

# Queuing Theory - Optimal Traffic Light Duration

Group 3

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# Problem Context

- Traffic congestion is a persistent and growing issue in Ho Chi Minh City.
- Current traffic light systems may not adapt efficiently to dynamic vehicle flows.
- Optimizing traffic light durations can significantly reduce waiting times and improve overall traffic flow.



Figure: A HCMC's crossroad in peak hour

# Markov Processes in Traffic Modeling

- Traffic patterns can be modeled as stochastic systems due to their random and dynamic nature.
- Markov processes are a powerful tool to describe the probabilistic transitions of vehicles through intersections.
- By modeling each direction as a queue and traffic signals as service phases, we can analyze system behavior and optimize light durations.

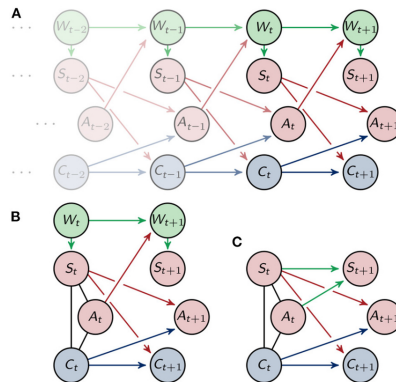


Figure: Sample processes

# Relevance & Impact: Why This Project Matters

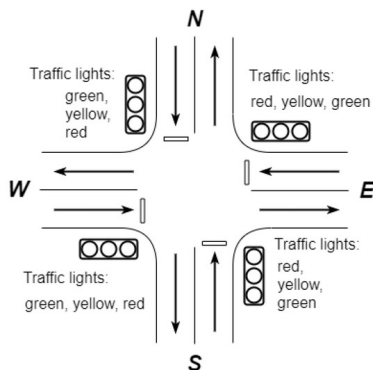


Figure: A model of traffic lights

- Course relevance: Applying continuous-time Markov chains and stochastic modeling.
- Real-world value: Quantitative tool for traffic signal optimization in congested cities.
- Class interest: Relatable, visual, and shows how math can drive real change.

# Continuous-Time Markov Chain

## Overview:

Continuous-time Markov chain models

- Transitions between discrete states
- Duration of time in each state (exponentially distributed) (\*)

Each model is specified by

- Transition matrix  $\tilde{\mathbf{P}}$
- Initial distribution  $\alpha$
- Exponential time parameters  $\lambda_{S_i}$ ,



# Continuous-Time Markov Chain

## Markov Property

A continuous-time stochastic process  $(X_t)_{t \geq 0}$  with discrete state space  $\mathcal{S}$  is a continuous-time Markov chain if:

$$P(X_{t+s} = j \mid X_s = i, X_u = x_u, 0 \leq u < s) = P(X_{t+s} = j \mid X_s = i)$$

for all  $s, t \geq 0, i, j, x_u \in \mathcal{S}$ , and  $0 \leq u < s$ .

## Time-Homogeneous Property

The process is said to be time-homogeneous if this probability does not depend on  $s$ . That is,

$$P(X_{t+s} = j \mid X_s = i) = P(X_t = j \mid X_0 = i), \quad \text{for all } s \geq 0$$

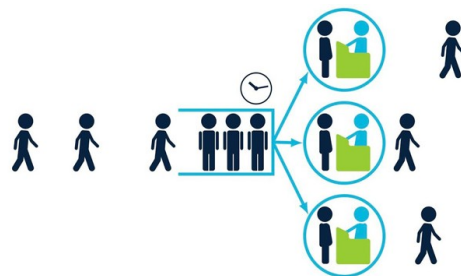


# Queueing Theory

**Queueing theory** is the study of waiting lines, or queues.

## General framework:

- 1 *Customers* arrive at a facility for service.
- 2 They wait for service, creating a *queue*.
- 3 When the service is completed, they leave the system.



## Applications:

- Traffic light control
- Call centers
- Cloud computing
- Emergency services

# Queuing Models

## Standard notation

A queuing model is described by the standard notation of the form

$$A/B/n,$$

in which

- $A$ : arrival time distribution
- $B$ : service time distribution
- $n$ : number of servers.

# Queuing Models: The $M/D/1$ Queue

A queuing model of the form

$$M/D/1$$

consists of

- **M**: Markovian (Poisson) arrival time distribution
- **D**: Deterministic service time
- **1**: One server

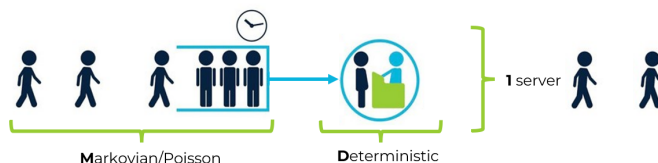


Figure: An  $M/D/1$  queue

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## Key Properties

- Arrival rate:  $\lambda$
- Service time:  $1/\mu$  (fixed)
- Utilization:  $\rho = \lambda/\mu$

# Little's Law

## Theorem (Little's Formula)

In a queuing system, let

- $L$ : average number of customers in the system
- $\lambda$ : arrival rate
- $W$ : average time a customer spends in the system

then the system is stable when

$$L = \lambda W.$$

## Applications

- System design and capacity planning
- Estimating unknown parameters

# Problem Formulations

- Vehicles arrive at intersections as a Poisson process with rate  $\lambda$ .
- Service rate during green is deterministic:  $\mu$  cars/s.
- Two scenarios modeled:
  - (a) Paired directions (NS and EW alternate).
  - (b) Independent directions (N, E, S, W take turns).
- Modeled as  $M/D/1$  queues with interruptions.
- Yellow time is fixed: 8s for (a), 16s for (b).
- Objective: Minimize average waiting time  $W$  by optimizing green durations.

