

Teletraffic Engineering

Oral Exam's Proofs and Notions

August 17, 2018

1. Definition of a Stochastic Process, index space, state space and sample path.
2. Definition of the differences between a discrete-time and continuous-time chain [with plots]
3. [!] Definition of a Markoff Process and Homogeneous Markoff Process.
 - (a) Markoff Property in Discrete-Time and Homogeneous Discrete-Time Markoff Process
 - (b) Markoff Property in Continuous-Time and Homogeneous Continuous-Time Markoff Process
4. **Proof** of the PMF (W_i) of time (amount of steps) spent in a state i over discrete-time to get $E\{W_i\}$, the average time spent in a state i .
5. [!] **Proof** of the Chapman-Kolmogoroff Equation in discrete-time to get the CK-Equation in scalar and then matrix form
6. Definition of condition of ergodicity (steady-state) for a discrete-time Markoff chain and ergodic process' matrix.
 - (a) Definition of Probability of state occupancy $p_i(n)$
7. **Proof** to find transient behaviour $\underline{p}(n)$ and $\underline{p}_i(n)$ from $\underline{p}(0)$
8. Definition of stationary probability vector \underline{z} and meaning of stationarity of a Markoff chain.
9. Definition of asymptotic or limit probability vector \underline{p}
10. **Proof** of the Flow-Conservation Principle from the transient behaviour's equation $\underline{p}(n+1)$ (in scalar form). Meaning and goal of FCP.
 - (a) Usage of FCP for transient-behaviour analysis
 - (b) Usage of FCP for steady-state analysis [Stationary Equations]
11. Definition of probability of first return to state j in n steps $f_j^{(n)}$ [with plots]
12. Definition of probability of ever returning to state j f_j .
 - (a) Classification of a state [Transient vs Recurrent] based on f_j
 - (b) Definition of Periodicity of a recurrent state j . Strongly periodic vs weakly periodic state j .
13. Definition of mean recurrence time M_j for recurrent state j .
 - (a) Classification of a recurrent state j based on M_j [Positive-Recurrent vs Null-Recurrent]

14. Definition of Irreducible Chain
 - (a) 1st Fundamental Theorem for states' classification
 - (b) Stationary solution's admittance for an irreducible chain
 - (c) Limit solution for ergodic HDTMC
15. 2nd Fundamental Theorem for the ergodicity of a chain. [Infinite-state vs finite-state Markoff chain]
16. Definition of probability of occupancy of a state p_j for a positive recurrent state j .
 - (a) M_j and v_{ij}
17. [!] **Proof** of the Chapman-Kolmogoroff Equation in continuous-time to get the CK-Equation in scalar and then matrix form
18. Stationary probability vector and ergodicity condition for a CTMC.
19. [!] Definition of rate transition matrix \underline{V} and transition rate v_{ij} for a continuous-time Markoff Chain
 - (a) Expression of $h_{ij}(\Delta\tau)$ with the Taylor-MacLaurin Expansion for terms on the main diagonal and outside the main diagonal
 - (b) Proof of FCP for a Continuous-time Markoff Chain
20. Sufficient condition for the existence of an ergodic solution of a HCTMC [Finite States vs infinite states]
21. **Proof** of Forward and the Backward CK-Equations in continuous-time case starting from the CK-equation [Relation between $H(t)$ and \underline{V}].
22. [!] **Proof** of the exponential distribution for the memory-less property of the time spent in a state over continuous time [comparison with discrete-time distribution + plot of exp. distribution for τ, t and $t + \tau$]
23. Definition of Homogeneous Birth-Death Discrete-Time Markoff Chain [Three-diagonal matrix]
 - (a) **Proof** of the Condition of Ergodicity of the chain, applying FCP
 - (b) Behaviour of p_i for a Birth - Death DTMC for $b_i = b, d_i = d$
24. Definition of Homogeneous Birth-Death Continuous-Time Markoff Chain
 - (a) FCP for transient analysis
 - (b) FCP for stationary analysis
25. [!] **Proof** of a pure Birth HCTMC as a Poisson RV's distribution.
26. Three packet switching architectures and issues related to them, along with solution. Application and usage for them.
27. [!] GEO/GEO/1 queues' parameters analysis for $P\{Service\}$, $P\{Busy\ slot\}$. Model usage and ergodicity condition for it.
28. [!] Solving Chapman-Kolmogoroff Equation for Pure-Birth HCTMC

- (a) **Proof** of the exponential distribution for order-1 Interbirth time [Starting from a pure-birth HCTMC].
29. Definition of Moment generating function $M(s)$.
- (a) Definition of Γ -order Moment
 - (b) Definition of Variance of a R.V. $Var\{X\}$
 - (c) Definition of Coefficient of Variation of a R.V. C_v
 - (d) $E\{X\}, E\{X^2\}, VAR\{X\}$ for the 1-order moment
 - (e) $E\{X\}, E\{X^2\}, VAR\{X\}$ for the 2-order moment
30. [!] **Proof** of the PDF of the n -order Interbirth time as an Erlang- n distributed R.V.
- (a) $E\{n\}, VAR\{n\}$
 - (b) PDF of the Γ -distribution
31. [!] Discrete-Time Bernoulli Process, Bernoulli Distribution, Binomial Distribution and state Probability $p_i(n)$. Application and usage of Bernoulli Process
- (a) $P_{ON}(t), P_{OFF}(t)$
 - (b) State probability $p_n(t)$
 - (c) For a Bernoulli Process X : Generating function $G_x(z), E\{X\}, E\{X^2\}, VAR\{X\}$
 - (d) For a Bernoulli R.V. Θ : $E\{\Theta\}, E\{\Theta^2\}, VAR\{\Theta\}$
32. [!] Axiomatic definition of a Poisson Process
33. [!] **Proof** of the Poisson Process as limiting case of a discrete-time Bernoulli Process
34. For a Poisson R.V: X : Generating function $G_x(z), E\{X\}, E\{X^2\}, VAR\{X\}$
35. [!] **Proof** that the combination of n independent Poisson processes yields a Poisson process
36. Deterministic Decomposition of a Poisson Process not being a Poisson Process
37. [!] **Proof** of the statistical/probabilistic decomposition of a Poisson Process into n Poisson Processes
38. [!] Continuous-Time Bernoulli Process. State, usage of such process.
- (a) Distribution of Continuous-Time Bernoulli Process
 - (b) **Proof** of the Transient Behaviour analysis as binomial distribution of a Continuous-Time Bernoulli Process
39. [!] **Proof** of the PDF of the arrival time over an interval $(0, t)$ as Poisson distribution.
40. Queueing Systems: Kendall's Notation's 6 parameters.
41. Definition of P_B, P_L, P_{BS}, P_D . Definition for Markovian queues.
42. Definition of $E\{T\}, E\{T_S\}, E\{T_W\}, E\{n\}, E\{ns\}, E\{nw\}$ for Markovian queues
43. Definition of Markovian queue' ergodicity condition. State characterization and properties
44. [!] Definition of A, Traffic intensity.

- (a) When do we have $E\{n\} = E\{ns\} = A$?
 - (b) Ergodicity condition of A .
45. [!] **Proof** of the Traversal time $E\{T\}$ in a $M|M|1$ queue, with derivation of $E\{T_W\}$ by the PASTA property.
46. Definition of average values of frequencies $\Lambda_o, \Lambda, \Lambda_L, \Gamma, \Gamma_{Max}$ and their value for a finite Markovian queue
47. [!] $M|M|N_S$ queues, state probability occupancy p_n, p_{NS} , ergodicity condition
- (a) Why do we increase the frequency of termination of service by $n * \mu$ in an $M|M|N_S$ queue?
 - (b) **Proof** of $E\{T_W\}$ by the PASTA property in an $M|M|N_S$ queue.
 - (c) Ergodicity condition for $M|M|N_S$ queue
 - (d) $E\{T_W\}$ for $M|M|N_S$ queue
48. [!] **Proof** of the Erlang-C formula to find P_D in $M|M|N_S$ queues. [Recursive Erlang-C Formula, plot]
49. [!] Performance comparison of $E\{T_S\}$ between:
- (a) $M|M|1$ with one waiting line for one queue
 - (b) N_S many $M|M|1$ queues with one waiting line per queue.
 - (c) $M|M|N_S$ queue with one waiting line for all N_S servers.
50. $M|M|\infty$ queue. State probability $p_n, E\{T_W\}$ and proof of Poisson Distribution for an $M|M|\infty$ queue
51. [!] **Proof** of the Erlang-B formula to find P_L in $M|M|N_S|0$ queues. Definition and application of the Erlang-B Formula
- (a) Definition of A, Erlang
 - (b) Property of the insensibility of the Erlang-B formula
 - (c) Recursive form of Erlang-B formula
52. [!] **Proof** of Little's Formula.
53. [!] Definition of Embedded Markoff Chain in an $M|G|1$ queue
54. [!] **Proof** of the Pollaczek-Kinchin Formula in an $M|G|1$ queue ($E\{n\}, E\{T_W\}$ in an $M|G|1$ queue) through the mean-value analysis at steady-state
55. Definition of global and local $E\{T_W\}, E\{n\}, E\{ns\}, E\{nw\}$ in an $M|G|1$ queue with no priority classes
- (a) Definition of global and local $E\{T_W\}, E\{n\}, E\{ns\}, E\{nw\}$ with priority classes
56. [!] Definition of virtual and residual time with no priority classes $E\{T_v\}, E\{T_R\}$
- (a) Definition of virtual and residual time with priority classes $E\{T_v\}, E\{T_R\}$
 - (b) **Proof** of $M|G|1$ queue with priorities to find $E\{T_W\}$
 - (c) Conservation law for the virtual time

57. [!] Find p_n in an $M|M|1|N_W$ queue
- (a) **Proof** to find N_ϵ for the percentile of an $M|M|1|N_W$ queue. Meaning and usage of percentiles.
58. [!] **Proof** to find N_ϵ for the percentile in an $M|M|1|\infty$ queues.
59. [!] **Proof** of exponentially-distributed PDF of the waiting time $E\{T_W\}$ in $M|M|1$ queues
60. [!] **Proof** of exponentially distributed PDF of the queueing time $E\{T\}$ in $M|M|1$ queues
61. [!] **Proof** of the Burke Theorem to find that the interdeparture time is independent and exponentially distributed in $M|M|1$ queues. (Markovian nature of a non-markovian queue)
62. Definition of Open Markovian Network of Queues without feedback
- (a) State of the network
- (b) State probability of an open markovian network of queues
- (c) Ergodicity condition of an open markovian network of queues
63. Difference between Open Markovian Network of Queues and Open Network of Markovian Queues
64. Requirements of the Jackson Theorem for Open Markovian Network of queues
- (a) Open Markovian Network of Queues without Feedback vs with Feedback
- (b) [!] "Feeling" of **Proof** of the Jackson Theorem for Open Markovian Network of queues through balance equations
65. Closed Markovian Network of Queues' definition, state probability p_i
66. [!] Gordon-Newell Theorem for a Closed Markovian Network of Queues
- (a) **Proof** of the Gordon-Newell Theorem to come to a product-form solution
- (b) Operating with the Gordon-Newell Theorem [4 steps for this]
67. [!] Average traversal/transit time $E\{T\}$ in a network of queues
68. BCMP Networks' idea and characterization
- (a) State probability definition
- (b) Product-Form solution

TELEGRAPHIC ENGINEERING

PROOFS & NOTIONS

1) STOCHASTIC PROCESS.

A stochastic process consists of a family of R.V.s, indexed by a certain index / usually t , time.

$$\{X(t), t \in T\}$$

INDEX SPACE:

It is the set of all possible indexes t of the stochastic process.

STATE SPACE:

It is the set of R.V.s. corresponding to the indexes (of a time series)

EXAMPLE:

Consider the index space of a time series:

$$\{t_1 \leq t_2 \leq t_3 \dots \leq t_n\}$$

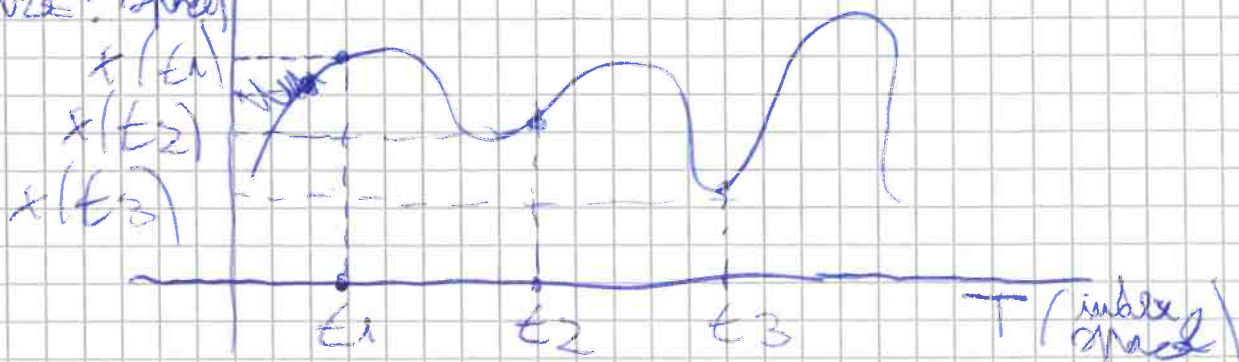
\Rightarrow The corresponding state space is:

$$\{X(t_1) \leq X(t_2) \leq X(t_3) \leq \dots \leq X(t_n)\}$$

SAMPLE PATH.

Set of R.V.s. taken at different time indexes of the process.

EXAMPLE: ^{State space}



2) DISCRETE-TIME CHAIN

A discrete-time chain consists of a chain indexed by discrete values t
 \Rightarrow DISCRETE INDEX SPACE T

$$t \in \mathbb{N} = \{0, 1, 2, 3, \dots\}$$

For a DISCRETE-STATE, DISCRETE-TIME CHAIN we hence have:

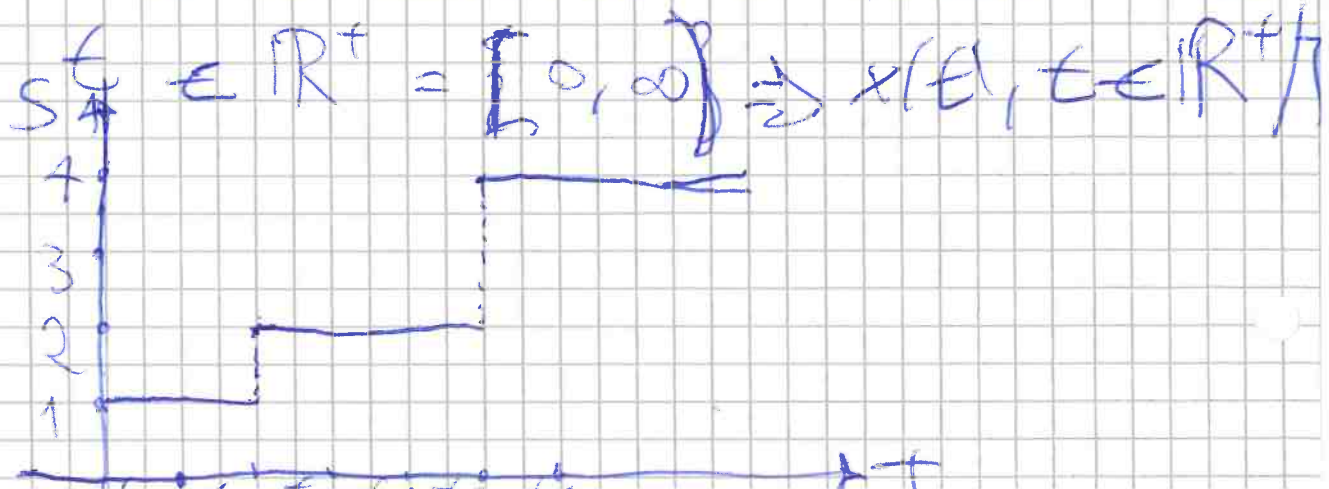


Generally, we take (n) as a step index over discrete-time:

$$X_n \quad n \in \mathbb{N}$$

CONTINUOUS-TIME CHAIN

A continuous-time chain indexed by real when over a CONTINUOUS INDEX SPACE T



3) MARKOFF PROCESS:

A Stochastic Process is said to be a MARKOFF PROCESS if the MARKOVIAN property holds for it.

MARKOVIAN PROPERTY:

If the present is given, then the future is CONDITIONALLY INDEPENDENT from the past, and it only depends ^(conditionally) on the present.

For a TIME SEQUENCE:

$$t_0 \leq t_1 \leq t_2 \leq \dots \leq t_n$$

DISCRETE / CONTINUOUS - STATE SPACE

$$P\{x(t_n) \leq z_n \mid x(t_{n-1}) = z_{n-1}, \dots, x(t_0) = z_0\}$$

FUTURE PRESENT PAST

$$= P\{x(t_n) \leq z_n \mid x(t_{n-1}) = z_{n-1}\}$$

HOMOSENEOUS MARKOFF PROCESS:

It is a Markoff process that does not depend on the individual time ~~indices~~ t_n but only on the difference between consecutive time indexes.

[i.e. A shift in time by n -steps is irrelevant] \Rightarrow Difference $t - t_n$ only matters

$$P\{x(t) \leq z \mid x(t_n) = z_n\} \\ = P\{x(t - t_n) \leq z \mid x(0) = z_0\}$$

CONTINUOUS STATE SPACE - STATE SPACE

2) DISCRETE-TIME MARKOFF PROPERTY

→ Consider the PMF instead of the PDF

~~$P\{X_n = z_n | X_{n-1} = z_{n-1}, \dots, X_0 = z_0\}$~~
 ~~$= P\{X_n = z_n | X_{n-1} = z_{n-1}\}$~~

$P\{X_n = z_n | X_{n-1} = z_{n-1}, \dots, X_0 = z_0\}$
 $= P\{X_n = z_n | X_{n-1} = z_{n-1}\}$

HOMOGENEOUS DISCRETE-TIME MARKOFF PROCESS

$h_{ij}(n) = P\{X_n = j | X_{n-1} = i, X_0 = 1\}$ ONE-STEP TRANS. PROBABILITY

$\Rightarrow h_{ij} = P\{X_n = j | X_{n-1} = i\}$ (Only current position matters to next transition)

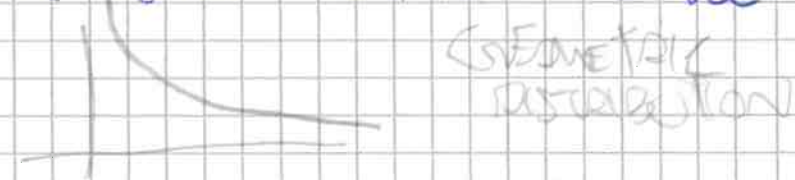
CONTINUOUS-TIME MARKOFF PROPERTY

$P\{X(t) = z_n | X(t-1) = z_{n-1}, \dots, X(0) = z_0\}$
 $= P\{X(t) = z_n | X(t-1) = z_{n-1}\}$

HOMOGENEOUS CONTINUOUS-TIME MARKOFF PROCESS

$h_{ij}(t) = P\{X(t+\tau) = j | X(t) = i\}$

Again, only the "current" position in the present matters to determine the next transition



4) PMF & TIME SPENT IN A STATE i
 (over DISCRETE-TIME)

\Rightarrow We want to find: $P\{W_i = n\}$
 i.e. P. to stay in a state for n steps

$P\{W_i = 1\} = 1 - h_{ii}$
 $P\{W_i = 2\} = h_{ii} \cdot (1 - h_{ii})$
 $P\{W_i = 3\} = (h_{ii})^2 \cdot (1 - h_{ii})$

\odot h_{ii}
 P. to remain in same state i .

$\Rightarrow P\{W_i = n\} = (h_{ii})^{n-1} \cdot (1 - h_{ii})$

~~$E\{W_i\} = \sum_{n=1}^{\infty} n \cdot (h_{ii})^{n-1} \cdot (1 - h_{ii})$~~

\Rightarrow We can now find the $E\{W_i\}$
 AVERAGE TIME SPENT in a STATE i .

Take the AVG. of the TIME spent. (Saying 1, 2, 3, ...)

$$E\{W_i\} = \sum_{n=1}^{\infty} n \cdot (h_{ii})^{n-1} \cdot (1 - h_{ii})$$

$$= (1 - h_{ii}) \cdot \sum_{n=1}^{\infty} n \cdot (h_{ii})^{n-1} = \frac{(1 - h_{ii})}{h_{ii}} \cdot \sum_{n=1}^{\infty} h_{ii}^n$$

$$= \frac{1 - h_{ii}}{h_{ii}} \cdot \frac{h_{ii}}{1 - h_{ii}} = \frac{1}{1 - h_{ii}}$$

$\Rightarrow E\{W_i\} = \frac{1}{1 - h_{ii}}$

\Rightarrow The AVG. time spent in a state i is GEOMETRICALLY-DISTRIBUTED.

5) PROOF OF CK EQUATION IN DISCRETE-TIME.

C-K EQUATION in DISCRETE-TIME:

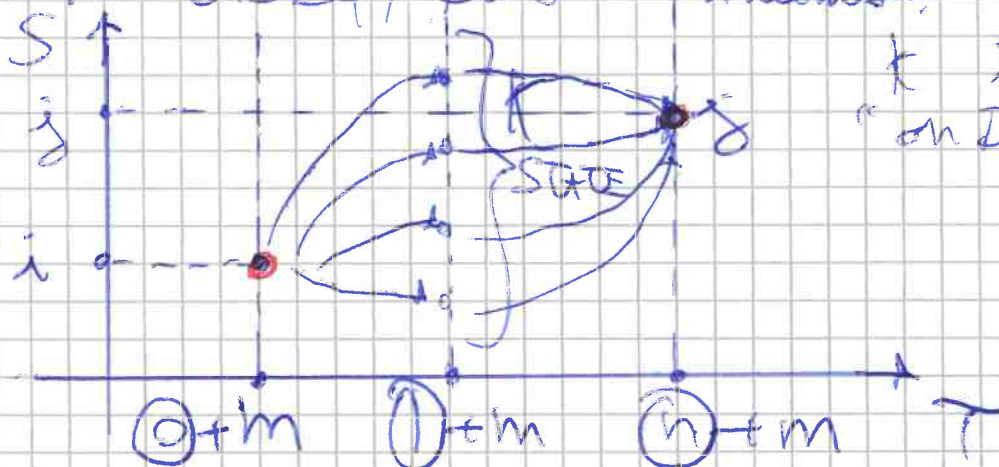
(MATRIX FORM)

$$H^{(n)} = H^{(1)} \cdot H^{(n-1)}$$

In SCALAR FORM it is the MATRIX-PRODUCT

$$h_{ij}^{(n)} = \sum_{k \in S} h_{ik}^{(1)} \cdot h_{kj}^{(n-1)}$$

GRAPHICALLY, this



means:

k is a state "on the way"

By HOMOGENEITY of a MARKOFF PROCESS:

$$h_{ij}^{(n)} = P\{X_n = j \mid X_0 = i\}$$

By the TOTAL PROB. THEOREM:

$$h_{ij}^{(n)} = \sum_{k \in S} P\{X_n = j, X_1 = k \mid X_0 = i\}$$

By the BAYES THEOREM:

$$h_{ij}^{(n)} = \sum_{k \in S} P\{X_n = j \mid X_1 = k, X_0 = i\} \cdot P\{X_1 = k \mid X_0 = i\}$$

$$\Rightarrow h_{ij}^{(n)} = \sum_{k \in S} P_{ij}^{(n-1)} | X_{n-1} = k | \cdot P_{jk} | X_0 = i |$$

$$h_{ij}^{(n)} = \sum_{k \in S} h_{kj}^{(n-1)} \cdot h_{ik}^{(1)}$$

C-K EQUATION
~~MATRIX FORM~~
 SCALAR FORM

C-K EQUATION in MATRIX FORM:

$$\underline{h}^{(n)} = \underline{h}^{(n-1)} \cdot \underline{h}^{(1)}$$

\Rightarrow COORDINATE

$$\underline{h}^{(n)} = \underline{h} \cdot \underline{h}^{(n-1)}$$

$$\Rightarrow \underline{h}^{(n+1)} = \underline{h} \cdot \underline{h}^{(n)}$$

$$\underline{h}^{(n+2)} = \underline{h} \cdot \underline{h}^{(n+1)}$$

$$\Rightarrow \underline{h}^{(n)} = \underline{h}^n \quad \text{by INDUCTION}$$

6) CONDITION OF ERGODICITY FOR A LOW DISCRETE-TIME MARKOFF CHAIN.

If the following limit exists, then we have a single solution q (ERGODIC SOLUTION) which is independent from the INITIAL CONDITIONS. (This solution is also stationary)

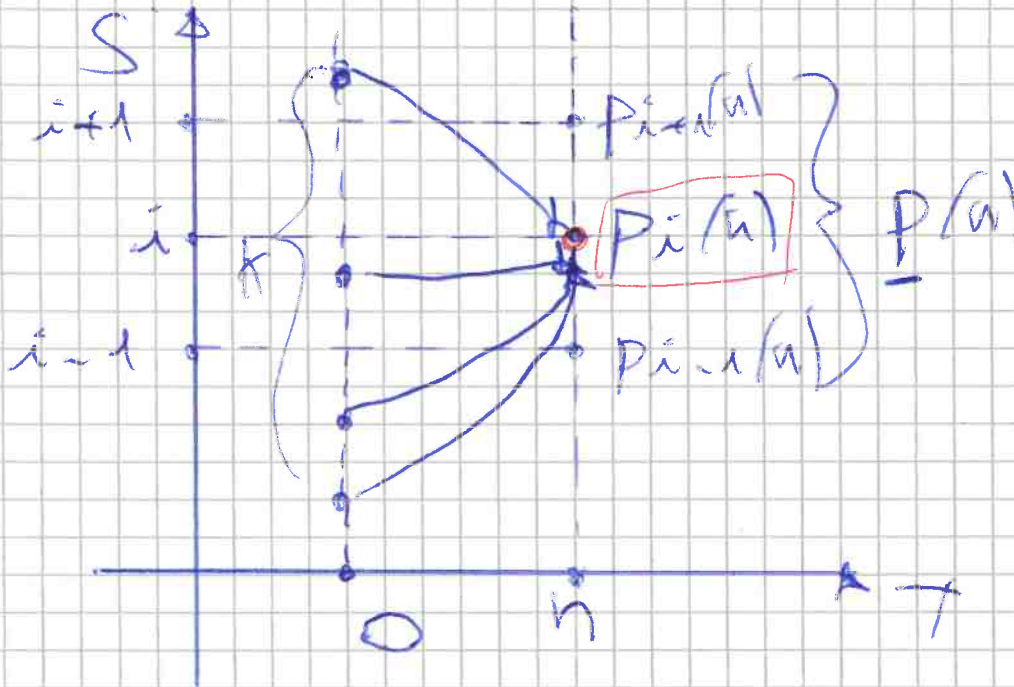
$$\lim_{n \rightarrow \infty} \underline{h}^{(n)} = \begin{bmatrix} q_1 & q_1 & q_1 & \dots \\ q_1 & q_1 & q_1 & \dots \\ q_1 & q_1 & q_1 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} = \underline{i}^T \cdot \underline{q} = \begin{bmatrix} 1 \\ 1 \\ 1 \\ \vdots \end{bmatrix} \cdot \underline{q}$$

OR:

$$\lim_{n \rightarrow \infty} P(n) = \lim_{n \rightarrow \infty} P(0) \cdot \underline{u}^{(n)} = \lim_{n \rightarrow \infty} P(0) \cdot \underline{1} \cdot \underline{g} = \underline{g}$$

Became $P(n) = P(0) \cdot \underline{u}^{(n)}$

a) PROBABILITY OF STATE OCCUPANCY $P_i(n)$



$$P_i(n) = P\{X_n = i\}$$

= P. to be in state i at step n.

7) TRANSIENT BEHAVIOUR $P(n), P(n+1)$

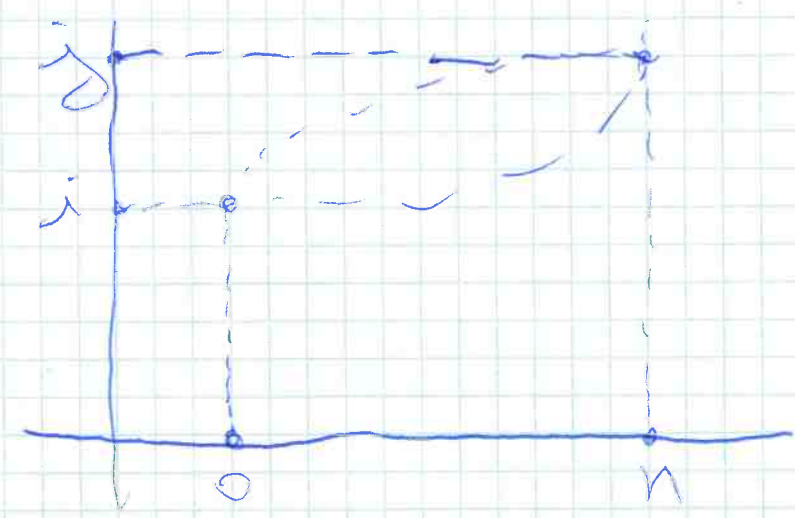
By the TOTAL PROB. THEOREM.

$$P_i(n) = \sum_{k \in S} P\{X_n = i | X_0 = k\}$$

~~$P_i(n)$~~ By the RADEES THEOREM.

