \Lambda$$

where $\gamma = 1/L$ as usual ordains the range of microscopic Interactions.

Here $V: R \rightarrow R$ via,

$$V(r) = \begin{cases} J_0, & \text{if } 0 < r < 1 \\ 0, & \text{otherwise} \end{cases}$$



Which enforces:

- Exclusion princile
 - Vehicles do not go backward in traffic
 - Local effect of the interactions
- (thus once again, more realistic traffic conditions)

The Traffic Model

$$\frac{d}{dt} Ef(\sigma) = EMf(\sigma)$$

or in more detail,

$$\frac{d}{dt} Ef(\sigma) = E \sum_{\substack{x \in \Lambda \\ y \neq x}} c(x, y, \sigma) [f(\sigma^*) - f(\sigma)]$$

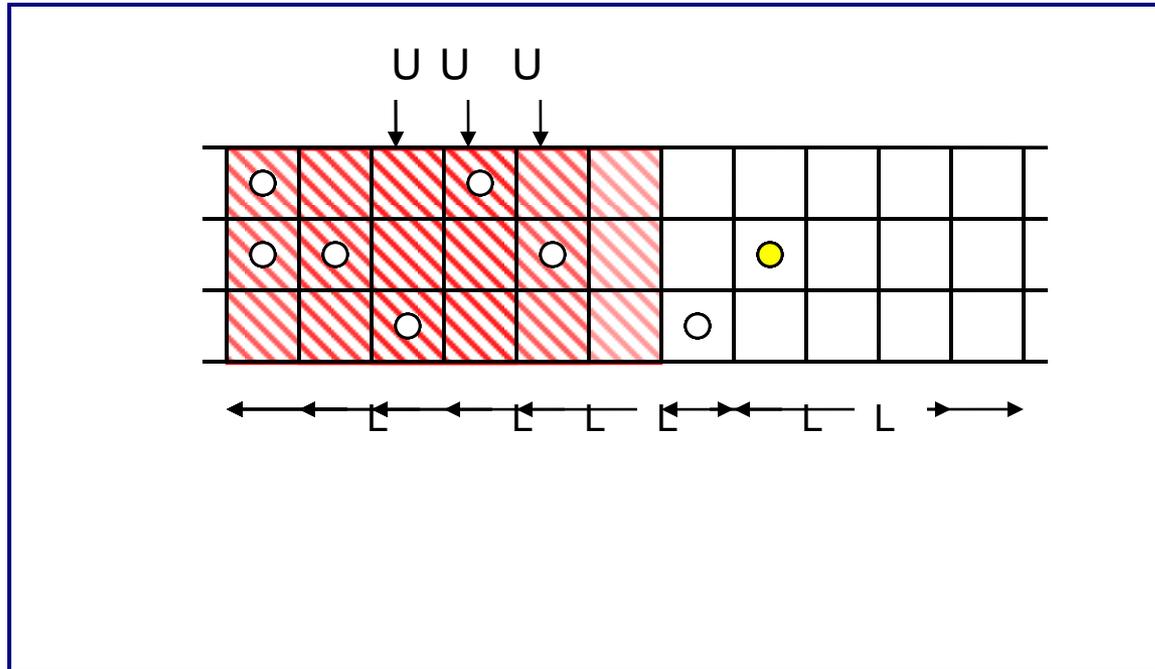
which based on the [spin-exchange rate](#) $c(x, y, \sigma)$ for $y=x+1$ gives,

$$\frac{d}{dt} Ef(\sigma) = E \sum_{x \in \Lambda} c_0 \sigma(x)(1 - \sigma(x+1)) e^{-U(x, \sigma)} [f(\sigma^{x, x+1}) - f(\sigma)]$$

The probability of a spin-exchange between x and $y=x+1$ during time $[t, t+Dt]$ is

$$c(x, y, \sigma) \Delta t + O(\Delta t^2)$$

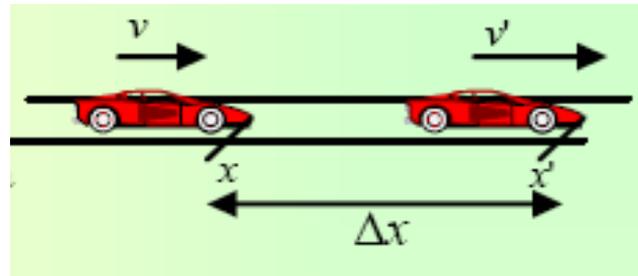
A simple schematic describing the traffic model dynamics



Free Parameters and Calibration

The model is characterized by the following three undetermined parameters:

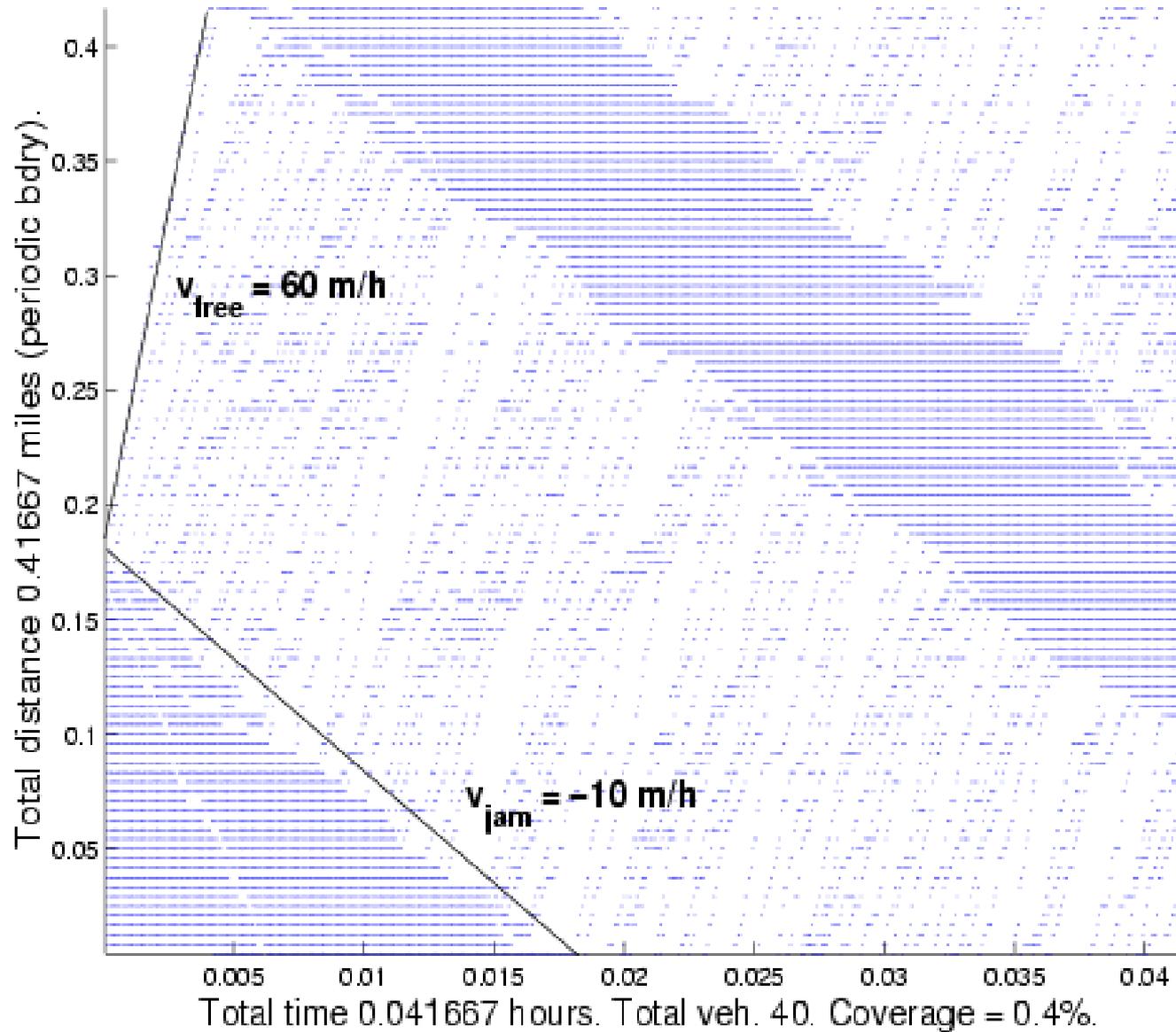
- τ_0 - the characteristic time of the stochastic process
- J_0 - the strength of the interactions
- L - the interaction potential range



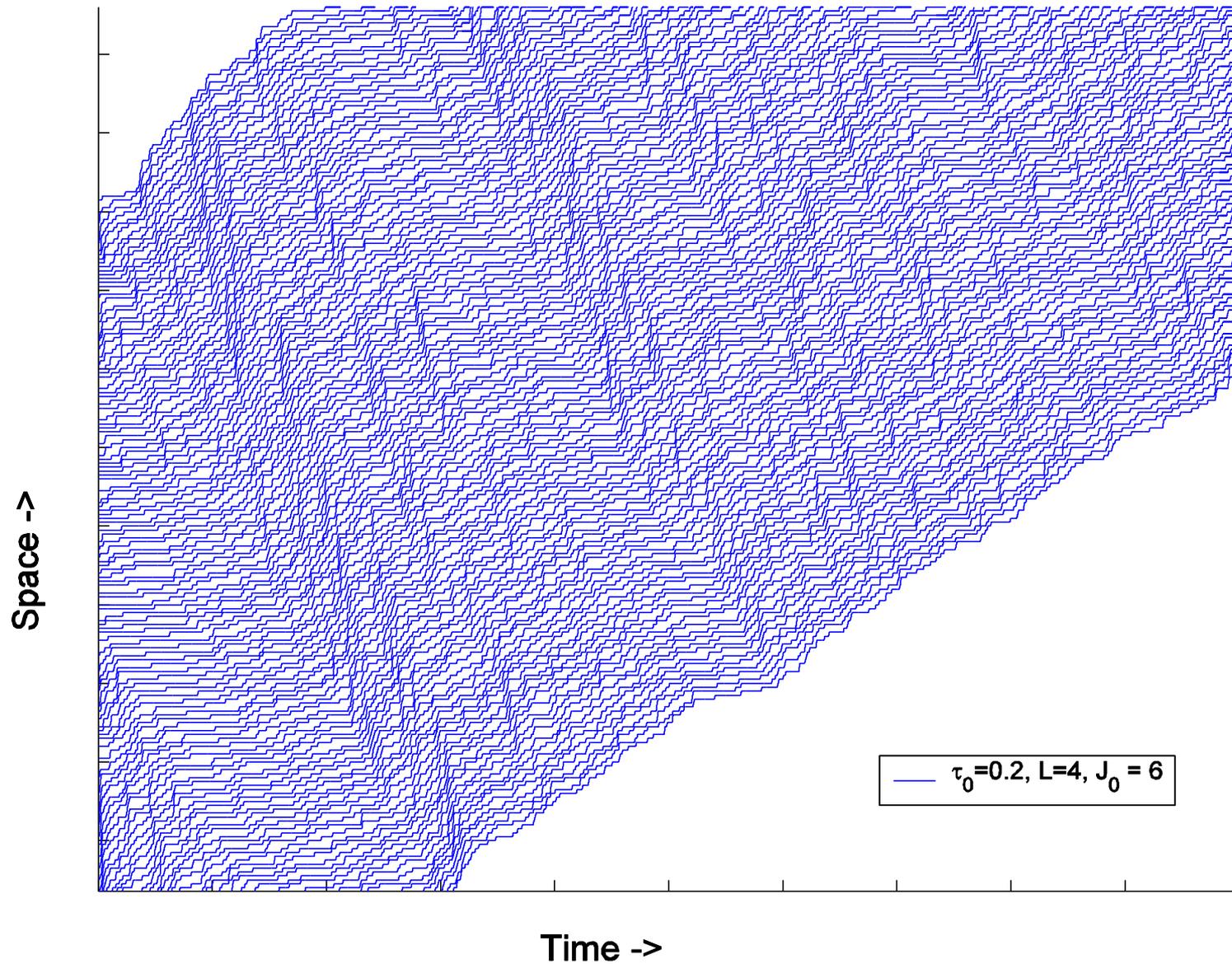
Cell length is assumed to be 22 feet (average vehicle size plus safe distance).