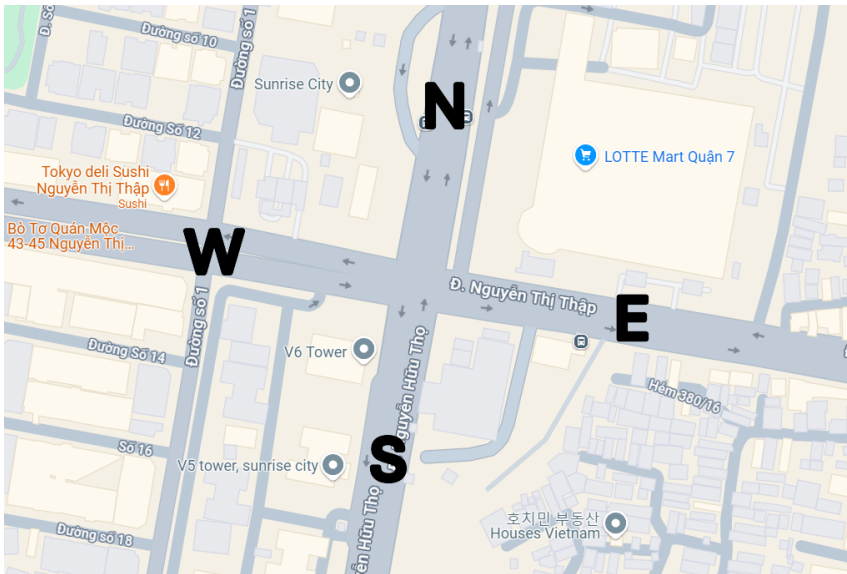
# Passenger Car Unit (PCU) Conversion Table

**Conversion Coefficient from Vehicle Types to PCUs**

Vehicle Type	Motorcycle	Car ( $\leq 12$ seats)	Other Vehicles	
			Bus (12–30 seats)	Truck (<2 tons)
PCU Value	0.30	1.00	1.25	1.50

Source: JICA (2004), *Urban Transport Master Plan – Ho Chi Minh City*, Chungshuk Engineering & Bach Khoa (2006, p.49)

# Nguyen Huu Tho - Nguyen Thi Thap Crossroad Layout





# Traffic Count Data

**Traffic Count Data with PCU Conversion Values**

Location	Motorbike	Car	Bus	Truck (<2 tons)	PCU/7min	PCU/s
Nguyen Huu Tho (N)	358	53	2	14	183.90	0.437857
Nguyen Huu Tho (S)	315	35	2	19	160.50	0.382143
Nguyen Thi Thap (E)	446	65	1	40	260.05	0.619167
Nguyen Thi Thap (W)	422	46	1	30	218.85	0.521071

*Data collected from 7:30–8:00 AM, May 12, 2025*

# Simulations

- Numerical optimization:
  - **Scenario (a)**: Used `minimize_scalar` to find optimal  $G_{NS}$ .
  - **Scenario (b)**: Solved using Lagrange multipliers and `root_scalar`.
- Animation Simulations:
  - Visualized queue lengths over time using `matplotlib.animation`.
  - Green/red phases alternate per scenario logic.
- Inputs:
  - $\lambda_N = 0.438$ ,  $\lambda_S = 0.382$ ,  $\lambda_E = 0.619$ ,  $\lambda_W = 0.521$
  - Service rate  $\mu = 5.5$
  - Cycle time  $C = 110s$

# Optimized Green Time Allocation

**Comparison of Green Durations**

<b>Approach</b>	<b>Real Green (s)</b>	<b>Opt. Green a (s)</b>	<b>Opt. Green b (s)</b>
Nguyen Huu Tho (N)	60	49.24	22.36
Nguyen Huu Tho (S)	60	49.24	21.12
Nguyen Thi Thap (E)	42	52.76	26.34
Nguyen Thi Thap (W)	42	52.76	24.18

*Total cycle time = 110 s (includes 4s Yellow per phase).*

# Discussion

- Queueing model offers analytical insight into signal optimization.
- Trade-off:
  - Simpler set-up in Scenario (a), but lower risk of accidents in Scenario (b)
- Simulations confirm theoretical predictions and effectiveness of optimization
- Practical considerations:
  - Traffic variability
  - Real-time adaptation
  - Data collection over a period of time
- Framework can be extended to adaptive traffic light control.