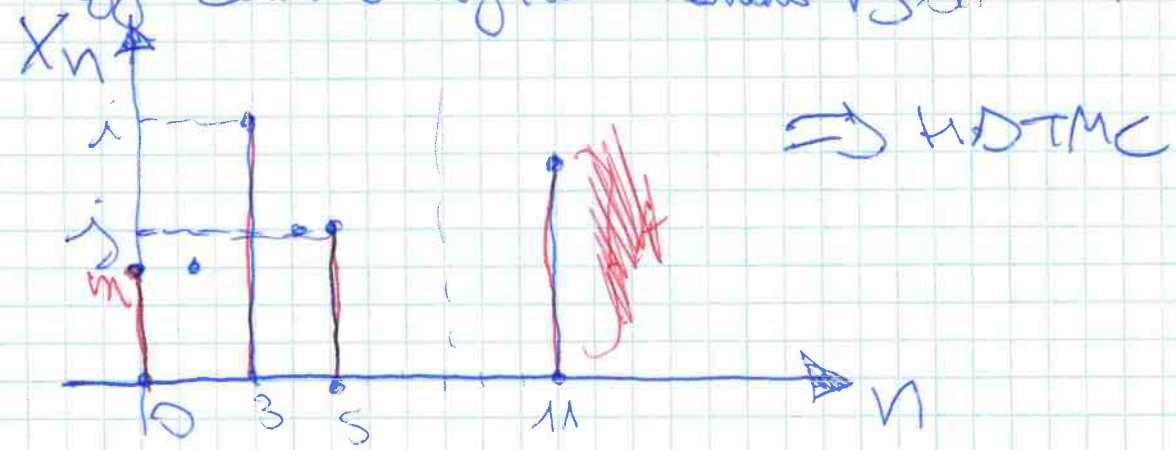
TRANSITION PROBABILITY in (N) steps

$$h_{ij}^{(n)} = P\{X_n = j \mid X_0 = i\}$$



JOINT PMF of a MARKOFF CHAIN:

We know the CHARACTERIZATION of a Markoff chain if we know its JOINT PMF.



$$P\{X_3 = i, X_5 = j \mid X_{11} = k\}$$

$$= \sum_{m \in S} P\{X_3 = i, X_5 = j, X_{11} = k, X_0 = m\}$$

$$P\{A, B\} = P\{A|B\} \cdot P\{B\}$$

~~$$= \sum_{m \in S} P\{X_{11} = k, X_5 = j \mid X_3 = i, X_0 = m\} \cdot P\{X_0 = m\}$$~~

$$= \sum_{m \in S} P\{X_{11} = k \mid X_5 = j, X_3 = i, X_0 = m\} \cdot P\{X_5 = j \mid X_3 = i, X_0 = m\}$$

~~XXXX~~

$$= \sum_{m \in S} P\{X_1 = k | X_5 = j, X_3 = i, X_0 = m\} \cdot P\{X_5 = j | X_3 = i, X_0 = m\} \cdot P\{X_3 = i | X_0 = m\} \cdot P\{X_0 = m\}$$

$$= \sum_{m \in S} h_{jk}^{(6)} \cdot h_{ij}^{(2)} \cdot h_{mi}^{(3)} \cdot p_m(0)$$

ABSORBING STATE / TRAP:

It is a state ~~where~~ ^{that}, once ~~reached~~ reached, can no longer be escaped from!

↳ It is characterized by the following state

PROBABILITY VECTOR:

$$\underline{P} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}$$

⇒ When one such state is present in the Markov Chain, then we do NOT consider the chain Ergodic / although a steady state ~~is~~ ^{exists} & a unique asymptotic solution independent from the initial condition exists.

$$P_i(n) = \sum_{k \in S} P\{X_{n-1} = k | X_0 = i\} \cdot P\{X_0 = k\}$$

$$= \sum_{k \in S} h_{ki}^{(n)} \cdot P\{X_0 = k\}$$

$$= \sum_{k \in S} P(k) \cdot h_{ki}^{(n)}$$

$$\underline{P(n)} = \underline{P(0)} \cdot \underline{U}^n$$

or:

$$\underline{P(n+1)} = \underline{P(n)} \cdot \underline{U}$$

We can then show
 $\Rightarrow \begin{cases} \underline{P(n)} = \underline{P(0)} \cdot \underline{U}^n \\ \underline{P(0)} = \underline{P_0} \end{cases}$

8) STATIONARITY PROBABILITY VECTOR

The stationarity probability vector \underline{z} is a vector that solves the following equation:

$$\underline{z} = \underline{z} \cdot \underline{U}$$

(i.e. it is the left vector of eigenvalue 1)

$$\sum_{i \in S} z_i = 1$$

$$0 \leq z_i \leq 1$$

The behavior among these states is stationary. NB: there can be more than one such vector.

9) LIMIT PROBABILITY VECTOR

$$\lim_{n \rightarrow \infty} \underline{P(n)} = \underline{P}$$

$$0 \leq p_i \leq 1$$

If the limit exists, it is $\sum_i p_i = 1$

If the limit exists, we can then show:

$$\boxed{P = P \cdot \underline{u}}$$

~~AP~~

→ And P is independent from the INITIAL CONDITIONS.

(10) FLOW - CONSERVATION PRINCIPLE - Proof.

$$\underline{P}(n+1) = \underline{P}(n) \cdot \underline{U}$$

In **SCALAR FORM**

$\underline{P}(n) = [p_{11}(n), p_{12}(n), \dots, p_{1n}(n)]$
 VECTOR containing
 P type in every state
 at step (n).

$$P_j(n+1) = \sum_{i \in S} p_i(n) \cdot h_{ij}$$

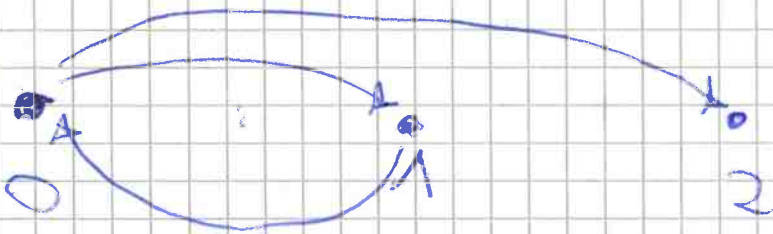
$$P_j(n+1) = \underbrace{\sum_{i \neq j} p_i(n) \cdot h_{ij}}_{\text{from } i \text{ to } j} + \underbrace{p_j(n) \cdot h_{jj}}_{\text{from } j \text{ to } j}$$

$$P_j(n+1) = \sum_{i \neq j} p_i(n) \cdot h_{ij} + p_j(n) \cdot [1 - \sum_{i \neq j} h_{ji}]$$

$$P_j(n+1) - p_j(n) = \sum_{i \neq j} p_i(n) \cdot h_{ij} - p_j(n) \sum_{i \neq j} h_{ji}$$

ENTERING j from i LEAVING j to i

a) EX. FCP TRANSIENT EQUATIONS



$$p_0(n+1) - p_0(n) = \underbrace{p_1(n) \cdot h_{10}}_{\text{ENTERING } j \text{ from } i} - \underbrace{p_0(n) \cdot [h_{01} + h_{20}]}_{\text{LEAVING } j \text{ to } i}$$

b) FCP STEADY-STATE \Rightarrow Col 2 of \underline{U}

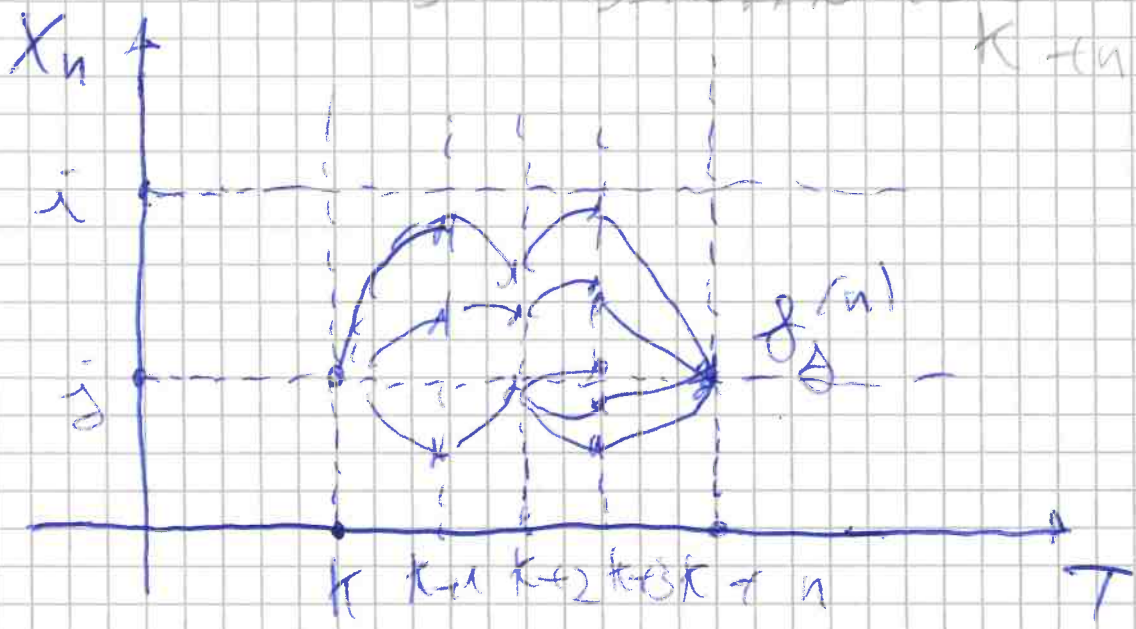
$$0 = p_1 \cdot h_{10} - p_0 [h_{01} + h_{20}]$$

$$\Rightarrow p_1 h_{10} = p_0 [h_{01} + h_{20}]$$

(11) P. of first return to state j in n steps. $f_{jj}^{(n)}$

$f_{jj}^{(n)}$ = P of first return to state j after n steps

$f_{jj}^{(n)} = P \{ X_{k+1} \neq j, X_{k+2} \neq j, \dots, X_{k+n} = j \mid X_k = j \}$
 "STEPS IN BETWEEN k th step and $k+n$ th step"



(12) P. of ever returning to state j . f_{jj}

$f_{jj} = \sum_{n=1}^{\infty} f_{jj}^{(n)}$

= Sum of all possible probabilities to go back to state j with any arbitrary amount of steps n .

$f_{jj} < 1 \Rightarrow$ TRANSIENT STATE \Rightarrow RECURRENT STATE $f_{jj} = 1$

If $f_j = 1 \Rightarrow$ "we will surely ~~come~~ ^{have to state j}"
 RECURRENT STATE j

$$\Rightarrow \exists n: h_{jj}^{(n)} > 0$$

b) If we found that a state is RECURRENT

$$\Rightarrow \exists n: h_{jj}^{(n)} > 0$$

"There is a finite probability of coming back to state j ."

\Rightarrow A state j (RECURRENT) may also be PERIODIC:

$$\exists n: h_{jj}^{(n)} > 0$$

$n = \# \text{STEPS}$

PERIOD = $d_j = \text{GCD of } n =$

$$d_j \geq 1$$

\Rightarrow STATE j is PERIODIC

$$d_j = 1$$

\Rightarrow STATE j is APERIODIC

Strongly PERIODIC STATES:

Weakly PERIODIC STATES:

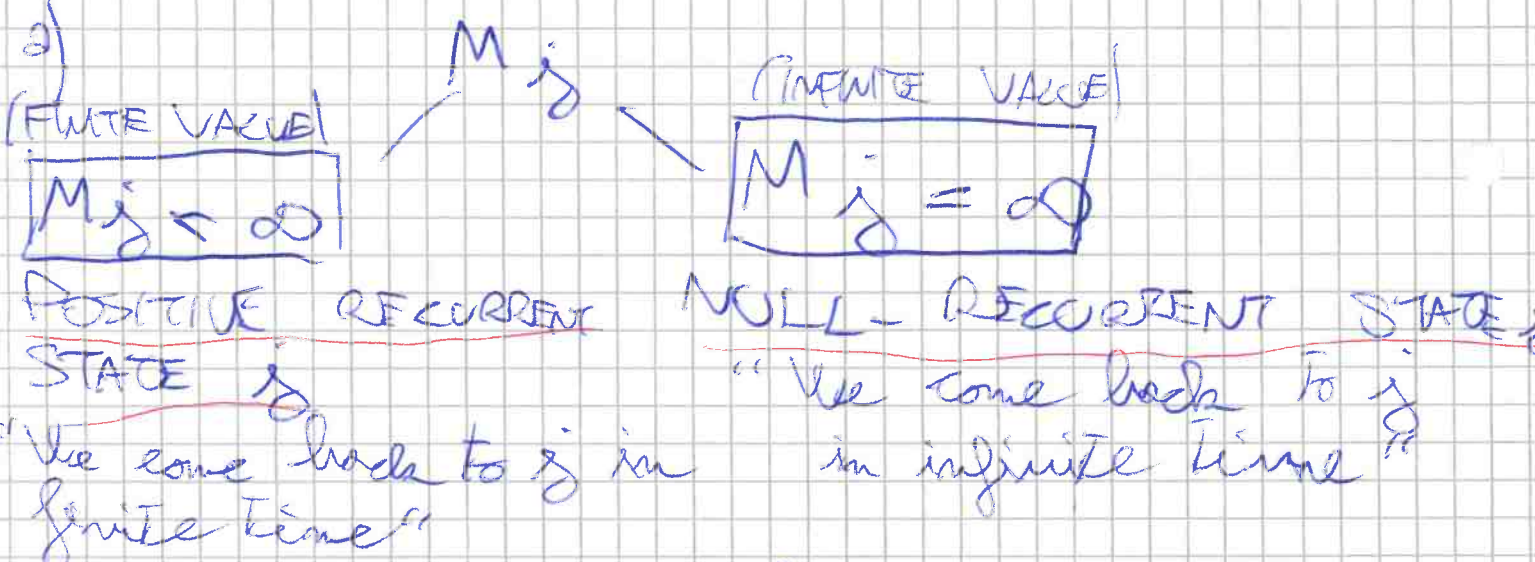
Over multiples of d_j (period), we always have the same numbers on the main diagonal
 Over multiples of d_j (period), we have differing numbers on the main diagonal

13 MEAN RECURRENCE TIME M_j for RECURRENT STATE is

$M_j = \text{AVG.}$ amount of time after which we will come back to j .

Take AVG. for different steps n

$$M_j = \sum_{i=1}^{\infty} n \cdot f_{jj}^{(n)}$$



~~13.1 STATE FUNDAMENTAL PROPERTIES~~

14 A Markov Chain is said to be IRREDUCIBLE if none of its SUBSETS of STATES is CLOSED. (i.e. from any state, you can reach any other state)

A subset A of states is said to be CLOSED if it is not possible to move from the states of A to the states of \bar{A} .

$$\sum_{i \in A} \sum_{j \notin A} h_{ij} = 0$$

17) (A) 1ST FUNDAMENTAL THEOREM FOR STATE CLASSIFICATION.

If a Markov Chain is IRREDUCIBLE, then all of its STATES are of the SAME TYPE.

- a) Either all states are TRANSIENT
- b) Or all states are NULL-RECURRENT
- c) Or all states are POSITIVE-RECURRENT

An IRREDUCIBLE MARKOV CHAIN cannot include TRAP STATES (from ~~from~~ ~~it~~, we ~~can~~ ~~reach~~ each other state)

PERIODICITY in MARKOFF CHAINS

In an IRREDUCIBLE MARKOFF CHAIN,

- a) Either all states are APERIODIC (PERIOD = 1)
- b) Or all states are PERIODIC.

(B) STATIONARY SOLUTIONS / PROBABILITIES

A MDTMC can admit multiple asymptotic solutions, based on the initial conditions, by solving:

$$\underline{z} = \underline{z} \cdot \underline{U}, \quad z_j = \sum_{i \in S} z_i \cdot n_{ji}$$

(C) LIMIT SOLUTION for an ERGODIC MDTMC

A probability distribution $p_i, i \in S$ is a LIMIT PROBABILITY if:

$$p_i = \lim_{n \rightarrow \infty} p_j(n) \quad \forall i \in S$$

$$P = \lim_{n \rightarrow \infty} P(n)$$

19) 2nd FUNDAMENTAL THEOREM:

For all $WDTMC$, APERIODIC, IRREDUCIBLE:

If $\lim_{n \rightarrow \infty} P_{ij}^{(n)}$ EXISTS and is independent from the INITIAL conditions:
 [\Rightarrow A steady-state exists]

IF all states are TRANSIENT or NULL-RECURRENT

$P_{ij} = 0 \forall i, j$

LIMIT PROBABILITIES

IF all states are POSITIVE RECURRENT

$P_{ij} > 0 \forall i, j \in S$

LIMIT PROBABILITIES are also a STATIONARY DISTRIBUTION

All states $i \in S$ are ERGODIC & the chain is ERGODIC.

NB: For a WDTMC, APERIODIC, IRREDUCIBLE, all POSITIVE-RECURRENT \Rightarrow All states are ERGODIC.

The chain is ERGODIC.

2) FINITE # STATES IRREDUCIBLE, APERIODIC MARKOFF CHAIN \Leftrightarrow INFINITE # STATES IRREDUCIBLE, APERIODIC MARKOFF CHAIN

$P_{ii} > 0$

ERGODIC CHAIN \Leftrightarrow All states TRANSIENT or NULL-RECURRENT \Leftrightarrow All states POSITIVE RECURRENT

INFINITE # STATES / A PERIODIC, (REDEUCIBLE) MARKOFF CHAIN

$P_j = 0$
 All NULL-RECURRENT STATES

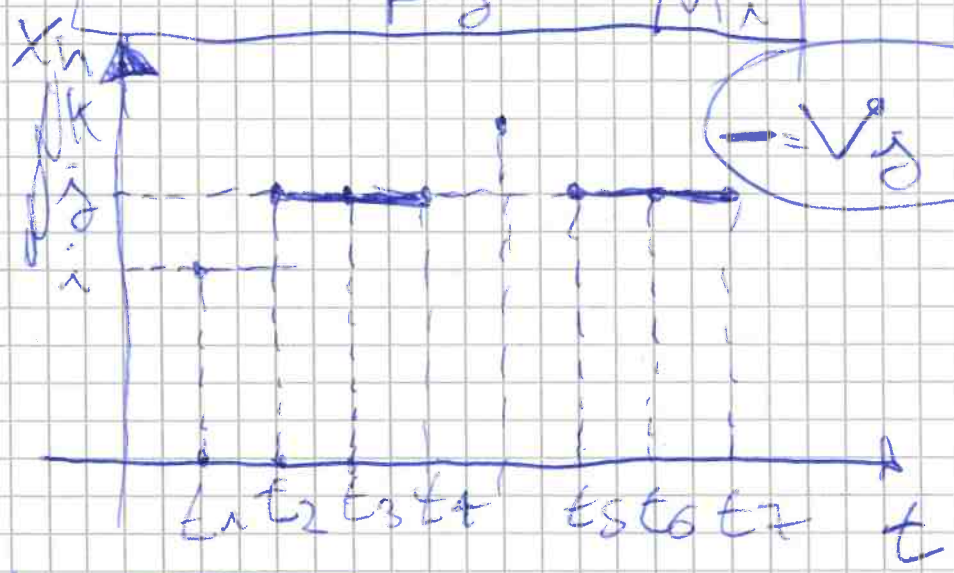
All \Rightarrow POSITIVE-RECURRENT STATES
 PERIODIC CHAIN

16 For a POSITIVE-RECURRENT STATE j , AT STEADY-STATE P_j

$P_j = \lim_{N \rightarrow \infty} \frac{V_j(N)}{N}$ $V_j(t) = \text{Time spent in state } j$

V_{ij} = Avg. # visits to a STATE i between two successive visits to state j .

$$V_{ij} = \frac{P_i}{P_j} = \frac{M_{ij}}{M_{ji}}$$



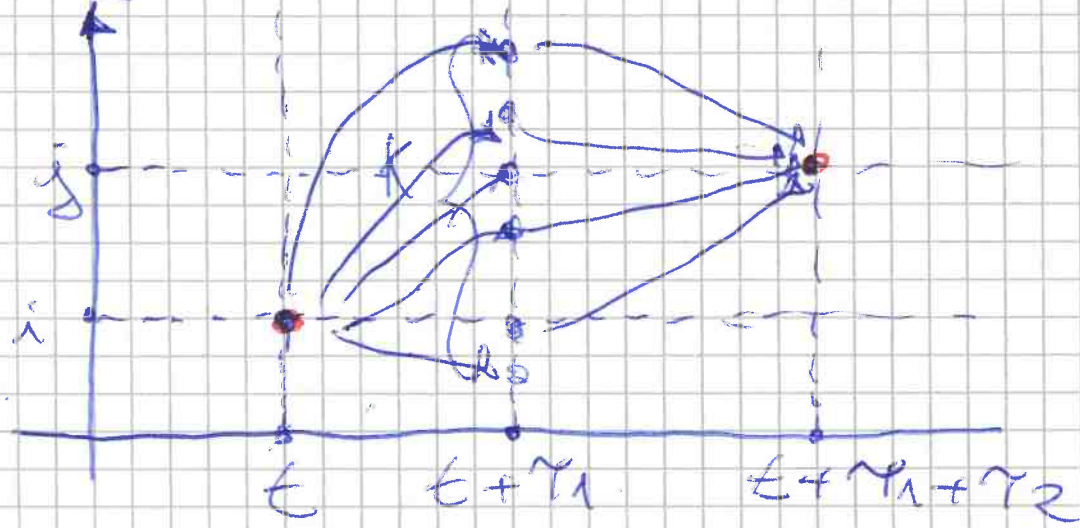
$$M_{ij} = \frac{1}{P_j}$$

$$P_j = \frac{1}{M_{ij}}$$

17) CK-EQUATION IN CONTINUOUS-TIME

$$H(\tau_1 + \tau_2) = H(\tau_1) \cdot H(\tau_2)$$

PROOF IN GRAPHICAL FORM, we have:



Proof: in scalar form:

$$h_{ij}(\tau_1 + \tau_2) = P\{X(t + \tau_1 + \tau_2) = j \mid X(t) = i\}$$

By the TOTAL PROBABILITY THEOREM: $X(t) = i$

$$h_{ij}(\tau_1 + \tau_2) = \sum_{k \in S} P\{X(t + \tau_1 + \tau_2) = j, X(t + \tau_1) = k \mid X(t) = i\}$$

By the BAYES THEOREM: $P\{A, B\} = P\{A|B\} \cdot P\{B\}$

$$= \sum_{k \in S} P\{X(t + \tau_1 + \tau_2) = j \mid X(t + \tau_1) = k\} \cdot P\{X(t + \tau_1) = k \mid X(t) = i\}$$

$$P\{X(t + \tau_1) = k \mid X(t) = i\}$$

$$= \sum_{k \in S} P\{X(t + \tau_1 + \tau_2) = j \mid X(t + \tau_1) = k\} \cdot P\{X(t + \tau_1) = k \mid X(t) = i\}$$

$$= \sum_{k \in S} h_{kj}(\tau_2) \cdot h_{ik}(\tau_1)$$

IN MATRIX FORM:

$$H(\tau_1 + \tau_2) = H(\tau_2) \cdot H(\tau_1)$$

(18) STATIONARITY PROBABILITY VECTOR IN CONTINUOUS-TIME: $t \in \mathbb{R}, t \geq 0$

$$\underline{P} = \underline{P} - \frac{d}{dt} P(t) \quad \forall t$$

(NB: There may be multiple STATIONARY PROBABILITY VECTORS)

ERGODICITY CONDITION - CONTINUOUS-TIME

$$I_f: \lim_{t \rightarrow \infty} P(t) = \underline{P}$$

Then the limit exists & it is independent from the INITIAL CONDITIONS & it is also the ^{STATIONARY} PROBABILITY VECTOR

(19) RATE TRANSITION MATRIX \underline{V}

$\underline{V} = [V_{ij}]$ - It is the cell-wise derivative for $t=0$.

RATE TRANSITION V_{ij} :

$$V_{ij} = \left. \frac{d}{dt} h_{ij}(t) \right|_{t=0} \quad \left[\text{Matrix of NUMBERS, and functions} \right]$$

NORMALIZATION CONDITION for \underline{V} :

$$\sum_{j \in S} V_{ij} = 0$$

(A row sums up to 0)

NORMALIZATION CONDITION for $\underline{h}(t)$

$$\sum_{j \in S} h_{ij}(t) = 1$$

① $h_{ij}(\Delta T)$ with TAYLOR-MACLAURIN EXPANSION.

Use L'Hôpital's Test:

$$v_{ij} = \frac{d}{dT} h_{ij}(t) \Big|_{t=0}$$

For a very small interval ΔT , take the TAYLOR-MACLAURIN EXPANSION of $h_{ij}(\Delta T)$

$$\sum_{n=0}^{\infty} \frac{f^{(n)}(x_0)}{n!} (x-x_0)^n$$

⇒ For $h_{ij}(\Delta T)$:

NEGLIGIBLE OF HIGHER ORDER

$$h_{ij}(\Delta T) = h_{ij}(0) + v_{ij} \cdot \Delta T + o(\Delta T)$$

⇒ This is a LINEAR APPROXIMATION of $h_{ij}(\Delta T)$ (but first 2 terms are enough)

⇒ Through $h_{ij}(\Delta T)$, we can express components on the main diagonal of the subtraction of the ~~ones~~ ones NOT on the main diagonal.

$$v_{ii} = - \sum_{j \neq i} v_{ij}$$

For V :

$$\begin{bmatrix} & & & \\ & & & \\ & & & \\ & & & \end{bmatrix}$$

$$\begin{bmatrix} - & - & - & - \\ & 0 & & \\ & & & \\ & & & \end{bmatrix}$$

$$v_{ij} = -v_{ij}$$

12 (5) TRANSIENT BEHAVIOUR FOR RCTIVE

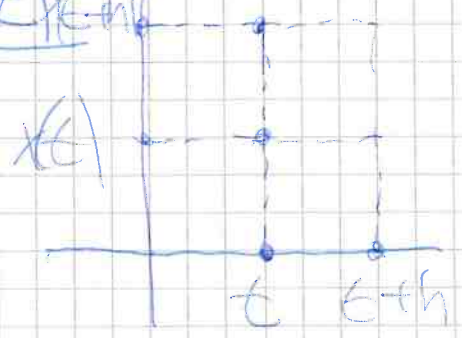
We know:
$$\begin{cases} P(s+\gamma) = P(s) \cdot \underline{H}(\gamma) \\ \underline{H}(\gamma) = \underline{I} \end{cases}$$

$$P(s+\gamma) - P(s) = P(s) \cdot \underline{H}(\gamma) - P(s)$$

$$\lim_{\gamma \rightarrow 0} \frac{P(s+\gamma) - P(s)}{\gamma} = \lim_{\gamma \rightarrow 0} P(s) \cdot \frac{\underline{H}(\gamma) - \underline{H}(0)}{\gamma}$$

We know the definition of DERIVATIVE

$$\frac{d}{dt} x(t) = \lim_{h \rightarrow 0} \frac{x(t+h) - x(t)}{h}$$



$$\Rightarrow \frac{d}{dt} P(s) = P(s) \cdot \underline{V}$$

$$\underline{P}(s) = \underline{P}_0$$

$$\underline{V} = \frac{d}{dt} \ln s \Big|_s$$

$$\Rightarrow \frac{d}{dt} P_j(s) = \sum_{i \in S} P_i(s) \cdot V_{ij}$$

IN SCALAR FORM!

$$P(s) = P(s) \cdot e^{\underline{V}t} = P(s) \left[\underline{I} + \sum_{n=1}^{\infty} \frac{\underline{V}^n t^n}{n!} \right]$$

ERGODIC BEHAVIOUR (i.e. if the chain is
ERGODIC)
→ A steady-state EXISTS!

$$\begin{cases} P \cdot \underline{v} = 0 \\ P \cdot \underline{1}^T = 1 \end{cases}$$

$$\underline{V} = \begin{bmatrix} \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

$$V_{ij} = \begin{cases} V_{ij} \leq 0 & \text{if } j = i \quad \left[\begin{array}{l} \text{MAIN DIAG} \\ \text{NEG} \end{array} \right] \\ V_{ij} > 0 & \text{if } j \neq i \quad \left[\begin{array}{l} \text{OFF-DIAG} \\ \text{POSITIVE} \end{array} \right] \end{cases}$$

balances the one at the j

Also:

$$\text{highd} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$$

\Rightarrow We can then write $\text{high}(DT)$ for the two cases, based on the value of highd

$$\text{high}(DT) = \text{highd} + V_{ij} \cdot DT + O(DT^2)$$

$$\Rightarrow \text{high}(DT) = \begin{cases} V_{ij} DT + O(DT^2) & \text{if } j \neq i \\ 1 - \sum_{i \neq j} V_{ij} DT + O(DT^2) & \text{if } j = i \end{cases}$$

(the main diagonal)
+ (opposite of main diagonal's value)

LINEAR BEHAVIOUR

PROOF OF FCP IN CONTINUOUS-TIME

$$V_{ij} = - \sum_{i \neq j} V_{ij} \quad \left[\frac{d p_j(t)}{dt} = \sum_{i \in S} p_i(t) \cdot V_{ij} \right]$$

$$\frac{d p_j(t)}{dt} = \sum_{i \neq j} p_i(t) \cdot V_{ij} + p_j(t) \cdot V_{jj}$$

$$\Rightarrow \frac{d p_j(t)}{dt} = \sum_{i \neq j} p_i(t) \cdot p_{ij}(t) - p_j(t) \sum_{i \neq j} p_{ji}(t)$$

ENTERING j from i
LEAVING j to i

② SUFFICIENT CONDITION FOR THE EXISTENCE OF FORMAL SOLUTION FOR MCTMC:

~~1~~ • FINITE # STATES

An IRREDUCIBLE MCTMC is FORMAL

• INFINITE # STATES; IRREDUCIBLE MCTMC

All WLL-RECURRENT STATES:

$$\exists \lim_{t \rightarrow \infty} p_j(t) = 0$$

All POSITIVE-RECURRENT STATES:

$$\exists \lim_{t \rightarrow \infty} p_j(t) = p_j > 0$$

③ PROOF OF FORWARD & BACKWARD

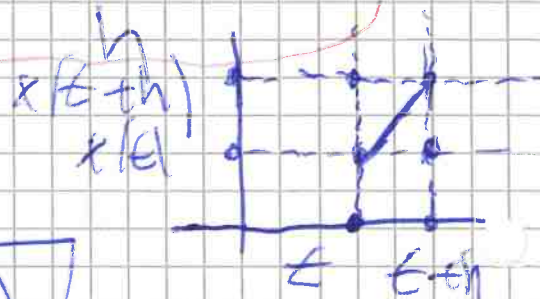
CHAPMAN-KOLMOGOROFF EQUATION (CONTINUOUS TIME)

Recall the definition of DERIVATIVE (TIME)

$$\frac{d x(t)}{dt} = \lim_{h \rightarrow 0} \frac{x(t+h) - x(t)}{h}$$

Recall the C-K CONTINUOUS-TIME EQUATION:

$$\frac{d}{dt} u(t+\theta) = \frac{d}{dt} u(t) - \frac{d}{dt} u(\theta)$$



For $\theta > 0$:

$$u(\epsilon + \theta) = u(\epsilon) \cdot u(\theta)$$

Set $u(\epsilon) = I$

$$u(\epsilon + \theta) - u(\epsilon) = u(\epsilon) \cdot u(\theta) - u(\epsilon) \cdot I = u(\theta) - I$$

$$\lim_{\theta \rightarrow 0^+} \frac{u(\epsilon + \theta) - u(\epsilon)}{\theta} = \lim_{\theta \rightarrow 0^+} u(\epsilon) \frac{u(\theta) - I}{\theta}$$

$$\left\{ \begin{aligned} \frac{d}{dt} u(\epsilon) &= u(\epsilon) \cdot v \end{aligned} \right.$$

$$\left\{ \begin{aligned} u(\epsilon) &= I \end{aligned} \right.$$

FORWARD C-K EQUATION

$$\left. \frac{d}{dt} u(\epsilon) \right|_{\epsilon=0} = v$$

$$= v$$

$$\left\{ \begin{aligned} \frac{d}{dt} u(\epsilon) &= v \cdot u(\epsilon) \end{aligned} \right.$$

$$\left\{ \begin{aligned} u(\epsilon) &= I \end{aligned} \right.$$

BACKWARD C-K EQUATION

21) PROOF of the EXPONENTIAL DISTRIBUTION
 for the MEMORYLESS PROPERTY of ~~TIME~~ CONTINUOUS TIME
 TIME SPENT in a STATE



We know the exponential distribution has PDF for X:

~~$f(x) = \lambda \cdot e^{-\lambda x} \cdot \mu(x)$~~

Goal: Show that

$f(x) = \lambda \cdot e^{-\lambda x} \cdot \mu(x)$

PDF of EXPONENTIAL DISTRIBUTION for time spent in a state $\Rightarrow \lambda$.