$$\Delta t_{cell} = \frac{22 \text{ feet}}{65 \text{ miles/hour}} \approx \frac{1}{4} \text{ sec.}$$

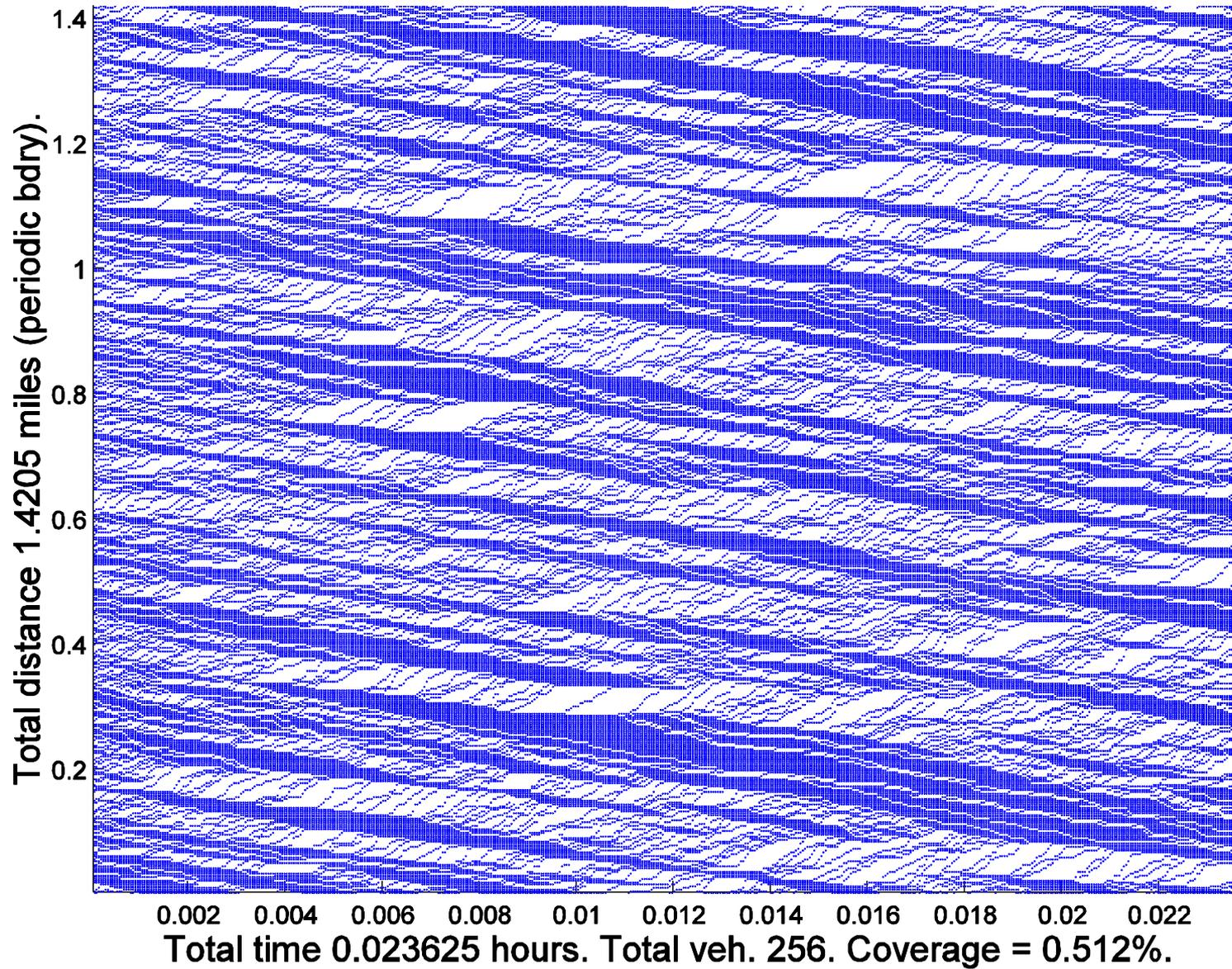
Spatial and temporal vehicle allocations.



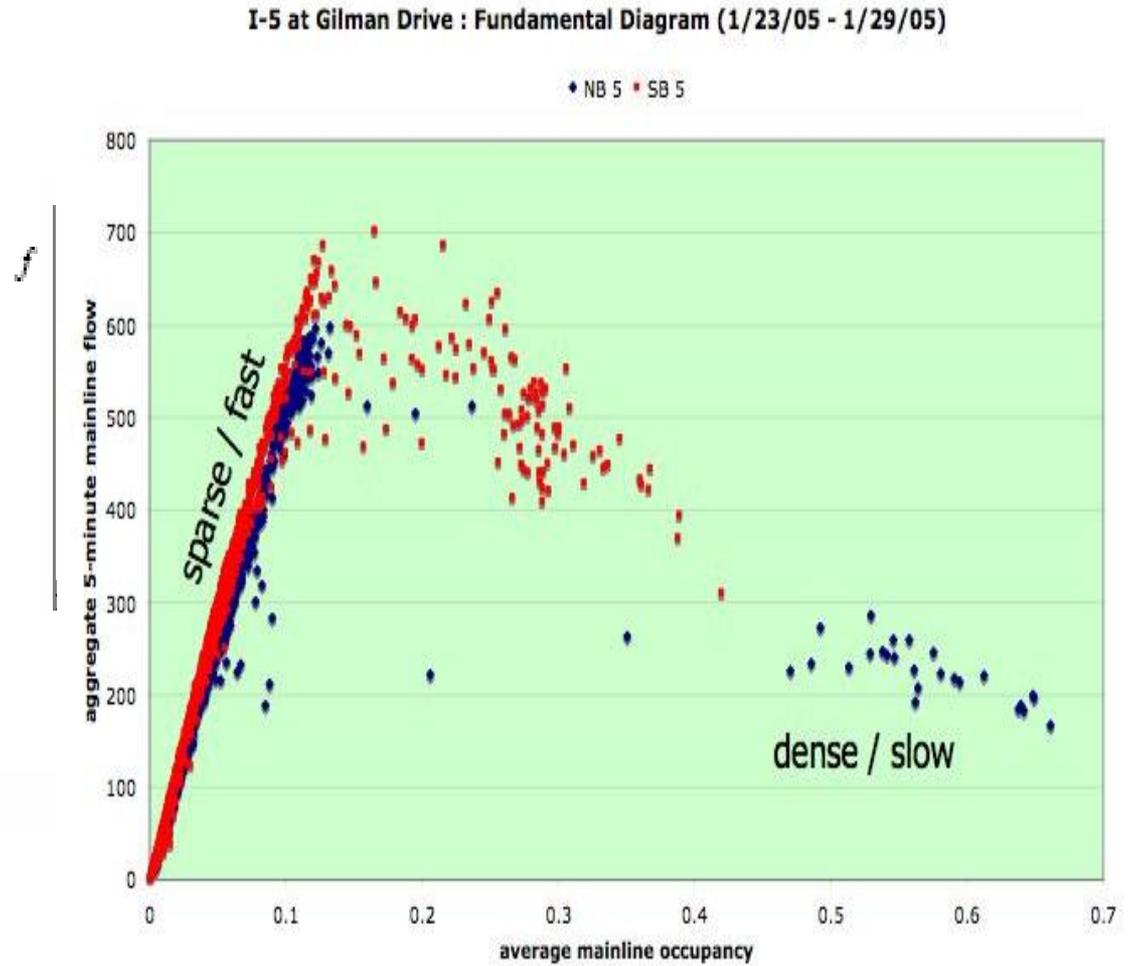
Spatial and temporal vehicle trajectories.

