CE781A

TRAFFIC SIMULATION

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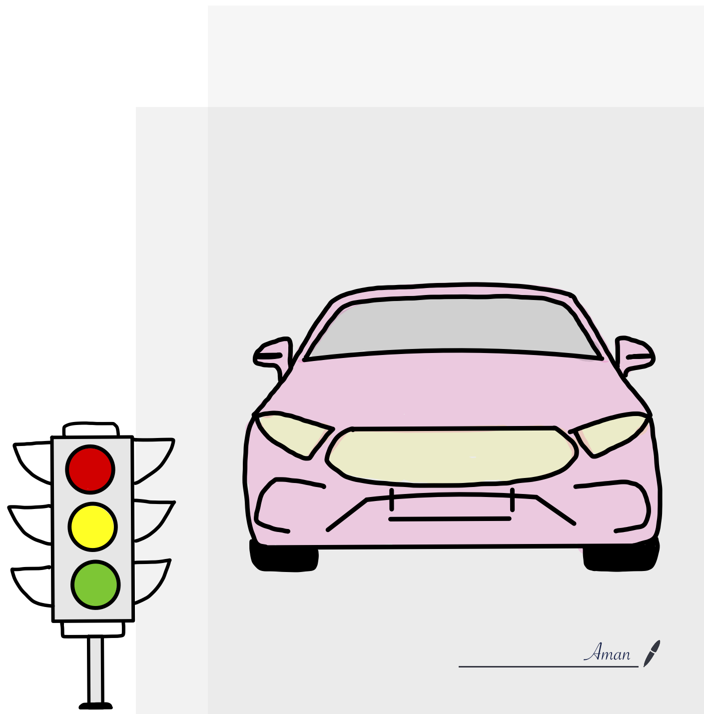


Settings 0.4 thick
H1 → H2 → H3 → H4 →

CE781A Traffic Simulation

Traffic Flow Dynamics — By Martin Trieber
(Matlab/Python)

{ Quiz → 40%
MS/ES → 60% }

8 Jan 2024 (Mon)

computer simulation

mimic real world traffic scenario setting in the computer using mathematical model.

Why simulation ?

1. To design and operate traffic system
2. Traffic Flow : highly complex and non-linear behaviour (multiple vehicles)
3. Check new traffic facility eg. Bus-bay, intersection, traffic signal, different settings /scenario that are difficult to do in field.

Types of Traffic simulation

1. Macroscopic simulation

- Represents collection of vehicles
- Locally aggregated vehicles
- Useful for understanding traffic flow on a larger scale

Models

1. First order (LWR) model
2. Second order model

} → system of non-linear PDEs → Numerical Methods (FD, FV, FE)

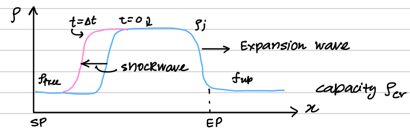
- Boundary cond^n
- Initial cond^n

$Q = 1/\bar{h}$

$\rho = 1/\bar{s}$

Models using
- Fluid Flow Analysis
- Gas - Kinetic Theory
- Convert microscopic to macroscopic model

Disordered traffic → Indian traffic



2. Microscopic simulation

Models individual vehicles

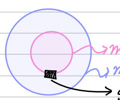
Models
- Car Following Model
- Lane changing Model

} → system of non-linear PDEs ↳ solved using numerical tecniques

Commercial Softwares
1. VISSIM (Germany)
2. AIMSim (Spain)
3. TransModeler (USA)

3. Mesoscopic Simulation

Combines partly aggregate (macro) and partly individual (micro)



→ giving a proper interface is challenging

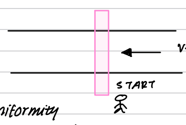
Random Event

- Before conducting the experiment, you don't know the outcomes But you know the possible outcomes eg. tossing a coin

Random Number

- Real number lies b/w 0 to 1
  $0 \leq R \leq 1$
- Generate vehicle type using random numbers
- 'rand' built-in function to generate them

$r_1 = 0.8$ Bus
$r_2 = 0.002$ TW
$r_3 = 0.46$ Car
⋮
$r_{100} =$ ~ ~



1. uniformity
2. independent

		cumm.	cumm. fraction
TW	25	25	0.25
Car	25	50	0.50
Auto	25	75	0.75
Bus/Truck	25	100	1.00
	100		

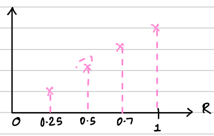
10 Jan 2024 (Wed)

$\boxed{\text{RN}}$ Blackbox

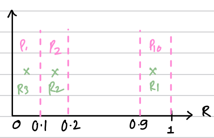
$RN_1 = 0.89 \rightarrow$ Bus
$RN_2 = 0.46 \rightarrow$ car

'rand' in MATLAB — good random no. generator

Two qualities
1. uniformity — equal probable everywhere ⟶ eg toss coin {H, T} $P(X=H) = 0.5$, $P(X=T) = 0.5$
2. Independence — doesn't get affect from previous event.



R — continuous random variable
$P(0.25) = P(0.5) = P(0.75) = 0$
meaningless to talk abt it.



R ≈ continuous random variable
10 Intervals
$P_1 = P_2 = P_3 = \cdots = P_{10}$
uniformity
Interval size — same

$P_1 \; (0 \leq R \leq 0.1)$
$P_2 \; (0.1 \leq R \leq 0.2)$
$P_3 \; (0.2 \leq R \leq 0.3)$

mid-square method (By John von Neumann, CS professor)

Algorithm — Iterative method

Step1: Initialize with 4 digit number (Z_0)
Step2: Square (Z_0^2) i.e. 8 digit number
Step3: Consider middle 4 digits (Z_1)
Step4: Introduce decimal point before Z_1 ($0.Z_1$)
Step5: Repeat step 2 using Z_1 (not $0.Z_1$)

eg:— consider 2 digit no for simplicity

Iteration 1	Iteration 2	Iteration 3
1. $Z_0 = 77$	1. $Z_1 = 92$	1. $Z_2 = 46$
2. $Z_0^2 = 77^2 = 5929$	2. $Z_1^2 = 8464$	2. $Z_2^2 = 2116$
3. $Z_1 = 92$	3. $Z_2 = 46$	3. $Z_3 = 11$
4. $R_1 = 0.92$	4. $R_2 = 0.46$	4. $R_3 = 0.11$

After some iterations, again $Z_2 = 46$ will come up. Thus, there is a cycle that will repeat in method. Always, this cycle will be there. In computers, cycle is unavoidable.

mid sq. method — useful for generating number sequence
cycle period (Z_0 to Z_{i-1}) → cycle repeats

generate larger cyles, how? Z_0 = seed value (initial value)
cycle length depends on Z_0.

· computer always generate dependent random variable.
· vanishing random variable.

pseudo random variable — combuter generated random variable (artificial)
— not pure because cycle is unavoidable and dependent

Vanishing RV

$Z_0 = 73$	32	02	
$Z_0^2 = 5329$	1024	0004	
$Z_1 = 32$	02	00	random variable now vanishes....
$R_1 = 0.32$	0.02	0.0	

For a good RV generator
1. ↑ cycle length
2. avoid vanishing
3. uniformity

Linear congruential method

$x_{i+1} = (ax_i + c) \bmod m.$

a - multiplier
c - increment
mod - remainder
x_0 = seed value

$x_{i+1} = \{0, 1, 2, 3, \dots, m-1\}$

$R_{i+1} = \{\frac{0}{m}, \frac{1}{m}, \frac{2}{m}, \dots, \frac{m-1}{m}\}$ ⟶ you can choose to divide by $(m-1)$ as well