PROOF: MEMORYLESS PROPERTY: EX: $t = \text{ONE HOUR}$, $\tau = \frac{1}{2} \text{ HOUR}$

$P\{W \leq t + \tau \mid W > t\} = P\{W > \tau\}$

"The probability that my phone call will last longer than one hour and a half, KNOWING it has already lasted one hour = P that my phone call will last longer than half an hour"
 [i.e. The past is totally irrelevant for the future. Only the present matters to find it].

~~STATEMENT~~

PROOF: Complementing & substituting t by τ :
 \Rightarrow "Phone call lasting less than x "

$P\{W \leq t + \tau \mid W > \tau\} = P\{W \leq t\}$

By the BAYES THEOREM:

$P\{A \mid B\} = \frac{P\{A \cap B\}}{P\{B\}}$

$$\frac{P\{W \leq t + \tau, W > \tau\}}{P\{W > \tau\}} = P\{W \leq t\}$$

$$= \frac{P\{\tau < W \leq t + \tau\}}{P\{W > \tau\}} = P\{W \leq t\}$$

We know the ~~PROBABILITY~~ ~~DISCRETE~~ ~~FUNCTION~~ ~~DISCRETE~~ ~~FUNCTION~~ $F_w(x)$

$$F_w(x) = (1 - e^{-\lambda x}) \cdot \mu(x) = P\{W \leq x\}$$

$$= \frac{F_w(t + \tau) - F_w(\tau)}{1 - F_w(\tau)} = F_w(t) - \underbrace{F_w(0)}_0$$

$$= F_w(t + \tau) - F_w(\tau) = [F_w(t) - F_w(0)] [1 - F_w(\tau)]$$

Take the LIMIT for $t \rightarrow 0$.

$$\lim_{t \rightarrow 0} \frac{F_w(t + \tau) - F_w(\tau)}{t} = \frac{[F_w(t) - F_w(0)]}{t} [1 - F_w(\tau)]$$

$$F_w'(0) = F_w'(0) [1 - F_w(\tau)]$$

Now set $A(\tau) = 1 - F_w(\tau) = e^{-\lambda \tau} \cdot \mu(\tau)$

$$\Rightarrow F_w(\tau) = 1 - A(\tau) = 1 - e^{-\lambda \tau} \cdot \mu(\tau)$$

$$\Rightarrow F_w'(\tau) = -A'(\tau) = \lambda \cdot e^{-\lambda \tau}$$

$$A'(\tau) = -\lambda \cdot e^{-\lambda \tau} \cdot \mu(\tau)$$

We know $F_w(t) = [1 - e^{-\lambda t}] \cdot \mu(t)$
 \Rightarrow For $\tau = 0$:

$$F_w'(0) = \lambda \quad F_w(0) = 0$$

$$A'(0) = 1 \quad A(0) = 1$$

$$\Rightarrow \underbrace{F_w'(t)}_{-A'(t)} = \underbrace{F_w(0)}_{\lambda} \underbrace{[1 - F_w(t)]}_{A(t)}$$

$$\Rightarrow \begin{cases} -A'(t) = \lambda \cdot A(t) \\ A(0) = 1 \end{cases} \quad \left\| \begin{array}{l} \text{DIFFERENTIAL} \\ \text{EQUATION,} \\ \text{solvable via} \\ \text{L-Transform.} \end{array} \right.$$

$$\Rightarrow \boxed{\mathcal{L}} \Rightarrow \begin{cases} s \cdot A(s) - A(0) = -\lambda A(s) \\ A(s) \cdot (s + \lambda) = 1 \end{cases}$$

$$\Rightarrow \boxed{A(s) = \frac{1}{s + \lambda}}$$

$$\Rightarrow \mathcal{L}^{-1} \Rightarrow \boxed{A(t) = e^{-\lambda t}} \quad \mu(t) = 1 - F_w(t)$$

$$F_w(t) = 1 - A(t) = [1 - e^{-\lambda t}] \cdot \mu(t)$$

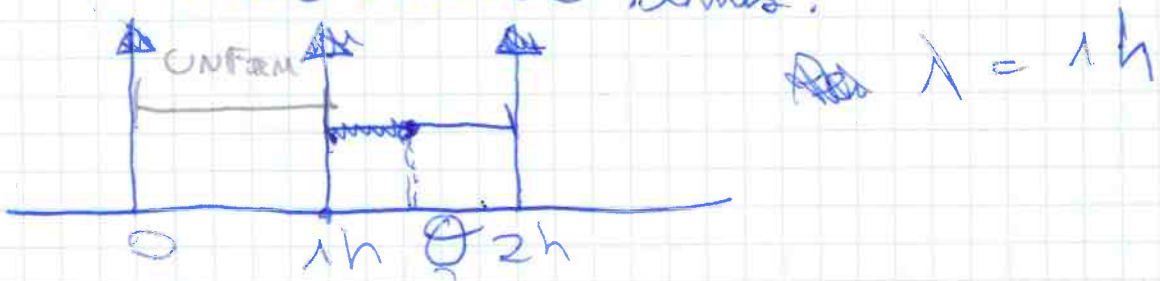
\hookrightarrow EXPONENTIAL PROB. DISTRIBUTION FUNCTION

$$\boxed{g_w(t) = \lambda \cdot e^{-\lambda t} \cdot \mu(t)} \quad \hookrightarrow \text{EXPONENTIAL PDF}$$

$\hookrightarrow \mu(t)$, TIME SPENT IN A STATE

AVERAGE RESIDUAL TIME'S PARADOX (LAFOR PLOT)

• If we have DETERMINISTIC (uniform) distribution of the arrival times.



If arriving to the BUS STATION randomly.

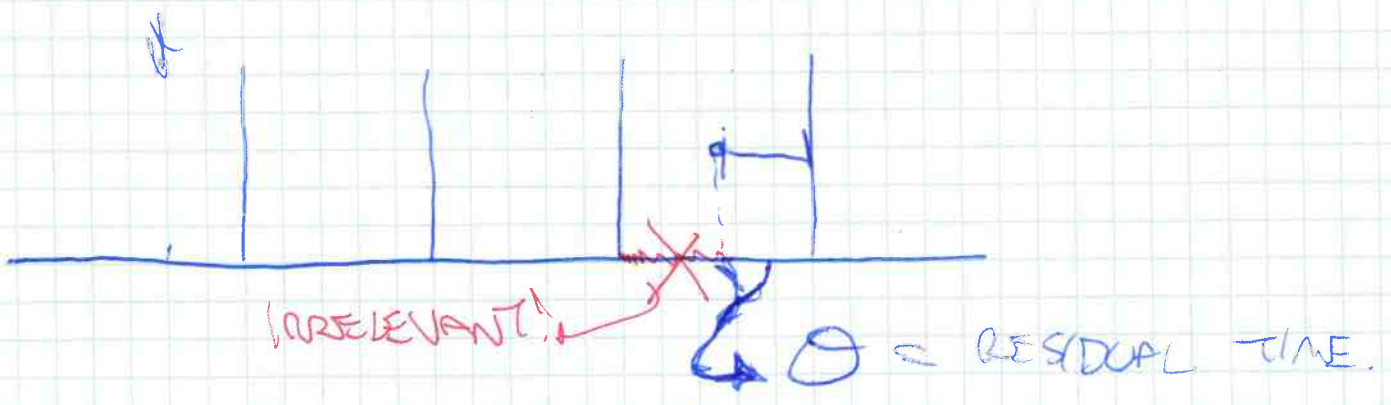
$\theta =$ RESIDUAL TIME.

$E\{\theta\} = 0.5$

NB: The residual time is the time remaining to be waited for the next arrival to occur. (i.e. next bus' arrival).

• If we have ~~POISSON~~ arrivals from a POISSON PROCESS.

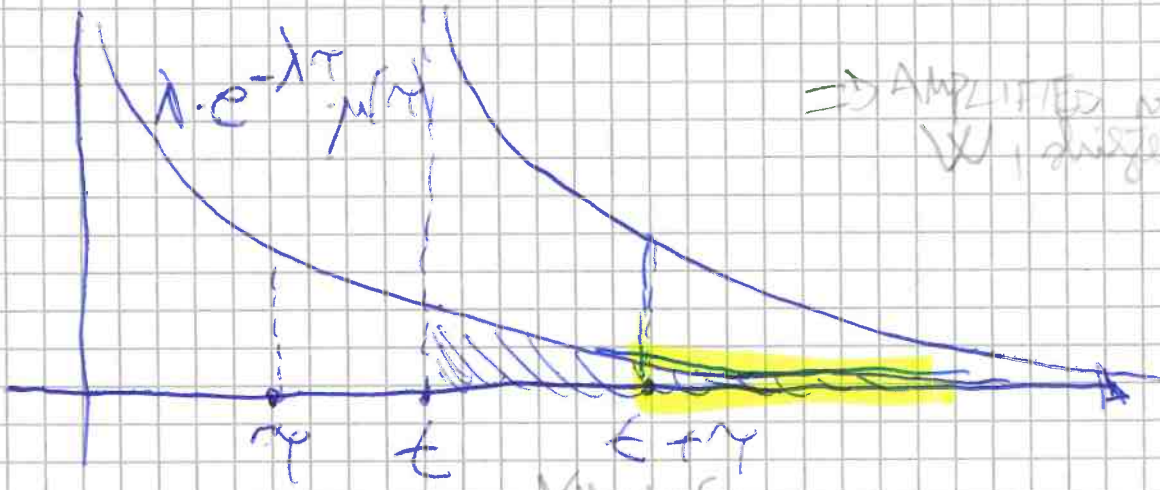
(i.e. arrivals are exponentially distributed) with same AVG. arrival rate.



Paradox of the RESIDUAL TIME! $E\{\theta\} = 1$ (because MEMORYLESS)

become ~~arrivals~~ Forget about the PAST!
 (because ~~arrivals~~ are exponentially distributed)
 Store MEMORYLESS property holds.
 ↳ Noobs!

So, in CONTINUOUS TIME, we have:



$$P\{W > t + \tau \mid W > t\} = P\{W > \tau\}$$

Even if you sleep over time, you will get an **EXPONENTIALLY-DISTRIBUTED** copy of the **TIME** spent in a state, W .
(this also happens if you have repeated observations)

③ HOMOGENEOUS BIRTH-DEATH DISCRETE-TIME MARKOV CHAIN

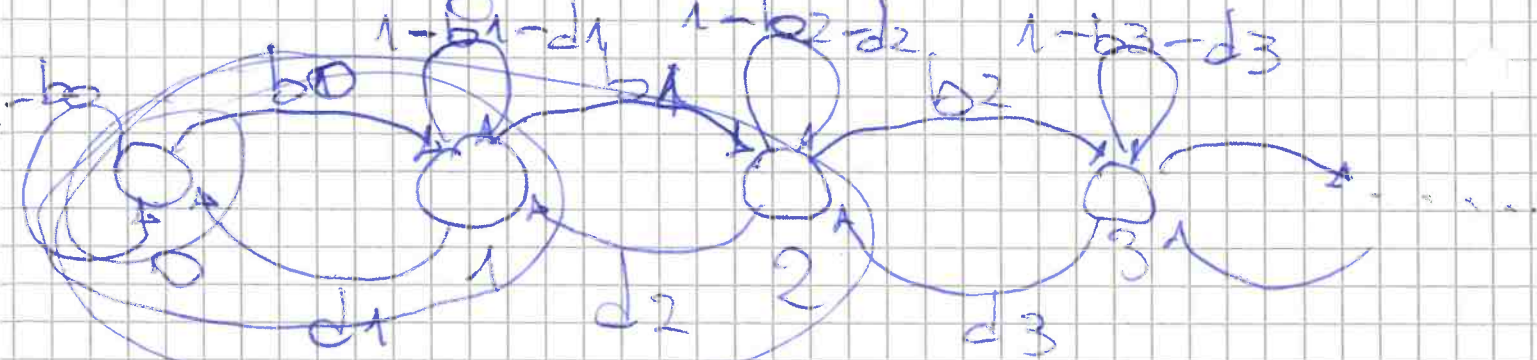
A HOMOGENEOUS BIRTH-DEATH DT Markov Chain is a Markov Chain where only ~~the~~ types of transitions are possible:

- Birth b_i $j = i + 1$
- Death d_i $j = i - 1$
- 1 Birth b_i & 1 Death d_i $j = i$
- No Birth, No Death $j = i = 0$

⇒ This results in the following transition

$$h_{ij} = \begin{cases} b_i & j = i + 1, i \geq 0 \\ d_i & j = i - 1, i \geq 1 \\ 1 - b_i - d_i & j = i \\ 1 - b_0 & j = i = 0 \end{cases}$$

The resulting MARKOFF chain is then:



And the transition matrix \underline{M} is:

$$\underline{M} = \begin{bmatrix} 0 & 1 & 0 & 0 & \dots \\ 1 - d_0 & d_0 & 0 & 0 & \dots \\ 0 & d_1 & 1 - b_1 - d_1 & 0 & \dots \\ 0 & 0 & d_2 & 1 - b_2 - d_2 & b_2 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

TRI-DIAGONAL TRANSITION MATRIX

② **ERGODICITY CONDITION:**

Infinite # STATES, APERIODIC?

or $b_i < 1$
 $0 < d_i < 1$
APERIODIC

$b_0 = 1$
 $\Rightarrow \dots (b_i + d_i = 1)$
 \Rightarrow PERIODIC with PERIOD = 1
 (NB: NO RIPPLES)

$d_0 < 1$ **RECURRE**
 $b_i + d_i \neq 1$

Are there ^{all} states POSITIVE RECURRENT?
 (i.e. $P_i > 0$) $\forall i \in S$

⇒ Apply FCF to the GRAPH:

$$d_1 \cdot p_1 = b_0 \cdot p_0 \Rightarrow p_1 = \frac{b_0 \cdot p_0}{d_1} = \frac{b_0}{d_1} \cdot p_0$$

$$d_2 \cdot p_2 = b_1 \cdot p_1 \Rightarrow p_2 = \frac{b_1 \cdot p_1}{d_2} = \frac{b_1}{d_2} \cdot \frac{b_0}{d_1} \cdot p_0$$

$$d_3 \cdot p_3 = b_2 \cdot p_2 \Rightarrow p_3 = \frac{b_2 \cdot p_2}{d_3} = \frac{b_2}{d_3} \cdot \frac{b_1}{d_2} \cdot \frac{b_0}{d_1} \cdot p_0$$

$$\Rightarrow p_3 = \frac{b_2}{d_3} \cdot \frac{b_1}{d_2} \cdot \frac{b_0}{d_1} \cdot p_0$$

In general:

⇒ ~~$$p_i = \frac{b_{i-1} \cdot p_{i-1}}{d_i}$$~~
$$p_i = \frac{b_{i-1} \cdot p_{i-1}}{d_i}$$

AND:

$$p_i = \frac{b_0 \cdot b_1 \cdot b_2 \dots b_{i-1} \cdot p_0}{d_1 \cdot d_2 \cdot d_3 \dots d_i}$$

$$\Rightarrow p_i = p_0 \cdot \prod_{j=0}^{i-1} \frac{b_j}{d_{j+1}}$$

⇒ Like before now apply the NORMALIZATION condition

$$\sum_{i=0}^{\infty} p_i = 1 \Rightarrow \sum_{i=0}^{\infty} p_0 \cdot \prod_{j=0}^{i-1} \frac{b_j}{d_{j+1}} = 1$$

Take p_0 out:

$$p_0 + \sum_{i=1}^{\infty} p_0 \cdot \prod_{j=0}^{i-1} \frac{b_j}{d_{j+1}} = 1$$

$$p_0 \left[1 + \sum_{i=1}^{\infty} \prod_{j=0}^{i-1} \frac{b_j}{d_{j+1}} \right] = 1$$

$$\Rightarrow p_0 = \frac{1}{1 + \sum_{i=1}^{\infty} \prod_{j=0}^{i-1} \frac{b_j}{d_{j+1}}}$$

If the series **DIVERGES**

If

ALL NULL RECURRENT STATES

$$p_0 = 0$$

$$\Rightarrow p_i = 0$$

If the series **CONVERGES**

If

ALL POSITIVE RECURRENT STATES \Rightarrow **ERGODIC CHAIN**

ERGODIC CHAIN

$$0 < p_0 < 1$$

$$\Rightarrow 0 < p_i < 1$$

This occurs if:

"We'll never come back to them", $\exists \prod_{j=0}^{\infty} \frac{b_j}{d_{j+1}} < 1$

MORE BRNS THAN DEATHS:

$$b_i \geq d_{i+1}$$

$$\Rightarrow b_i < d_{i+1}$$

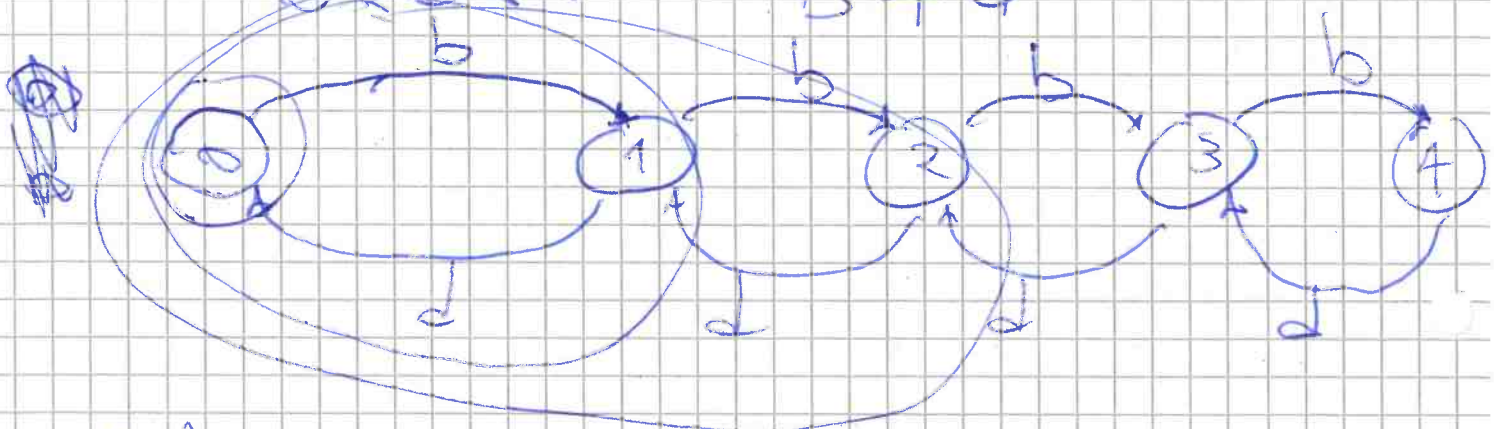
(b) Assume $b_i = b, d_i = d$ (APERIODIC CHAIN)

$$\Rightarrow 0 < b < 1$$

$$b + d \neq 1$$

$$0 < d < 1$$

$$b \neq 0$$



\Rightarrow Apply F.P.D.

$$\begin{aligned}
 b \cdot p_0 &= d \cdot p_1 \Rightarrow p_1 = \frac{b}{d} p_0 \\
 b \cdot p_1 &= d \cdot p_2 \Rightarrow p_2 = \frac{b}{d} p_1 = \frac{b}{d} \frac{b}{d} p_0 \\
 b \cdot p_2 &= d \cdot p_3 \Rightarrow p_3 = \frac{b}{d} p_2 = \frac{b}{d} \frac{b}{d} \frac{b}{d} p_0 \\
 b \cdot p_3 &= d \cdot p_4 \Rightarrow p_4 = \frac{b}{d} p_3 = \frac{b}{d} \frac{b}{d} \frac{b}{d} \frac{b}{d} p_0
 \end{aligned}$$

$$\Rightarrow p_i = \left(\frac{b}{d} \right)^i p_0$$

\Rightarrow Apply The NORMALIZATION CONDITION:

$$\sum_{i=0}^{\infty} p_i = 1 \Rightarrow \sum_{i=0}^{\infty} \left(\frac{b}{d} \right)^i p_0 = 1 \Rightarrow p_0 \sum_{i=0}^{\infty} \left(\frac{b}{d} \right)^i = 1$$

$$\Rightarrow p_0 = \frac{1}{\sum_{i=0}^{\infty} \left(\frac{b}{d} \right)^i}$$

$$\sum_{i=0}^{\infty} (\alpha)^i = \frac{1}{1-\alpha}$$

$$\text{if } \frac{b}{d} \geq 1$$

$$\text{if } \frac{b}{d} < 1$$

\Rightarrow SERIES DIVERGES

\Rightarrow SERIES CONVERGES

All states ~~are~~ ~~will~~ RECURRENT All states POSITIVE RECURRENT

Chain is ERGODIC

$$\Rightarrow p_0 = 0$$

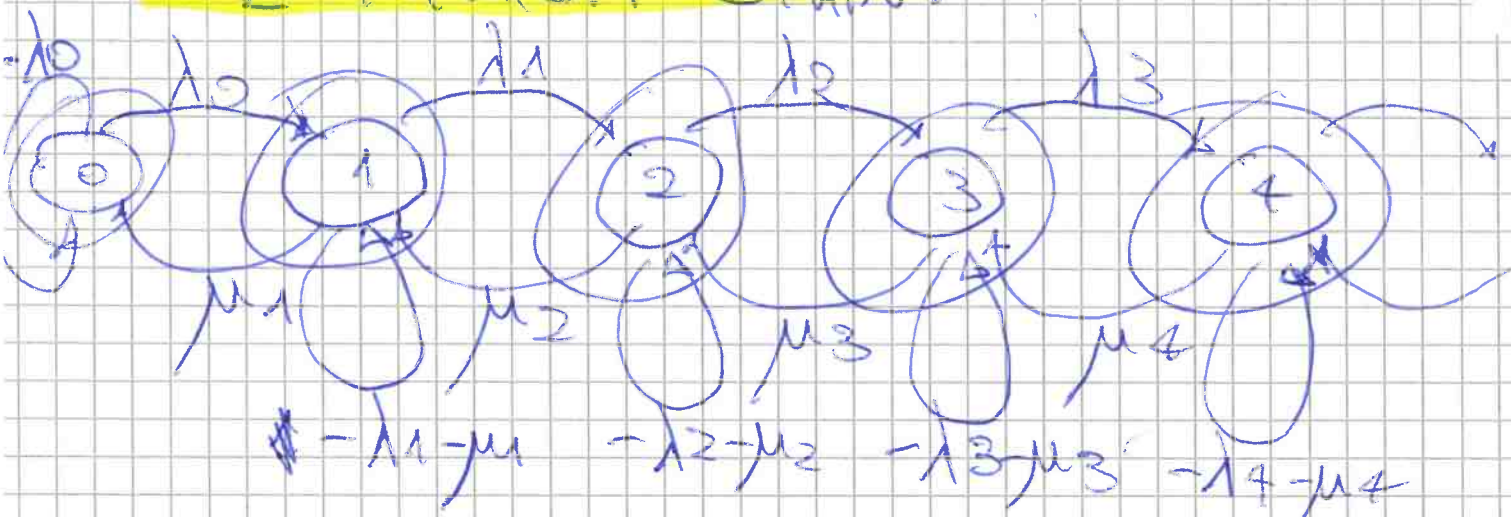
$$\Rightarrow p_i = 0$$

$$p_0 = \frac{1}{1 - \frac{b}{d}} \quad (\text{like M/M/1})$$

$$\Rightarrow p_i = \left(\frac{b}{d} \right)^i \left(1 - \frac{b}{d} \right)$$

GEOMETRIC BEHAVIOUR (DECAY)

24 HOMOGENEOUS BIRTH-DEATH CONTINUOUS-TIME MARKOFF CHAIN.



$V = [v_{ij}]$ $v_{ij} = \begin{cases} \lambda_i & j=i+1 \\ \mu_i & j=i-1 \\ -\lambda_i - \mu_i & j=i \neq 0 \\ -\lambda_0 & j=i=0 \\ 0 & \text{elsewhere} \end{cases}$

Upper triangular, 3-DIAGONAL MATRIX.

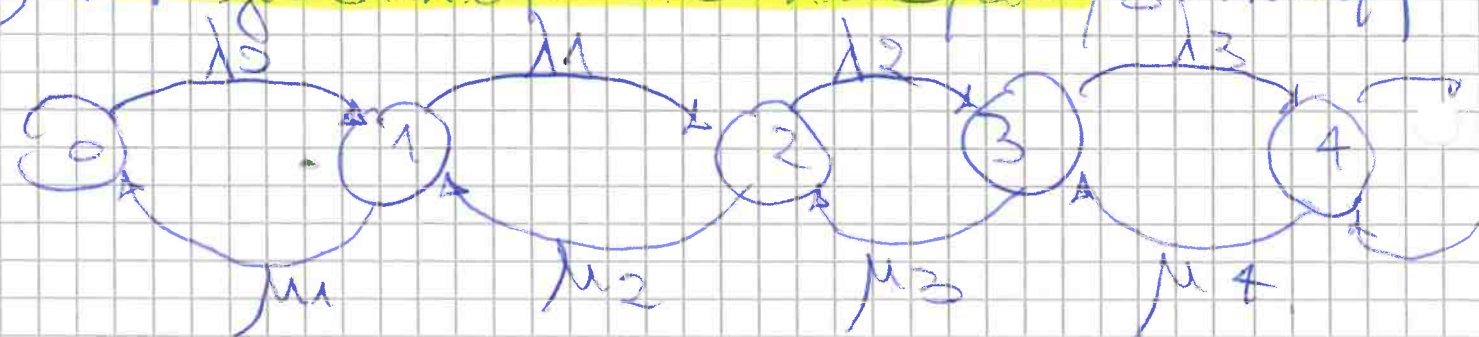
Ⓐ FCP for TRANSIENT ANALYSIS:

$\frac{d}{dt} p_0(t) = p_0(t) \mu_1 - p_0(t) \lambda_0$

$\frac{d}{dt} p_i(t) = p_i(t) \mu_2 - p_i(t) \lambda_1$

$\frac{d}{dt} p_i(t) = p_i(t) \mu_{i+1} + p_i(t) \lambda_{i-1} - p_i(t) (\lambda_i + \mu_i)$

Ⓑ FCP for STEADY-STATE ANALYSIS (STATIONARY)



$$\lambda_0 \cdot p_0 = \mu_1 \cdot p_1 \Rightarrow p_1 = \frac{\lambda_0}{\mu_1} p_0$$

$$\lambda_1 \cdot p_1 = \mu_2 \cdot p_2$$

$$\Rightarrow p_2 = \frac{\lambda_1}{\mu_2} p_1 = \frac{\lambda_1}{\mu_2} \cdot \frac{\lambda_0}{\mu_1} p_0$$

$$\lambda_2 \cdot p_2 = \mu_3 \cdot p_3$$

$$\Rightarrow p_3 = \frac{\lambda_2}{\mu_3} p_2 = \frac{\lambda_2}{\mu_3} \cdot \frac{\lambda_1}{\mu_2} \cdot \frac{\lambda_0}{\mu_1} p_0$$

$$\Rightarrow p_i = \frac{\lambda_0 \cdot \lambda_1 \cdot \lambda_2 \cdots \lambda_{i-1}}{\mu_1 \cdot \mu_2 \cdot \mu_3 \cdots \mu_i} p_0$$

$$\Rightarrow p_i = p_0 \cdot \prod_{j=0}^{i-1} \frac{\lambda_j}{\mu_{j+1}}$$

By the normalization condition $\sum_{i=0}^{\infty} p_i = 1$

$$\Rightarrow \sum_{i=0}^{\infty} p_0 \cdot \prod_{j=0}^{i-1} \frac{\lambda_j}{\mu_{j+1}} = 1$$

$$p_0 + p_0 \sum_{i=1}^{\infty} \prod_{j=0}^{i-1} \frac{\lambda_j}{\mu_{j+1}} = 1$$

$$p_0 \left[1 + \sum_{i=1}^{\infty} \prod_{j=0}^{i-1} \frac{\lambda_j}{\mu_{j+1}} \right] = 1$$

$$p_0 = \frac{1}{1 + \sum_{i=1}^{\infty} \prod_{j=0}^{i-1} \frac{\lambda_j}{\mu_{j+1}}}$$

$$P_0 = \frac{1}{1 + \sum_{k=1}^{\infty} \prod_{j=0}^{k-1} \frac{\lambda_j}{\mu_{j+1}}}$$

SERIES DIVERGES

$$\frac{\lambda_j}{\mu_{j+1}} > 1$$

All states are null-recurrent

$$P_0 = 0$$

SERIES CONVERGES

$$\frac{\lambda_j}{\mu_{j+1}} < 1$$

$$\Rightarrow \lambda_j < \mu_{j+1}$$

All states are positive recurrent

Chain is ERGODIC

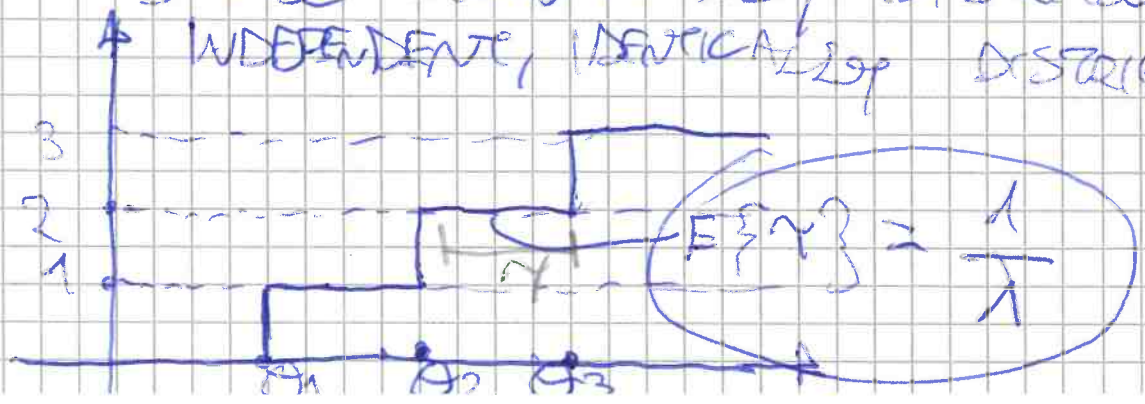
$$0 < P_0 < 1$$

(25) PURE-BIRTH KINETIC as a POISSON R.V.