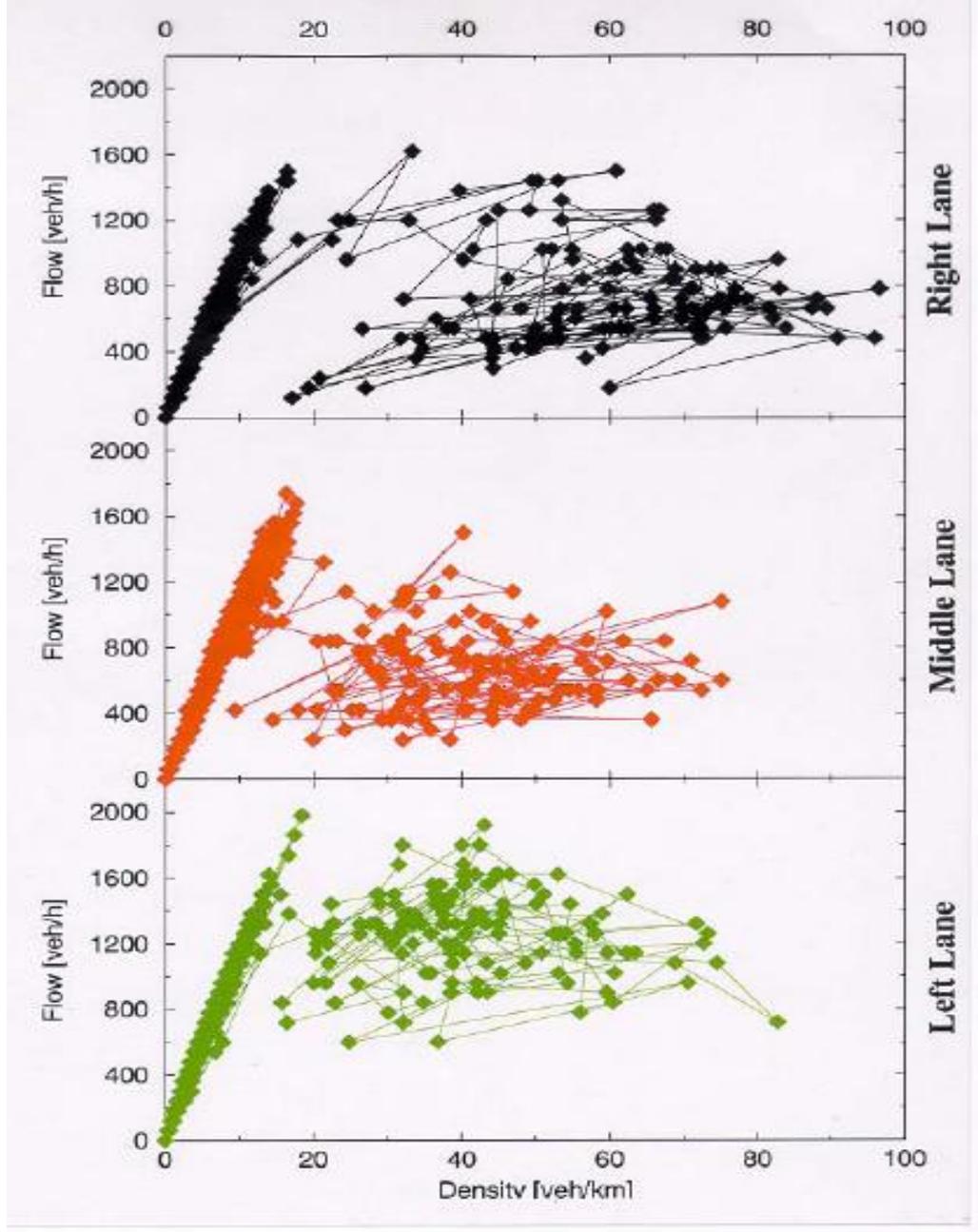


Spatial and temporal vehicle allocations.

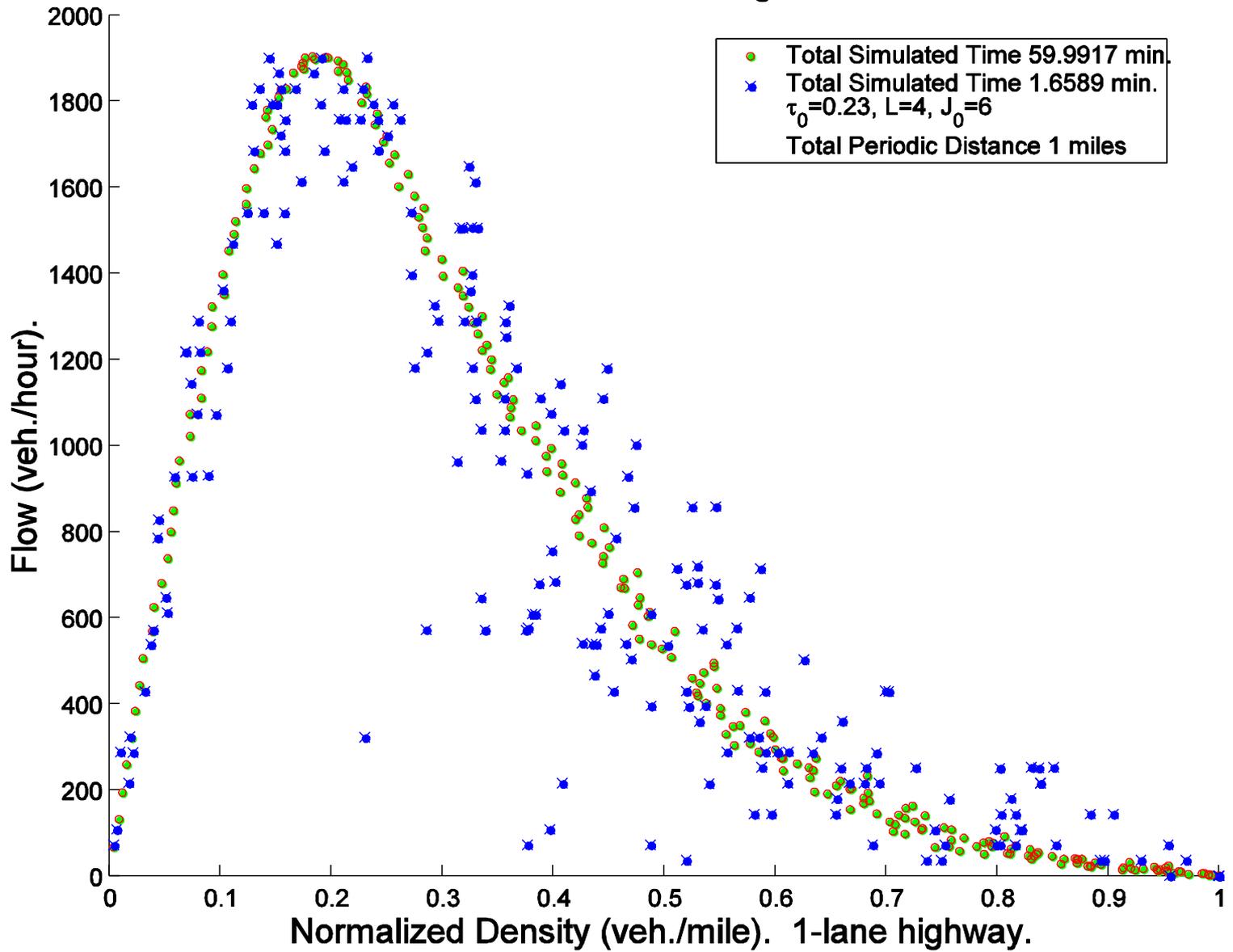


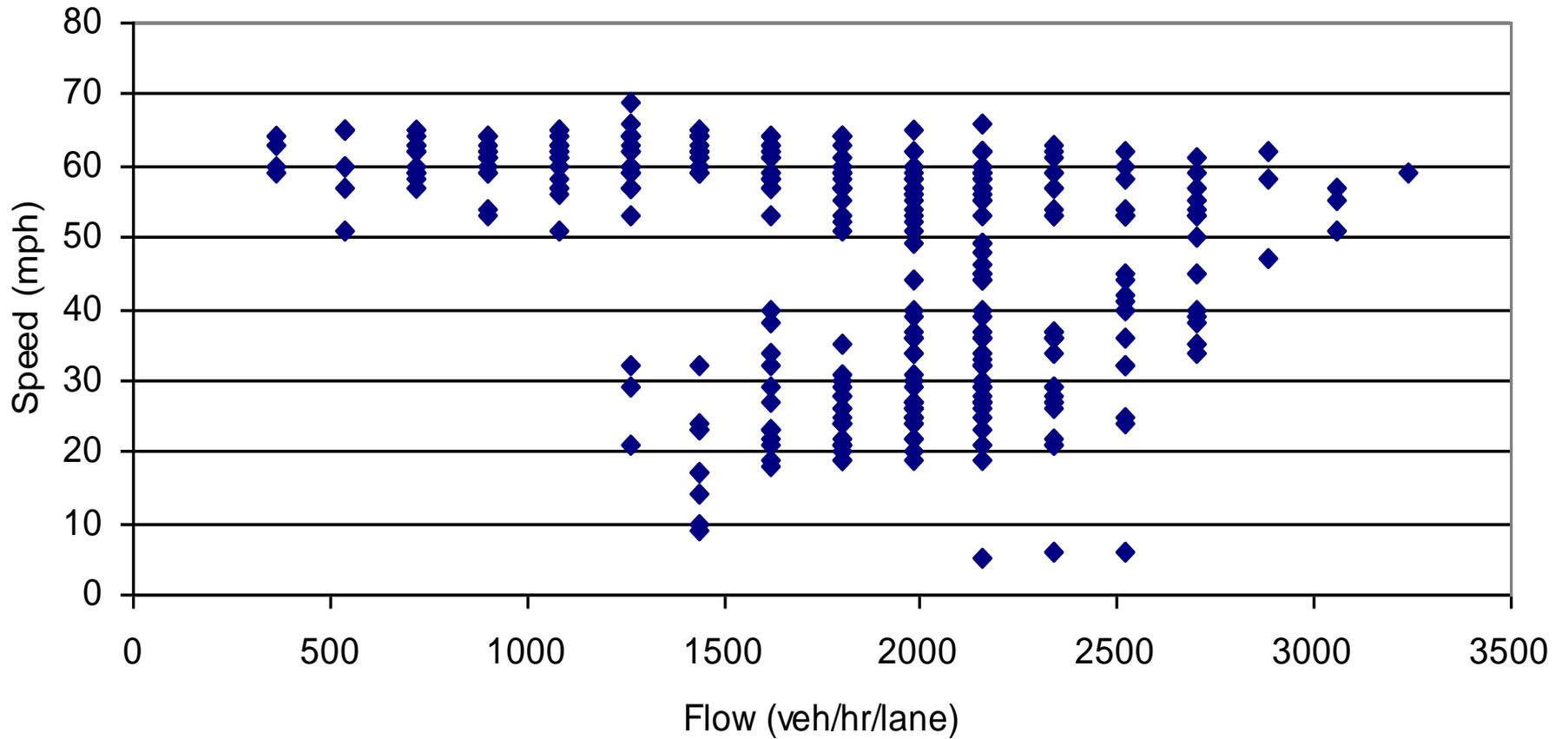
Flow-Density Experimental Data





Fundamental Diagram.