$R_{i+1} = \{0, \dots; 1\}$ Random number

Assumption: $m > 0$, $a < m$, $x_0 < m$, $c < m$

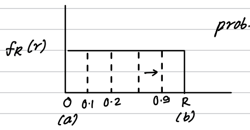
eg :- $x_1 = (17 \times 27 + 43) \bmod 100 = 502 \bmod 100 = 2$ $R_1 = 0.02$
$x_2 = (17 \times 2 + 43) \bmod 100 = 77$ $R_2 = 0.77$
$x_3 = (17 \times 77 + 43) \bmod 100 = 52$ $R_3 = 0.52$

cycle — max cycle time possible $= m$
choose $m = 2^{31}$ or 2^{48}, based on your computer storage
this guarantee large cycle length

$m = 100$
$X_{i+1} = \{0, 1, 2, \dots 99\}$
$R_{i+1} = \{0, 0.01, 0.02, \dots, 0.99\}$ ↳ continuous R.V.

continuous RV
1. uniformity ⟶ To ensure uniformity b/w (a, b) (ll, ul)
2. independence we choose uniform distribution

pdf of uniform distribution
$0 \to 1$
capital → RV
small → numerical values (RV)



prob. = area under curve

Area under the curve = total probability $R \to [0, 1]$
width × height = 1
$(b-a) \times f_R(0) = 1$

$$\boxed{f_R(r) = \frac{1}{b-a}}$$ pdf

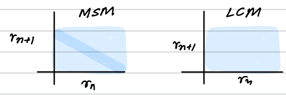
~ uniform (0,1)
~ mean $R = \frac{a+b}{2} = 0.5$
~ varience $= \frac{(b-a)^2}{12} = \frac{1}{12}$

R → uniform (0.5, 1/12) distribution

$m = 6075$
$a = 106$
$c = 1283$

} LCM is better than MSM

$R_n \to (5000)$
$R_m \to (5000)$



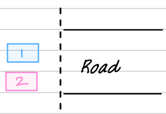
1. vehicle type
2. time headway
3. speed

$t_1 = 10$ sec
$t_2 = 25$ sec
$t_3 = 186$ sec

Random Variable

17 Jan (Wed)

PDF $X = \frac{1}{\lambda} \ln(R)$



Inputs
1. vehicle type (RN)
2. time headway (exponential distribution)

Speed
1) Desired speed
2) Entry speed
} • speed ~ Normal Distribution

Normal Random Variable

Normal PDF $f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ (μ, σ)

Standard Normal PDF $f_X(x) = \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{x^2}{2}}$ $(0, 1)$

$$F_X(x) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx = 1$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} dx$$ ⟶ non-elementary function

Assume two standard normal RN
$X \sim N(0,1)$ $Y \sim N(0,1)$

$f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$ $f_Y(y) \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}}$

pdf X pdf Y

X & Y independent $\Rightarrow \rho = 0$ (corelation coeff.)

$\rho = 0 \not\Rightarrow$ X & Y independent

Joint PDF of X & Y

$$f_{X,Y}(x,y) = f(X) \cdot f(Y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} = \frac{1}{2\pi} e^{-\frac{(x^2+y^2)}{2}}$$

↳ legtimate PDF?

CDF

$$F_{X,Y}(X \leq x', Y \leq y') = \int_{-\infty}^{x'} \int_{-\infty}^{y'} \frac{1}{2\pi} e^{-\frac{(x^2+y^2)}{2}} dx\,dy$$

$$= \frac{1}{2\pi} \int_{-\infty}^{x'} \int_{-\infty}^{y'} e^{-\frac{(x^2+y^2)}{2}} dx\,dy$$

X, Y → cartesian coordinate system
Changing to Polar coordinate system

$r^2 = x^2 + y^2$
$\tan^{-1}\left(\frac{y}{x}\right) = \theta$
$r\,dr\,d\theta = dx\,dy$

R, θ $0 \leq R \leq \infty$
$0 \leq \theta \leq 2\pi$

$$F_{R,\theta}(R \leq r', \theta \leq \tilde{\theta}) = \frac{1}{2\pi} \int_0^{r'} \int_0^{\tilde{\theta}} e^{-r^2/2} r\,dr\,d\theta$$

$$= \frac{1}{2\pi} \int_0^{r'} e^{-r^2/2} \int_0^{\tilde{\theta}} d\theta \; r\,dr$$

$$= \frac{1}{2\pi} \int_0^{r'} e^{-r^2/2} \int_0^{2\pi} d\theta \; r\,dr$$

$$= \int_0^{r'} e^{-r^2/2} r\,dr$$ ($\lim r' \to \infty$) ⟶ Now solvable!

$$F_{R,\theta} = \int_0^{r'} e^{-r^2/2} r\,dr$$

Put $s = \frac{r^2}{2}$ $ds = \frac{2r\,dr}{2}$

$$F_{S,\theta} = \int_0^{s'} e^{-s} ds$$

$$\lim_{s \to \infty} F_{S,\theta} = -\left[e^{-s}\right]_0^{s'} = -\left[e^{-\infty} - e^0\right] = 1$$

Thus, we have proved it is a legtimate PDF.

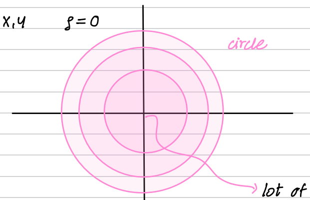
$$F_{X,Y}(x,y) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{(x^2+y^2)}{2}} dx\,dy$$

Objective: we want standard normal random variable.

$x, y \quad \rho = 0$

$\rho = 0$ circle from top
$\rho \neq 0$ ellipse from top

circle



fix R
θ - equally likely
θ follows uniform distribution
$0 \leq \theta \leq 2\pi$
$\theta = 2\pi u_1 \rightarrow$ uniform RN $(0,1)$

lot of data will be at center (mean)

$$F_{R,\theta} = \frac{1}{2\pi} \int_0^{r'} \int_0^{\theta'} e^{-r^2/2} \, r \, dr \, d\theta \qquad \theta' \rightarrow 2\pi, \; r' \rightarrow \infty$$

$$F_{R,\theta} = \frac{1}{2\pi} \int_0^{r'} e^{-r^2/2} \int_0^{2\pi} d\theta \; r \, dr = \int_0^{r'} e^{-r^2/2} \, r \, dr$$

r^2 follow exponential distribution

$s = \frac{r^2}{2} \qquad ds = r \, dr$

$$F_{S,\theta} = \int_0^{s'} e^{-s} ds = \left[-e^{-s}\right]_0^{s'}$$

$$u_2 = \left[-e^{-s}\right]_0^{s'}$$

$$u_2 = 1 - e^{-s'}$$

$$u_2 = 1 - e^{-r^2/2}$$

$$e^{-r^2/2} = 1 - u_2$$

$$-\frac{r^2}{2} = \ln(1 - u_2)$$

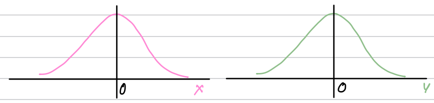
$$r^2 = -2\ln(1 - u_2) \qquad 0 \leq R < \infty$$

$$r = \pm\sqrt{-2\ln(u_2)}$$

$$r = \sqrt{-2\ln(u_2)} \qquad \theta = 2\pi u_1 \qquad u_1 \sim R(0,1)$$
$$R = \sqrt{-2\ln u_2} \qquad u_2 \sim R(0,1)$$

$$\left.\begin{aligned} X &= R\cos\theta = \sqrt{-2\ln u_2}\,\cos(2\pi u_1) \\ Y &= R\sin\theta = \sqrt{-2\ln u_2}\,\sin(2\pi u_2) \end{aligned}\right\} \quad x, y \sim \text{standard normal var.}$$

convert back polar $\rightarrow$ cartesian



Box-muller transformation

$$\left.\begin{aligned} X &= \sqrt{-2\ln u_2}\,\cos(2\pi u_1) \\ Y &= \sqrt{-2\ln u_2}\,\sin(2\pi u_1) \end{aligned}\right\} \quad \text{Standard Normal Random Variable}$$

$$v_{car} \sim N(\underset{\mu}{60 \text{ kmph}}, \underset{\sigma}{5 \text{ kmph}})$$

$$v_{truck} \sim N(40 \text{ kmph}, 3 \text{ kmph})$$

$$x = \frac{v_{car} - \mu_{car}}{\sigma_{car}} \qquad y = \frac{v_{truck} - \mu_{truck}}{\sigma_{truck}}$$

$\downarrow$ $N(0,1)$ SNRV $\qquad \downarrow$ $N(0,1)$ SNRV

$$v_{car} = \mu_{car} + \sigma_{car}\sqrt{-2\ln u_2}\,\cos(2\pi u_1)$$
$$v_{truck} = \mu_{truck} + \sigma_{truck}\sqrt{-2\ln u_2}\,\sin(2\pi u_1)$$

$$v_{car} = 60 + 5\sqrt{-2\ln u_2}\,\cos(2\pi u_1)$$
$$v_{truck} = 40 + 3\sqrt{-2\ln u_2}\,\sin(2\pi u_1)$$

Disadvantage $\quad -\infty < v_{car} < +\infty$
$\rightarrow$ Truncated Normal Distribution

$\{50 \leq v_{car} \leq 70\}$
$\downarrow$
At end, regenerate this limit.