~~Consider a POISSON / COUNTING PROCESS~~

Consider a PURE-BIRTH KINETIC, where:

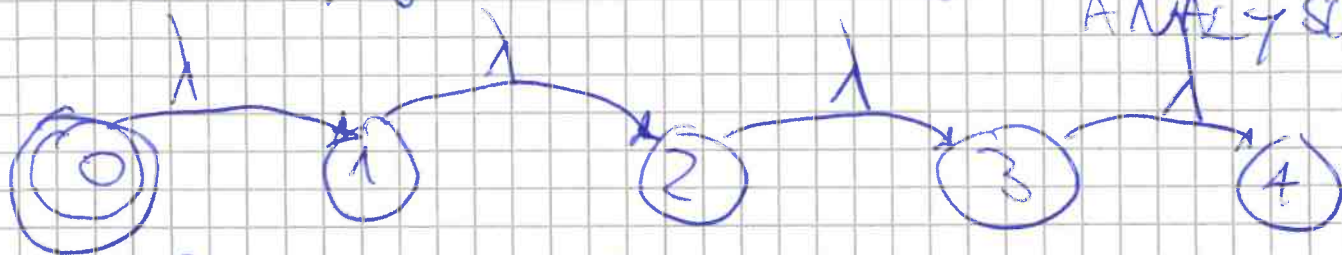
- ARRIVALS ARE EXPONENTIALLY-DISTRIBUTED & INDEPENDENT, IDENTICALLY-DISTRIBUTED.



RATE of ARRIVALS = $\lambda = \lambda_i$ (Always the same!)

INTER ARRIVAL - RATE = $\frac{1}{\lambda}$

\Rightarrow Apply FCP to it for TRANSIENT ANALYSIS:



For $\frac{d}{dt} p_0(t) = -\lambda p_0(t)$

$\frac{d}{dt} p_1(t) = -\lambda p_1(t) + \lambda p_0(t)$

$\frac{d}{dt} p_2(t) = -\lambda p_2(t) + \lambda p_1(t)$

can't solve

$\frac{d}{dt} p_i(t) = -\lambda p_i(t) + \lambda p_{i-1}(t)$

However we can still solve by applying \mathcal{L}

$\frac{d}{dt} p_0(t) = -\lambda p_0(t)$

$P(t) = (1, 0, 0, 0, \dots)$

$s \cdot p_0(s) - p_0(0) = -\lambda p_0(s)$

$p_0(s) \cdot (s + \lambda) = 1$

$\Rightarrow p_0(s) = \frac{1}{s + \lambda}$

$\Rightarrow p_0(t) = e^{-\lambda t} \cdot 1(t)$

\Rightarrow Now take: $\frac{d}{dt} p_i(t)$ for $i \neq 0$

$$\frac{d}{dt} p_i(t) = \lambda p_{i-1}(t) - \lambda p_i(t)$$

$$s \cdot p_i(s) - p_i(0) = \lambda p_{i-1}(s) - \lambda p_i(s)$$

$$p_i(s) \cdot (s + \lambda) = \lambda p_{i-1}(s)$$

$$p_i(s) = \frac{\lambda}{s + \lambda} p_{i-1}(s)$$

Take $i=1$:

$$p_1(s) = \frac{\lambda}{s + \lambda} p_0(s) = \frac{\lambda}{s + \lambda}$$

$$\Rightarrow p_1(s) = \frac{\lambda}{(s + \lambda)^2}$$

$$\Rightarrow p_2(s) = \frac{\lambda}{s + \lambda} \cdot p_1(s) = \frac{\lambda}{s + \lambda} \cdot \frac{\lambda}{(s + \lambda)^2} =$$

$$p_2(s) = \frac{\lambda^2}{(s + \lambda)^3}$$

\Rightarrow By INDUCTION:

$$p_n(s) = \frac{\lambda^n}{(s + \lambda)^{n+1}}$$

We know:

$$\frac{\lambda^n}{(s + \lambda)^{n+1}} = \frac{\lambda^n}{n!} \sum_{k=0}^{\infty} \frac{(-1)^k}{(s + \lambda)^{k+1}} \cdot e^{-\lambda t}$$

$$\Rightarrow P_n(t) = \frac{\lambda^n \cdot t^n}{n!} \cdot e^{-\lambda t} = \frac{(\lambda t)^n \cdot e^{-\lambda t}}{n!}$$

POISSON DISTRIBUTION

$$= \frac{(\lambda t)^n \cdot e^{-\lambda t}}{n!}$$

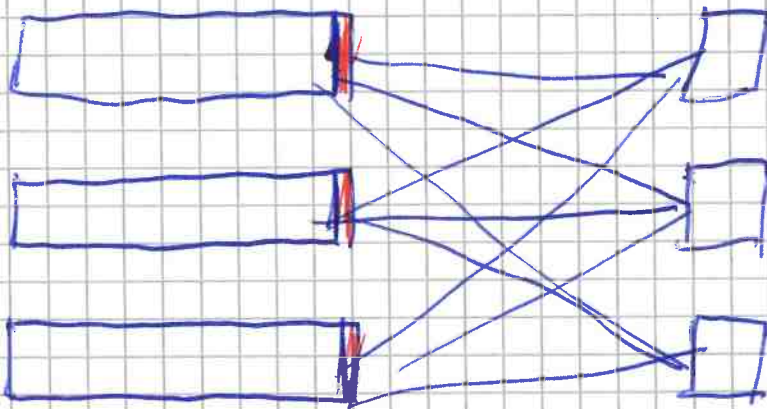
Probability of finding the process in state n over t time.

P. of having n arrivals in interval $[0, t]$

\Rightarrow Generally we have only distribution for arrivals

26 PACKET-SWITCHING ARCHITECTURES

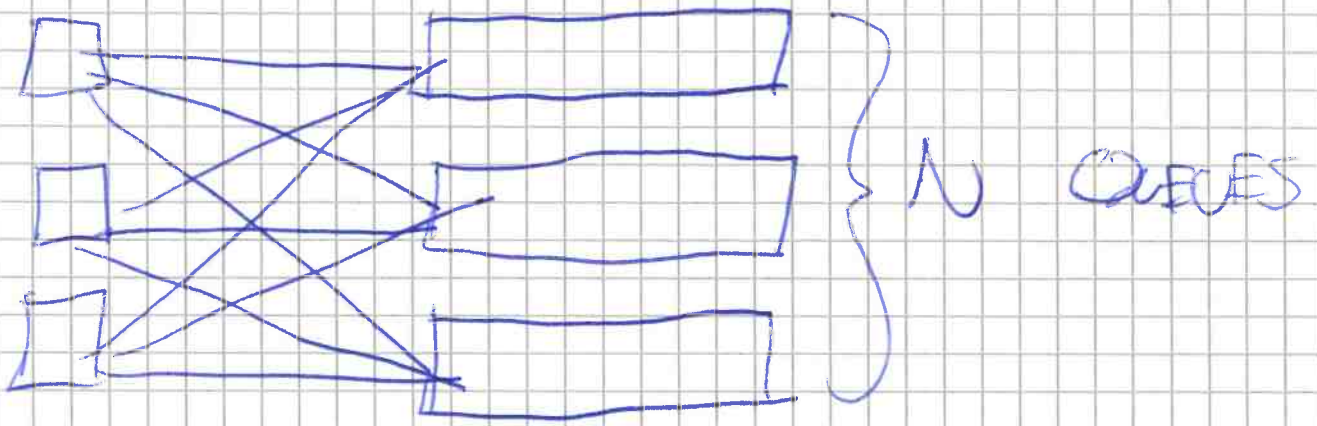
① INPUT QUEUING: A buffer is located at every INPUT LINE.



HOL / Head-of-Line problem: where packets transmitted one after the other are "queued" even if they have different destinations.

② OUTPUT QUEUING:

Queues are located at every output line \Rightarrow No longer blocked with different destinations - packets.



$N \times$ SPEEDUP FACTOR ($N = \#$ VIRTUAL BUFFERS)

③ VIRTUAL OUTPUT QUEUING

Use N "virtual" buffers per ~~INPUT~~ ^{AT BUFFERS} QUEUE \Rightarrow SCHEDULING PROBLEM.

"Which queue ought to be served?"

\Rightarrow Such architectures are used within packet switches. [With fixed-size packets, we can best analyze a system].

GEOMETRIC ARRIVALS

GEOMETRIC SERVICE

② Geo/Geo/1 Queue

It is a discrete-time queue used to model fixed-size packets arrivals to a system (Ex: ATM), where we have a BERNULLI RVS arriving (have a cell or not have it ~~Busy~~ Busy)

GEOMETRIC ARRIVALS

& GEOMETRIC SERVICE

$P\{\text{busy slot}\} = \alpha$
 $P\{\text{empty slot}\} = 1 - \alpha$

$E\{A\} = \frac{1}{\alpha}$

~~PROBABILITY~~

$$P\{\text{SERVICE}\} = \beta$$

$$P\{\text{NO SERVICE}\} = 1 - \beta$$

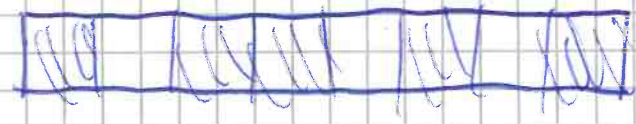
$$E\{S\} = \frac{1}{\beta}$$

GEOMETRIC INTERARRIVAL TIME:

⇒ We have already shown that:

$$P\{A=k\} = \alpha(1-\alpha)^{k-1} \quad [k \text{ ARRIVALS}]$$

$$E\{A\} = \frac{1}{1-\alpha}$$



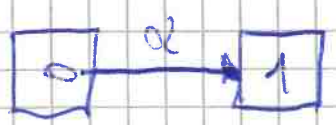
GEOMETRIC INTER-SERVICE TIME:

$$P\{B=k\} = \beta(1-\beta)^{k-1} \quad [k \text{ SERVICES}]$$

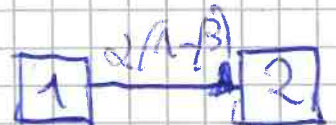
$$E\{B\} = \frac{1}{1-\beta}$$

STATE = #CUSTOMERS in the QUEUE

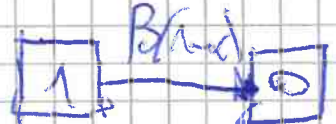
TRANSITIONS:



ONE ARRIVAL



ONE ARRIVAL, NO SERVICE



NO ARRIVAL, BUT SERVICE



NO ARRIVAL, NO SERVICE

OR
1 ARRIVAL, 1 SERVICE

PROBABILITY of REMAINING in the SAME STATE

① NO ARRIVALS & NO SERVICE

$$1 - [\alpha(1-\beta) + \beta(1-\alpha)]$$

$$= 1 - \alpha + \alpha\beta - \beta + \alpha\beta$$

$$= 1 - \alpha - \beta + 2\alpha\beta$$

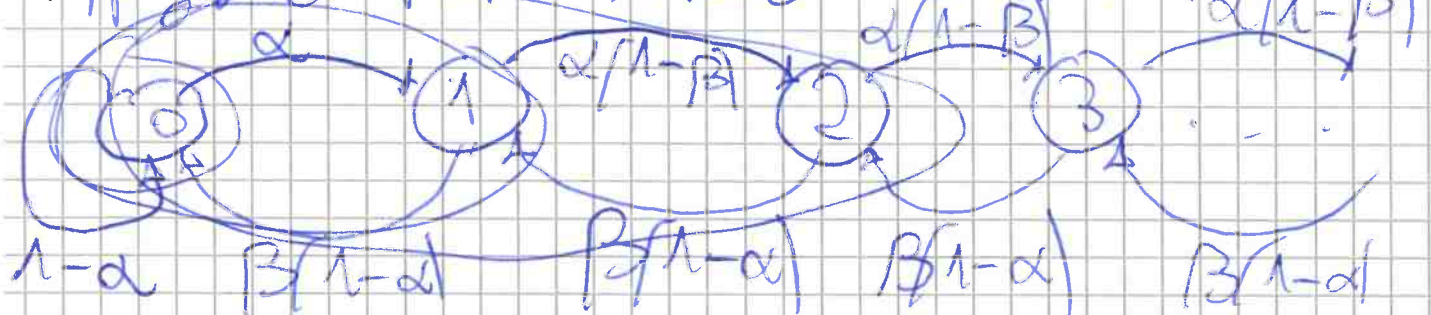
② 1 SERVICE, 1 ARRIVAL ~~& NO~~

$$\alpha\beta + (1-\alpha)(1-\beta)$$

SERVICE & ARRIVAL ~~OR~~ NO SERVICE, NO ARRIVAL

③ Ergodicity condition;

Apply the FCP To the DAGRAM:



If $\alpha = 1 \Rightarrow$ NOT PERIODIC! (NULL-recurrent)
 $\beta = 0 \Rightarrow$ Aperiodic (A ripple effect)

$0 < \alpha < 1 \Rightarrow$ PERIODIC with PERIOD = 2
 $0 < \beta < 1$

Apply the BALANCE EQUATIONS through the FCP.

~~$$\alpha p_0 = \beta(1-\alpha)p_1 \Rightarrow p_1 = \frac{\alpha}{\beta(1-\alpha)} p_0$$

$$\alpha p_1 = \beta(1-\alpha)p_2 \Rightarrow p_2 = \frac{\alpha}{\beta(1-\alpha)} p_1$$~~

$$\alpha p_0 = \beta(1-\alpha) p_1 \Rightarrow p_1 = \frac{\alpha}{\beta(1-\alpha)} p_0$$

$$\alpha(1-\beta) p_1 = \beta(1-\alpha) p_2 \Rightarrow p_2 = \frac{\alpha(1-\beta)}{\beta(1-\alpha)} p_1$$

$$\alpha(1-\beta) p_2 = \beta(1-\alpha) p_3$$

$$p_2 = \frac{\alpha(1-\beta) \cdot \alpha}{\beta(1-\alpha) \cdot \beta(1-\alpha)} p_0$$

$$\Rightarrow p_3 = \frac{\alpha(1-\beta)}{\beta(1-\alpha)} p_2 = \left[\frac{\alpha}{\beta(1-\alpha)} \right]^2 (1-\beta) p_0$$

$$\Rightarrow p_3 = \left[\frac{\alpha}{\beta(1-\alpha)} \right]^3 (1-\beta)^2 p_0$$

In general, for i :

$$p_i = \frac{\alpha(1-\beta)}{\beta(1-\alpha)} p_{i-1}$$

$$\Rightarrow p_i = \left[\frac{\alpha}{\beta(1-\alpha)} \right]^i (1-\beta)^{i-1} p_0$$

$$p_i = \left[\frac{\alpha(1-\beta)}{\beta(1-\alpha)} \right]^{i-1} \cdot \left(\frac{\alpha(1-\beta)}{\beta(1-\alpha)} \right) p_0$$

$$\Rightarrow p_i = \left[\frac{\alpha(1-\beta)}{\beta(1-\alpha)} \right]^i \frac{p_0}{1-\beta}$$

Apply the NORMALIZATION CONDITION $\sum_{i=0}^{\infty} p_i = 1$

$$p_0 + \sum_{i=1}^{\infty} \left[\frac{\alpha(1-\beta)}{\beta(1-\alpha)} \right]^i \frac{p_0}{1-\beta} = 1$$

$$p_0 + \frac{p_0}{1-\beta} \left(\sum_{i=1}^{\infty} \left[\frac{\alpha(1-\beta)}{\beta(1-\alpha)} \right]^i \right) = 1$$

If this series converges \Rightarrow All states are POSITIVE RECURRENT & Chain is ERGODIC

IF $\frac{\alpha(1-\beta)}{\beta(1-\alpha)} < 1$

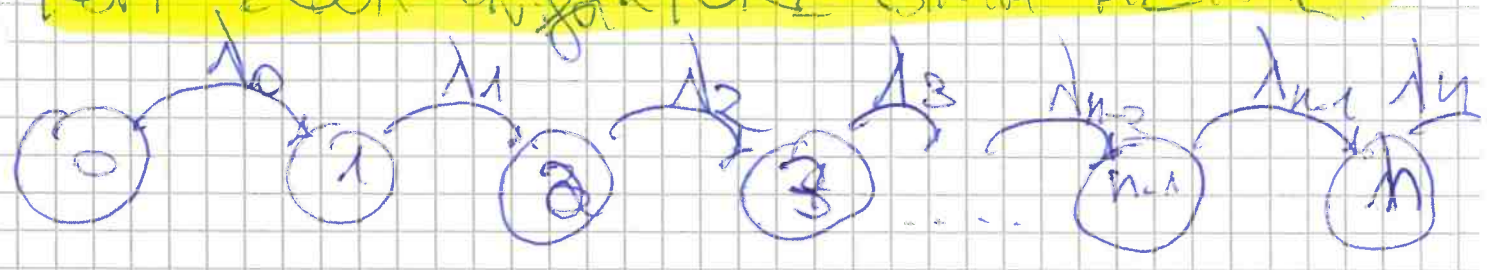
$$\alpha(1-\beta) < \beta(1-\alpha)$$

$$\alpha - \alpha\beta < \beta - \alpha\beta$$

ERGODICITY
CONDITION

$$\Rightarrow \alpha < \beta$$

Q8) SOLVING THE (FORWARD) CHAPMAN-KOLMOGOROFF EQUATION FOR A PURE-BIRTH MCTMC



FORWARD KOLMOGOROFF EQUATION:

$$\begin{cases} \frac{d}{dt} H(t) = \underline{H}(t) \cdot \underline{V} \\ \underline{H}(0) = \underline{I} \end{cases}$$

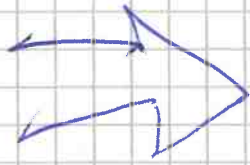
In SGM Form, this is:

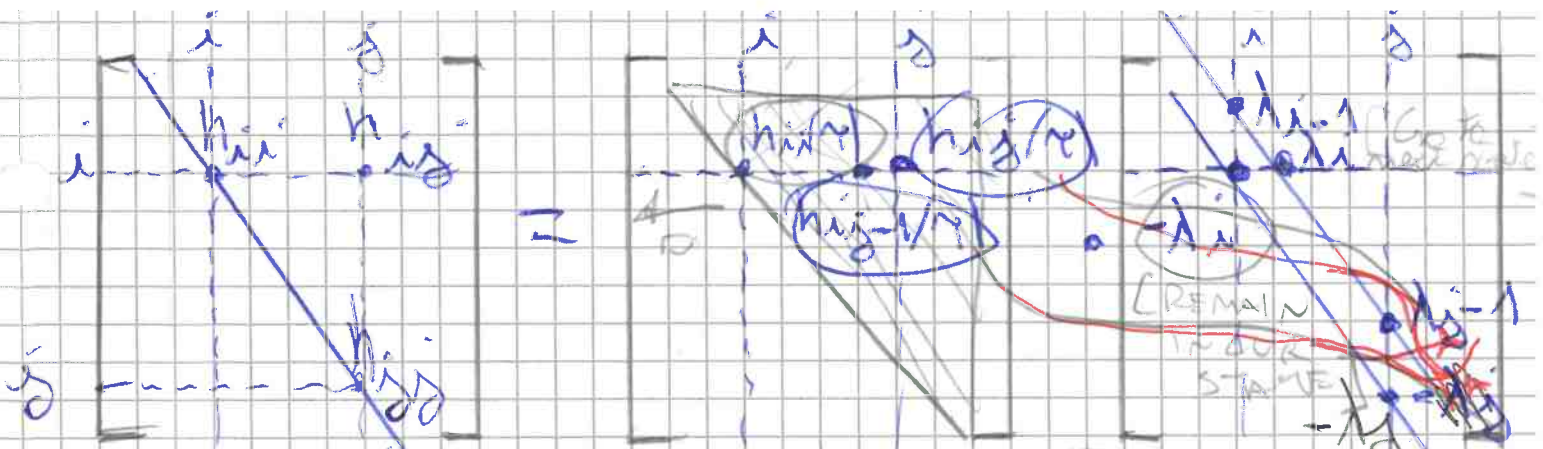
$$\frac{d}{dt} h_{ij}(t) = \sum_{k \in S} h_{ik}(t) v_{kj}$$

Where: $\sum_{j \in S} h_{ij}(t) = 1$

and $\underline{H}(0) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ & & & \uparrow & \\ & & & & \uparrow \\ & & & & & 1 \end{bmatrix}$

$$\underline{H}(0) [h_{ij}(0)] = \begin{cases} h_{ij}(0) = 1 & \forall i=j \\ h_{ij}(0) = 0 & \forall i \neq j \end{cases}$$





$$\frac{d}{dt} \underline{h}(\tau) = \underline{A}(\tau) \underline{h}(\tau)$$

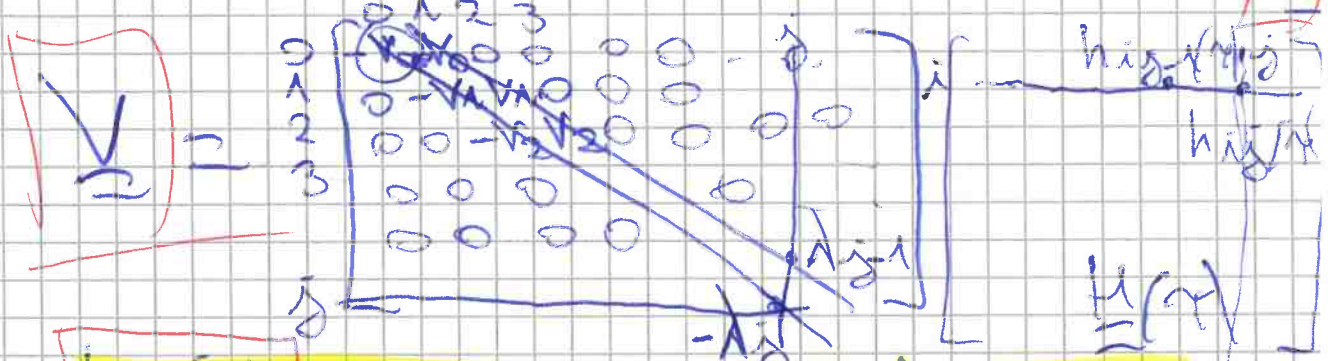
Never jump to a state

$$\underline{h}(\tau) = \underline{U}(\tau) \underline{h}(0)$$

$$\underline{V}(\tau) = \underline{L}(\tau) \underline{h}(0)$$

DIAGONAL MATRIX $\underline{U}(\tau)$

NOW: BI-DIAGONAL MATRIX FOR \underline{V}



$\underline{U}(\tau)$ TRIANGULAR MATRIX

Never jump from i to a state

~~MATRIX~~ MATRIX MULTIPLICATION can be expressed as:

MAIN DIAGONAL
OUT MAIN DIAGONAL

$$\frac{d}{dt} h_{ii}(\tau) = -\lambda_i \cdot h_{ii}(\tau)$$

(ROW i X COLUMN j)

$$\frac{d}{dt} h_{ij}(\tau) = \lambda_{j-1} \cdot h_{ij-1}(\tau) - \lambda_j \cdot h_{ij}(\tau)$$

$$\underline{h}(0) = \underline{I}$$

NOFCP

BRN-1

(1) Solve the DIFF. EQUATION for the main diagonal (one unknown only!)

$$\frac{d}{dt} h_{ii}(\tau) = -\lambda_i \cdot h_{ii}(\tau)$$

$$s \cdot h_{ii}(s) - h_{ii}(0) = -\lambda_i \cdot h_{ii}(s)$$

$$\Rightarrow h_{ii}(s) = \frac{h_{ii}(0)}{s + \lambda_i} \quad \text{because } H(0) = I$$

$$\Rightarrow h_{ii}(s) = \frac{1}{s + \lambda_i}$$

$$\Rightarrow h_{ii}(t) = e^{-\lambda_i t} \cdot u(t) \Rightarrow \text{COMPONENTS OF TRANSFER FUNCTION}$$

$$P(t+\tau) = P(t) \cdot U(\tau)$$

$$P(t) = P(0) \cdot U(t)$$

Counter starts value λ_0 at time 0.

Remember: $P_{ij}(t) = \sum_{k \in S} P_{ik}(t) \cdot h_{kj}(t)$

We will hence get:

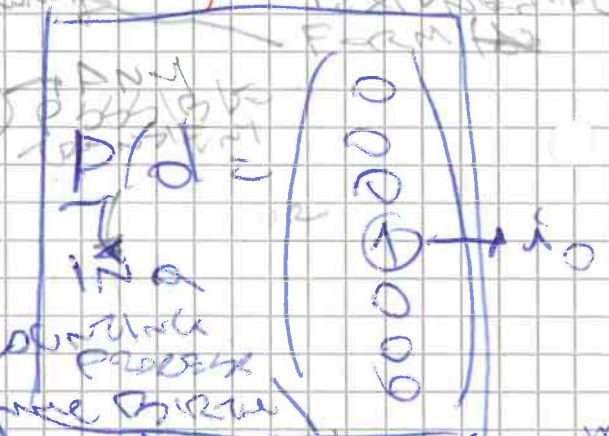
$$P_{ij}(t) = h_{i0j}(t) \quad \forall j$$

Only components left are the ones on the λ_0 row.

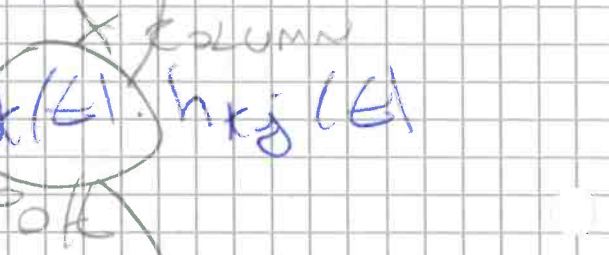
$$U(t) =$$

INITIALLY: Triangular Superior

AFTERWARDS: Only components on λ_0 row



initial values



\Rightarrow ~~P~~ $P(E) = \lambda_0$ -row

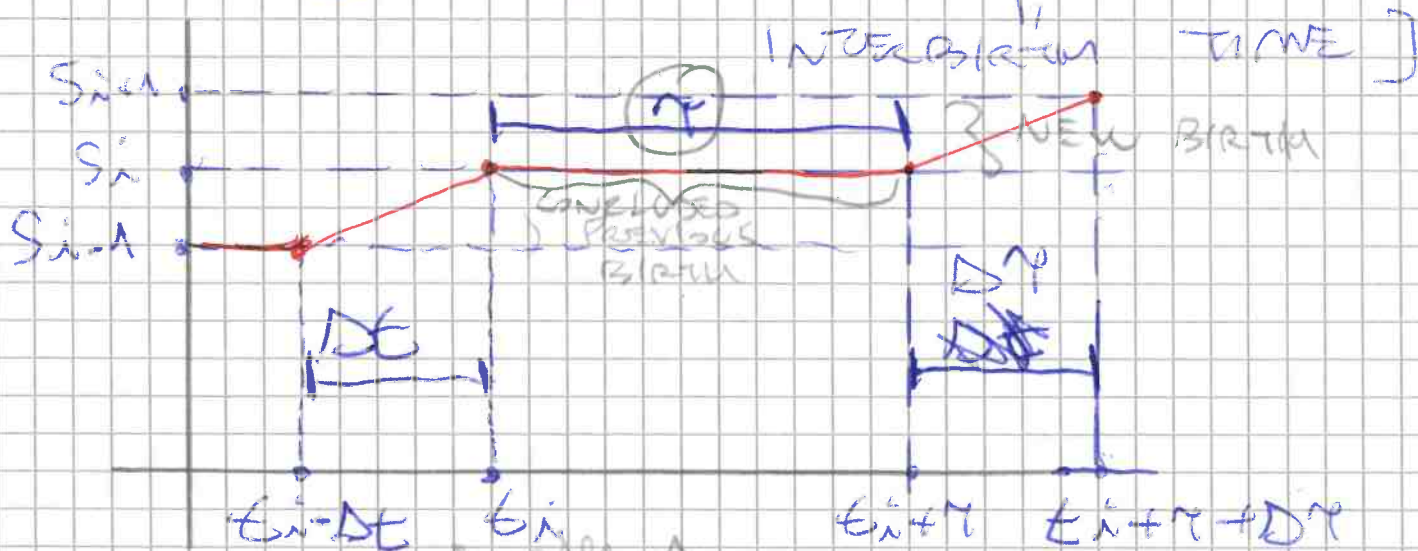
$$P(E) = \begin{bmatrix} p_1(E) & p_2(E) & \dots & p_n(E) \\ \vdots & \vdots & & \vdots \\ h_{101} & h_{102} & \dots & h_{10n} \end{bmatrix}$$

This is all not too bad!
~~ANALYSIS~~ stops here!