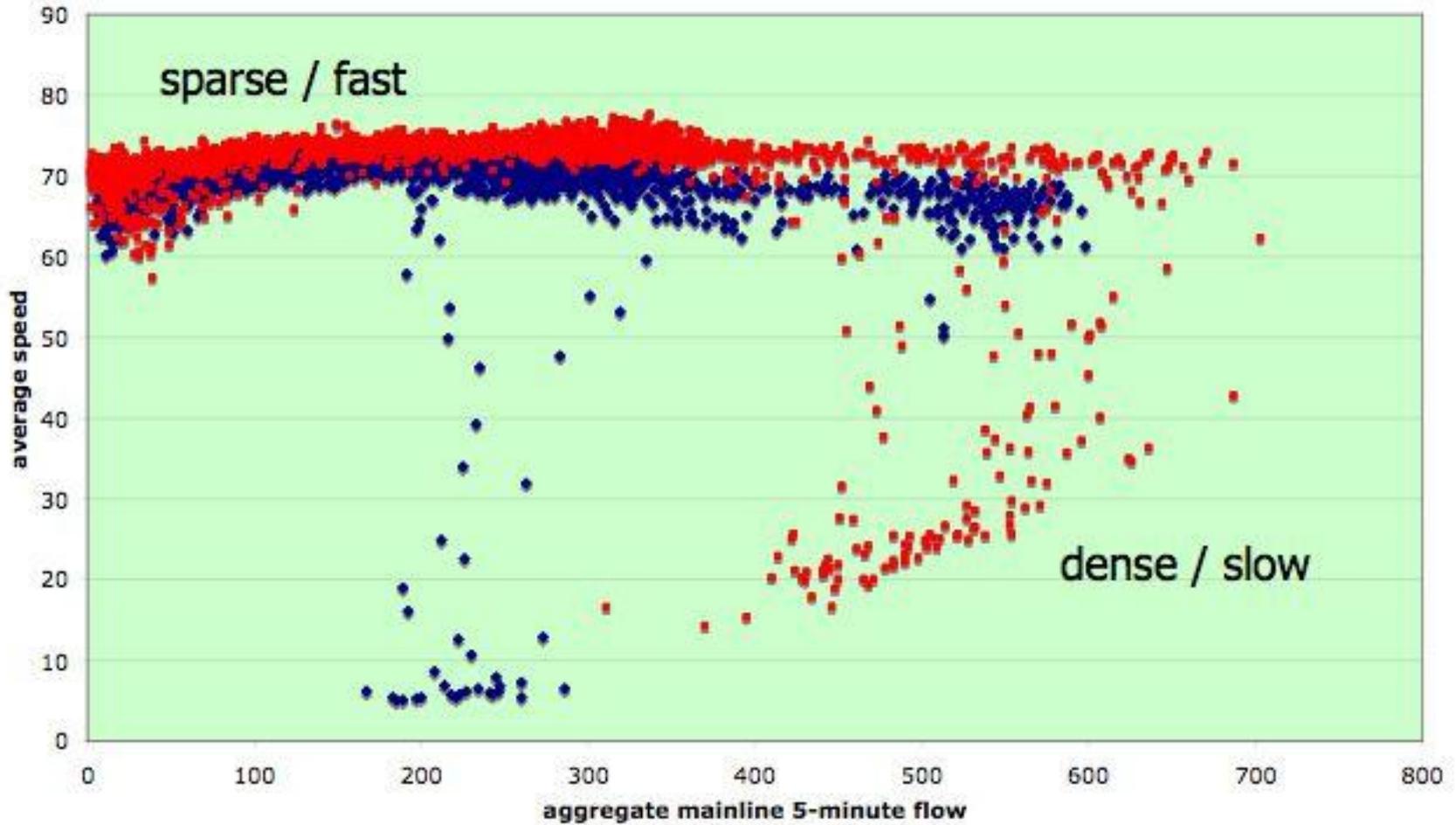




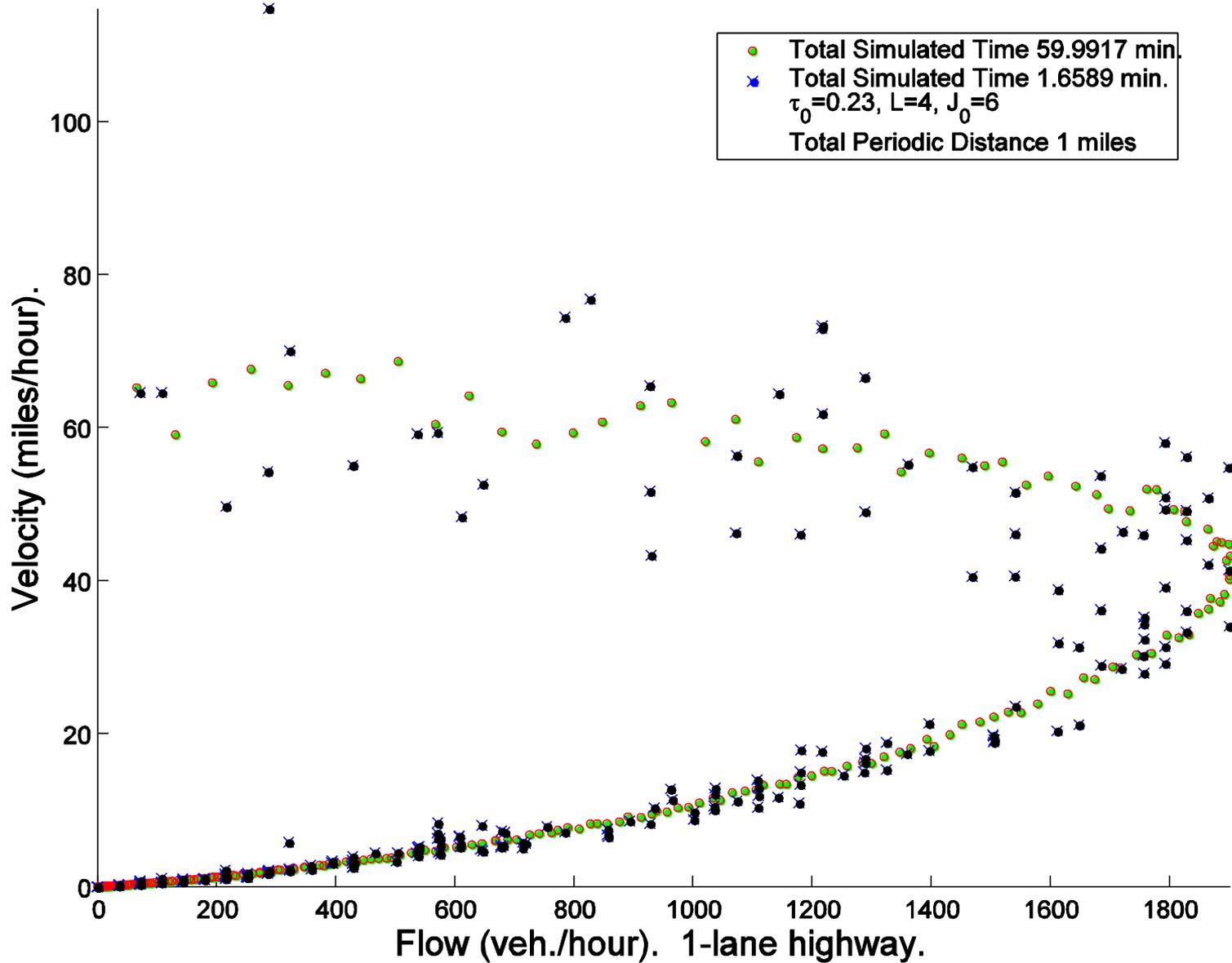
Velocity-Flow Diagram (real freeway data from San Antonio) [Halkias & Mahmassani (MTI 2005)]

I-5 at Gilman Drive : Speed vs. Flow (1/23/05 - 1/29/05)

◆ NB 5 ■ SB 5



Velocity - Flow relationship



Deterministic Closures

Recall the traffic flow model is, $\frac{d}{dt} Ef(\sigma) = EMf(\sigma)$ or

$$\frac{d}{dt} Ef(\sigma) = E \sum_{x \in \Lambda} c_0 \sigma(x)(1 - \sigma(x+1)) e^{-U(x, \sigma)} [f(\sigma^{x, x+1}) - f(\sigma)]$$

where $U(x, \sigma) = \sum_{\substack{z \neq x \\ z \in \Lambda}} J(x, z) \sigma(z)$

In particular we pick $f(\sigma) = \sigma(z)$ for some fixed z in L and we can simplify $f(\sigma^{x, x+1}) - f(\sigma)$ as follows

Since,
$$\sigma^{x,x+1}(z) = \begin{cases} \sigma(z), & z \neq x, z \neq x+1 \\ \sigma(x+1), & z = x \\ \sigma(x), & z = x+1 \end{cases}$$

Then we have,
$$f(\sigma^{x,x+1}) = \sigma^{x,x+1}(z) = \begin{cases} \sigma(z) & , x \neq z, x \neq z-1 \\ \sigma(z+1), & x = z \\ \sigma(z-1), & x = z-1 \end{cases}$$

and therefore,
$$f(\sigma^{x,x+1}) - f(\sigma) = \begin{cases} 0 & , x \neq z, x \neq z-1 \\ \sigma(z+1) - \sigma(z), & x = z \\ \sigma(z-1) - \sigma(z), & x = z-1 \end{cases}$$

Deterministic Closures

Therefore $\frac{d}{dt} Ef(\sigma) = EMf(\sigma)$ becomes

$$\frac{d}{dt} E\sigma_t(z) = -Ec_0\sigma(z)(1-\sigma(z+1))e^{-U(z,\sigma)} + Ec_0\sigma(z-1)(1-\sigma(z))e^{-U(z-1,\sigma)}$$

where $U(x, \sigma) = \sum_{\substack{z \neq x \\ z \in \Lambda}} J(x, z)\sigma(z)$

Exact but not yet closed for $E\sigma_t(z) = \text{Prob}(\sigma_t(z) = 1)$

Suppose that J has uniform (J=J₀), weak long interactions.

Finite Difference Scheme

The LLN formally applies and the fluctuations of $\sum_{y \neq x} J(y-x)\sigma(y)$ about their mean will be small.