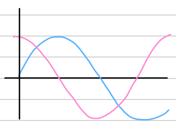
Log Normal Random Variable

Take its log.

- Install — Automated Driving Toolbox $\rightarrow$ For lab!
  Next class - IDM

$\rightarrow$ Model
$\rightarrow$ Implementation
$\rightarrow$ Data (Sim. Setup)
$\rightarrow$ Noise
$\rightarrow$ Calibration $\rightarrow$ everything they calibrate.
succeed in some data only
not all the data
Parameter reaching optimal value then
also do the calibration.

Lab #2



$$\left.\begin{aligned} x &= \sqrt{-2\ln u_1}\,\cos(2\pi u_2) \\ y &= \sqrt{-2\ln u_1}\,\sin(2\pi u_2) \end{aligned}\right\}$$

function [output variable] = functionname (input variable)
end

output variable = functionname(input variable)

Input Variables $\qquad$ 19 Jan (Fri)

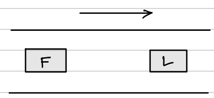
Move the vehicles
1) models
$\rightarrow$ longitudinal dynamics — Car Following Model
$\rightarrow$ lateral dynamics — Lane Changing Model

CAR FOLLOWING MODEL

$\rightarrow$ mathematical formulation
$\rightarrow$ coupled ODE

$$\begin{cases} \dfrac{dx}{dt} = v \\ \dfrac{dv}{dt} = f(s, v_f, v_l) \end{cases}$$

$f \rightarrow$ social force
f is not a physical force
$\rightarrow$ Newtonian mechanics
$F = ma$ ✗



1) Newton's third law
2) Reaction time

Independent variable
1) space gap (s)
2) speed of the follower
3) Relative speed b/w leader and follower (Δv)

$$\Delta v = v_f - v_l$$

1) Eulerian framework — inside vehicle sit.
2) Lagrangian framework — outside veh. fix. the position
$\rightarrow$ Car Following model

Car following model
$\rightarrow$ describes all the driving regimes
$\rightarrow$ free flow (empty road)
$\rightarrow$ steady state $\left(\frac{dv}{dt} = 0\right)$
$\rightarrow$ dynamic situations

smooth transitions b/w different traffic regimes $\qquad \frac{dv}{dt}$ $\downarrow$ smooth & continuous

$$\text{jerk} = \frac{d^2v}{dt^2} = \text{some finite value}$$

Intelligent Driver Model (IDM)

· First principles (

$$\frac{dv}{dt} = \underbrace{\text{free}}_{\text{term}} + \underbrace{\text{interactive}}_{\text{term}}$$

$$\text{free term} = a\left(1-\left(\frac{v}{v_0}\right)^\delta\right)$$

$$\text{interactive term} = -a\left(\frac{s'}{s}\right)^2$$
(congested traffic)

a = max. acceleration (modal parameter)
v = current speed of vehicle
v_0 = desired speed of vehicle (modal parameter)
s' = desired spacing
s = actual spacing
δ = a modal parameter

$$s' = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}}$$

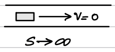
T = desired time gap
v = current speed of veh
$\Delta v = v_f - v_l$
s_0 = minimum gap
a = max. acceleration
b = comfortable deceleration

$$\frac{dv}{dt} = a\left(1-\left(\frac{v}{v_0}\right)^\delta\right) - a\left(\frac{s'}{s}\right)^2$$

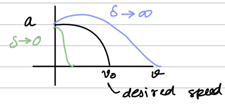
why time gap? —

$v_1, v_2 >> v_3, v_4$

Case-1 Empty Road



$$\frac{dv}{dt} = a\left(1-\left(\frac{v}{v_0}\right)^\delta\right)$$



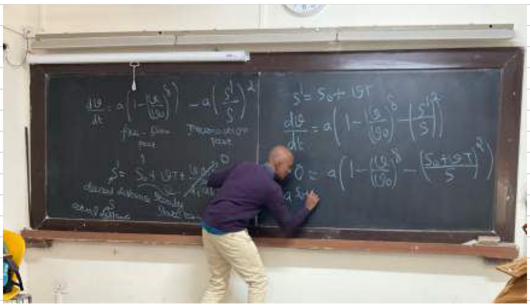
$v = 0 \Rightarrow \frac{dv}{dt} = a$ (max acc^n)

$v = v_0 \Rightarrow \frac{dv}{dt} = 0$

Why δ?
to control shape of the curve.

24 Jan (Wed)

$$\frac{dv}{dt} = a\left(1-\left(\frac{v}{v_0}\right)^\delta\right) - a\left(\frac{s'}{s}\right)^2$$



$$s' = s_0 + vt$$

$$\frac{dv}{dt} = a\left(1-\left(\frac{v}{v_0}\right)^\delta - \left(\frac{s'}{s}\right)^2\right)$$

$$0 = a\left(1-\left(\frac{v}{v_0}\right)^\delta - \left(\frac{s_0+vT}{s}\right)^2\right)$$

$$\frac{a\,(s_0+vT)^2}{s^2} = a\left(1-\left(\frac{v}{v_0}\right)^\delta\right)$$

$$\frac{(s_0+vT)^2}{s^2} = 1-\left(\frac{v}{v_0}\right)^4 \qquad \delta = 4$$

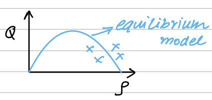
$$v, s \qquad \frac{s^2}{(s_0+vT)^2} = \frac{1}{1-\left(\frac{v}{v_0}\right)^4}$$

$$s^2 = \frac{(s_0+vT)^2}{1-\left(\frac{v}{v_0}\right)^\delta}$$

$$s_e = \frac{(s_0+vT)}{\sqrt{1-\left(\frac{v}{v_0}\right)^\delta}}$$

Steady state gap

Generally, $\delta = 4$
v_e (equil^m speed)



$$\rho = \frac{1}{s_e + l}$$

$$\rho_{avg} = \frac{1}{\text{distance headway}}$$

Steady state means $\frac{dv}{dt} = 0$

$$\boxed{Q = \rho v}$$

$$s' = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}}$$

free part = 0
steady state part = 0

1) free flow part
2) steady state part
3) dynamical part (signal)

$$\frac{dv}{dt} = a\left(1-\cancel{\left(\frac{v}{v_0}\right)^\delta}^{\,0} - \left(\frac{s'}{s}\right)^2\right)$$

$$\frac{dv}{dt} = -a\left(\frac{s'}{s}\right)^2$$

$$\frac{dv}{dt} = -a\left(\frac{\frac{v\Delta v}{2\sqrt{ab}}}{s}\right)^2$$

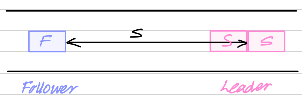
$$\frac{dv}{dt} = -\frac{\cancel{a}\,v^2\Delta v^2}{4\cancel{a}bs^2} = -\frac{v^2\Delta v^2}{4bs^2}$$