\Rightarrow COMPLEX to evaluate components
not on the MAIN DIAGONAL!

ORDER-1 INTERBIRTH TIME:

Goal: Understand PDF of ORDER-1 INTERBIRTH TIME. [INTERARRIVAL TIME]



INTERARRIVAL Time passing in-between two BIRTHS (i.e. two arrivals).

⇒ Precisely define interbirth time & find its DISTRIBUTION.

PROOF: Is there INTERBIRTH TIME effectively EXPONENTIAL? ⇒ find PDF for

DENSITY FUNCTION
I'm looking for P. that here INTERBIRTH time

$$g_i(\tau) \cdot \Delta T = P\{t_{i+1} + \Delta T | S_{i+1}, t_i | S_i, t_{i-1} | S_{i-1}\}$$

⇒ Rewrite it using the BAYES theorem.

$$g_i(\tau) \cdot \Delta T = P\{t_{i+1} + \Delta T | S_{i+1}, t_i + \Delta T = S_i, t_i | S_i, t_{i-1} | S_{i-1}\}$$

$$P\{t_{i+1} + \tau | S_i, t_i | S_i, t_{i-1} | S_{i-1}\}$$

$$P_i \frac{d}{dt} P_i = P_i (\lambda_i + \mu_i) = S_i + \lambda_i \frac{d}{dt} P_i$$

$$P_i \frac{d}{dt} P_i = S_i \frac{d}{dt} P_i = S_i$$

$h_{ii}(\tau)$ [REMAIN in same state over time τ]

$$\Rightarrow \frac{d}{dt} h_{ii}(\tau) = -\lambda_i h_{ii}(\tau)$$

$$\Rightarrow \frac{d}{dt} h_{ii}(\tau) = -\lambda_i h_{ii}(\tau)$$

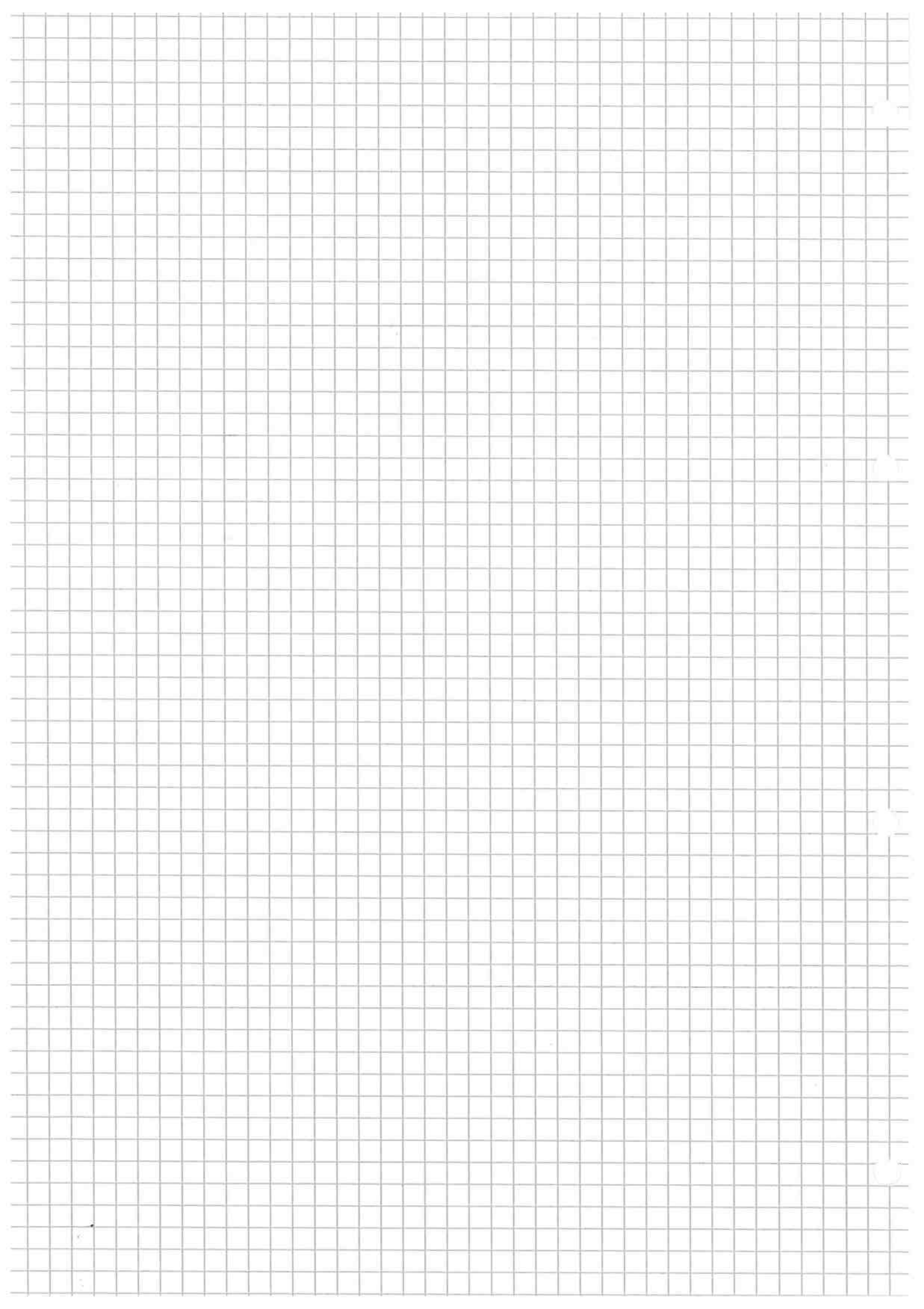
(Became I.I.A. ARRIVAL)

$$\Rightarrow \frac{d}{dt} h_{ii}(\tau) = -\lambda_i h_{ii}(\tau)$$

EXPONENTIAL DISTRIBUTION of the FIRST-ORDER INTER-BIRTH TIME

(i.e. SOJOURN TIME for a UCTMC)

N-ORDER INTERBIRTH Time passing between N births



29) MOMENT GENERATING FUNCTION (M/G):

We know:

$$E\{x\} = \int_0^{+\infty} x \cdot f(x) dx$$

EXPECTED
VALUES
DEFINITION

$$M(s) = E\{e^{sx}\} = \int_0^{+\infty} f(x) \cdot e^{sx} dx$$

From the \mathcal{L} -transform, we know:

$$\mathcal{L}\{f(x)\} = \int_0^{+\infty} f(x) \cdot e^{-sx} dx$$

If $s = -s \Rightarrow$ You get the MOMENT GENERATING FUNCTION.

$$M(s) = \mathcal{L}\{f(x)\}$$

a) Γ -ORDER MOMENT:

$$E\{x^\Gamma\} = \frac{d^\Gamma}{ds^\Gamma} M(s) \Big|_{s=0}$$

b) DEFINITION of VARIANCE:

$$\text{VAR}\{x\} = E\{x^2\} - (E\{x\})^2$$

c) COEFFICIENT of VARIATION:

$$CV = \frac{\sqrt{\text{VARIANCE}}}{E\{X\}} = \frac{\text{STANDARD DEVIATION}}{E\{X\}}$$

④ M/B, $E\{X\}$, $E\{X^2\}$ for the EXP. P.D.F.

$$f(x) = \lambda \cdot e^{-\lambda x} \cdot \mu(x)$$

$$M/B = \int_0^{\infty} \lambda \cdot e^{-\lambda x} \cdot \mu(x) dx = \frac{\lambda}{s-\lambda}$$

$$E\{X\} = \frac{d}{ds} \frac{\lambda}{s-\lambda} = \frac{\lambda}{(s-\lambda)^2} \Big|_{s=0} = \frac{\lambda}{\lambda^2} = \frac{1}{\lambda}$$

$$E\{X^2\} = \frac{d}{ds^2} \frac{\lambda}{s-\lambda} = \frac{2\lambda}{(s-\lambda)^3} \Big|_{s=0} = \frac{2\lambda}{\lambda^3} = \frac{2}{\lambda^2}$$

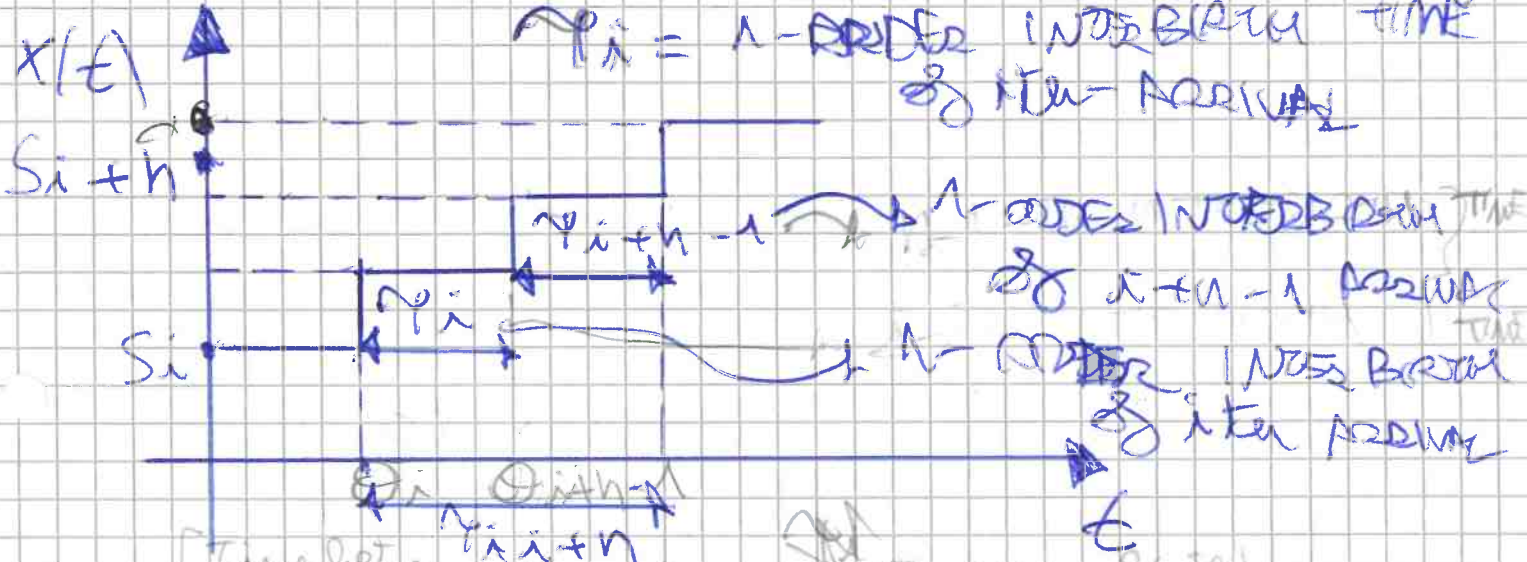
$$\text{VAR}\{X\} = E\{X^2\} - (E\{X\})^2$$

$$\text{VAR}\{X\} = \frac{2}{\lambda^2} - \left(\frac{1}{\lambda}\right)^2 = \frac{1}{\lambda^2}$$

$$CV = \frac{\sqrt{\frac{1}{\lambda^2}}}{\frac{1}{\lambda}} = \frac{\frac{1}{\lambda}}{\frac{1}{\lambda}} = 1$$

30 PDF of the n-order INTERBIRTH TIME are an Erlang-n DISTRIBUTED R.V.

Consider a processor with n-many ORDER-1 INTERBIRTHS (Sum of n 1-order INTERBIRTHS)



$$f(\tau) = \lambda \cdot e^{-\lambda \tau}$$

From τ_i to τ_{i+n-1} there are n CONTINUED ARRIVAL RATE TRANSFER RATES (n-many ARRIVALS) n-order PDF

$$f_{i+n}(t) = \lambda^{i+n-1} \cdot \tau_{i+n-1}(t)$$

$$\tau_{i+n} = \sum_{k=0}^{n-1} \tau_{i+k}$$

$$e^{-\lambda t} \cdot \lambda(t)$$

$$f_i(t) = \lambda \cdot \tau_i(t)$$

Take $E\{\tau_i\}$:

$$E\{\tau_{i+n}\} = \sum_{k=0}^{n-1} E\{\tau_{i+k}\} = \sum_{k=0}^{n-1} \frac{1}{\lambda}$$

Since τ_{i+k} are independent from one another.

~~Does $\tau_{i+n} = \sum_{k=0}^{n-1} \tau_{i+k}$~~

$$\text{VAR}\{T_{i+n}\} = \sum_{k=0}^{n-1} \frac{1}{\lambda^{i+k}} = \sum_{k=0}^{n-1} \lambda^{-i-k} = \lambda^{-i} \sum_{k=0}^{n-1} \lambda^{-k}$$

$f_{i+k}(s) = \frac{\lambda^{i+k}}{s + \lambda^{i+k}}$

~~Taking the L-Transform~~

⇒ The ~~n-order~~ PDF is hence given by:

$$f_{i+n}(t) = f_{i+0}(t) \otimes f_{i+1}(t) \otimes \dots \otimes f_{i+n-1}(t)$$

Convolution of independent PDFs

⇒ Taking the L-Transform of the convolution

$$f_{i+n}(s) = \prod_{k=0}^{n-1} \frac{\lambda^{i+k}}{s + \lambda^{i+k}}$$

In the special case of a Poisson process:

$$\lambda^{i+k} = \lambda$$

$$f_{i+n}(s) = \prod_{k=0}^{n-1} \frac{\lambda}{s + \lambda} = \frac{\lambda^n}{(s + \lambda)^n}$$

$\frac{1}{(s + \lambda)^n} \rightarrow \frac{t^{n-1}}{(n-1)!} \cdot e^{-\lambda t}$

We know:

$$\frac{1}{(s + \lambda)^n} \xrightarrow{\mathcal{L}^{-1}} \frac{t^{n-1}}{(n-1)!} \cdot e^{-\lambda t}$$

n-FOLDING DISTRIBUTION

$$\Rightarrow f_{i+n}(t) = \frac{\lambda^n \cdot t^{n-1}}{(n-1)!} \cdot e^{-\lambda t}$$

$$= \lambda \cdot \frac{(\lambda t)^{n-1}}{(n-1)!} \cdot e^{-\lambda t}$$

→ We hence have found the **ERLANG-N DISTRIBUTION**.

$$f_{i+n}(t) = \frac{\lambda \cdot (\lambda t)^{n-1}}{(n-1)!} e^{-\lambda t} \mu(t)$$

$$\textcircled{a} E\{Y_{i+n}\} = \frac{n}{\lambda} \quad (\text{n. EXP. distribution's mean})$$

$$\text{VAR}\{Y_{i+n}\} = \frac{n}{\lambda^2} \quad (\text{n. EXP. distribution's variance})$$

$$\text{CV} = \frac{\sqrt{\frac{n}{\lambda^2}}}{\frac{n}{\lambda}} = \frac{\sqrt{n}}{\lambda} \cdot \frac{\lambda}{n} = \frac{\sqrt{n}}{n} = \frac{1}{\sqrt{n}}$$

Gamma-Distribution: $\Gamma(v) = (v-1)!$

$$f_{v/\lambda} = \frac{\lambda \cdot (\lambda t)^{v-1}}{\Gamma(v)} e^{-\lambda t} \mu(t)$$

$$E\{T\} = \frac{v}{\lambda} \quad \text{VAR}\{T\} = \frac{v}{\lambda^2}$$

NB: The **Gamma-Distribution** is a more general distribution than the **ERLANG-N** one

2A) DISCRETE-TIME BERNOLLI PROCESS

• **BERNOLLI R.V.:** R.V. that can only have a 0 or 1 value.

• **BERNOLLI DISTRIBUTION:** Distribution characterizing a BERNOLLI R.V. (PMF).

$$P\{X=0\} = q = 1-p = \text{FAILURE}$$

$$P\{X=1\} = p = \text{SUCCESS}$$

Where X is a BERNOLLI R.V.

0	1	2	3	4	5	6	7	8
---	---	---	---	---	---	---	---	---

• GEOMETRIC (NON-ARITHMETIC) TIME

BERNOLLI PROCESS

Sum of n -independent BERNOLLI R.V.S.

BINOMIAL DISTRIBUTION

Distribution characterizing a Bernolli Process (PMF).

$$P\{X_n = i\} = P_i(n) = \binom{n}{i} p^i \cdot q^{n-i}$$

$$E\{x^2\} = \frac{d}{dz^2} (q + pz)^N + \frac{d}{dz} (q + pz)^N \Big|_{z=1}$$

$$= \frac{d}{dz} N \cdot p \cdot (q + pz)^{N-1} + Np$$

$$= Np(N-1) \cdot p \cdot (q + pz)^{N-1} + Np$$

$$= N \cdot p^2 \cdot (N-1) + Np$$

$$= \cancel{Np \cdot p} + N^2 p^2 - Np^2 + Np$$

$$= Np \cdot (Np + q)$$

$$E\{x^2\} = Np \cdot (Np + q)$$

$$\Rightarrow \text{VAR}\{x\} = E\{x^2\} - (E\{x\})^2$$

$$= Np(Np + q) - (Np)^2$$

$$= \cancel{N^2 p^2} + Npq - \cancel{N^2 p^2}$$

$$\Rightarrow \text{VAR}\{x\} = N \cdot pq$$

(b) For a BINOMIAL R.V.: Θ :

$$E\{\Theta\} = 0 \cdot q + 1 \cdot p = p$$

\Rightarrow We can hence see that:

$$E\{x\} = \sum_{i=1}^N E\{\Theta_i\} = N \cdot p$$

$$E\{\theta^2\} = 0 \cdot q + 1^2 \cdot p = p$$

$$\begin{aligned} \text{VAR}\{\theta\} &= E\{\theta^2\} - (E\{\theta\})^2 \\ &= p - p^2 = p(1-p) = p \cdot q \end{aligned}$$

$$\text{VAR}\{t\} = \sum_{i=1}^N \text{VAR}\{\theta_i\} = N \cdot p \cdot q$$

(32) AXIOMATIC DEFINITION of a POISSON PROCESS:

The Poisson Process consists of a COUNTING PROCESS with UNITARY INCREASES.

\Rightarrow A counting process with unitary increases is a Poisson Process if the following conditions hold:

(1) PROBABILITY of one arrival in the infinitesimal time interval dt is:

$$P\{1 \text{ arrival in } dt\} = \lambda dt + o(dt)$$

$\lambda = 1$ ~~for unitary~~ INF. of higher order

(2) PROBABILITY of NO (0) ARRIVALS in dt is:

$$P\{0 \text{ arrivals in } dt\} = 1 - \lambda dt + o(dt)$$

(3) Disjoint intervals are characterized by INDEPENDENT EVENTS (i.e. The memoryless property holds)

(4) $P\{2 \text{ or more arrivals in } dt\} = o(dt)$

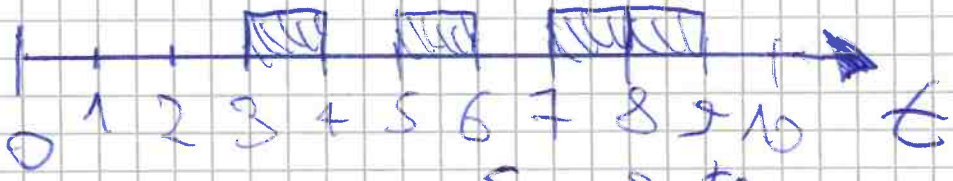
$$= \left\{ \begin{array}{l} P\{0 \text{ arrivals in } dt\} + P\{1 \text{ arrival in } dt\} \\ + P\{2 \text{ arrivals in } dt\} \end{array} \right.$$

FIGURE 11.5 OR 11.15
OR MORE

$$= \textcircled{1}$$

33) PASSION PROCESS AS A LIMITING CASE OF A DISCRETE-TIME BERNOULLI PROCESS (FOR $M \rightarrow \infty$ ATTENDERS)

Consider a period $(0, t)$ sub-divided into small sub-intervals. The probability to be in a certain sub-interval is **BINOMIAL (BINOMIAL DISTRIBUTION)**



$M = \# \text{ SLOTS}$ $t = \text{Sum of the duration of the different slots / intervals } dt$

$$dt = \frac{t}{M}$$

$t = \text{OVERALL TIME}$

Duration of one mini-interval (slot)

$$P = \lambda \cdot dt = P. \text{ to have an arrival in } dt$$

$$q = 1 - \lambda dt = P. \text{ not to have an arrival in } dt$$

$$\Rightarrow P_i(t) = P_{iM/M} = P. \text{ to have } M \text{ slots occupied (STATE PROBABILITY)}$$

$$P_m/M! = \binom{M}{m} (\lambda \Delta t)^m \cdot (1 - \lambda \Delta t)^{M-m}$$

$$\Delta t = \frac{c}{m}$$

$$= \frac{M!}{m!(M-m)!} \left(\frac{\lambda \cdot c}{M}\right)^m \left(1 - \frac{\lambda c}{M}\right)^{M-m}$$

HAVE TERMS before (M-m)!

$$p = \lambda \Delta t$$

$$q = 1 - \lambda \Delta t$$

~~$$= \frac{M}{M} \cdot \frac{M-1}{M} \cdot \frac{M-2}{M} \cdot \frac{M-3}{M} \cdots \frac{M-m+1}{M} \cdot \frac{(\lambda c)^m}{M^m} \cdot \frac{(1 - \lambda c)^{M-m}}{M^{M-m}}$$~~

~~lim~~
~~M → ∞~~

m terms

$$\frac{M \cdot (M-1) \cdot (M-2) \cdots (M-m+1)}{m! \cdot (M-m)!} \cdot \frac{(\lambda c)^m}{M^m} \cdot \frac{(1 - \lambda c)^{M-m}}{M^{M-m}}$$

$$\lim_{M \rightarrow \infty} \frac{M \cdot (M-1) \cdots (M-m+1)}{M^m} \cdot \frac{(\lambda c)^m}{m!} \cdot \frac{(1 - \lambda c)^{M-m}}{(1 - \lambda c)^m}$$

$$\frac{(1 - \lambda c)^M}{(1 - \lambda c)^m}$$

NUM. & DENOMINATOR have the same order of infinity

WELL-KNOWN LIMIT $\lim_{M \rightarrow \infty} (1 - \lambda c)^M = e^{-\lambda c}$

$$\lim_{M \rightarrow \infty} \frac{(\lambda c)^m}{m!} \cdot e^{-\lambda c} = P_m/M! = \lim_{M \rightarrow \infty} P_m/M! = P_m/\lambda c$$

POISSON - DISTRIBUTION is a LIMITING CASE of a BERNULLI DISTRIBUTION

$$P_m/\lambda c = \lim_{M \rightarrow \infty} P_m/M! = e^{-\lambda c} \cdot \frac{(\lambda c)^m}{m!}$$

3A ~~PROBLEM~~ ~~HA~~ For $X \sim \text{Poisson R.V.}$

$G_X(z)$, $E\{X\}$, $E\{X^2\}$, $\text{VAR}\{X\}$

~~$G_X(z) = \sum_{n=0}^{\infty} P_n \cdot z^n$~~ $E\{z^X\} = \sum_{n=0}^{\infty} P_n \cdot z^n$

For $X \sim \text{Poisson R.V.}$

$P_n = \frac{e^{-\lambda} \cdot (\lambda)^n}{n!}$ ~~$P_n = \frac{e^{-\lambda} \cdot (\lambda)^n}{n!}$~~

$\lambda = \lambda \cdot 1$

$\Rightarrow P_n = \frac{e^{-\lambda} \cdot (\lambda)^n}{n!}$

$\Rightarrow G_X(z) = \sum_{n=0}^{\infty} \frac{e^{-\lambda} \cdot (\lambda z)^n}{n!} = e^{-\lambda} \cdot \sum_{n=0}^{\infty} \frac{(\lambda z)^n}{n!}$

$\Rightarrow G_X(z) = e^{-\lambda} \cdot e^{\lambda z} = e^{\lambda(z-1)}$

$\Rightarrow G_X(z) = e^{\lambda(z-1)}$

$e^{\lambda z}$

$E\{X\} = \frac{d}{dz} G_X(z) \Big|_{z=1} = \lambda \cdot e^{\lambda(z-1)} \Big|_{z=1}$

$E\{X\} = \lambda$

$\frac{d}{dz} G_X(z) \Big|_{z=1}$

$E\{X^2\} = \frac{d^2}{dz^2} G_X(z) \Big|_{z=1} = \frac{d}{dz} \lambda \cdot e^{\lambda(z-1)} \Big|_{z=1}$

$= \lambda \cdot \lambda \cdot e^{\lambda(z-1)} \Big|_{z=1} = \lambda^2 + \lambda = \lambda(\lambda+1)$

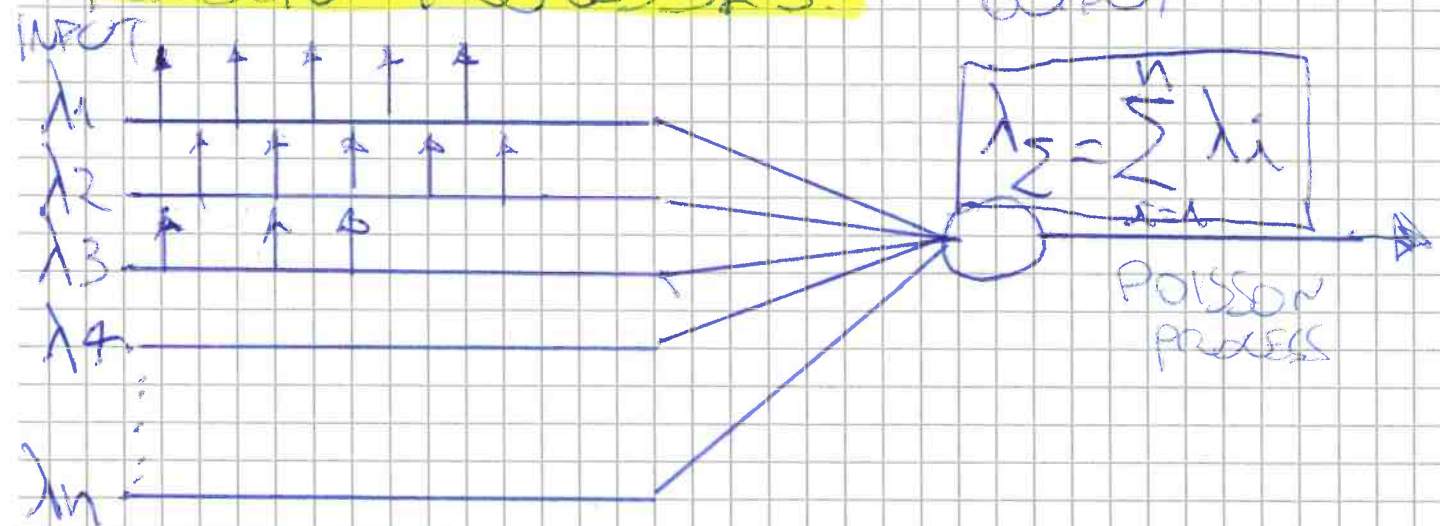
$$E\{x^2\} = \lambda(\lambda + 1)$$

$$\begin{aligned} \text{VAR}\{x\} &= E\{x^2\} - (E\{x\})^2 \\ &= \lambda(\lambda + 1) - \lambda^2 = \lambda \end{aligned}$$

$$\Rightarrow \text{VAR}\{x\} = \lambda$$

$$CV = \frac{\sqrt{\sigma^2}}{E\{x\}} = \frac{\sqrt{\lambda}}{\lambda} = \frac{1}{\sqrt{\lambda}}$$

23) COMBINATION of n -independent POISSON PROCESSES:



$\lambda_1, \lambda_2, \dots, \lambda_n$ are the ARRIVAL RATES of n POISSON PROCESSES.