Then in the long range interaction limit we have,

$$Ee^{-U(x,\sigma)} = Ee^{-\sum J(y-x)\sigma(y)} \stackrel{N,L \rightarrow \infty}{\approx} e^{-\sum J(y-x)E\sigma(y)} + o_N(1)$$

Let $u(z,t) = E\sigma_t(z)$ then we obtain an approximate *semi-discrete finite difference scheme*:

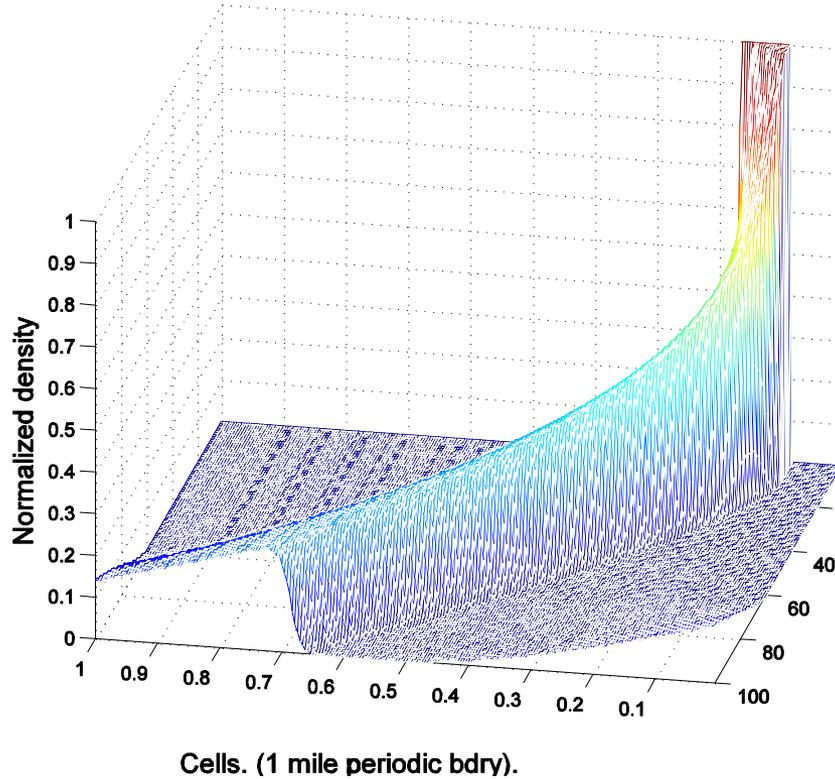
$$\frac{d}{dt}u(z,t) + F(z+1,t) - F(z,t) = 0$$

where $F(z,t) = c_0 u(z-1,t)(1-u(z,t))e^{-J_0 u(z-1,t)}$

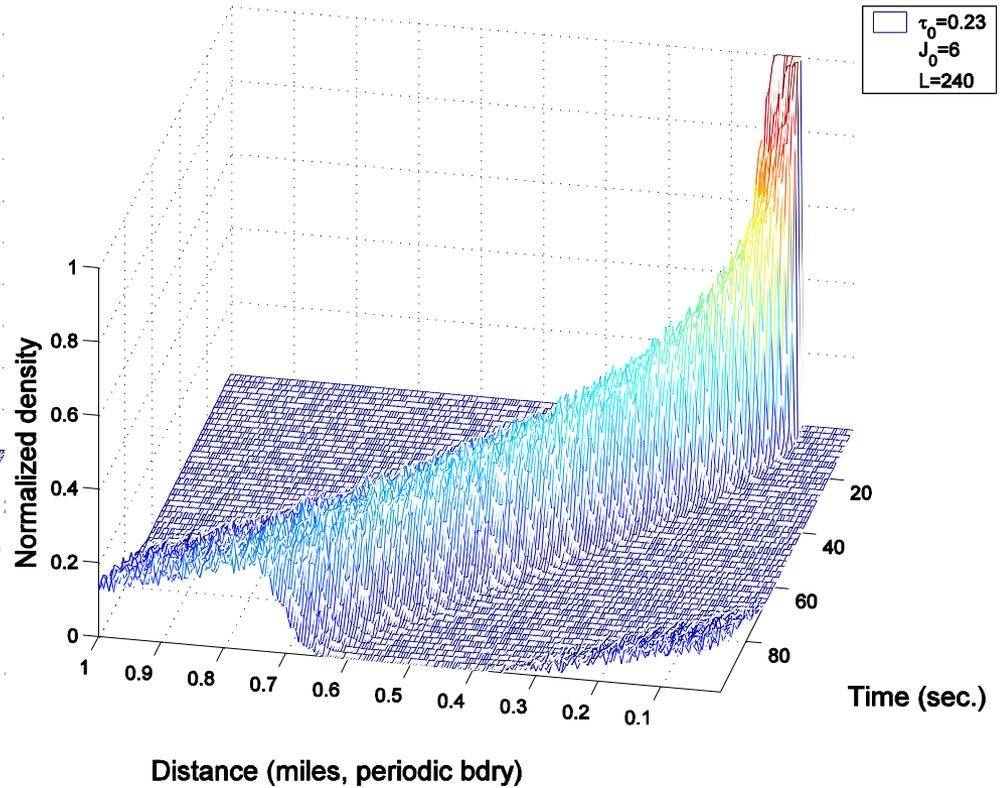
For a periodic lattice this scheme is conservative.

Comparisons between semi-discrete scheme and microscopic stochastic model

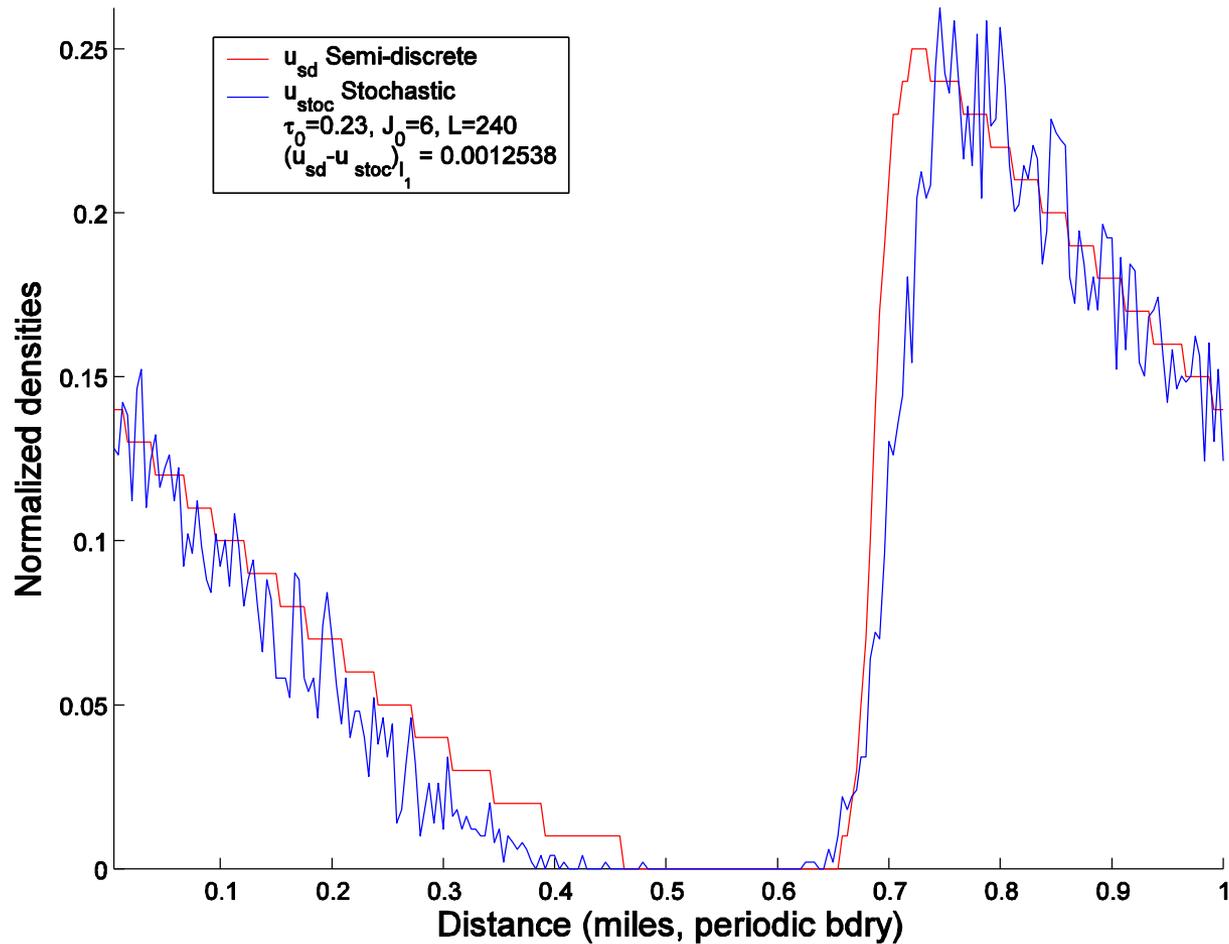
Semi-discrete spatial and temporal vehicle allocations



Stochastic Spatial and temporal vehicle allocations.



Stochastic vs Semi-discrete densities at time t=100 sec.



Potential Radius L	240	100	50	10	4	1
l_1 Rel. Error	.0013	.0029	.0051	.0066	.0126	.02

PDE model

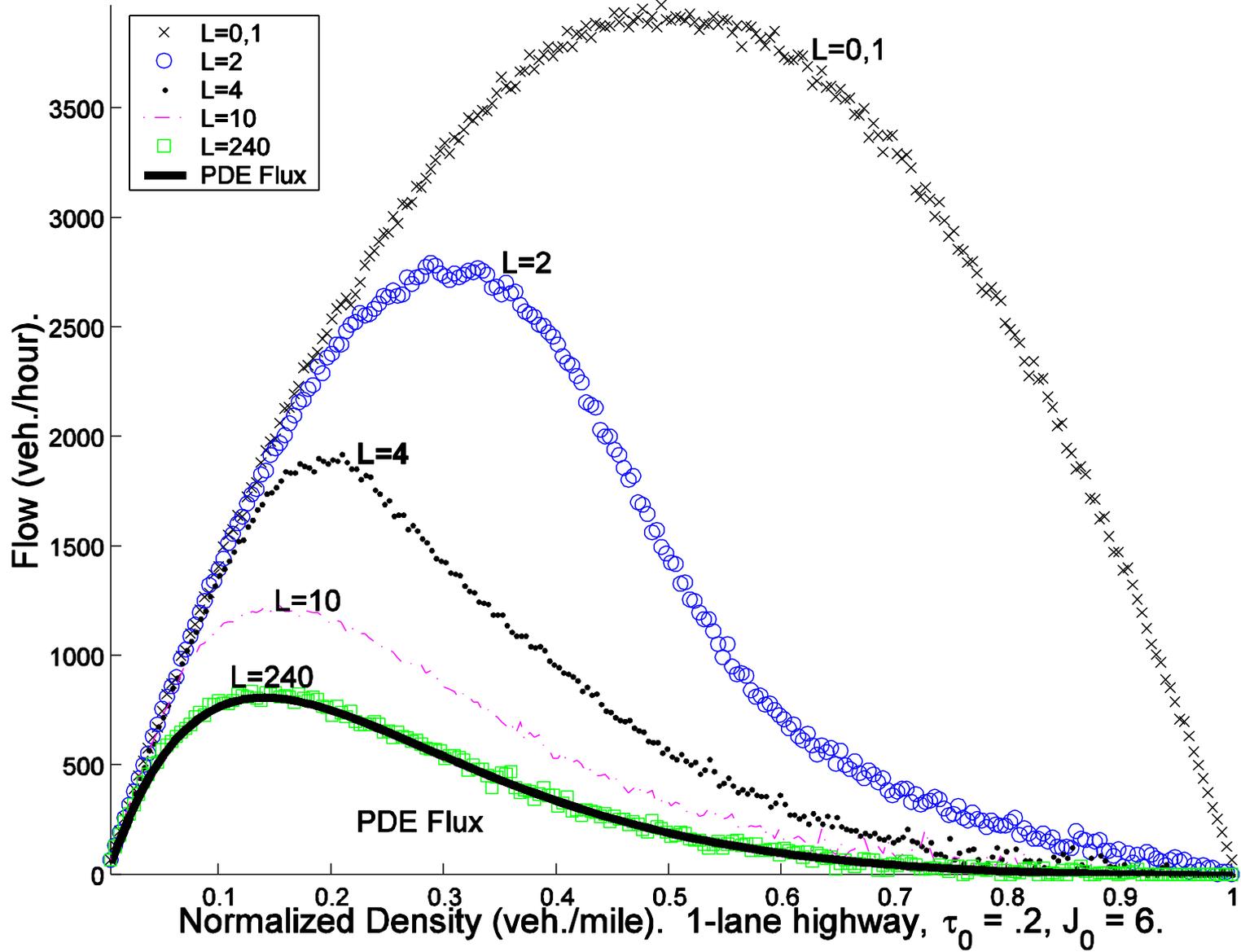
Expanding in Taylor we obtain, $\frac{d}{dt}u + [hc_0u(1-u)e^{-J \circ u}]_z = O(h^2)$