$$\Delta v = v_f - \cancel{v_l}^{\,0} = 0$$

$$\Delta v = v_f = 0$$

$$\frac{dv}{dt} = \frac{-v^2\Delta v^2}{4bs^2} = -\frac{v^4}{4bs^2} = -\frac{b_{kin}^2}{b}$$

where, $b_{kin} = \left(\frac{v^2}{2s}\right)$



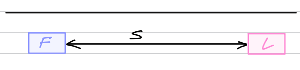
leader speed = 0

$$v^2 = u^2 + 2as$$
$$0 = u^2 + 2as$$
$$a = \frac{-u^2}{2s}$$

$$\boxed{\frac{dv}{dt} = -\frac{b_{kin}^2}{b}}$$

(dynamic part)
b = comfortable deceleration
$= 2\ m/sec^2$

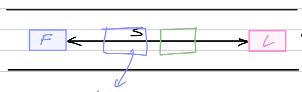
Case 1 $\quad t = t_1$



parked vehicle
$v_l = 0$

$\frac{v^2}{2s} = b_{kin} = 4 \ m/sec$ $\qquad \frac{dv}{dt} = \frac{-b_{kin} \times b_{kin}}{b} = \frac{-4 \times 4}{20} = -8$

overcompensating — bcoz dangerous situation there
abblying hard breaking



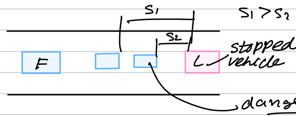
parked vehicle
$v_L = 0$

$b_{kin} = 3$

here
safer (less danger) — due to hard breaking
Intelligent model.

$t = t_1 + \Delta t$
$\frac{dv}{dt} = -\frac{3 \times 3}{20} = -4.5 \ m/s^2$

Case - 2



$s_1 > s_2$
stopped vehicle
danger? yes

$\frac{dv}{dt} = -\frac{b_{kin}^2}{b}$

$b_{kin} = 2 \ m/s^2$
$b = 4 \ m/s^2$ $\Big\}$ $\frac{dv}{dt} = \frac{-2 \times 2}{4} = -1$

mild braking

$t + \Delta t$

$b_{kin} = 4 \ m/s^2$
$b = 4 \ m/s^2$

$\frac{dv}{dt} = -\frac{4 \times 4}{4} = -4 = b$

Intelligent Driver Model
Best model
so far)

OPTIMUM VELOCITY MODEL → Jabanese Model
Some Drawbacks

FULL VELOCITY DIFFERENCE MODEL → some drawbacks → modified

MODIFIED FULL VELOCITY DIFFERENCE MODEL → Good one. but won't teach (no time)

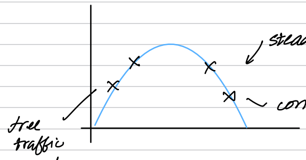
Steady State
↑ max acc^n → anticipations ↑ → steady state (means) $\quad$ (steady state always form | in jam also)

$s_e = \frac{s_0 + vT}{\sqrt{1 - \left(\frac{v}{v_0}\right)^{\delta}}}$ maintain steady state gap.

Now → Density ↓ ~ steady state
(Free traffic steady state)

Then → Density ↑ ~ steady state
(congested steady state)

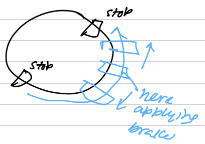
Steady state always achieve.



steady state lies exactly on the curve
congested steady state
free traffic steady state

Now → Making two traffic lights

$b = 0.9 \ m/s^2$

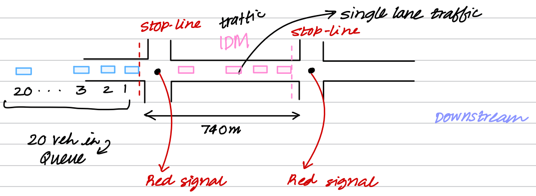


stop
stop
here applying brake

b ↑ then apply brake 's' distance ves.

b → (Anticipation Parameter)

CITY TRAFFIC



stop line
traffic
IDM
single lane traffic
stop-line
740 m
20 veh in Queue
Red signal
Red signal
Downstream

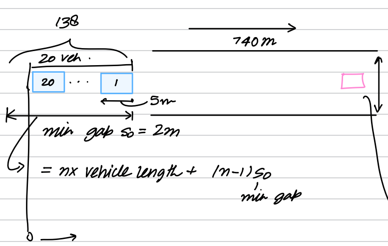
20 vehicles
speed = 0
All vehicle type cars $\Bigg\}$ No headway needed at the moment
No vehicle speed needed at the moment

Assume: Downward traffic signal always red.

MOBIL (A lane changing model)
Discrete lane changing model

lab # 3

878 m



138
20 veh
740 m
3.5 m
5 m
single lane road
car only traffic

min gab $s_0 = 2m$

$= nx$ vehicle length $+ (n-1) s_0$
min gap

speed = 0
length of virtual veh = 0
width of virtual veh = width of road.

IDM Model

$\frac{dv}{dt} = a\left(1 - \left(\frac{v}{v_0}\right)^{\delta} - \left(\frac{s'}{s}\right)^2\right)$

$= s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}}$

$= s_0 + max\left(0, vT + \frac{v\Delta v}{2\sqrt{ab}}\right)$ ~ always maintain to a min.

$= \cancel{s_0 + (-ve)}$

Virtual veh. speed = 0
length of virtual veh = 0
width of virtual veh = length of stop line. $\Bigg\}$ veh. won't stop later.

$\Delta v = v_f - v_L$
$\Delta v = 0$
$v_L = 0$

$\Delta v = v(\text{counter}) - v(\text{counter} - 1)$
$s_2 =$ vehicle (counter − 1) − length of vehicle − vehicleXcoord(counter)

$\Delta t = 0.1 \ sec$
$\boxed{\Delta t = 1 \ sec}$
$t = 6.2 \ sec$

time step.
$\Delta t \leq$ Average Driver Reaction Time
0.8 sec.

Why?
Bcoz driver react in this time

$\Delta t = 2 sec$

$vT + \frac{v\Delta v}{2\sqrt{ab}}$

$s' = s_0 + max\left(0, vT, \frac{v\Delta v}{2\sqrt{ab}}\right)$

Seperately – why?

$t = 1$ sec — time step $= 1$ sec
First veh — second veh.
ACC — $\Delta v = v(1sec) - v_L(1sec)$

update speed
update position } $t = 2$ sec

$v = u + at$

second veh.
$\Delta v = v(1sec) - v(1sec)$
$s =$ Leader position – veh.

$v = u + at$

Apply ac^n at starting time (IDM Model)

$t = 0$ $\Delta t = 0.1$ sec

$t = 140$ sec

$t = 0$ sec → IDM model ACC (20) ⟶ update speed, position

$t = 0.1$ sec →

⋮

$t = 140$ sec $= \frac{140}{0.01} = 14000$ }

IDM Model — 31 Jan (Wed)

→ Simulation Software
→ Calibrate simulation model using real world data.
→ Find optimum parameter values
→ Replicate different driving regimes closely with field data.

Types of data in traffic flow

1. cross-sectional data (Q, ρ, v)

2. trajectory (spatio-temporal dynamics of all vehicles)

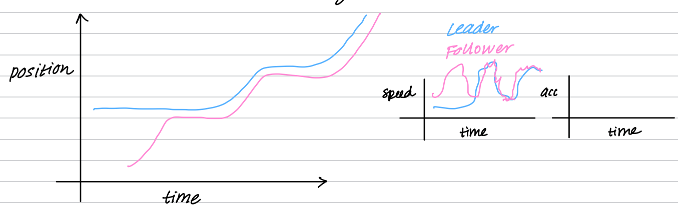
XFCD (x–floating car data) ⟶ spatio-temporal dynamics (vehicles)

Trajectory Data ⟶ Better for calibration
Two trajectories — NGSIM (New Generation Sim.)
open-source data
USDOT collected this data

F — Follower
L — Leader

position ⟶ primary data – using this data
speed, Acc } derived quantity

Calc. speed & acc using primary data



Why choose this trajectory data?