We want to show that

INPUT:

n -many POISSON PROCESSES
(independent from one another)

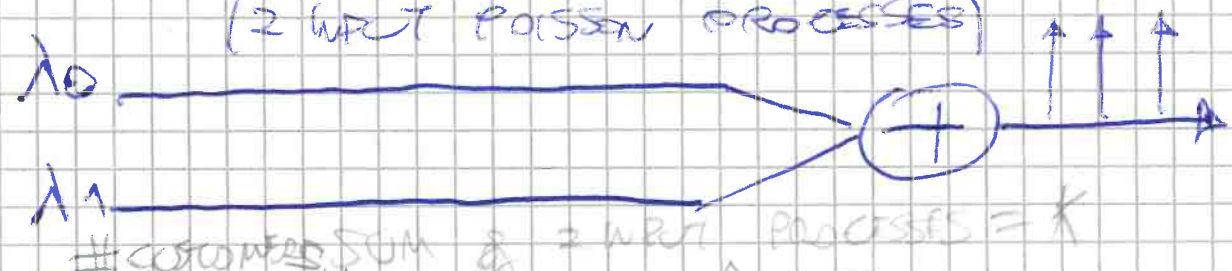
OUTPUT:

A POISSON PROCESS

AVP λ Process λ Process λ Process λ following distribution:

$$P\{k(t) = k\} = \frac{(\lambda t)^k e^{-\lambda t}}{k!} \quad P\{k(t) = k\} = \sum_{n=0}^k P\{k_1(t) = n, k_2(t) = k-n\}$$

Now consider a 2-ARRIVAL PROCESS ($n=2$)
(2 WRIT POISSON PROCESSES)



CUSTOMERS SUM of 2 WRIT PROCESSES = K

$$P\{k(t) = k\} = P\{k_1(t) = n, k_2(t) = k-n\}$$

Because of INDEPENDENCE $= \sum_{n=0}^k P\{k_1(t) = n, k_2(t) = k-n\}$

$$\Rightarrow P\{k(t) = k\} = \sum_{n=0}^k P\{k_1(t) = n\} \cdot P\{k_2(t) = k-n\}$$

$$= \sum_{n=0}^k \frac{(\lambda_1 t)^n e^{-\lambda_1 t}}{n!} \cdot \frac{(\lambda_2 t)^{k-n} e^{-\lambda_2 t}}{(k-n)!}$$

$$= \frac{e^{-\lambda_1 t} e^{-\lambda_2 t}}{k!} \sum_{n=0}^k \frac{(\lambda_1 t)^n \cdot (\lambda_2 t)^{k-n}}{(k-n)! \cdot n!}$$

$$= \frac{e^{-\lambda_1 t} e^{-\lambda_2 t}}{k!} \sum_{n=0}^k \binom{k}{n} (\lambda_1 t)^n (\lambda_2 t)^{k-n}$$

$$P\{k(t) = k\} = \frac{(e^{-\lambda_1 t} e^{-\lambda_2 t}) [(\lambda_1 + \lambda_2)t]^k}{k!}$$

$$= e^{-(\lambda_1 + \lambda_2)t} \cdot \frac{[(\lambda_1 + \lambda_2)t]^k}{k!}$$

$$\lambda_\Sigma = \lambda_1 + \lambda_2$$

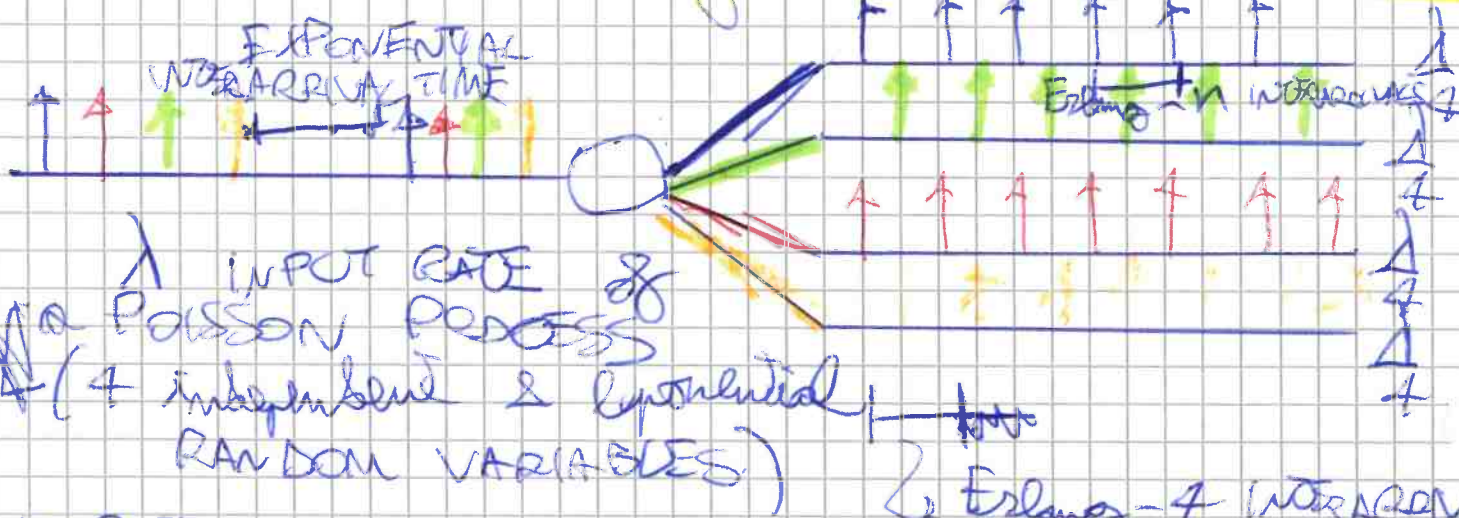
It is not the number of arrivals to state that, if we are given a many input process on processes, the output are not all processes

$$= e^{-\lambda_\Sigma t} \cdot \frac{[\lambda_\Sigma t]^k}{k!} = P\{K/E = k\}$$

POISSON PROCESS

COMBINATION of n independent Poisson Processes

36 DETERMINISTIC DECOMPOSITION of a POISSON PROCESS



λ INPUT RATE of a POISSON PROCESS (n independent & exponential RANDOM VARIABLES)

Erlang- n INTERARRIVAL

INPUT:

Exponentially distributed, independent RANDOM VARIABLES of a POISSON PROCESS



= DETERMINISTIC DECOMPOSITION
 "The 'lane' to which a R.V. goes to is known a-priori."

OUTPUT:

No Poisson Process, but n Erlang- n processes

② $P_{ON}(t)$, $P_{OFF}(t)$:

Can be found by analyzing the STATE TRANSITION DIAGRAM for $N=1$.



$$\Gamma_{OFF}: \begin{cases} \frac{d}{dt} P_{OFF}(t) = -\lambda P_{OFF}(t) \\ P_{OFF}(0) = 1 \end{cases}$$

\Rightarrow By 2:

$$s \cdot P_{OFF}(s) - P_{OFF}(0) = -\lambda P_{OFF}(s)$$

$$P_{OFF}(s) / (s + \lambda) = 1$$

$$\Rightarrow P_{OFF}(s) = \frac{1}{s + \lambda}$$

$$\Rightarrow P_{OFF}(t) = e^{-\lambda t} \cdot \mu(t) = q$$

$$P_{ON}(t) + P_{OFF}(t) = 1$$

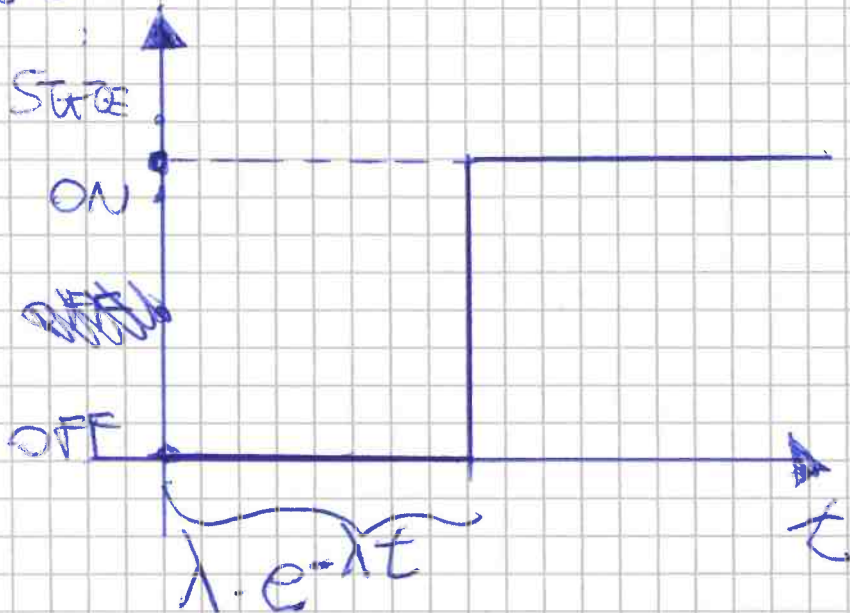
$$\Rightarrow P_{ON}(t) = 1 - P_{OFF}(t) =$$

$$P_{ON}(t) = (1 - e^{-\lambda t}) \cdot \mu(t) = p$$

$$P_{ON}(t) = (1 - e^{-\lambda t}) \cdot \mu(t) = \textcircled{p}$$

$$P_{OFF}(t) = e^{-\lambda t} \cdot \mu(t) = \textcircled{q}$$

$\Rightarrow \delta P_{OFF}(t) = \lambda \cdot e^{-\lambda t} \cdot \mu(t) \Rightarrow$ PDF of the $P_{OFF}(t)$



For a TOTAL # OF ELEMENTS = N
 # ACTIVE ELEMENTS = n

BINOMIAL

$$P_n(t) = \binom{N}{n} p^n \cdot q^{N-n}$$

For $n=0$:
 $p_{(ON)}$
 $p_{(OFF)}$

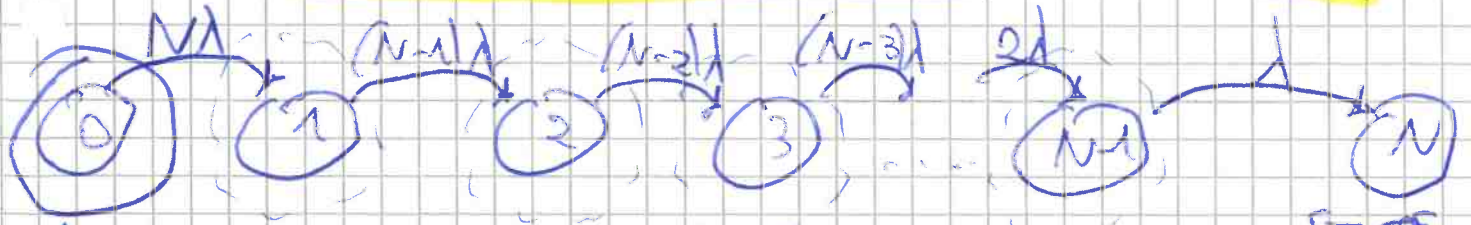
$$P_n(t) = \binom{N}{n} \cdot (1 - e^{-\lambda t})^n \cdot (e^{-\lambda t})^{N-n}$$

$$E\{n(t)\} = N \cdot p = N \cdot (1 - e^{-\lambda t}) \cdot \mu(t)$$

$$E\{VAR\{n(t)\}\} = N \cdot pq = N \cdot (1 - e^{-\lambda t}) \cdot e^{-\lambda t}$$

\Rightarrow FORMAL PROOF \Rightarrow

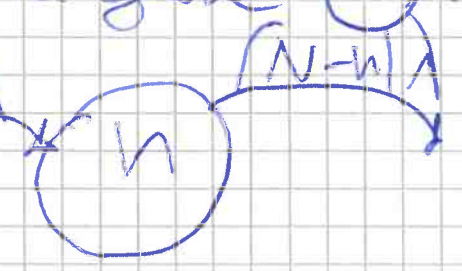
TRANSIENT - BEHAVIOUR ANALYSIS of CONTINUOUS - TIME BRNOLLI PROCESS.



$N = \text{MAX POPULATION}$

For a generic STATE n :

$n = \text{current \# activated (N-n-u)} \text{ elements}$



PCP in TRANSIENT STATE:

$$\Gamma_0: \begin{cases} \frac{d}{dt} p_0(t) = -N\lambda p_0(t) \\ \frac{d}{dt} p_1(t) = N\lambda p_0(t) - (N-1)\lambda p_1(t) \\ \frac{d}{dt} p_2(t) = (N-1)\lambda p_1(t) - (N-2)\lambda p_2(t) \\ \vdots \end{cases}$$

$$\Gamma_n: \frac{d}{dt} p_n(t) = (N-n+1)\lambda p_{n-1}(t) - (N-n)\lambda p_n(t)$$

\Rightarrow Apply \mathcal{L} to Γ_0 .

$$s \cdot p_0(s) - p_0(0) = -N\lambda p_0(s) \quad p_0(0) = 1$$

$$p_0(s) \cdot (s + N\lambda) = 1$$

$$p_0(s) = \frac{1}{s + N\lambda}$$

\Rightarrow Apply \mathcal{L} to Γ_1 .

$$s \cdot p_1(s) - p_1(0) = N\lambda p_0(s) - (N-1)\lambda p_1(s)$$

$$P_1(s) \cdot [s + (N-1)\lambda] = N\lambda P_0(s)$$

$$\Rightarrow P_1(s) = \frac{N\lambda P_0(s)}{[s + (N-1)\lambda]} = \frac{N\lambda}{(s + N\lambda)(s + (N-1)\lambda)}$$

2) Apply 2 to F_2 :

$$s \cdot P_2(s) - P_2(s) = (N-1)\lambda P_1(s) - (N-2)\lambda P_1(s)$$

$$P_2(s) \cdot [s + (N-2)\lambda] = (N-1)\lambda P_1(s)$$

$$\Rightarrow P_2(s) = \frac{(N-1)\lambda P_1(s)}{[s + (N-2)\lambda]} = \frac{N \cdot (N-1)\lambda^2}{[s + (N-2)\lambda]}$$

In general, for F_n :

$$P_n(s) = \frac{(N-n+1)\lambda P_{n-1}(s)}{s + (N-n)\lambda}$$

\Rightarrow Substituting $P_0(s), \dots, P_{n-1}(s)$ into $P_n(s)$:

$$P_n(s) = \frac{(N-n+1)\lambda}{s + (N-n)\lambda} \cdot \frac{(N-n+2)\lambda}{s + (N-n+1)\lambda} \cdot \dots \cdot \frac{N\lambda}{s + (N-1)\lambda} \cdot \frac{1}{s + \lambda}$$

$\begin{matrix} n=N & n=N-1 & n=1 & n=0 \\ \text{LIFE-} & & & \\ \text{MOST} & & & \\ 0 \leq n \leq N & P_1(s) & P_{n-1}(s) & P_0(s) \end{matrix}$

$P_n(s)$ to the multiplication of $n+1$ poles (term)

$$P_n(s) \xrightarrow{\mathcal{L}^{-1}} P_n(t) = \sum_{i=0}^n A_i e^{-(N-i)\lambda t}$$

NB: Sum of all components is 1!

$$\Rightarrow \binom{k}{k_1} \frac{\lambda^{k_1}}{k_1!} \frac{\lambda^{k_2}}{k_2!} = \frac{k!}{k_1! k_2!} \lambda^{k_1} \cdot \lambda^{k_2}$$

\Rightarrow In general, for n :

$$P\{k_1/E=t_1, k_2/E=t_2, \dots, k_n/E=t_n \mid K/E=k\}$$

\parallel

$$\frac{k!}{k_1! \cdot k_2! \cdot k_3! \cdot \dots \cdot k_n!} \cdot \lambda^{k_1} \cdot \lambda^{k_2} \cdot \dots \cdot \lambda^{k_n}$$

We now need to study the term: $P\{K/E=k\}$ which we know is POISSONIAN.

$$P\{K/E=k\} = \frac{(\lambda E)^k \cdot e^{-\lambda E}}{k!} \quad \mu(E) = \lambda E$$

$$\sum_{i=1}^k k_i = 1$$

$$P\{K/E=k\} = \frac{(\lambda E)^{k_1+k_2+\dots+k_n} \cdot e^{-\lambda E} \cdot (\lambda t_1 t_2 + \dots + \lambda t_n)}{k!}$$

\Rightarrow Now put everything together:

$$P\{k_1/E=t_1, k_2/E=t_2, \dots, k_n/E=t_n\} = \frac{k!}{k_1! k_2! \dots k_n!} \frac{\lambda^{k_1}}{k_1!} \frac{\lambda^{k_2}}{k_2!} \dots \frac{\lambda^{k_n}}{k_n!} \frac{(\lambda E)^k \cdot e^{-\lambda E}}{k!} \cdot e^{-\lambda t_1} \cdot e^{-\lambda t_2} \dots e^{-\lambda t_n}$$

$$= \frac{(r_1 \lambda t)^{k_1}}{k_1!} e^{-\lambda r_1 t} \cdot \frac{(r_2 \lambda t)^{k_2}}{k_2!} e^{-\lambda r_2 t} \cdots \frac{(r_n \lambda t)^{k_n}}{k_n!} e^{-\lambda r_n t}$$

POISSON PROCESS with rate r_1 POISSON PROCESS (r_2) POISSON PROCESS (r_n)

N - many POISSON PROCESSES!
as OUTPUT (independent from one another)

3.8 CONTINUOUS-TIME BERNOULLI PROCESS

A CONTINUOUS-TIME BERNOULLI PROCESS has a set of N members, that can be "switched on" in a time interval Δt (OFF \Rightarrow ON).

STATE = # MEMBERS that are turned on.
(i.e. # activated elements)

INITIALLY:

FINALLY:

$n=0$ [All elements are SWITCHED OFF] $n=N$ [All elements are SWITCHED ON]

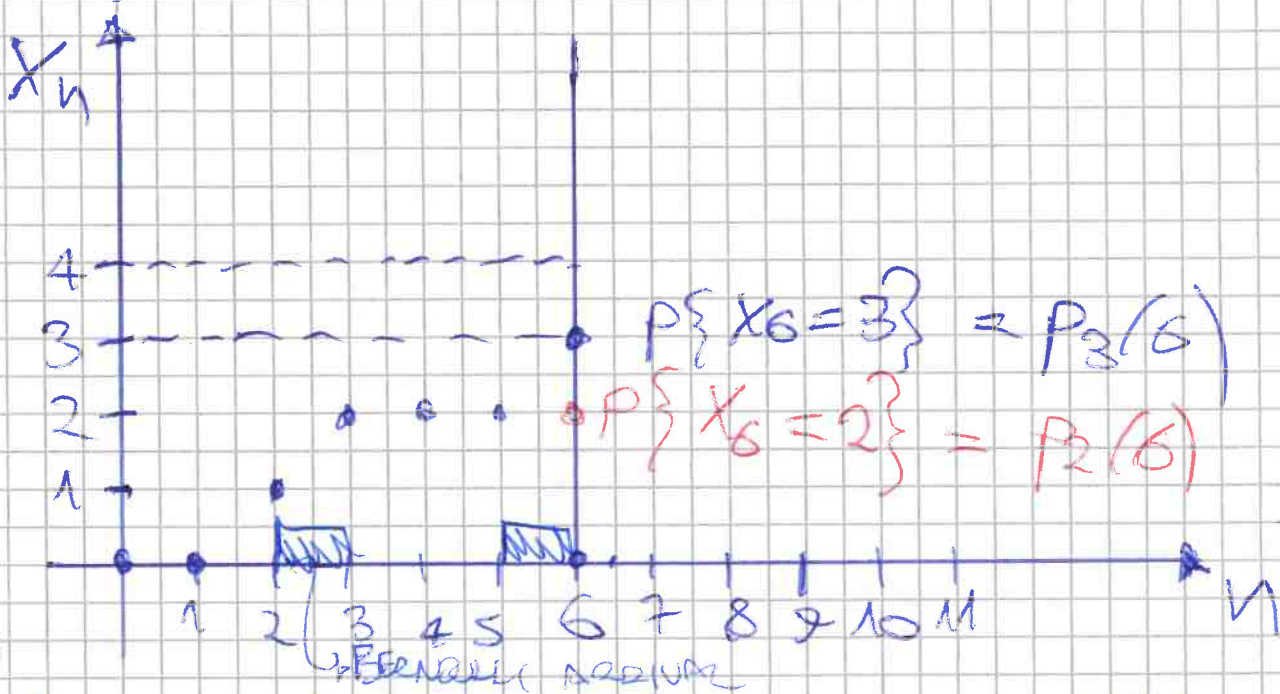
USAGE / APPLICATION:

It is used in cellular / land system [PBX / ~~land~~ system] or 2G / 3G system.

STATE of a CELL = # Users using cells SYSTEM (i.e. # cells used)

processors that are ready

BINOMIAL DISTRIBUTION (VISUALIZED)



APPLICATION & USAGE of a BERNOULLI-PROCESS:

Used in systems with ARRIVALS to SLOTS-TIME INTERVALS (EX. PDH, SDH) with ATM

② For a Bernoulli process X :

$$G_X(z) = E\{z^X\} = \sum_{n=0}^{\infty} p_n \cdot z^n \quad z \Rightarrow z^{-1}$$

$$E\{X\} = \frac{d}{dz} G_X(z) \Big|_{z=1} \quad \text{[MOMENT of ORDER 1]}$$

$$E\{X^2\} = \frac{d^2}{dz^2} G_X(z) \Big|_{z=1} + \frac{d}{dz} G_X(z) \Big|_{z=1} \quad \text{[MOMENT OF ORDER 2]}$$

~~The Binom $p_n = \binom{n}{k}$~~

We know:

$$P_n = \binom{N}{n} p^n \cdot q^{N-n}$$

$$G_X(z) = \sum_{n=0}^{\infty} P_n \cdot z^n$$

$$\Rightarrow G_X(z) = \sum_{n=0}^N \binom{N}{n} p^n \cdot q^{N-n} \cdot z^n$$

$$= \sum_{n=0}^N \binom{N}{n} (p \cdot z)^n \cdot q^{N-n}$$

~~$G_X(z) = \dots$~~

We know:

$$\sum_{n=0}^N \binom{N}{n} a^{N-n} \cdot b^n = (a+b)^N$$

$$\Rightarrow G_X(z) = (q + pz)^N$$

X is a Bernoulli process

We can now compute $E\{X\}$, $E\{X^2\}$, $\text{VAR}\{X\}$

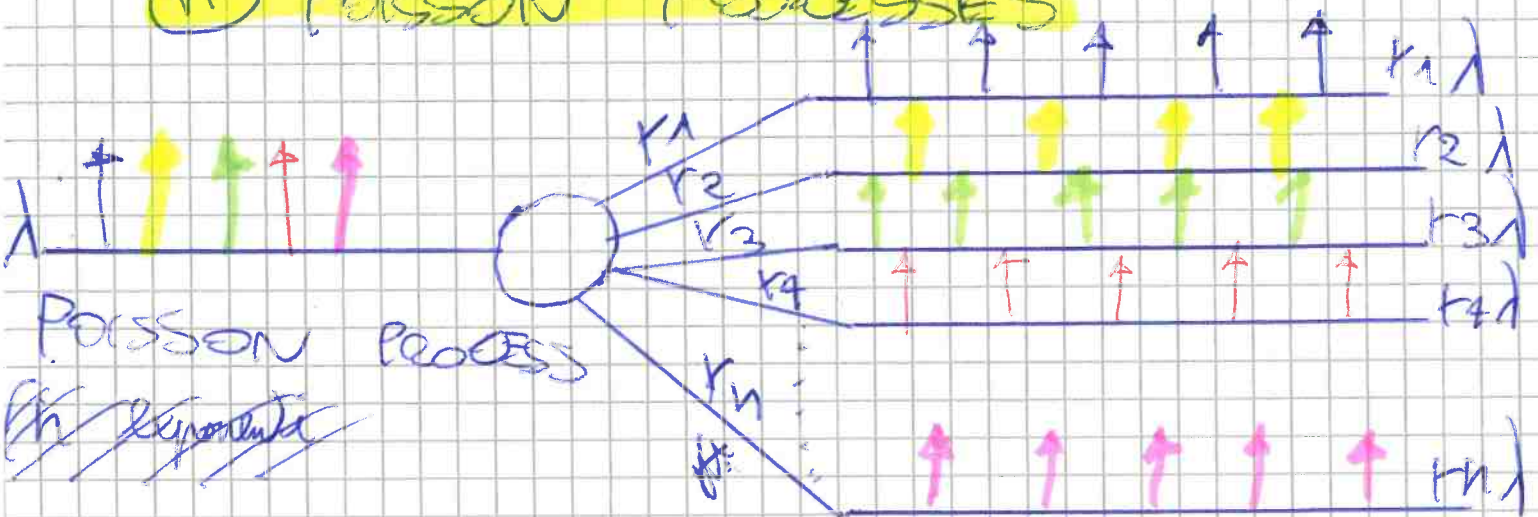
$$E\{X\} = N \cdot p \cdot (q + pz)^{N-1} \Big|_{z=1} = Np \underbrace{(p+q)}_1^N$$

Because:

$$E\{X=0\} + E\{X=1\} = 1$$

$$\Rightarrow E\{X\} = Np$$

57 STATISTICAL / PROBABILISTIC DECOMPOSITION of a POISSON PROCESS INTO POISSON PROCESSES



r_i = Probability to "pick" a certain LANE (CONSERVATIVE DEVICE)
 Summing up to 1
 "Dice roll" upon deciding the lane.

$\sum_{i=1}^n r_i = 1$

INPUT:

One POISSON PROCESS [Sum of n independent exponential R.V.s.]
 - \circ = Probabilistic choice of a lane.

OUTPUT:

n -independent POISSON PROCESSES (one per lane).

PROOF: We need to study the joint PMF of the considered R.V.s.

~~to~~ Show independence of the considered R.V.s. of the process.

$K(t) = \#$ ARRIVALS in $(0, t)$ ^{(ALL LANES) A PERIODS} for the INPUT PROCESS

$K_i = P.$ of choosing the i th-lane

$K_i(t) = \#$ ARRIVALS to lane i in $(0, t)$

$$K(t) = \sum_{i=1}^n K_i(t) \quad \text{Sum of all ARRIVALS}$$

\Rightarrow Show independence of the DISCRETE RVs of the process.

$P\{K_1(t) = k_1, K_2(t) = k_2, K_3(t) = k_3, \dots, K_n(t) = k_n\}$

$= P\{K_1(t) = k_1, K_2(t) = k_2, \dots, K_n(t) = k_n, K(t) = k\}$

By the BAYES THEOREM: NOT ADDING ANYTHING NEW

$P\{A, B\} = P\{A|B\} \cdot P\{B\}$ POISSON-DISTRIBUTED $P\{K|A\} = k\}$

$= P\{K_1(t) = k_1, K_2(t) = k_2, \dots, K_n(t) = k_n | K(t) = k\} \cdot P\{K(t) = k\}$

Now consider this for $n=2$ for sake of SIMPLICITY

$$P\{K_1(t) = k_1, K_2(t) = k_2 | K(t) = k\}$$

k_1 k_2 k

$\underbrace{\hspace{1.5cm}}_p$ $\underbrace{\hspace{1.5cm}}_q$ $\underbrace{\hspace{1.5cm}}_1$

$k_2 = k - k_1$

k_1 CHOICES of TYPE 1, k_2 CHOICES of TYPE 2

$\left[\text{BINOMIAL DISTRIBUTION} \right]$ (REMAINING ONES, OR TRIALS)

$P\{K_1(t) = k_1, K_2(t) = k_2 | K(t) = k\} = \binom{k}{k_1} p^{k_1} q^{k_2}$

$$P_N(s) = \sum_{i=0}^{N-1} A_i e^{-(N-i)\lambda t} \cdot \mu(t)$$

by long division

$\underbrace{A_i}_{\text{NUMERATOR}}$ of the fraction.

$$\mathcal{L}^{-1}(\cdot) = + \quad \mathcal{L}^{-1}(\cdot) = (\cdot)$$

We now need to find A_i by PARTIAL FRACTION DECOMPOSITION

$$A_i = P_N(s) \cdot [s + (N-i)\lambda]$$

$0 \leq i \leq N$
 A_i has the following form $\frac{N!}{(N-i)!}$ $s = -(N-i)\lambda$

$$A_i = \frac{N \cdot (N-1) \cdot (N-2) \cdots (N-n+1)}{\lambda^n}$$

$$\frac{[-(n-i)] \cdot [-(n-i+1)] \cdots [-2] \cdot [-1] \cdot [1] \cdot [2] \cdots [i-1] \cdot [i]}{\lambda^n}$$

For some terms, we have POSITIVE & NEGATIVE terms

Recall: $s = -(N-i)\lambda$ but they are all MULTIPLE of λ .

For the LEFT-MOST TERM (POLE)

$$\frac{s + (N-n)\lambda}{s = -(N-i)\lambda}$$

$$= -N\lambda + i\lambda + N\lambda - n\lambda = i\lambda - n\lambda = \boxed{-n\lambda}$$

For the RIGHT-MOST TERM (POLE):

$$\frac{s + N\lambda}{s = -(N-i)\lambda} = -N\lambda + i\lambda + N\lambda = \boxed{i\lambda}$$

We now now substitute A_i into part (after some modifications)

$$A_i = \frac{N!}{(N-i)! (n-i)! (-\lambda)^{n-i} \lambda}$$

$$A_i = \frac{N!}{(N-n)!(n-i)!i!} \lambda^{n-i}$$

⇒ Substitute A_i into $P_n(t)$

$$P_n(t) = \sum_{i=0}^n A_i \cdot e^{-(N-i)\lambda t} \cdot \mu^i$$

$$= \sum_{i=0}^n \frac{N!}{(N-n)!(n-i)!i!} \lambda^{n-i} \cdot e^{-(N-i)\lambda t}$$

$$= e^{-N\lambda t} \cdot e^{n\lambda t} \cdot \sum_{i=0}^n \frac{N! n!}{(N-n)! n! (n-i)! i!} (\lambda t)^{n-i}$$

$$= e^{-N\lambda t} \cdot e^{n\lambda t} \cdot \binom{N}{n} \sum_{i=0}^n \frac{n! (\lambda t)^{n-i}}{(n-i)! i!} (e^{-\lambda t})^{n-i}$$

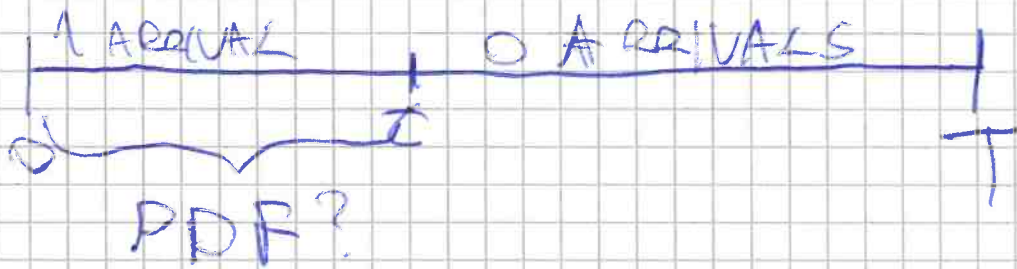
$$= e^{-N\lambda t} \cdot e^{n\lambda t} \cdot \binom{N}{n} \sum_{i=0}^n \frac{n!}{(n-i)! i!} (1 - e^{-\lambda t})^{n-i}$$

$$= \binom{N}{n} \underbrace{e^{(N-n)\lambda t}}_{q^{N-n}} \cdot \underbrace{(1 - e^{-\lambda t})^n}_{p^n}$$

⇒ BINOMIAL DISTRIBUTION OF CONTINUOUS-TIME BENEVOLENT PROCESS

$$e^{-N\lambda t} \cdot e^{n\lambda t} \cdot \binom{N}{n} \sum_{i=0}^n \binom{n}{i} (1 - e^{-\lambda t})^{n-i} (e^{-\lambda t})^i$$

(39) ~~UNIFORM~~ ~~POISSON~~ PDF & ~~INSTANT OF~~ ~~ARRIVAL~~ ~~TIME~~
 over an interval $(0, t]$ for POISSONIAN ARRIVALS



What is the PDF of ^{POISSONIAN} arrivals in $[0, t]$?