Rescaling time via $t \rightarrow th^{-1}$ in order to absorb h and omitting the $O(h^2)$ term, we obtain the following **macroscopic transport equation**:

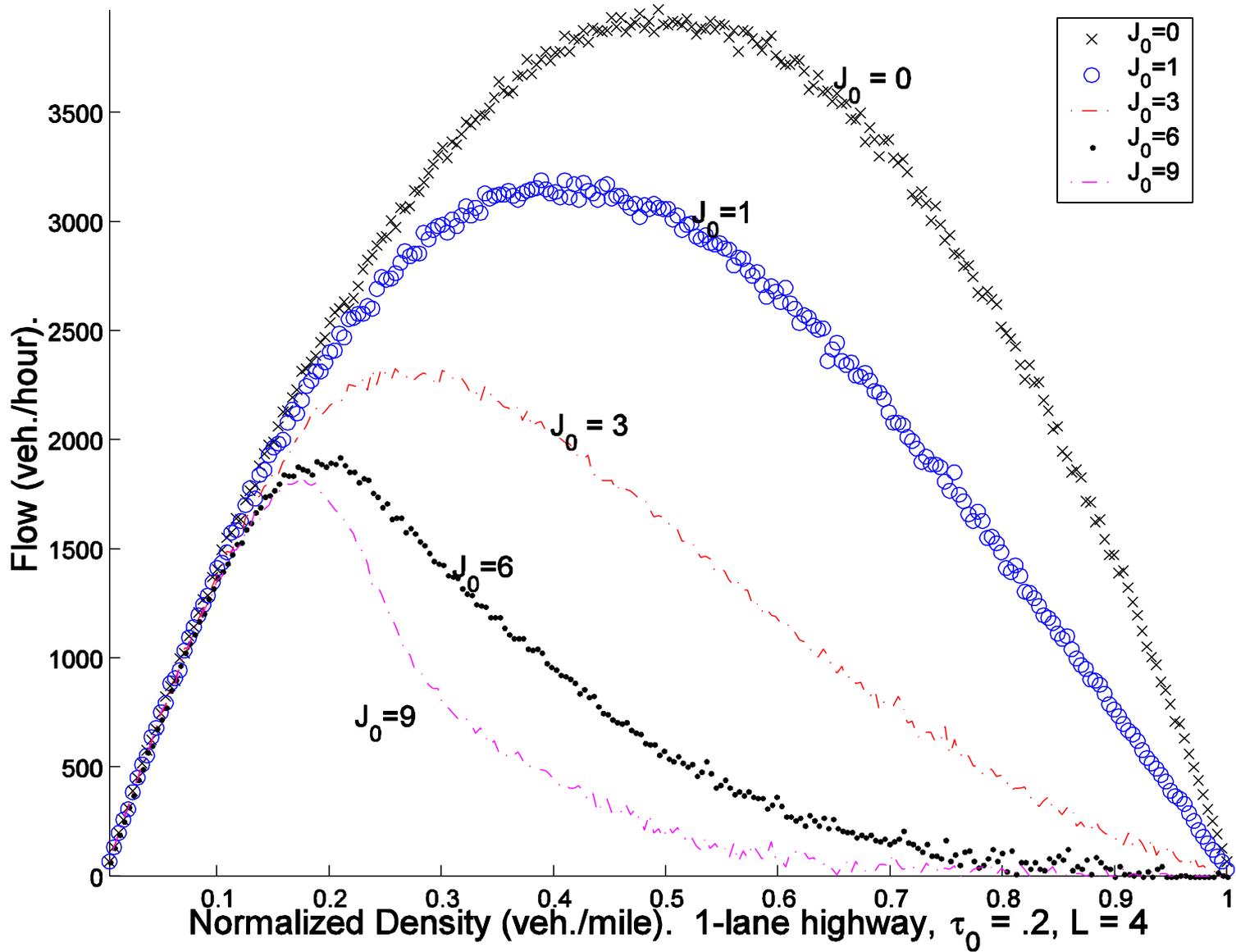
$$u_t + F(u)_z = 0$$

where the PDE flux is $F(u) = c_0u(1-u)e^{-J \circ u}$

Flux variation based on potential length L



Flux variation based on potential strength J_0



Hierarchical Comparisons

Expanding the convolution,

$$J \circ u = \int_z^\infty V(y-z)u(y)dy = \int_0^\infty V(x)u(x+z)dx = J_0u + J_1u_z + J_2u_{zz} + \dots$$

we can approximate the exponential via,

$$e^{-J \circ u} \approx e^{-J_0u} [1 - J_1u_z - J_2u_{zz}]$$

The traffic model PDE $u_t + cu(1-u)e^{-J \circ u} = 0$ therefore becomes...

The traffic model PDE,

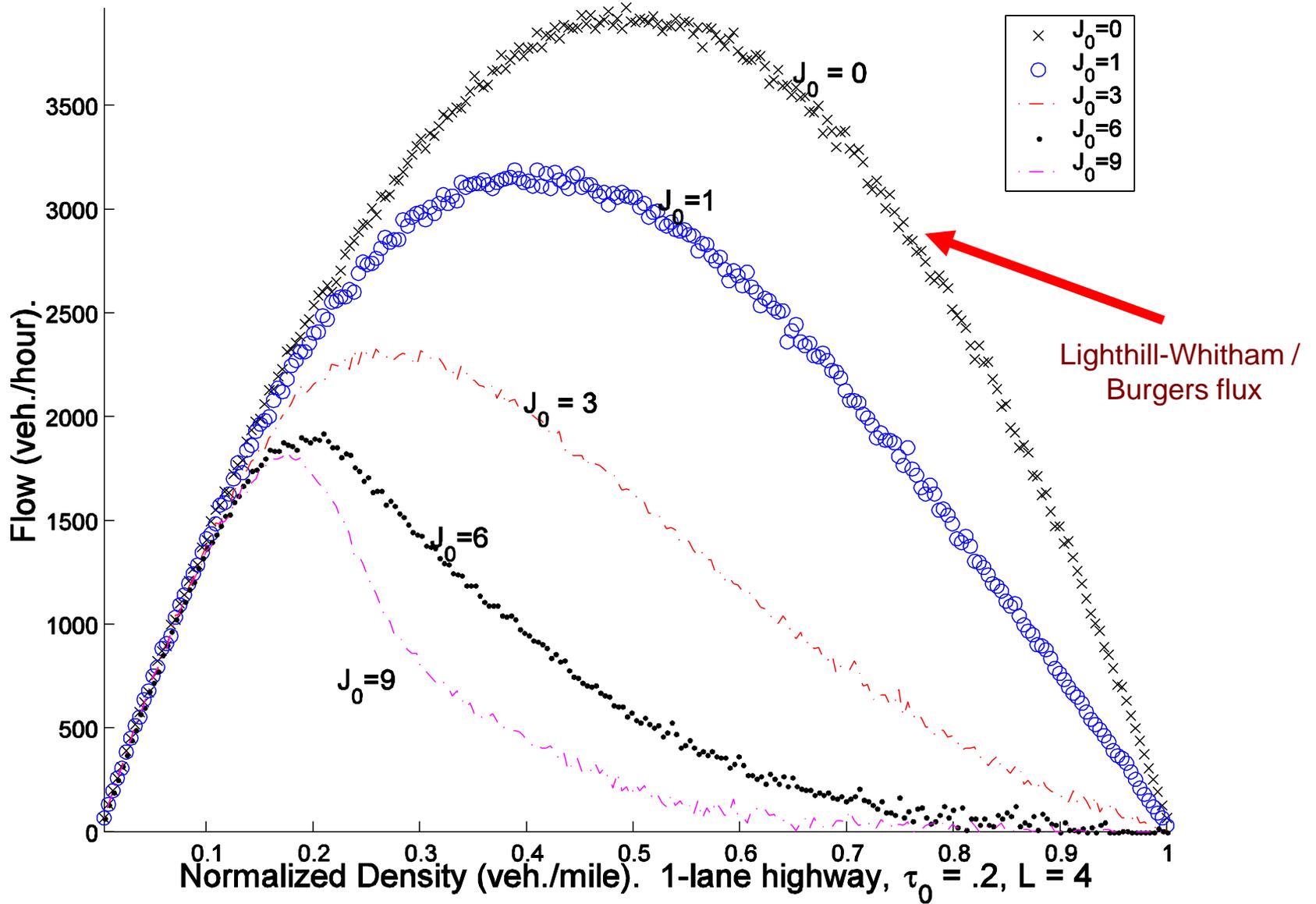
$$u_t + c_0 [u(1-u)e^{-J_0 u}]_z = \epsilon_0 [J_1 u(1-u)e^{-J_0 u}]_z + \epsilon_0 [J_2 u(1-u)e^{-J_0 u}]_{zz}$$

Note:

- No interactions (J=0):

Lighthill-Whitham/Burger's eq. $\rightarrow u_t + c_0 [u(1-u)]_z = 0$

Flux variation based on potential strength J_0



The traffic model PDE,

$$u_t + c_0 [u(1-u)e^{-J_0 u}]_z = \epsilon_0 [J_1 u(1-u)e^{-J_0 u}]_z + \epsilon_0 [J_2 u(1-u)e^{-J_0 u}]_{zz}$$

Note:

- No interactions (J=0):

Lighthill-Whitham/Burger's eq. $\rightarrow u_t + c_0 u(1-u) = 0$

- Long range (L=N) uniform (J=J₀) interactions:

Non-local flux $\rightarrow u_t + c_0 [u(1-u)e^{-J_0 u}]_z = 0$

- Including terms up to J₀ in the convolution,

Non-convex flux $\rightarrow u_t + c_0 [u(1-u)e^{-J_0 u}]_z = 0$

- Terms up to J₁

Nonlinear diffusive LWR type

- Full model is higher order dispersive (KDV type?)

with nonlinear coefficients

Multi-lane extensions

- We assume a two-dimensional domain (multi-lane highway).
- We introducing preferred direction in lane-changing via an anisotropy type potential. Thus our total interaction potential now consists of:

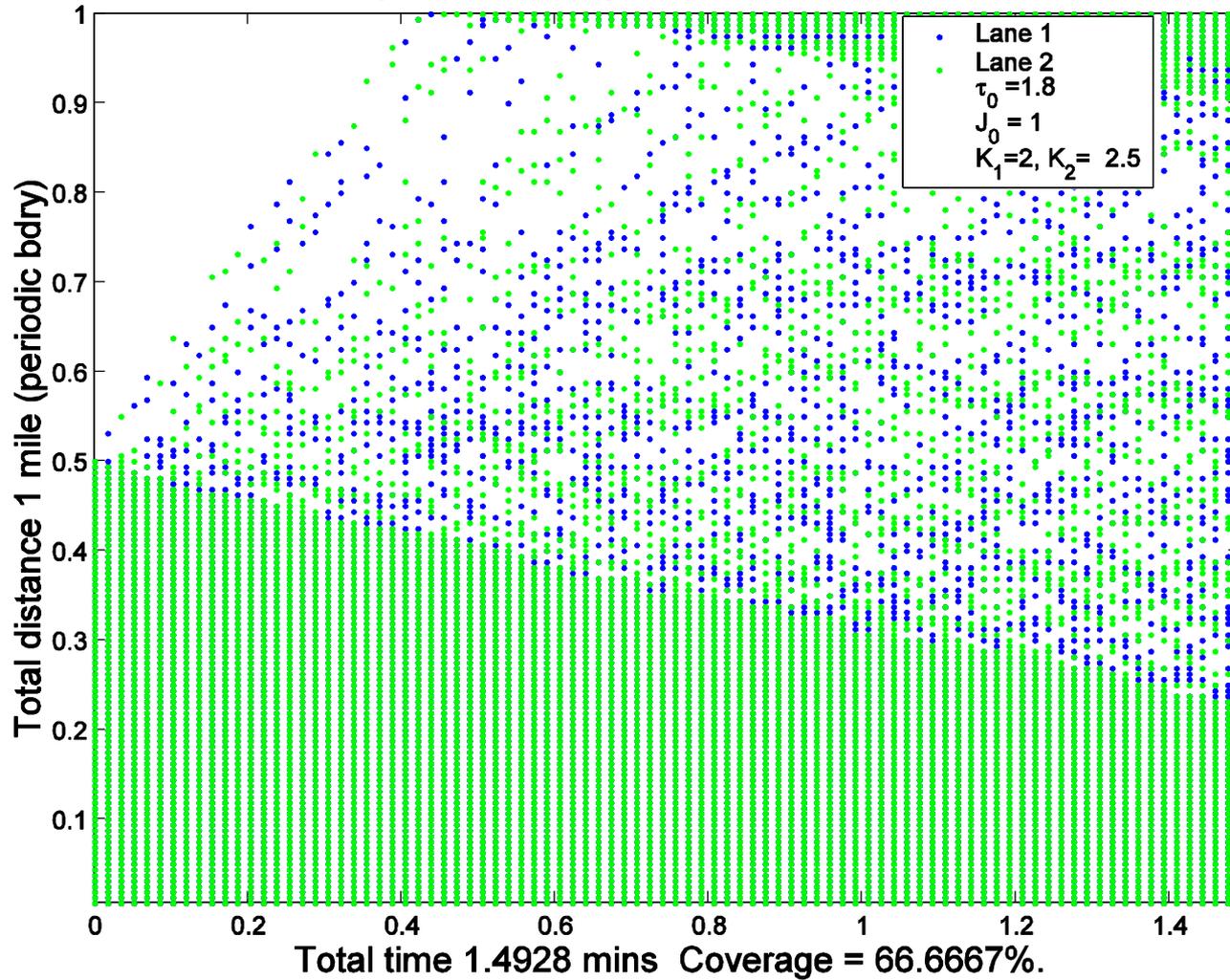
$$U(x) = U_e + U_a + h$$

where $U_a(x) = \sum_{y=nn} \psi(x, y)$ with $\psi(x, y) = \begin{cases} k_l & \text{if } y = x + 1 \\ k_r & \text{if } y = x - 1 \\ k_f & \text{if } y = x + n \end{cases}$

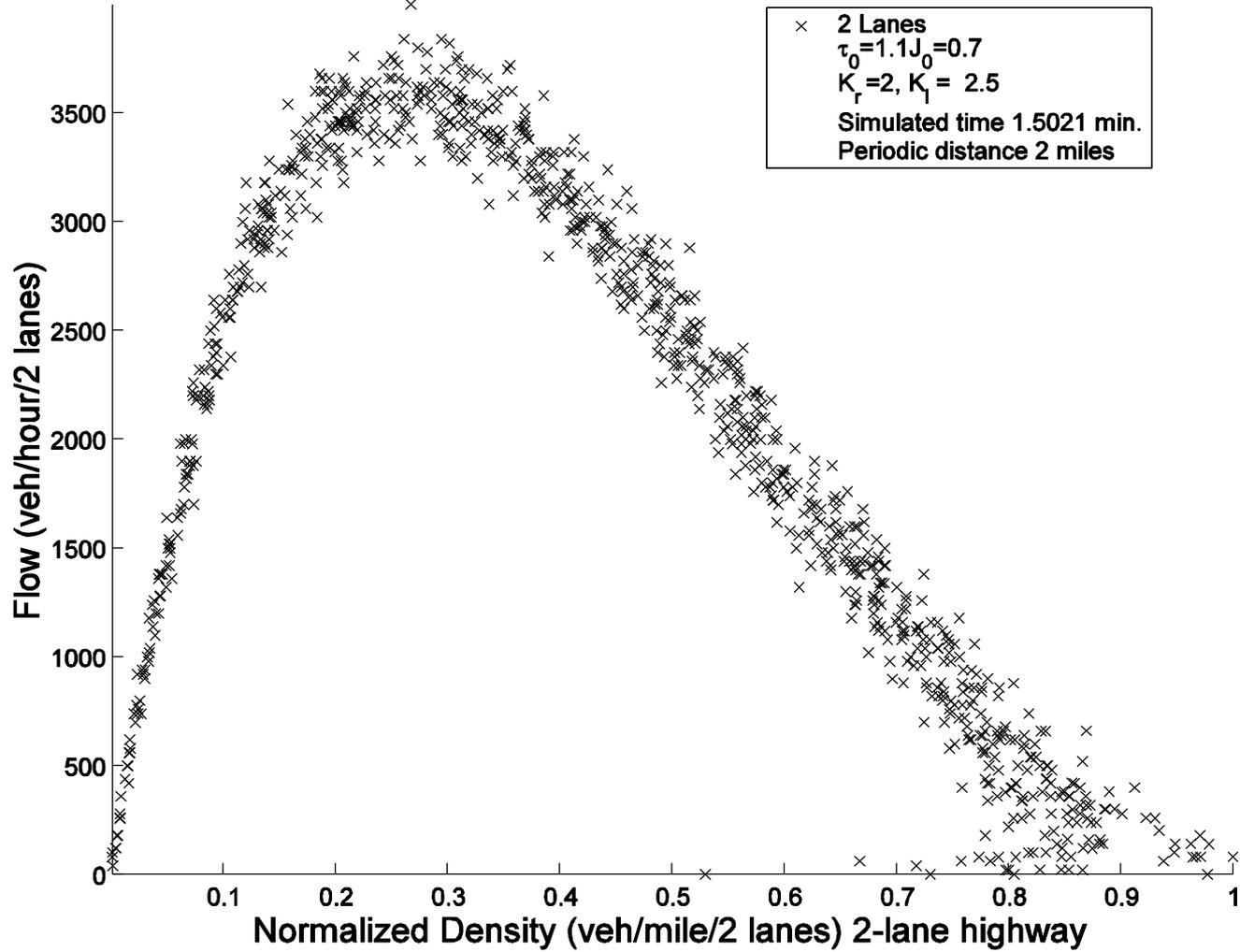
- Calibrate parameters:

# of Lanes	1	2	3	4
τ_0	0.23	1.1	1.85	1.9
J_0	6	0.7	0.7	0.5
Desired Velocity (mph)	65	62	68	72
Upstream Velocity (mph)	-10	-11	-12	-9.6

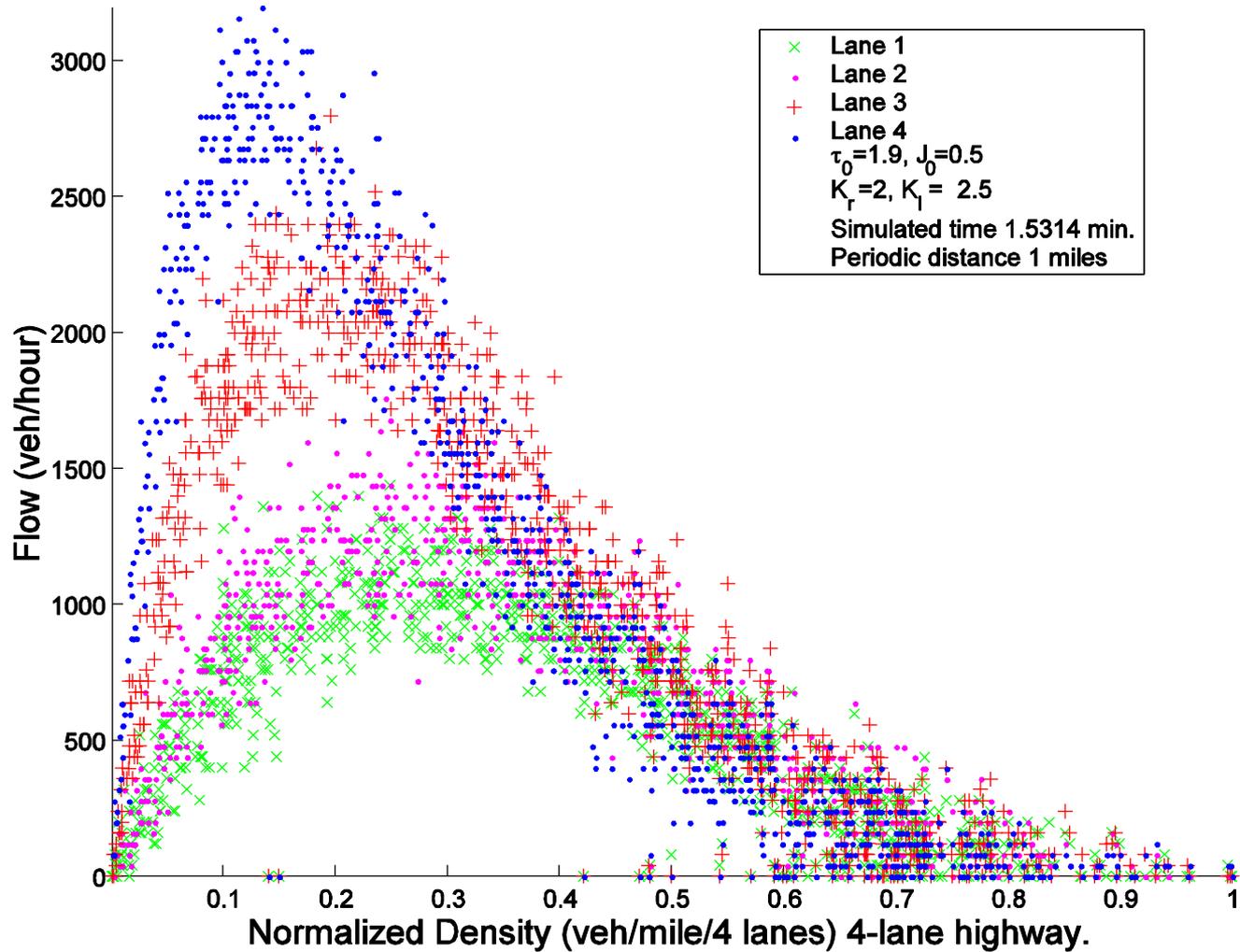
Spatial and temporal vehicle allocations