1) Follower — free accelerating $(t < 340s)$ → (a)
2) Crusing at desired speed $(340s \leq t < 342s)$ → (v_0)

---

3) approaching a standing vehicle from large distance $(342s \leq t \leq 350s)$ → (b) comfortable deceleration

4) accelerating behind leader $(350s \leq t < 360s)$

5) Following the leader near steady state $(360 \leq t \leq 365)$
↳ (T) desired time headway

6) decelerating behind a leader $(365 < t < 375)$

7) Standing $(7 \geq 375s)$ → s_0 (min. gap)

· position → primary data (NGSIM)
· speed: → Numerical Scheme (Finite Difference Method)

t_i — x_i
t_{i+1} — x_{i+1}
t_{i+2} — x_{i+2}
(point data)

Taylor Series

position → $f(t+\Delta t) = f(t) + \frac{\Delta t}{1!} f'(t) + \frac{\Delta t^2}{2!} f''(\mathcal{E})$

$t < \mathcal{E} < t + \Delta t$ (MVT)

$$\frac{f(t+\Delta t) - f(t)}{\Delta t} = f'(t) + \frac{\Delta t}{2!} f''(\mathcal{E})$$

$$\underbrace{\frac{f(t+\Delta t) - f(t)}{\Delta t} - f'(t)}_{\text{Error / Remainder term}} = \frac{\Delta t}{2!} f''(\mathcal{E})$$

↳ Truncation Error

order of accuracy $= O(\Delta t)$

F.D. $f'(t) = \frac{f(t+\Delta t) - f(t)}{\Delta t}$ → $O(\Delta t)$ accuracy order

B.D. $f'(t) = \frac{f(t) - f(t-\Delta t)}{\Delta t}$ → $O(\Delta t)$ accuracy order

---

C.D. $f(t+\Delta t) = f(t) + \frac{\Delta t}{1} f'(t) + \frac{\Delta t^2}{2!} f''(t) + \frac{\Delta t^3}{3!} f'''(\mathcal{E}_1)$

$f(t-\Delta t) = f(t) - \Delta t f'(t) + \frac{\Delta t^2}{2!} f''(t) - \frac{\Delta t^3}{3!} f'''(\mathcal{E}_2)$

$$\frac{f(t+\Delta t) - f(t-\Delta t)}{\Delta t} = 2 f'(t) + \frac{\Delta t^2}{3!}[f''(\mathcal{E}_1) + f''(\mathcal{E}_2)]$$

$$\frac{f(t+\Delta t) - f(t-\Delta t)}{2\Delta t} - f'(t) = \frac{\Delta t^2}{12}[f''(\mathcal{E}_1) + f''(\mathcal{E}_2)]$$

order of accuracy: $O(\Delta t^2)$

for $\Delta t < 1$, error is reduced (lesser error)
that's why we will use Central Difference.

✓ $f'(t) = \frac{f(t+\Delta t) - f(t-\Delta t)}{2\Delta t} =$ speed

$f''(t) = \frac{f'(t+\Delta t) - f'(t-\Delta t)}{2\Delta t}$ ⇒ $O(\Delta t^2)$

✓ $f''(t) = \frac{f(t+\Delta t) - 2f(t) - f(t-\Delta t)}{(\Delta t)^2}$ ⇒ $O(\Delta t^4)$ Better Accuracy
↳ = acceleration

we taking $\Delta t = 0.1$ sec, $f'(t) = 10$ times amplified the error
$f''(t) = 100$ times amplified (huge) }
$f''(t) = \frac{\sim}{\sim}$ → primary quantity, stick to it.

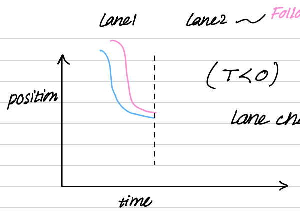
$v = -ve$ } can't go $-ve$

De-Noise

Inconsistencies in NGSIM data
1) Negative gap — F L
2) Negative Speed — $v = -20$ m/s
3) Unreasonable value of acceleration — $a = \pm 60$ m/s^2
4) Sudden jumps
vehicle forward and backwards

Negative gap — collision or overtake

Lane2 ~ Follower changing lane



$(T<0)$ Time headway $=(-ve)$

lane changing + overtaking

Internal consistency NGSIM — Position, speed, acc.

$v=\frac{dx}{dt}$ $\dot{v}=\frac{dv}{dt}$

$x(t)=x(0)+\int_0^t v(t')dt'$ } can't apply on discrete case.

$x(t)=x(0)+\sum_0^n v(t')\Delta t$

$v(t)=v(0)+\int_0^t a(t')dt$

$v(t)=v(0)+\sum_0^n a(t)\Delta t$, $n=\frac{t}{\Delta t}$

Lab#4

Internal consistency

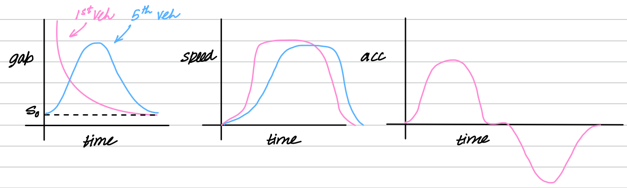
Platoon consistency

Initial gap (s_0) also consistent

$s(0)=x_L(0)-L-x_f(0)$

$s(t)=s_0+\int_0^t (v_L-v)dt$ $\forall t$ (all time)

If you consider position $\longrightarrow$ Central Difference Method.
Automatically platoon consistency satisfied.



ref time = 0, 0.1, 0.2

time stat = [ ]

timestat = [0, 0.1, ... (20)

gap stat, ~.......

time stat = [0.5, ---....... 5] 5, 10, . .

speed slot

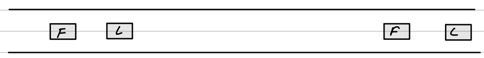
speed slot = [- - - - - -] magnified

$$\left[\begin{array}{l} - - - - - - \\ - - - - - - \end{array}\right] \begin{array}{l} 0.1 \\ 0.2 \end{array}$$

$$\left[\begin{array}{l} - - - - - \\ - - - - - \\ - - - - - \end{array}\right]$$

100 sec
$\Delta t = 1$ sec
time stat 101×1 speed stat 101×5
gap stat 101×5 acc stat 101×5

IDM Model — Discontinuous graph — lane changing
(Active & Passive lane changing)



error $=(x_s)_F-(x_d)_F$ ↘ Later

De-Noise

Convolution ~ combining two functions to produce the new function.
$(f,g)\longrightarrow(f*g)$

$(f*g)=\int_{-\infty}^{\infty} g(t)\,f(t-\tau)\,d\tau$

our data is discrete — use discrete convolution technique

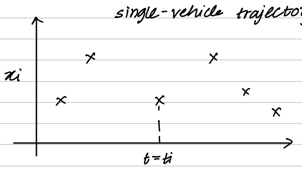
$(f*g)=\sum_{-\infty}^{+\infty} g(t)\,f(t-\tau)$

vehicle position (from field data)

We have to construct this function

How to construct this function?
We have to construct this fn mathematically.