\Rightarrow We want to draw it for ~~POISSONIAN~~ ^{UNIFORM-PSA}

$P\{1 \text{ arrival in } (0, t] \mid 1 \text{ arrival in } (0, T]\}$

By the BAYES THEOREM:

$$P\{A \mid B\} = \frac{P\{A, B\}}{P\{B\}}$$

$$P\{1 \text{ ARR}^A \text{ in } (0, t] \mid 1 \text{ ARR}^B \text{ in } (0, T]\} = \frac{P\{1 \text{ ARR in } (0, t], 1 \text{ ARR in } (0, T]\}}{P\{1 \text{ ARR in } (0, T]\}}$$

$$= \frac{P\{1 \text{ arrival in } (0, t], 1 \text{ arrival in } (0, T]\}}{P\{1 \text{ arrival in } (0, T]\}}$$

$$= \frac{P\{1 \text{ arrival in } (0, t], 0 \text{ arrivals in } (t, T]\}}{P\{1 \text{ arrival in } (0, T]\}}$$

$$= \frac{P\{1 \text{ arrival in } (0, t], 0 \text{ arrivals in } (t, T]\}}{P\{1 \text{ arrival in } (0, T]\}}$$

We know:
 POISSON DISTRIBUTION
 $\{k \text{ arrivals}\}$
 $P\{k\} = \frac{(\lambda t)^k}{k!} \cdot e^{-\lambda t} \cdot \mu(t)$

$$P\{k \text{ arrivals in } (0, t]\} = \frac{(\lambda t)^k \cdot e^{-\lambda t}}{k!} \cdot \mu(t)$$

$$P\{1 \text{ arrival in } (0, t]\} = (\lambda t) \cdot e^{-\lambda t} \cdot \mu(t)$$

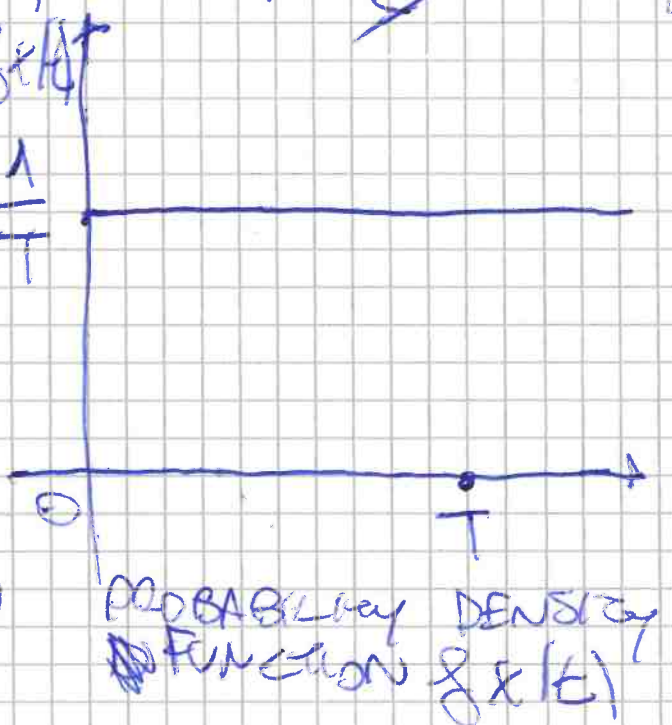
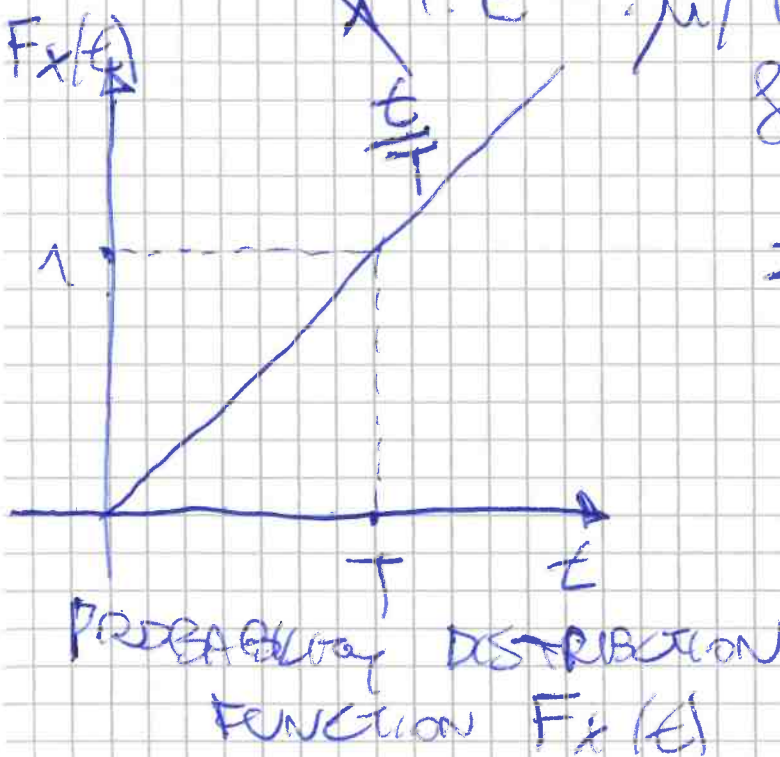
$$P\{0 \text{ arrivals in } (t, T]\} = \frac{(\lambda(T-t))^0}{0!} \cdot e^{-\lambda(T-t)} \cdot \mu(t)$$

$$P\{1 \text{ arrival in } (0, T]\} = \lambda T \cdot e^{-\lambda T} \cdot \mu(T)$$

\Rightarrow Because the POISSON PROCESS has INDEPENDENT
 & EVENTS in DISJOINT intervals are
 INDEPENDENT.

$$\frac{P\{1 \text{ arrival in } (0, t], 0 \text{ arrivals in } (t, T]\}}{P\{1 \text{ arrival in } (0, T]\}} = \frac{t}{T}$$

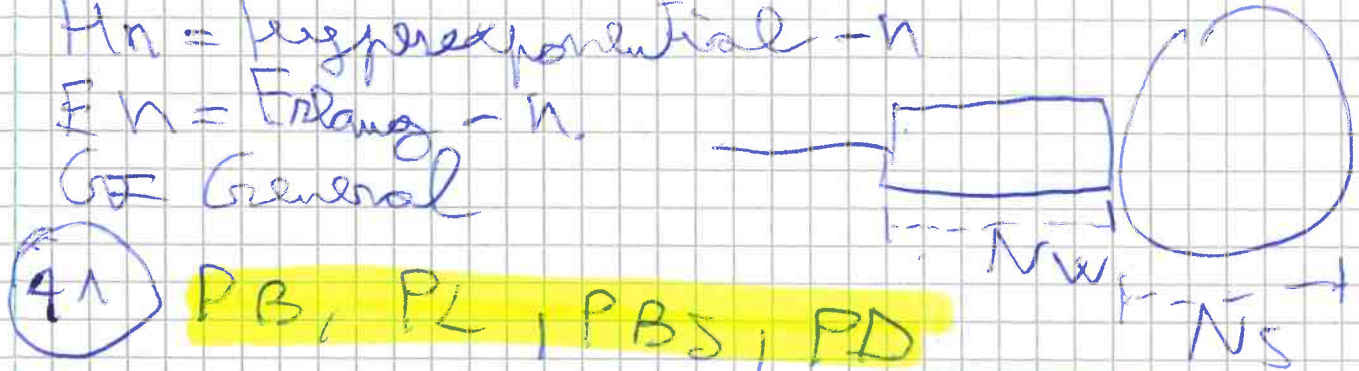
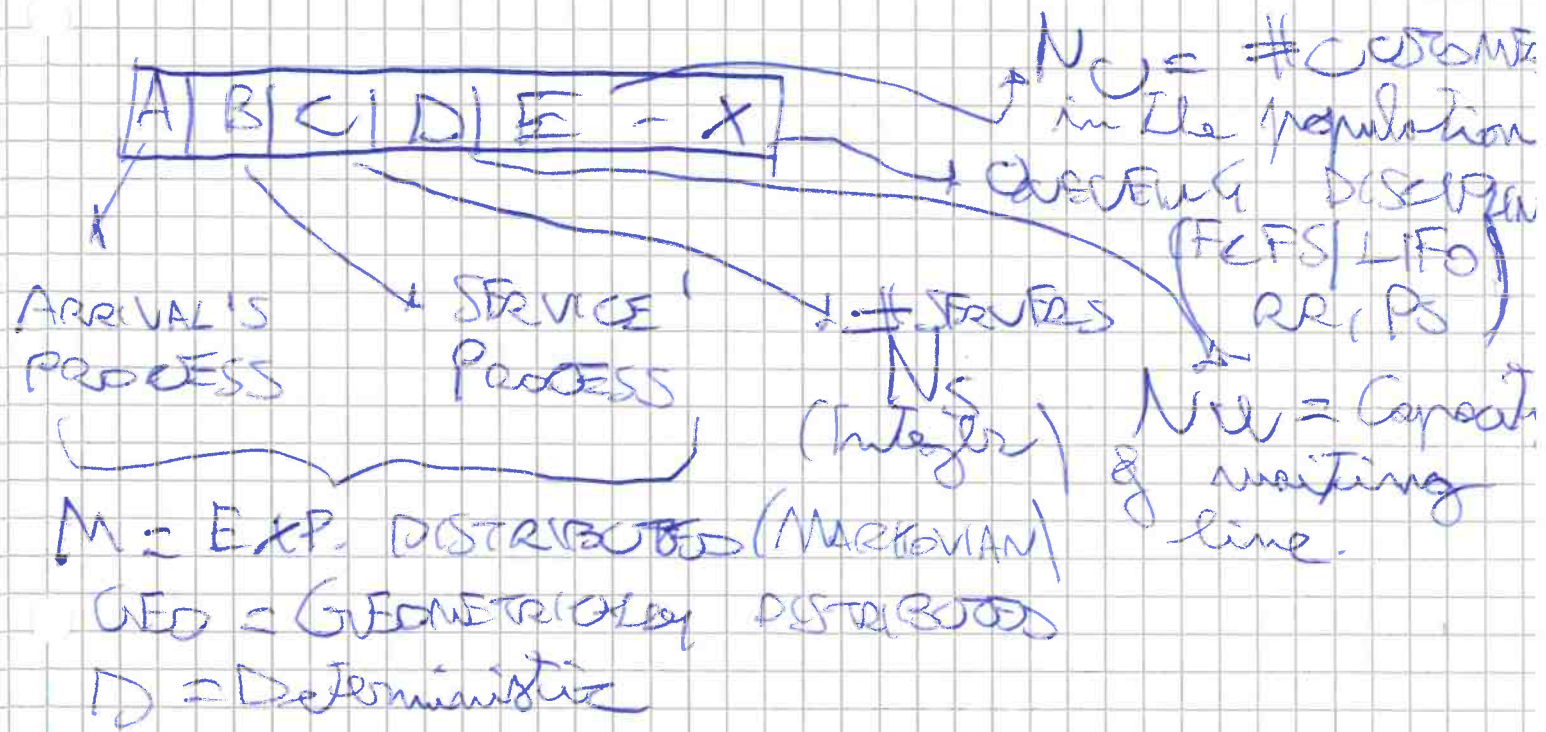
$$= \frac{\lambda t \cdot e^{-\lambda t} \cdot e^{-\lambda(T-t)}}{\lambda T \cdot e^{-\lambda T}} = \frac{t}{T} \cdot \frac{e^{-\lambda T}}{e^{-\lambda T}} = \frac{t}{T}$$



\Rightarrow If ARRIVALS are POISSONIAN - DISTRIBUTED
 in $(0, T) \Rightarrow$ They are SOFTLY - UNIFORMELY
 DISTRIBUTED on $(0, T)$

$\&$ arrivals are UNIFORM - DISTRIBUTED
 on an interval $(0, T) \neq$ ~~softly~~ POISSONIAN
 ARRIVALS in $(0, T)$

40 KENDALL'S NOTATION:



$P_B = P \} N = N_s$
 $(Servers \& waiting line both busy)$
 $N = N_w + N_s$

$$P_L = P\{ \text{Blocked queue} \mid \text{Request of service offered in dt} \}$$

by the Bayes Theorem:

$$P\{ A \mid B \} = \frac{P\{ A, B \}}{P\{ B \}}$$

$$P_L = \frac{P\{ \text{Blocked queue} \mid \text{Request of service offered in dt} \} \cdot P\{ \text{Request of service offered in dt} \}}{P\{ \text{Request of service offered in dt} \}}$$

$$P\{ A, B \} = P\{ A \mid B \} \cdot P\{ B \}$$

$$\frac{P\{ A \mid B \} \cdot P\{ B \}}{P_L} = \frac{P\{ \text{Request of service offered in dt} \mid \text{Blocked queue} \} \cdot P\{ \text{Blocked queue} \}}{P\{ \text{Request of service offered in dt} \}}$$

For a Poisson process:

$$P_L = P_B$$

[i.e. fact that queue is blocked has no IMPACT]

$$\Rightarrow P_L = P_B$$

$$P_B > 0 \Rightarrow P_L > 0$$

$$P_L = \frac{P\{ \text{Request of service rejected in dt} \}}{P\{ \text{Request of service offered in dt} \}}$$

$$P_B =$$

$$P\{B_S = P\} \quad n \geq N_0$$

in queue / waiting line

$$P_D = P\{ \text{Blocked service} \mid \text{Request of service accepted in dt} \}$$

By The Bayes Theorem:

$$P\{A|B\} = \frac{P\{A, B\}}{P\{B\}} \quad P\{A, B\} = P\{A|B\} \cdot P\{B\}$$

$$P_D = \frac{P\{ \text{Request of service accepted in dt} \mid \text{Blocked service} \}}{P\{ \text{Request of service accepted in dt} \}}$$

$$\#ACCEPTED = P\{ \text{request of service accepted in dt} \}$$

$$P_D = \frac{P\{ \text{Request of service accepted in dt} \mid \text{Blocked service} \}}{P\{ \text{Request of service accepted in dt} \}}$$

For a POISSON PROCESS

$$P_D = P_{B_S} \cdot \frac{\lambda dt}{\lambda dt}$$

$$\Rightarrow P_D = P_{B_S}$$

NB:

Blocked queue

≠

Blocked service

② P_B, P_L, P_{BS}, P_D for a MARCOVIAN QUEUE

$$P_B = P_N = P\{n=N\}$$

(Only in case of FINITE WAITING LINE)

$$P_B = P_L = \frac{\text{#OFFERS} \cdot P\{\text{Request of service offered in } dt \mid \text{Blocked?}\}}{\text{#OFFERS} \cdot P\{\text{Request of service offered in } dt\}}$$

$$= \frac{\lambda N \cdot P_B}{\sum_{i=0}^N p_i \cdot \lambda_i} = P_B \cdot \frac{\lambda N}{\sum_{i=0}^N p_i \cdot \lambda_i}$$

$\sum_{i=0}^N p_i = 1$

$$\Rightarrow \boxed{P_L = P_B}$$

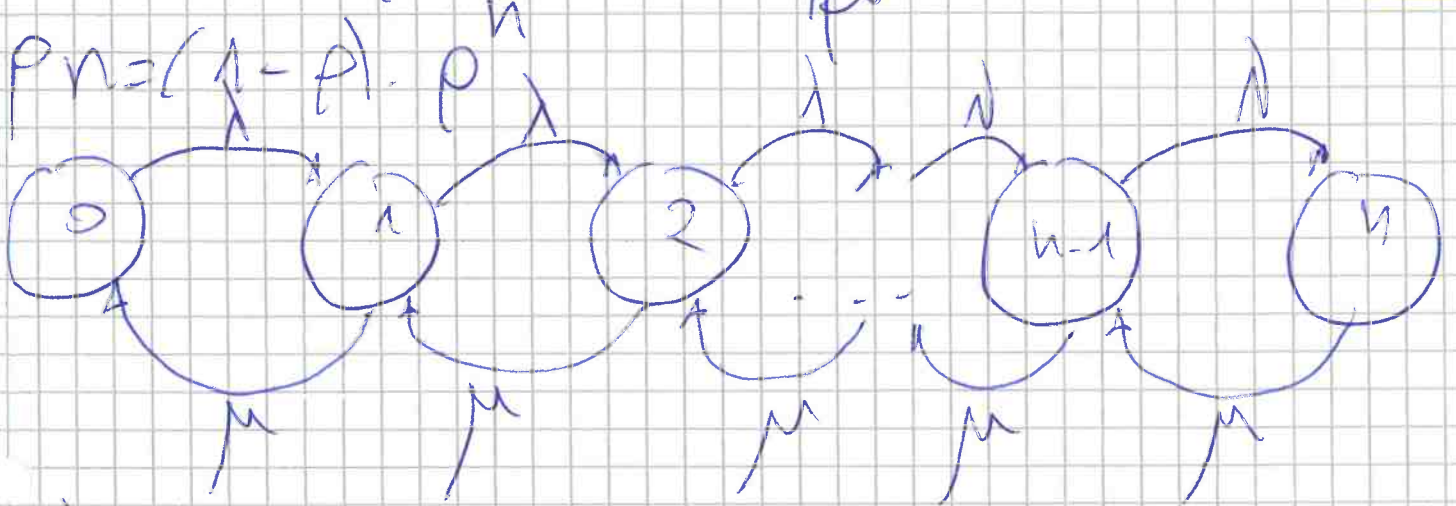
$$\boxed{P_{BS} = P\{n \geq N\} = \sum_{n=N}^N P_n = P_D}$$

$$P_D = \frac{P\{\text{Request of service accepted in } dt\}}{\text{#OFFERS} \cdot P\{\text{Request of service accepted in } dt\}}$$

FOR POISSON INDX: $P\{\text{Request of service accepted in } dt\}$

$$\boxed{P_D = P_{BS}} = \sum_{k=N_s}^{N-1} \lambda^k P_k dt = \sum_{k=0}^{N-1} \lambda^k P_k dt$$

(42) (b) ~~MB, PL, PB, PD, PM~~ PB, PL, PBs, PD, PM
 $E\{n\}, E\{n-w\}, E\{u\}$ for M/M/1 queue



$$\lambda p_0 = \mu p_1 \Rightarrow p_1 = \frac{\lambda}{\mu} p_0$$

$$\lambda p_1 = \mu p_2 \Rightarrow p_2 = \frac{\lambda}{\mu} p_1 = \left(\frac{\lambda}{\mu}\right)^2 p_0$$

$$\lambda p_2 = \mu p_3 \Rightarrow p_3 = \frac{\lambda}{\mu} p_2 = \left(\frac{\lambda}{\mu}\right)^3 p_0$$

$$\Rightarrow p_n = \left(\frac{\lambda}{\mu}\right)^n p_0 \quad \frac{\lambda}{\mu} = \rho$$

$$\Rightarrow p_n = \rho^n p_0$$

$$\sum_{n=0}^{\infty} p_n = 1 \Rightarrow \sum_{n=0}^{\infty} p_0 \cdot \rho^n = 1$$

$$\Rightarrow p_0 = \frac{1}{\sum_{n=0}^{\infty} \rho^n}$$

$$\Rightarrow p_0 = \frac{1}{1} = 1 - \rho$$

$$\Rightarrow \text{Indeed: } p_n = (1 - \rho) \rho^n$$

$$D_n = (1-d) \cdot \rho^n \rightarrow E\{n\} = \sum_{i=0}^{\infty} n \cdot p_n$$

$$E\{n\} = \sum_{n=0}^{\infty} n \cdot (1-d) \cdot \rho^n = (1-d) \sum_{n=0}^{\infty} n \cdot \rho^n$$

$$= (1-d) \cdot \frac{\rho}{1-\rho} = \frac{\rho}{1-\rho} = E\{u\}$$

$$\frac{\rho}{1-\rho} = E\{n\} = \frac{\rho}{1-\rho} = \frac{A}{1-A} = A$$

$$E\{n\} = 0 \cdot p_0 + 1 \cdot p_1 = 1/(1-\rho) = 1/(1-\rho)$$

$$E\{n\} = \sum_{n=0}^{\infty} n \cdot p_n$$

$$E\{n\} = \rho = \frac{A}{1-A}$$

$$E\{n\} = \sum_{i=1}^{\infty} (i - N_s) p_i = \sum_{i=1}^{\infty} (i - 1) p_i$$

$$= \sum_{i=1}^{\infty} (i - 1) p_i = \sum_{i=1}^{\infty} i \cdot p_i - \sum_{i=1}^{\infty} p_i$$

$$= \sum_{i=1}^{\infty} i \cdot (1-\rho) \cdot \rho^i - \sum_{i=1}^{\infty} (1-\rho) \cdot \rho^i$$

$$= (1-\rho) \cdot \sum_{i=1}^{\infty} i \cdot \rho^i - (1-\rho) \cdot \rho \cdot \sum_{i=1}^{\infty} \rho^{i-1}$$

$$= (1-\rho) \cdot \frac{\rho}{1-\rho} - (1-\rho) \cdot \rho \cdot 1$$

$$\Rightarrow E\{N_w\} = \frac{\rho}{1-\rho} - \rho = \frac{\rho - (1-\rho)\rho}{1-\rho} = \frac{\rho - \rho + \rho^2}{1-\rho}$$

$$\Rightarrow E\{N_w\} = \frac{\rho^2}{1-\rho}$$

$P_B = P\{n = N\} \Rightarrow$ because $N_w = \infty$

$$\Rightarrow P_D = P_B \Rightarrow$$

$$P_{BS} = P\{n \geq N\} = \sum_{i=N}^{\infty} p_i = \sum_{i=N}^{\infty} p_i = 1 - p_0$$

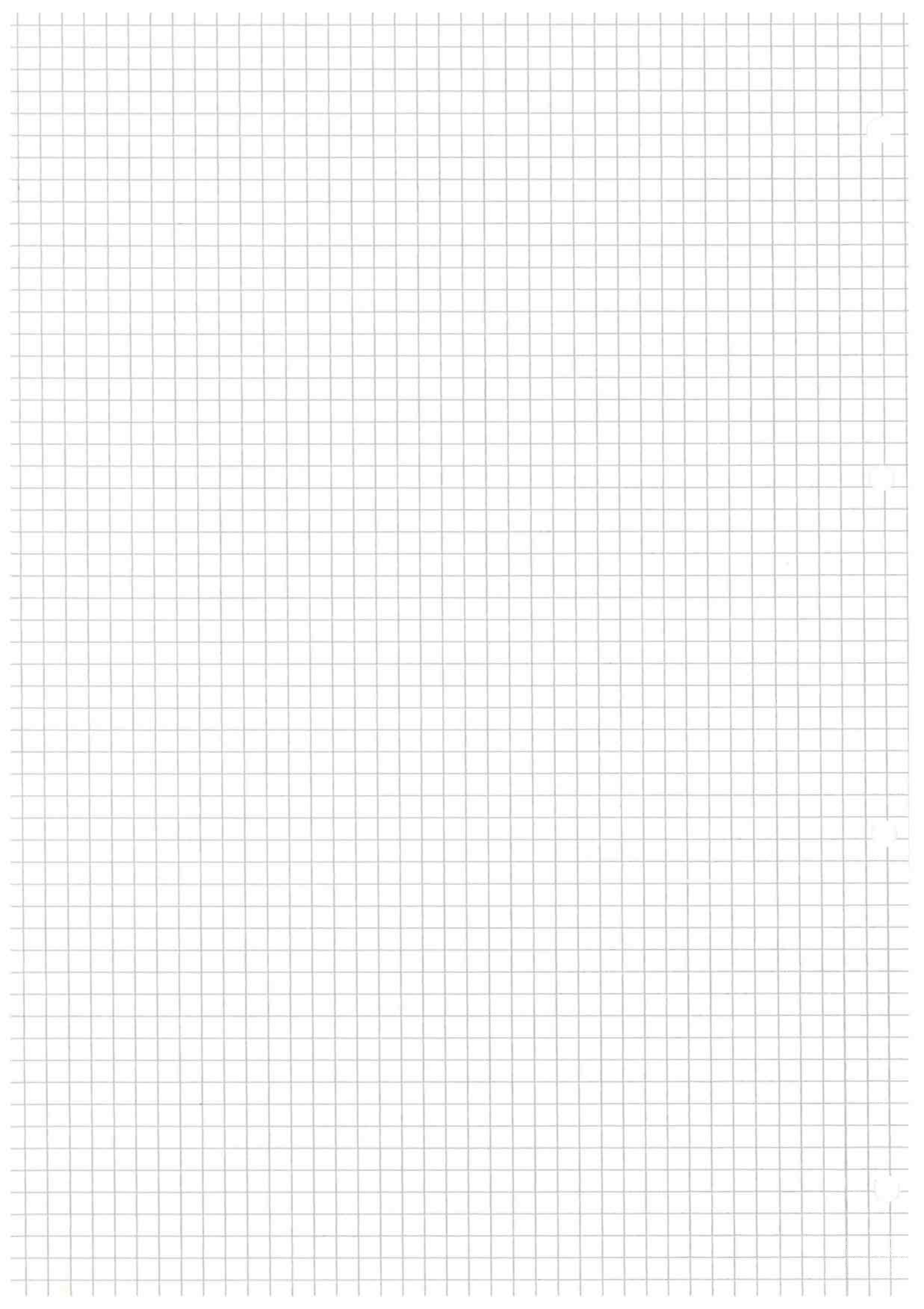
$$= 1 - 1 + \rho = \rho = P_D$$

$$E\{n\} = E\{T\} \cdot \lambda \Rightarrow E\{T\} = \frac{E\{n\}}{\lambda}$$

$$\Rightarrow E\{T\} = \frac{\frac{\rho^2}{1-\rho}}{\lambda(1-\rho)} = \frac{\rho}{\lambda(1-\rho)}$$

STEADY-STATE PROBABILITY PLOT





$$= \frac{\sum_{k=N_S}^{N-1} \lambda \pi_k d \epsilon}{\sum_{k=0}^{N-1} \lambda \pi_k d \epsilon} = \frac{P\{\text{Request of service accepted with delay in } d \epsilon\}}{P\{\text{Request of service accepted in } d \epsilon\}}$$

42) $E\{T\}, E\{TS\}, E\{TW\}$
 $E\{N\}, E\{NS\}, E\{NW\}$

$$E\{T\} = E\{TS\} + E\{TW\}$$

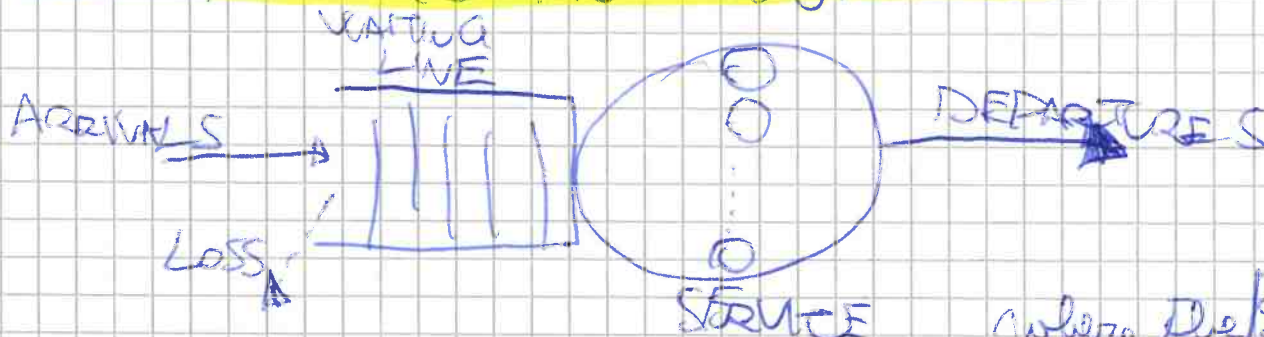
$$E\{N\} = \lambda \cdot E\{T\} \Rightarrow E\{T\} = \frac{E\{N\}}{\lambda} = \sum_{n=0}^{N-1} n \cdot \pi_n$$

$$E\{NS\} = \lambda \cdot E\{TS\} \Rightarrow E\{TS\} = \frac{E\{NS\}}{\lambda} = \sum_{n=0}^{N-1} n \cdot p_n$$

$$E\{NW\} = \lambda \cdot E\{TW\}$$

$$E\{N\} = E\{NS\} + E\{NW\} \Rightarrow E\{TW\} = \frac{E\{N\} - E\{NS\}}{\lambda}$$

43) MARKOVIAN QUEUES



a) A Markovian Queue is a QUEUE characterized by the # CUSTOMERS (and only by that!) where the STATE is

b) The evolution of the STATE of the system is a MARKOV CHAIN and a B & D MARKOV CHAIN.



44 $A = \text{TRAFFIC INTENSITY}$

$$A = \lambda \cdot E\{TS\} = \frac{\lambda}{\mu} \quad \text{For } M/M/1$$

(a) If $E\{nw\} = 0$

$$\Rightarrow E\{n\} = E\{ns\} = A$$

$$\rho = \frac{A}{N_s} < 1$$

$\Rightarrow A < N_s$

(b) ERGODICITY CONDITION:

$$A < N_s \Rightarrow A < 1 \quad (\text{For } M/M/1 \text{ QUEUE})$$

45 $\text{TRAVERSAL TIME } E\{T\}$ in $M/M/1$ QUEUE, $E\{T_w\}$ by PASTA PROPERTY

$$E\{T\} = E\{T_w\} + E\{TS\}$$

$$E\{T\} = \int_0^{\infty} z \cdot g_x(z) dz$$

$$E\{TS\} = \frac{1}{\mu} E\{T_w\} \quad \text{by the PASTA PROPERTY}$$

$$E\{T_w\} = \sum_{i=0}^{\infty} E\{T_w | i\} p_i \quad \text{[Case]}$$

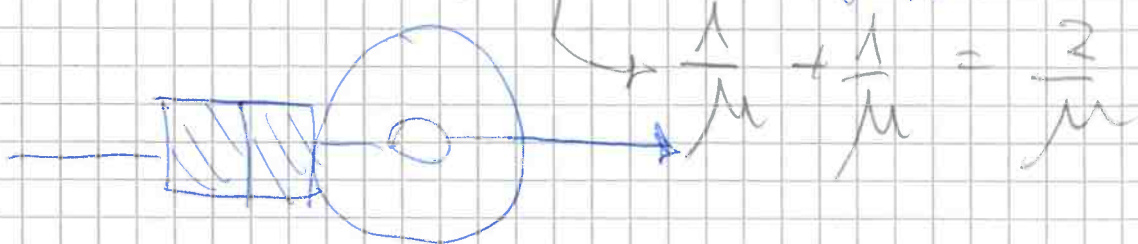
IF 0 customers in queue. $E\{T_w | 0\} = 0$

\Rightarrow No time spent in the waiting line.