Fundamental Diagram



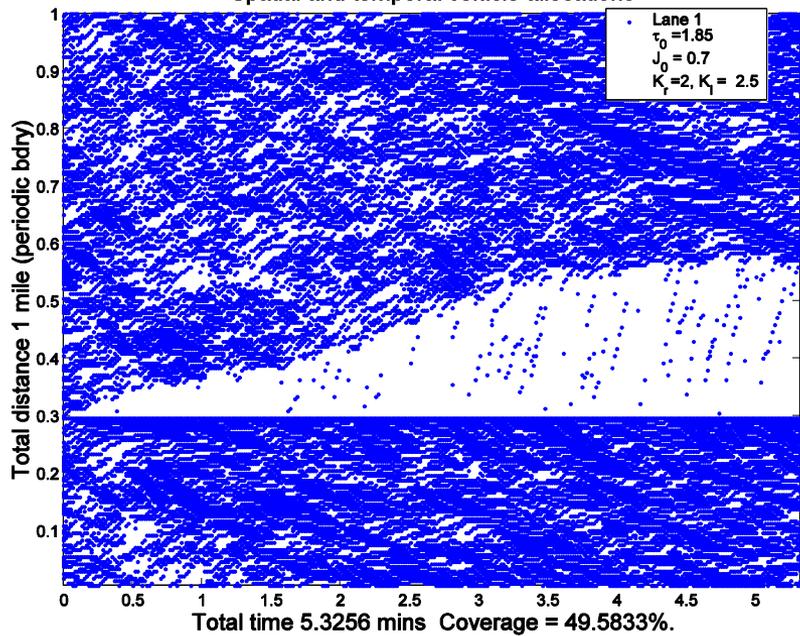
Fundamental Diagram



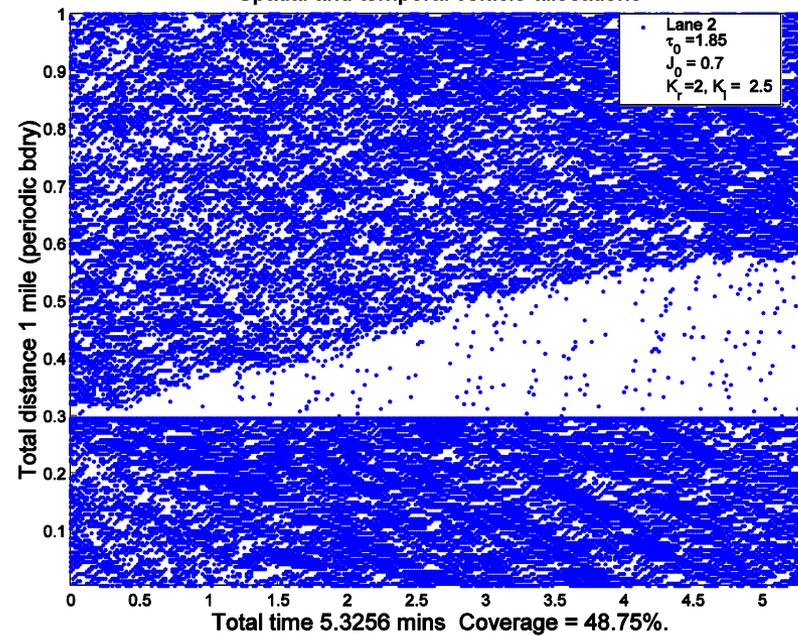
Test case toy problem: an incident

- Assume a 3-lane highway
- Let anisotropy coefficients: $K_r=2$, $K_l=2.6$, $K_f=8$
- Block lanes 1 and 2 (i.e. an accident)

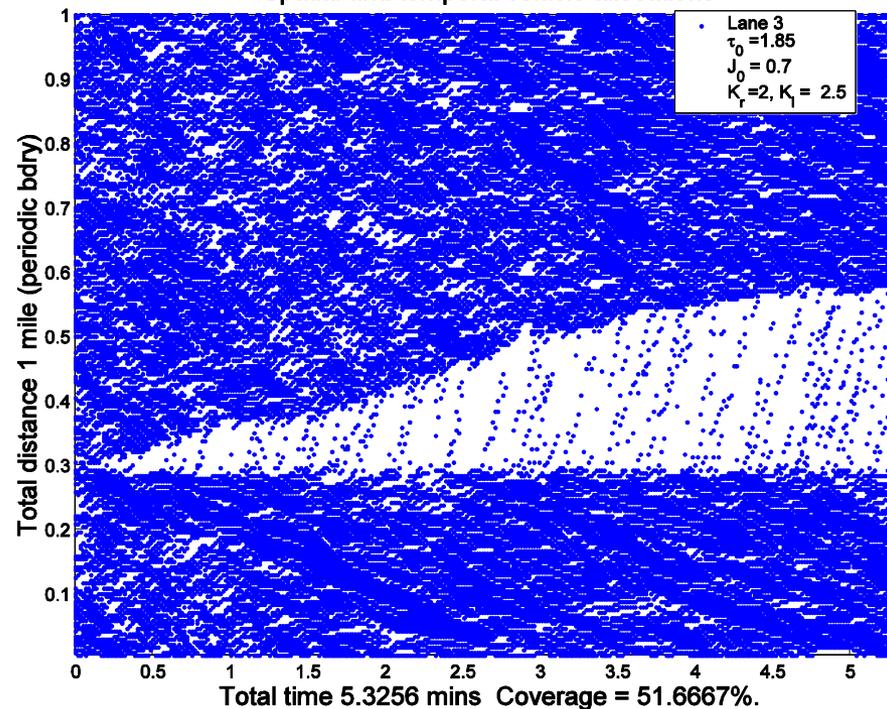
Spatial and temporal vehicle allocations



Spatial and temporal vehicle allocations



Spatial and temporal vehicle allocations



Conclusions

- ✓ Presented a **novel** modeling approach based on **microscopic Arrhenius spin-exchange dynamics**
- ✓ Extended method to **multi-lane traffic**
- ✓ Studied **deterministic closures** of the microscopic stochastic model at **different length scales**
- ✓ Obtained formal **hierarchical comparisons** with other well-known models of traffic
- ✓ Presented **Kinetic Monte Carlo simulations** which allows for comparisons with actual traffic data as well as other PDE models

References

- P.Athol. Interdependence of certain operational characteristics within a moving traffic stream. Highway Research Record, 58-97, 1972
- A.B.Bortz, M.H.Kalos and J.L.Lebowitz. A new algorithm for Monte Carlo simulations of Ising spin systems. J.Comput. Phys. 17:10, 1975
- C.Chowdhury, L.Santen and A.Schadschneider. Phys. Rep. 329:199, 2000
- E.F.Codd. Cellular Automata. Academic Press. New York. 1968
- M.Cremer and J.Ludwig. Mathematics and Computers in Simulation, 28:297, 1986
- C.F.Daganzo. Requiem for second-order fluid approximations of traffic flow. Transportation Research B, 29:277, 1995
- C.F.Daganzo, M.J.Cassidy and R.L.Bertini. Some traffic features at freeway bottlenecks. Transportation Research B, 33:25-42, 1999
- N.Dundon and A.Sopasakis. Stochastic modeling and simulation of multi-lane traffic, in progress
- L.Gray and D.Griffeath. The ergodic theory of traffic jams. J. Statist. Ohys., 105(3-4):413, 2001
- F.L.Hall. Traffic Flow Theory, Chapter 2, pg2-34. Washington, D.C.: US Federal Highway Administration, 1996
- CCM. Highway Capacity Manual. Technical Report, Transportation Research Board, 1985. Special Report 209
- D.Helbing. Gas-Kinetic derivation of Navier-Stokes-like traffic equations. Physical Review E, 53(3):2366, 1995
- D.Helbing, A.Hennecke, V.Shvetsov and M.Treiber Micro and macro simulation of freeway traffic. Math. Comp. Modelling, 35:517, 2002
- D.Helbing and M.Treiber. Gas-kinetic-based traffic model explaining observed hysteretic phase transition. Phys. Rev. Let., 3042-3045, 1998
- R.Illner, A.Klar and T.Materne. Vlassov-Fokker-Planck models for multilane traffic flow. Commun. Math. Sci., 1:1, 2003
- S.Jin and J.G.Liu. Relaxation and diffusion enhanced dispersive waves. Proc. Roy. Soc. London A., 446:555-563, 1994
- B.S.Kerner. Dependence of empirical fundamental diagram on spatial-temporal traffic patterns features.
- B.S.Kerner. S.L.Klenov and D.E.Wolf. Cellular automata approach to three-phase traffic theory. J.Phys.A:Math. Gen., 35:9971, 2002
- B.S.Kerner and P.Konhauser. Structure and parameters of cluster in traffic flow. Phys. Rev. E., 50:54-83, 1994
- B.S.Kerner and H.Rehborn. Experimental properties of phase transitions in traffic flow. Phys.Rev.Let., 49:4030, 1997
- A.Klar and R.Wegener. Kinetic derivation of macroscopic anticipation models for vehicular traffic. SIAM J Appl Math 60:1749-1766, 2000