New lec



De-noise or
Data smoothing technique

Discrete convolution

$(f*g)=\sum_{-\infty}^{\infty} f(t)\,g(t-\tau)$

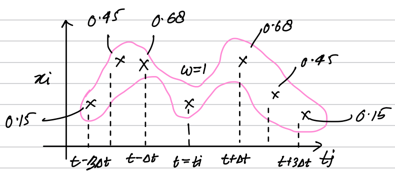
$f(t)\rightarrow$ from the data

weight function $g(t-\tau)$

Kernel function

$x_{t=t_i}\rightarrow$ smooth partition (or) position (after removing the noise)

traffic is non-linear.



weights

$0\leq w\leq 1$

weights are symmetric
(trusting $t=t_i$ point)
$w=1$

$\phi(t-\tau)$ Kernel function

$\phi\rightarrow$ localised (upto some local range)

$|t-\tau|\longrightarrow\infty$ } that is a localised function
$\phi\longrightarrow 0$

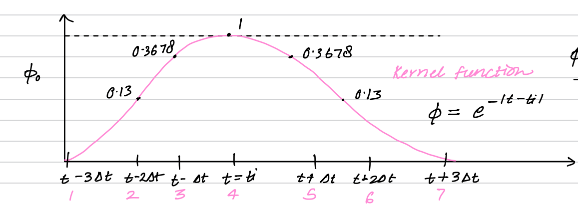
$\tau=t_i$
$t=(t-3\Delta t,\ t+3\Delta t)$

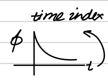
$\phi\rightarrow 0$ $|t-3\Delta t|$ $|t+3\Delta t|$

$\phi_0\rightarrow$ maximum at $\phi(t-\tau)=1$
$t-\tau=0$ or $t=t_i$, $\tau=t_i$
$t_i-t_i=0$

$\phi_0\rightarrow$ continuous function of $|t-\tau|$
$\phi_0\longrightarrow$ monotonically decreasing function
$\phi_0\longrightarrow$ symmetric

· If you apply any filter in data, then there will be artifacts.
↳ errors in the data. data is correct but wrong filter choice.





discont. cont. discont.

$\tilde{x} = \phi_0 x$

Kernel — position

convoluted function

Data — equidistant in time

instead of going to time, you have to use time index. ($\Delta t = 0.1$ sec)

$\phi = e^{-|t-ti|}$

$\phi = e^{-0} = 1 \quad (t = ti)$

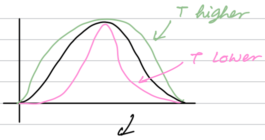
$t \rightarrow$ time index $= K$

$ti \rightarrow$ time index $= i$

$\phi = e^{-|K-i|} = e^{-|4-4|} = e^{-0} = 1 \quad (K = i)$

$\phi = e^{-|3-4|} = e^{-1} = 0.3678$

$\phi = e^{-|2-4|} = e^{-2} = 0.13$



$\phi = e^{\frac{-|K-i|}{T}}$

exponential moving average method

T – controls the shape of the curve

T higher – green curve

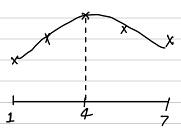
T lower – pink curve

$\tilde{x}_\alpha(i) = \sum_{K=i-D}^{i+D} x_\alpha(K) e^{-\frac{|i-K|}{\Delta}}$ → kernel function

position

field data

$i = 4 \quad D = 3$



Now, normalise $\tilde{x}_\alpha(i)$

$$\tilde{x}_\alpha(i) = \frac{1}{\sum_{K=i-D}^{i+D} e^{-\frac{|i-K|}{\Delta}}} \sum_{i-D}^{i+D} x_\alpha(K) e^{-\frac{|i-K|}{\Delta}}$$

{Normalization}

$\left\{ \frac{i-K}{\Delta} < \Delta \right\}$ always

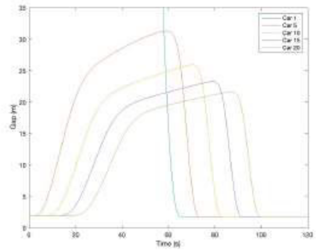
low pass filter

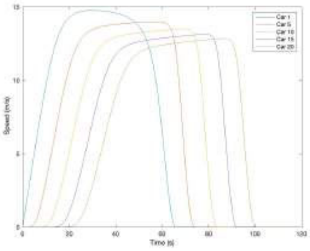
· low-pass filter ✓

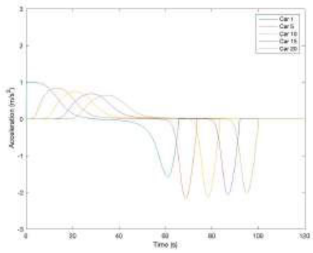
· high pass filter

· Install MATLAB

· Full charge







7 Feb 2024, wed

Data smoothing

$\phi(ti) = \sum \exp \frac{-|t-ti|}{\tau}$ → a model parameter

$\tilde{x}(ti) = \sum \phi_0(t-ti) x(t)$

reference of time

smoothed position → $\tilde{x}(ti) = \frac{1}{\sum \phi_0(t-ti)} \sum \phi_0(t-ti) x(t)$

time index equidistant in time

$$\tilde{x}(i) = \frac{1}{\sum_{K=i-D}^{i+D} \phi_0(K-i)} \sum_{K=i-D}^{i+D} \exp \frac{-|K-i|}{\Delta} x(K)$$

$\Delta = \frac{\tau}{dt}$ dt = time interval b/w two points

$T = 10$ sec

$dt = 2$ sec

starting point

$\Delta = 5$ points

$D = \min\{\alpha\Delta, i-1, N-i\}$

parameter

ending point

$\alpha = 3$

$D = \min(3 \times 5) = 15$

1 16 31

$i = 16$

total no. of points are always odd in number.

Model + Data

Calibration

Compare between measured and simulated quantity.

Real world data — car following model

Minimize difference b/w measured and simulated quantity

Find out optimum model parameters

Before calibration, Simulation setup

smoothed position → speed → Acc } both leader and follower

1. internal consistency
2. platoon consistency } already satisfied

Simulation setup

follower: $x(0) \quad v(0) \quad a(0)$ leader: $x_l(0) \quad v_l(0)$

$t = 0$

$t = t + \Delta t$

$t = t + 2\Delta t$

external input

$x^{sim}(0) = x^{data}(0)$

$v^{sim}(0) = v^{data}(0)$

$s^{sim}(0) = x_l^{data}(0) - L_l - x^{sim}(0)$

$\{x_l^{data}, v_l^{data}\} \ \forall t$

always this data comes from real world field data

Apply IDM Model at time $t=0$

Acc_IDM_model (s^{sim}, $v^{sim}(0)$, Δv^{sim})

$\Delta v^{sim}(0) = v^{sim}(0) - v_l^{data}(0)$

$\left(\frac{dv}{dt}\right)_{t=0}$

$s^{sim}(1) = x_l^{data}(1) - L - x^{sim}(1)$

$\Delta v^{sim}(1) = v^{sim}(1) - v_L^{data}$

$\Delta t = 1$ sec

$v = u + at$

$x_0 = s_0 + \left(\frac{u+v}{2}\right)\Delta t_{t=0}$

Acc_IDM_model ($s^{sim}(1)$, $v^{sim}(1)$, $\Delta v^{sim}(1)$)

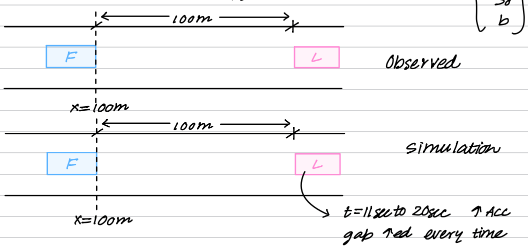
$X_{sim}(2)$

$v_{sim}(2)$

Parameters x, v, a, s

Position x

Obj. Func. $\min \dfrac{\sum_{i=0}^{n}\left[x_i^{data} - x_i^{sim}\right]}{n}$ $\left\{ a, v_0, T, S_0, b \right\}$

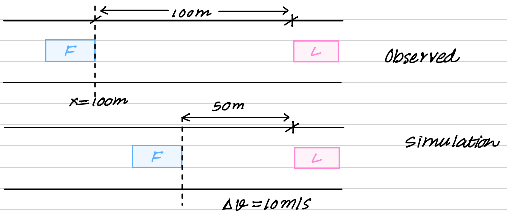


t=11sec to 20sec ↑Acc
gap ↑ed every time

zero error
can't find parameters
optimally can't find.

Speed v

$\Delta v = 10\,m/s$



Δv
$\text{error} = \underbrace{\frac{1}{n}\sum(\Delta v^{data} - \Delta v^{sim})^2}_{=0}$

$\Delta v \rightarrow$ correct parameter

Gap s

$s = x_l - L - x_f$ } good variable
$s \quad \Delta v$

Kyun?

$\text{error} = \frac{1}{n}\sum_{i=1}^{n}(s^{sim} - s^{data})^2$ minimize

$\text{absolute error} = \dfrac{\frac{1}{n}\sum_{i=1}^{n}(s^{sim} - s^{data})^2}{\frac{1}{n}\sum_{i=1}^{m}(s^{data})^2}$

$\left.\begin{matrix} s^{sim} = 110 \\ s^{data} = 10 \end{matrix}\right\}$ $(s^{sim} - s^{data})^2 = 100^2$ ~ numerator blows up
↓
more sensitive to larger gap difference
↓
free flow condition

$\text{relative error} = \frac{1}{n}\sum_{i=1}^{n}\left(\dfrac{s^{sim} - s^{data}}{s^{data}}\right)^2$ → more sensitive to small gap

$\left.\begin{matrix} s^{sim} = 10\,m \\ s^{data} = 5\,m \end{matrix}\right\}$ $\text{error} = \frac{10-5}{5} = 100\%$

$\left.\begin{matrix} s^{sim} = 105\,m \\ s^{data} = 100\,m \end{matrix}\right\}$ $\text{error} = \frac{105-100}{100} = \frac{5}{100} = 5\%$

for same diff. in s, different errors are coming up.

mix both

$\text{error mix} = \dfrac{\sum_{i=1}^{n}\dfrac{(s^{sim} - s^{data})^2}{|s^{data}|}}{\sum_{i=1}^{n}|s^{data}|}$

Free traffic and congested traffic

{analytical method, heuristics method}

(12 Feb, Tues)

Model
Data → De-noise
Objective Function

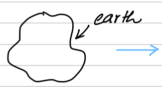
$f = \text{Error}_{rel} = \frac{1}{n}\sum\left(\frac{S_{obs} - S_{sim}}{S_{obs}}\right)^2$
→ Objective Function ~> minimize

$f(v_0, T, S_0, a, b)$ optimum model parameters

v_0, T, S_0, a, b
↓
0.1m/s (estimating optimum model parameters)

minimization problem

f is continuous function
f is not continuous function → mostly happen
(discontinuous) ↓
↓ evolutionary algorithm
lane changing happens, (Genetic Algorithms)
discontinuity happens!



DNA's
AT CG ~> optimal or sub-optimal solution

General structure (GA)

1) Initialization

Assume initial population (randomly) $\left\{ V_0, T, a, b, S_0 \right\}$ Random values ← 200 populations

$\left.\begin{matrix} V_0 = 15 \\ T = 1 \\ a = 1 \\ b = 1.5 \\ S_0 = 2.5 \end{matrix}\right\}$ $\text{fitness function} = \frac{1}{n}\sum\left(\frac{S_{obs} - S_{sim}}{S_{obs}}\right)^2$

$\left\{ \begin{matrix} LB \\ UB \end{matrix} \right\}$ GA automatically generate random values b/w LB and UB for all parameters (200 fitness functions)

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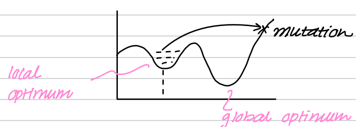
function(f)
$\min f(x)$ $x = v_0, T, a, b, S_0$

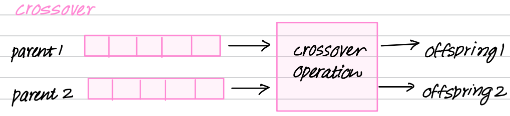
2) Evolution Loop

GA
1) Initialization (initial population → randomly)
2) Select parents & crossover
3) mutation — chromosomes
 error in genes
 - Increase explorative ability of GA
 - Create new innovative solution

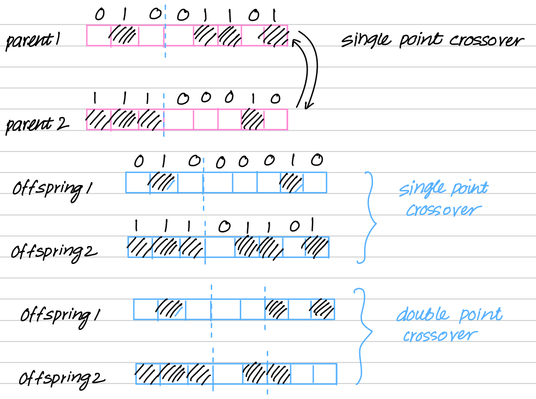


4) merge with population and offspring
5) Evaluate, sort and select
6) Check for termination criteria
 if not, go to step 2.

crossover



mathematical operator



uniform crossover

$x_1 = \{x_{11}, x_{12}, x_{13}, \dots x_{1n}\}$

$x_2 = \{x_{21}, x_{22}, x_{23}, \dots x_{2n}\}$

$\alpha_2 = \{\alpha_{21}, \alpha_{22}, \alpha_{23}, \dots \alpha_{2n}\}$

$\alpha = \{\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_n)$

$\alpha_i = 0$ or 1

$y_1 = \{y_{11}, y_{12}, y_{13}, \dots y_{1n}\}$

$y_2 = \{y_{21}, y_{22}, y_{23}, \dots y_{2n}\}$

$y_{1i} = \alpha_i x_{1i} + (1-\alpha_i) x_{2i}$

$y_{2i} = (1-\alpha_i) x_{1i} + \alpha_i x_{2i}$

200 population → 200 offsprings

Mutation

→ error in the genes   two genes
→ increase explorative ability of GA
→ new solution (local optimum)

$x \longrightarrow$ [mutation operator] $\longrightarrow x$ mutation rate

$x = (x_1, x_2, \dots x_n)$ $x_i' = (x_i', x_2', \dots x_n')$

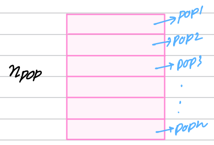
$x_i \in \{0,1\}$

$j = 1$ to n (RN)

$i = 10$

$x_i' = \begin{cases} x_i & j \neq i \\ 1 - x_i & i = 1 \end{cases}$

parent selection



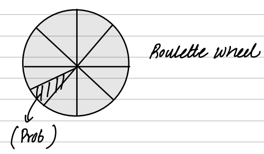
random selection
1) $R = \{1, 2, 3, \dots n\}$
↳ not effective
fitness function
2) Tournament selection
→ members (5) parents
→ select 5 best fitness function of parents

This is deterministic.

• Casino ~ Gangster
• MIT Professor
↳ Real life movie.

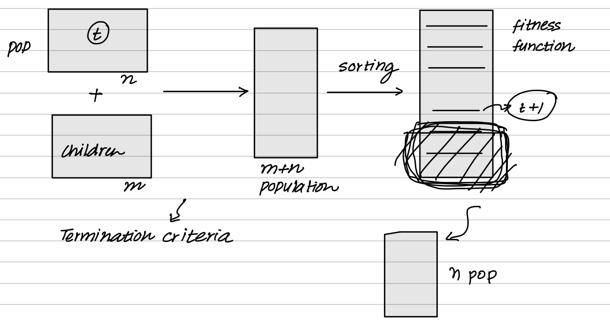
3) Roulette Wheel selection

$P_i = \dfrac{f_i}{\sum_{i=1}^{n} f_i}$ (Assign probability) here $n = 10$



Irany
German
French
Italian

Merge with Parent and Offspring



<u>14 Feb 2024, Wed</u>

min $f(V_0, T, a, b, S_0)$ discrete

$V_0 = LB \sim UB$
$T = LB \sim UB$ crossover operations
$a = LB \sim UB$

rel error $= f = \dfrac{1}{n} \sum_{i=1}^{n} \left(\dfrac{S_{data} - S_{sim}}{S_{data}} \right)^2$ also S_{obs} (same)

parent 1 ↳ $x_1 = (x_{11}, x_{12}, x_{13}, \dots, x_{1n})$ cross over

parent 2 $x_2 = (x_{21}, x_{22}, x_{23}, \dots, x_{2n})$

offspring 1 $y_1 = (y_{11}, y_{12}, y_{13}, \dots, y_{1n})$

offspring 2 ↳ $y_2 = (y_{21}, y_{22}, y_{23}, \dots, y_{2n})$

$\alpha = (\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_n)$ $\alpha \in (0,1)$ Random
$\alpha = 0.2$

$\left.\begin{aligned} y_{1i} &= \alpha_i x_{1i} + (1-\alpha_i) x_{2i} \\ y_{2i} &= (1-\alpha_i) x_{1i} + \alpha_i x_{2i} \end{aligned}\right\}$ Crossover

$\alpha \in (-\delta, 1+\delta)$ $\delta \rightarrow$ very very small number

It improves exploration ability of GA.

mutation

$x \longrightarrow$ [ ] $\longrightarrow x$

$(x_1, x_2, \dots x_j, \dots x_n)$ $(x_1', x_2', \dots x_j', \dots x_n')$

$x_j' = x_j + \delta$ ⇝ δ follows uniform distribution
uniform $(-\epsilon, +\epsilon)$
Limited range

Better use Gaussian
$\delta \rightarrow$ Gaussian
$\sim N(0, \sigma^2)$
Most of the fall near mean
(here mean = 0)

Revisit

$\min f = \dfrac{1}{n} \sum_{i=1}^{n} \left(\dfrac{S_{data} - S_{sim}}{S_{data}} \right)^2$

$S_{sim} = g(V_0, T, a, b, S_0)$

1) Initialisation → Initial population = 200

$\in (LB, UB)$	set 1	set 2	. . .	set 200		
V_0	15	30	.		$V_0 \rightarrow 200$	values
T	1	1.6	.		$T \rightarrow 200$	
a	0.1	4.0	.		$a \rightarrow 200$	
b	3.6	0.01	.		$b \rightarrow 200$	
S_0	6	5	.		$S_0 \rightarrow 200$	
	⇒ f_1	⇒ f_2	. . .	⇒ f_{200}		

f_1 = fitness function 1
f_2 = fitness function 2
⋮
f_{200} = fitness function 200

crossover	v	T	a	b	s_0
pop1 ~	15	1	0.1	3.6	6
pop2 ~	30	1.6	4.0	0.01	5

	v	T	a	b	s_0
offspring1	15	1	4	0.01	5
offspring2	30	1.6	0.1	3.6	6

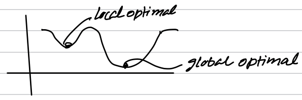
Similarly 200 population
⇓
200 offsprings.

200 pop + 200 offspring

$f_1, f_2, \ldots, f_{200}$ $f_1, f_2, \ldots, f_{200}$

Take best 200 based on fitness function

f_1
f_2
f_3
Best fitness



leaderrawData ~ After smoothing.
cs-rel ~ cumulative rel error
global var ~ can be accessed anywhere
. . . → continue

selectionfunc ~ select 2 pop out of 200 for crossover
MaxGeneration ~ max 420 iterations
└ max no. of iterations.

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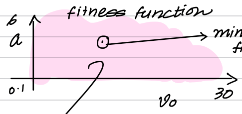
a = 0.1 to 6
V_0 = 0.1 to 30



$\tilde{a} = 3.17$
$\tilde{v_0} = 12.70$
$\tilde{s_0} = 3.59$
$\tilde{T} = 1.25$
$\tilde{b} = 1.74$
fixing

└ min rel error.
all other place higher

Fix any 3 and vary only 2 parameter.
Plot contour plots.
└ optimum value around blue (min) & yellow (max).

15 Feb 2024, Thurs

$\tilde{a} = f(s, v, \Delta v)$

Leader acc^n ~ no acc^n required — not included in parameters.

[1] [2] [3] [4] [5]
param = (a, v_0, T, s_0, b)

At $t=0$,
$s_{sim} = x_L - L - x$
$s_{obs} = x_L - L - x$ } same → bcoz $x^{sim}(0) = x^{data}(0)$

leader – externally controlled – field data

$t=0$ to 521 timesteps (521 data points)

$\Delta v = v - v_L$ {relative speed in IDM Model}

dyn. term $= \frac{v\Delta v}{2\sqrt{ab}}$

dyn. term $= \frac{\text{follower speed} \times \text{rel speed}}{2\sqrt{\text{param}(1) \times \text{param}(5)}}$

$a = \frac{dv}{dt} = f(s, v, \Delta v)$

$v = u + at$
$s = s_0 + ut + \frac{1}{2}at^2$

$t=0.1$ $\left\{ \begin{array}{ll} x_L^{data}(1) & x^{sim}(1) \\ x_L^{data}(1) & v^{sim}(1) \end{array} \right\}$ similarly repeat upto 521

$a = \frac{dv}{dt} = f(s, v, \Delta v) + \epsilon$

speedometer
↓
no error

error

Human perception error
└ compensated by driver anticipation.

(Ya iss class k baad??)

always declare any data ~ in main function.
Don't read anything inside iteration.

Genetic Algorithm ~ won't ask in Exam

16 Feb 2023

Not all model parameters
→ estimated
→ time 350s to 386s
$\{T, a, b, s_0, v_0\}$

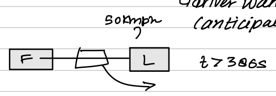
v_0 → desired speed
a → max. acceleration } can't find

→ time $t > 386s$
gap decreasing ~ anticipation behaviour
data 386s to 397s
desired time gap
$T = (-ve)$

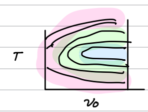
Consider whole trajectory data
T → some error → contain errors

$s = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}}$

$v(\uparrow)$ $s(\downarrow)$
$T = \frac{s}{v}$ } ~ not consistent with model
└ driver want to lane change.
(anticipation behaviour).



Investigation of the parameter space



indifferent w.r.t. desired speed

IDM Model
→ Radar Data set (Germany)
Data set does not contain
– freeflow
– approaching }

desired speed
v_0 = 20,000 km
└ unconstrained optimization

You have to choose correct model.
The model parameter have to be orthogonal

Parameter Orthogonal

diff. driving regimes → situation represent by diff. parameters.

· free acceleration → a
· crusing (v_0) → v_0 ~ fixed └ published values, max(v_i) └ max of all speed in data
· approaching → b comf. dec.
· following → T
· standing → s_0

Every parameter represent one driving regime only.
That is called parameter orthogonal.
Each parameter diff. parameter model / situation.
└ If not, more than one then some correlation will be there.

Ideal case

Each parameter → only one driving scenario

└ we can fix the problem even with incomplete dataset.

1. Fix values from published values
2. Fix values the max (v_i) ~ all v_i from data.

Quiz-1 $\frac{dv}{dt} = \frac{v_0(s) - v}{\tau} - \alpha(v - v_L)$ — linear term in rel. speed.

Fleming

└ not complete model

Model completeness

└ First vehicle

$v_L = 0$

$\frac{dv}{dt} = \downarrow$ decelerating, after some time −ve term dominates.

whenever calibrating ~

1. Tipping point → don't use this data ~ traffic jam (propogating) → Start pt. of stop & go wave
2. Test the data → contain all driving regimes
3. Fix that particular parameter
   other parameter → calibrate
   data or published values
4. LB and UB ~ restrict
5. good initial guess
6. Plot fitness landscape ~ unimodel
   └ data completeness.

GA ~ algorithm good ~ also lot of others.

└ optimization comes in this part.
(Evolutionary Algorithms)

7. Robustness ~ Model must be robust.