↳ There ~~are~~ ^{is} Δ customers in the queue:

$$E\{T_w | 1\} = \frac{1}{\mu} \quad \left[\begin{array}{l} \text{Waiting for } 1 \\ \text{customer to be served} \end{array} \right]$$

$$E\{T_w | 2\} = \frac{2}{\mu} \quad \left[\begin{array}{l} \text{Waiting for } 2 \\ \text{customers to be served} \end{array} \right]$$



PASTA PROPERTY

"Poisson Arrivals See Time Averages"

$$E\{T_w\} = \sum_{i=0}^{\infty} E\{T_w | i\} \cdot p_i \quad \text{[ARR]}$$

$$p_i^{(arr)} = p_i \quad \rightarrow P\{X_n = i\}$$

$$E\{T_w\} = \sum_{i=1}^{\infty} i \cdot \frac{1}{\mu} p_i = \frac{1}{\mu} \cdot \sum_{i=1}^{\infty} i \cdot p_i$$

$$E\{T_w | i\}$$

" $E\{n\}$ "

$$\Rightarrow E\{T_w\} = \frac{1}{\mu} \cdot \frac{\rho}{1-\rho}$$

" $\frac{\rho}{1-\rho}$ "

$\rho \rightarrow 0 \Rightarrow E\{T_w\} = 0$ [~~NO~~ UTILIZATION]
 \Downarrow
 WAITING TIME is 0

$\rho \rightarrow 1 \Rightarrow E\{T_w\} = \infty$ [UTILIZATION]
 \Downarrow
 WAITING TIME is ∞

$$\Rightarrow E\{T\} = E\{T_w\} + E\{T_s\}$$

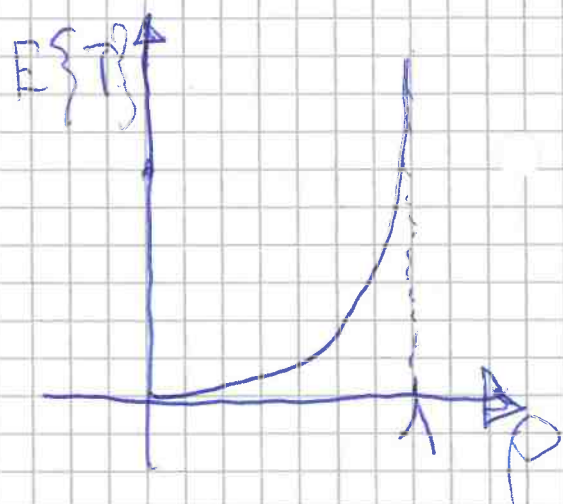
$$= \frac{1}{\mu} \left[\frac{\rho}{1-\rho} + 1 \right]$$

$$= \frac{1}{\mu} \left[\frac{\rho + 1 - \rho}{1-\rho} \right] = \frac{1}{\mu} \cdot \frac{1}{1-\rho}$$

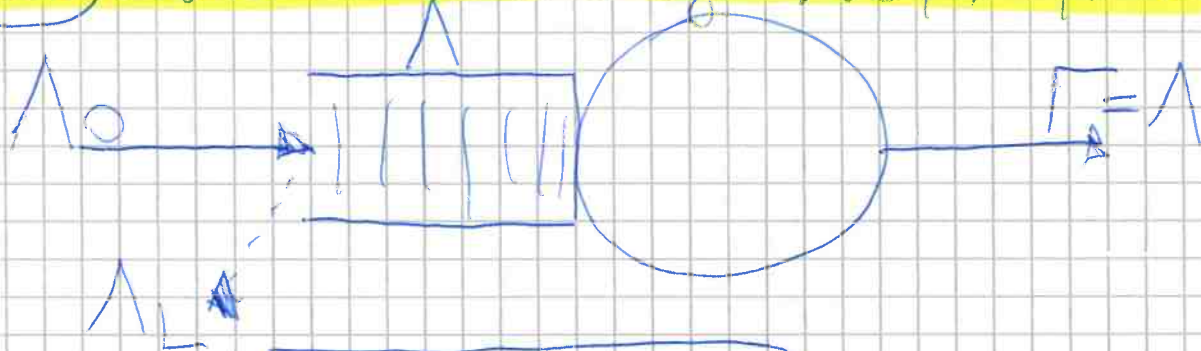
$$\Rightarrow E\{T\} = \frac{1}{\mu} \cdot \frac{1}{1-\rho}$$

$$\rho \rightarrow 0 \Rightarrow E\{T\} = \frac{1}{\mu}$$

$$\rho \rightarrow 1 \Rightarrow E\{T\} = \infty$$



46) AVERAGE VALUES of $\Lambda_0, \Lambda, \Lambda_L, \Gamma, \Gamma_{MAX}$



$$\Lambda_0 = \Lambda + \Lambda_L$$

$$\Gamma = \Lambda = \Lambda_0 (1 - P_L)$$

$$\Lambda_L = \Lambda_0 \cdot P_L$$

$\lambda < \Gamma_{MAX}$ With N_S Servers:

$$\Gamma_{MAX} = \mu \cdot N_S = \frac{N_S}{\{E\} \{TS\}}$$

$$\lambda < \frac{N_S}{\{E\} \{TS\}} \quad \lambda \cdot \{E\} \{TS\} < N_S$$

For a MARKOVIAN QUEUE: $A =$ TRAFFIC INTENSITY

$$\Lambda_0 = \sum_{k=0}^{\infty} \lambda_k P_k \quad (\text{everything})$$

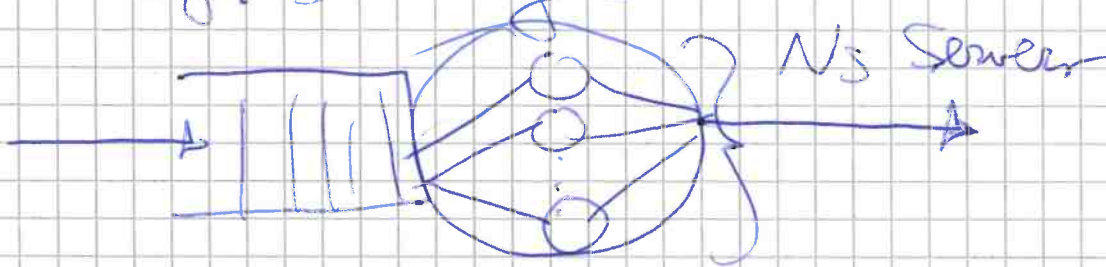
$$\Lambda_L = \lambda_N P_N = \lambda_N P_B \quad (\text{just saturated})$$

$$\Lambda = \Lambda_0 - \Lambda_L = \sum_{k=0}^{N-1} \lambda_k P_k \quad (\text{excluding saturated})$$

$$= (1 - P_B) \Lambda_0$$

(41) M/M/N/S QUEUE STATE PROBABILITY OCCUPANCY P_N

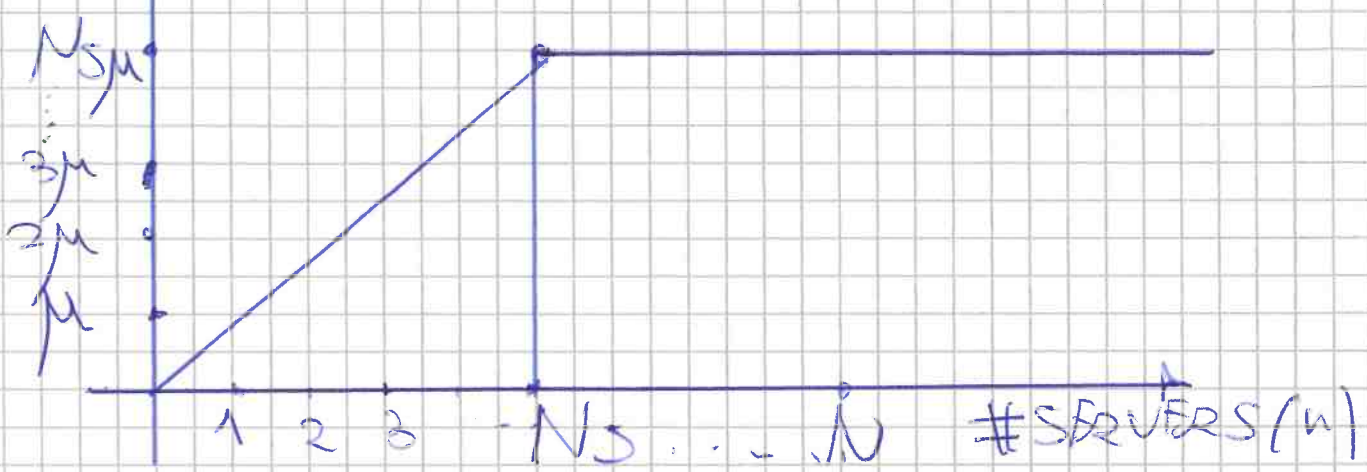
An M/M/N/S QUEUE is a queue divided by N_S - many servers.



Each server has exponential service & is independent from the other ones.
 [MEMORLESS & MARKOVIAN Property hold]

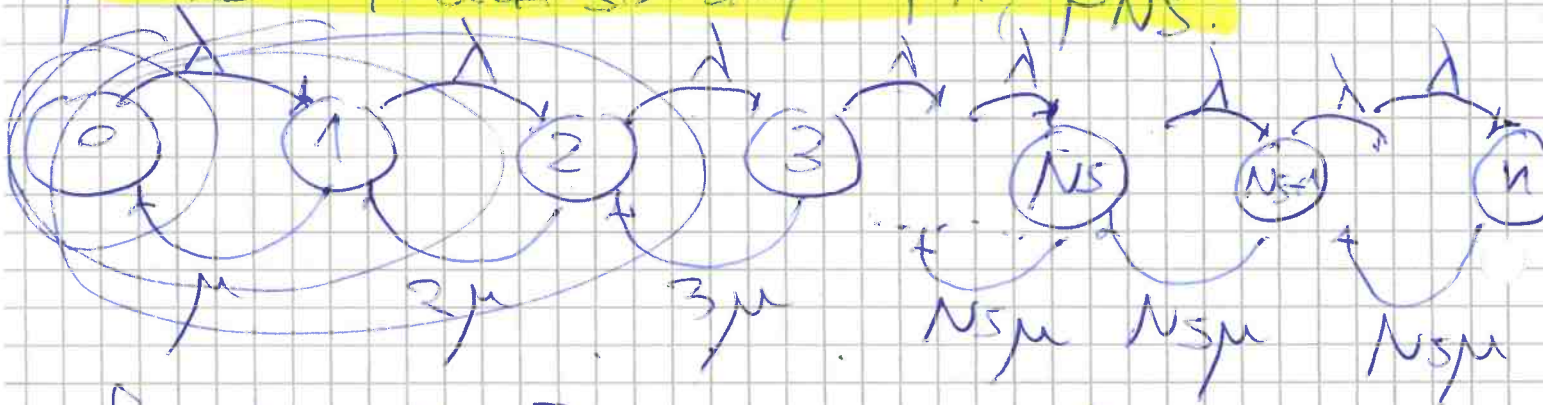
Throughput

$$N = N_u + N_s$$



a) We increase the THROUGHPUT up to $N_s \cdot \mu$ as the #SERVERS increases: Every server can process μ customers with rate $\mu \Rightarrow$ So, increasing the #SERVERS, we increase the #customers processable at the same time up to N_s / max #SERVERS in the system

b) STATE PROBABILITY P_n, P_{N_s}



Bring the FCFS in STEADY-STATE

$$P_1: \lambda P_0 = \mu P_1 \Rightarrow P_1 = \frac{\lambda}{\mu} P_0$$

$$P_2: \lambda P_1 = 2\mu P_2 \Rightarrow P_2 = \frac{\lambda}{2\mu} P_1 = \left(\frac{\lambda}{\mu}\right)^2 \frac{P_0}{2}$$

$$P_3: \lambda P_2 = 3\mu P_3 \Rightarrow P_3 = \frac{\lambda}{3\mu} P_2 = \left(\frac{\lambda}{\mu}\right)^3 \frac{P_0}{3 \cdot 2}$$

$$P_n: \Rightarrow P_n = \left(\frac{\lambda}{\mu}\right)^n \frac{P_0}{n!}$$

$$0 \leq n \leq N_s$$

$$P_{NS} = \left(\frac{\lambda}{\mu}\right)^{NS} \frac{1}{NS!} \cdot P_0$$

$$\Gamma_{NS} \lambda P_{NS} = NS \mu P_{NS+1} \Rightarrow P_{NS+1} = \frac{\lambda}{NS \mu} P_{NS}$$

$$\Gamma_{NS+1} \lambda P_{NS+1} = NS \mu P_{NS+2} \Rightarrow P_{NS+2} = \frac{\lambda}{NS \mu} P_{NS+1}$$

$$\Rightarrow P_{NS+2} = \frac{\lambda}{NS \mu} \frac{\lambda}{NS \mu} P_{NS} = \left(\frac{\lambda}{NS \mu}\right)^2 P_{NS}$$

$$\Rightarrow P_{NS+i} = \left(\frac{\lambda}{NS \mu}\right)^i P_{NS} \quad \begin{matrix} n \geq NS \\ i \geq 0 \end{matrix}$$

throughput cannot be (More than the max. # serves in the queue).

ERGODICITY CONDITION:

We have found in (d) that:

$$P_n = \left(\frac{\lambda}{\mu}\right)^n \frac{1}{n!} P_0 \quad 0 \leq n \leq NS$$

And that:

$$P_{n+i} = \left(\frac{\lambda}{\mu \cdot NS}\right)^i P_n \quad n > NS$$

$n \geq NS + i$

$$P_n = \begin{cases} \left(\frac{\lambda}{\mu}\right)^n \frac{1}{n!} P_0 & 0 \leq n \leq NS \\ \left(\frac{\lambda}{\mu}\right)^{n-NS} \frac{1}{NS! NS^{n-NS}} P_0 & n > NS \end{cases}$$

#times above

By the NORMALIZATION condition: $\sum_{i=0}^{\infty} p_i = 1$

$$\sum_{n=0}^{\infty} \left(\frac{\lambda}{\mu}\right)^n \frac{1}{n!} + p_0 \sum_{n=N_s}^{\infty} \left(\frac{\lambda}{\mu}\right)^n \frac{1}{N_s! N_s^{n-N_s}} = 1$$

$$p_0 \left[\sum_{n=0}^{N_s-1} \left(\frac{\lambda}{\mu}\right)^n \frac{1}{n!} + \sum_{n=N_s}^{\infty} \left(\frac{\lambda}{\mu}\right)^n \frac{1}{N_s! N_s^{n-N_s}} \right] = 1$$

$$\Rightarrow p_0 = \frac{1}{\sum_{n=0}^{N_s-1} \left(\frac{\lambda}{\mu}\right)^n \frac{1}{n!} + \sum_{n=N_s}^{\infty} \left(\frac{\lambda}{\mu}\right)^n \frac{1}{N_s! N_s^{n-N_s}}}$$

Now consider this term for the ERGODICITY CONDITION!

$$\frac{1}{N_s!} \sum_{n=N_s}^{\infty} \left(\frac{\lambda}{\mu}\right)^n \frac{1}{N_s^{n-N_s}} = \frac{1}{N_s!} \left(\frac{\lambda}{\mu}\right)^{N_s} \sum_{n=N_s}^{\infty} \left(\frac{\lambda}{\mu}\right)^{n-N_s} \frac{1}{N_s^{n-N_s}}$$

$$\Rightarrow \frac{1}{N_s!} \left(\frac{\lambda}{\mu}\right)^{N_s} \left(\sum_{n=N_s}^{\infty} \left(\frac{\lambda}{\mu}\right)^{n-N_s} \frac{1}{N_s^{n-N_s}} \right) = p_{N_s} \left(\frac{\lambda}{\mu}\right)^{n-N_s}$$

For $n - N_s = j$:

$$\sum_{j=0}^{\infty} \left(\frac{\lambda}{N_s \mu}\right)^j = \frac{1}{1 - \frac{\lambda}{N_s \mu}}$$

$$\sum_{i=0}^{\infty} \alpha^i = \frac{1}{1-\alpha} \quad \text{if } |\alpha| < 1$$

ERGODICITY condition:

$$\frac{\lambda}{\mu N_s} < 1 \Rightarrow \lambda < \mu \cdot N_s \Rightarrow \frac{\lambda}{\mu} < N_s \Rightarrow \lambda < N_s \mu$$

① Proof of $E\{T_w}$ by FOSTA PROPERTY in an M/M/NS QUEUE

$$E\{T\} = E\{T_w\} + E\{T_s\} = \frac{1}{\mu}$$

$$E\{T_w\} = \sum_{k=NS}^{\infty} E\{T_w | k\} P_k^{(over)}$$

Waiting time, where we have a queue for each server (i.e. more customers than servers)

For 2 servers (NS=2) (EXP. DISTRIBUTION & INDEPENDENT)

$$P\{T > t\} = P\{\min(T_1, T_2) > t\} = P\{T_1 > t, T_2 > t\} = e^{-\mu \cdot t} \cdot e^{-\mu \cdot t} = e^{-2\mu t}$$

⇒ We now want to find $E\{T_w | k\}$

$$E\{T_w | NS\} = \frac{1}{NS \cdot \mu}$$

(NS customers already in the queue when arriving to it) ⇒ Need to wait for them to be served

$$E\{T_w | NS+1\} = \frac{2}{NS \cdot \mu} = \frac{1}{NS \cdot \mu} + \frac{1}{NS \cdot \mu}$$

(NS+1 customers already in the queue when arriving to it) ⇒ Need to wait for them to be served.

$$E\{T_w | NS+n\} = \sum_{i=0}^n \frac{1}{NS \cdot \mu} = \frac{(n+1)}{NS \cdot \mu}$$

$$\Rightarrow NS+n = k \Rightarrow n = k - NS$$

$$E\{T_w | k\} = \frac{k - NS + 1}{NS \cdot \mu} \quad k \geq NS$$

$$\boxed{E\{T_w | K\} = \frac{K - NS + 1}{NS \cdot \mu} \quad K \geq NS}$$

$$\begin{aligned} E\{T_w\} &= \sum_{K=NS}^{\infty} E\{T_w | K\} \cdot Pr^{(K)} \\ &= \sum_{K=NS}^{\infty} \frac{K - NS + 1}{NS \cdot \mu} \cdot Pr^{(K)} \quad K \geq NS \\ &= \sum_{K=NS}^{\infty} \frac{K - NS + 1}{NS \cdot \mu} \cdot P_{NS} \cdot \binom{K - NS}{M - NS} \\ &= \frac{P_{NS}}{NS \cdot \mu} \sum_{K=NS}^{\infty} (K - NS + 1) \cdot \binom{K - NS}{M - NS} \end{aligned}$$

↑ WSTA PROPERTY (checked before)

Now set $\boxed{i = K - NS + 1}$

$\boxed{i - 1 = K - NS}$

$$\begin{aligned} &= \frac{P_{NS}}{NS \cdot \mu} \sum_{i=1}^{\infty} i \cdot \binom{i - 1}{M - NS} \\ &= \frac{P_{NS}}{NS \cdot \mu} \cdot \sum_{i=1}^{\infty} i \cdot \binom{i}{M - NS} \\ &= \frac{P_{NS}}{NS \cdot \mu} \cdot \frac{1}{1 - \frac{1}{NS \cdot \mu}} \\ &= \frac{P_{NS}}{NS \cdot \mu \cdot (1 - \frac{1}{NS \cdot \mu})} \end{aligned}$$

$$= \frac{PNS}{N\mu \cdot \left(\frac{N\mu - 1}{N\mu} \right)^2} = \frac{PNS}{N\mu \cdot \frac{(N\mu - 1)^2}{N\mu^2}}$$

$$= \frac{PNS \cdot N\mu}{(N\mu - 1)^2} = \frac{PNS \cdot N\mu}{(N\mu - 1)^2}$$

$$\Rightarrow E\{T_w\} = \frac{PNS - N\mu}{(N\mu - 1)^2}$$

Service time of one server

$$\Rightarrow E\{T\} = E\{T_w\} + E\{T_s\}$$

$$= \frac{PNS - N\mu}{(N\mu - 1)^2} + \frac{1}{\mu}$$

NB:
NFT rule
ONLY
APPROACH.

↓
No need to multiply by
NS

$$\sum_{n=NS}^{\infty} \alpha^n = \frac{\alpha^{NS}}{1-\alpha}$$

just

48

ERLANG - C FORMULA (for MIM/MS) QUEUES

Used to estimate the probability of experiencing delay
Easier to evaluate in EXOGENOUS SYSTEMS, P_D

where:

$$P_D = P_{BS} \rightarrow P_k = \frac{\left(\frac{\lambda}{\mu}\right)^k}{k!} \frac{1}{N_S!} \frac{1}{N_S^{k-N_S}}$$

$$P_D = P_{BS} = \sum_{k=N_S}^{\infty} P_k = \sum_{k=N_S}^{\infty} P_0 \cdot \left(\frac{\lambda}{\mu}\right)^k \frac{1}{k!} \frac{1}{N_S^{k-N_S}}$$

$$= \sum_{k=N_S}^{\infty} P_0 \left(\frac{\lambda}{\mu}\right)^k \frac{1}{k!} \frac{N_S^{N_S}}{N_S^k} = \sum_{k=N_S}^{\infty} P_0 \frac{\left(\frac{\lambda}{\mu}\right)^k}{k!} \frac{1}{N_S^{k-N_S}}$$

$$= \frac{N_S^{N_S}}{N_S!} \cdot \left(\frac{\lambda}{N_S \mu}\right)^{N_S} P_0 \sum_{k=N_S}^{\infty} \frac{\left(\frac{\lambda}{\mu}\right)^{k-N_S}}{(k-N_S)!}$$

$$= \frac{N_S^{N_S}}{N_S!} P_0 \frac{\left(\frac{\lambda}{N_S \mu}\right)^{N_S}}{1 - \frac{\lambda}{N_S \mu}} = \rho$$

CONVERGES FOR $\lambda < N_S \mu$

AVERAGE AMOUNT of WORK accepted by work server

$$= \frac{P_0}{N_S!} \frac{\left(\frac{\lambda}{\mu}\right)^{N_S}}{1 - \rho}$$

Where $\rho = \frac{\lambda}{N_S \mu}$
[BECAUSE NO LOSS] $\Rightarrow \frac{A_0}{N_S} = \frac{\lambda}{\mu \cdot N_S}$

$A_0 = \frac{\lambda}{\mu} \Rightarrow \rho = \frac{\lambda}{N_S \mu}$

So far, we have found that

$$P_D = P_B = \frac{\rho}{N_S!} \cdot \frac{(A/M)^{N_S}}{(M-\rho)}$$

$\frac{(A/M)^k}{k!} \cdot \frac{1}{N_S!} \cdot \frac{1}{N_S^{k-1}}$
 $\frac{(A/M)^{N_S}}{N_S!} \cdot \frac{1}{N_S^{N_S-1}}$

$$\Rightarrow P_D = \frac{1}{N_S!} \cdot \frac{(A/M)^{N_S}}{(M-\rho)}$$

$$P_0 = \sum_{k=0}^{N_S-1} \frac{(A/M)^k}{k!} \cdot \frac{1}{N_S!} + \frac{1}{N_S!} \cdot \frac{(A/M)^{N_S}}{(M-\rho)}$$

Multiply by the number of terms

ERLANG - C FORMULA | 2nd - 4th

$$A_0 = \frac{A}{M}$$

$$\rho = \frac{A}{N_S M} = \frac{A_0}{N_S}$$

A = TRAFFIC INTENSITY

$$P_D = \frac{1}{1 + \frac{N_S!}{A_0^{N_S}} \left(1 - \frac{A_0}{N_S}\right) \sum_{k=0}^{N_S-1} \frac{A_0^k}{k!}}$$

RECURSIVE ERLANG - C FORMULA

$$C_{N_S}(A_0) = \begin{cases} \frac{1 - A_0}{N_S - 1} & \text{if } N_S > 1 \\ \frac{N_S - 1}{A_0} - \frac{1}{C_{N_S-1}(A_0)} & \\ A_0 & N_S = 1 \end{cases}$$

For P_D in **M/M/1/N_S** **QUEUES**

~~BS~~ FULL STEPS FOR ERLANG-C FORMULA'S DERIVATION:

$$P_D = P_{BS} = \frac{P_0}{NS!} \cdot \frac{\left(\frac{A}{\mu}\right)^{NS}}{1-\rho}$$

We know that P_0 is:

$$P_0 = \frac{1}{\sum_{i=0}^{NS-1} \left(\frac{A}{\mu}\right)^i \frac{1}{i!} + \sum_{i=NS}^{\infty} \left(\frac{A}{\mu}\right)^i \frac{1}{NS!} \frac{1}{NS^{i-NS}}}$$

$\Rightarrow P_D$ is, substituting P_0 in it:

$$P_D = \frac{\left(\frac{A}{\mu}\right)^{NS}}{NS! (1-\rho)}$$

$$\sum_{i=0}^{NS-1} \left(\frac{A}{\mu}\right)^i \frac{1}{i!} + \sum_{i=NS}^{\infty} \frac{\left(\frac{A}{\mu}\right)^i \cdot NS^{NS}}{NS! \cdot NS^i}$$

$$= \frac{\left(\frac{A}{\mu}\right)^{NS}}{NS! (1-\rho)}$$

$$\sum_{i=0}^{NS-1} \left(\frac{A}{\mu}\right)^i \frac{1}{i!} + \frac{NS^{NS}}{NS!} \sum_{i=NS}^{\infty} \frac{\left(\frac{A}{\mu}\right)^i}{NS^i}$$

~~$$= \frac{\left(\frac{A}{\mu}\right)^{NS}}{NS! (1-\rho)}$$

$$\sum_{i=0}^{NS-1} \left(\frac{A}{\mu}\right)^i \frac{1}{i!} + \frac{NS^{NS}}{NS!} \sum_{i=NS}^{\infty} \frac{\left(\frac{A}{\mu}\right)^i}{NS^i}$$~~

$$\frac{NS \ NS}{NS!} \sum_{i=NS}^{+\infty} \left(\frac{\lambda}{M \cdot NS} \right)^i$$

$$= \frac{NS \ NS}{NS!} \frac{\left(\frac{\lambda}{M \cdot NS} \right)^{NS}}{\left(1 - \frac{\lambda}{M \cdot NS} \right)} = \frac{NS \ NS}{NS!} \left(\frac{\lambda}{M} \right)^{NS} \cdot \frac{1}{\lambda^{NS}}$$

For $\frac{\lambda}{M \cdot NS} = \rho$ $\lambda = A_0$

$$= \frac{(A_0)^{NS}}{NS! (1-\rho)}$$

$$\Rightarrow PD = \frac{(A_0)^{NS}}{NS! (1-\rho)} \sum_{k=0}^{NS-1} \frac{(A_0)^k}{k!} + \frac{1}{NS! (1-\rho)}$$

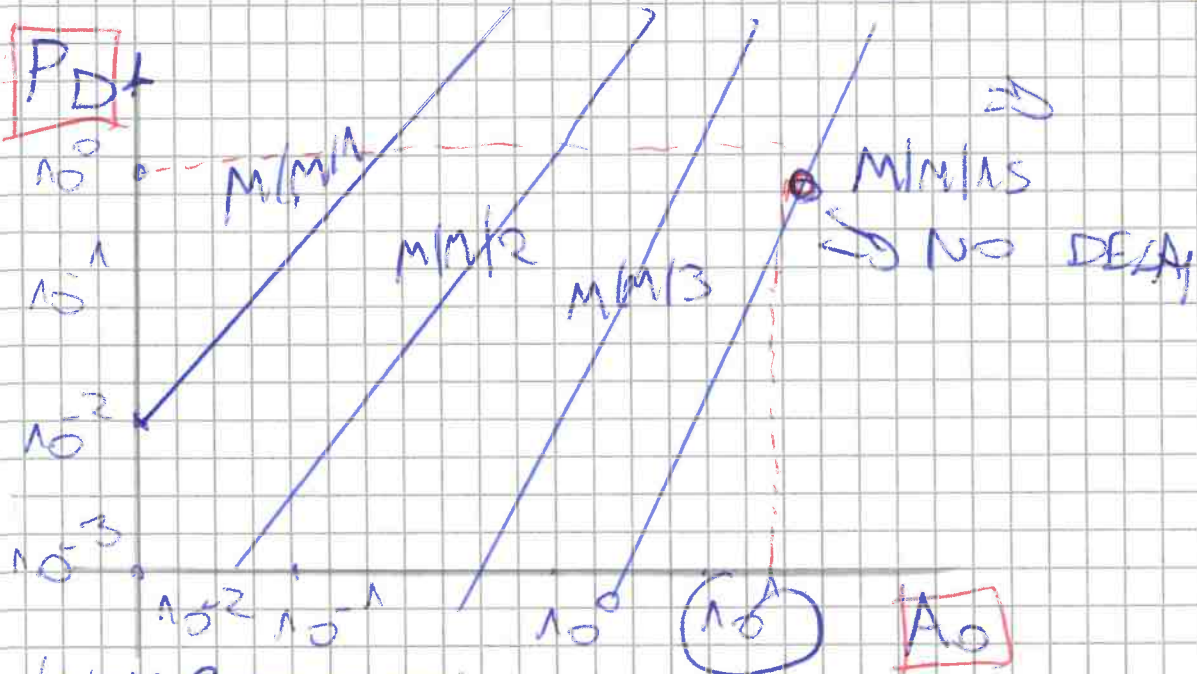
$$\Rightarrow PD = \frac{1}{NS! (1-\rho) \sum_{k=0}^{NS-1} \frac{(A_0)^k}{k!} + 1}$$

$$P = \frac{A_0}{NS}$$

EDLING-C FORMULA

$$PD = \frac{NS! (1 - \frac{A_0}{NS})}{(A_0)^{NS}} \sum_{k=0}^{NS-1} \frac{(A_0)^k}{k!} + 1$$

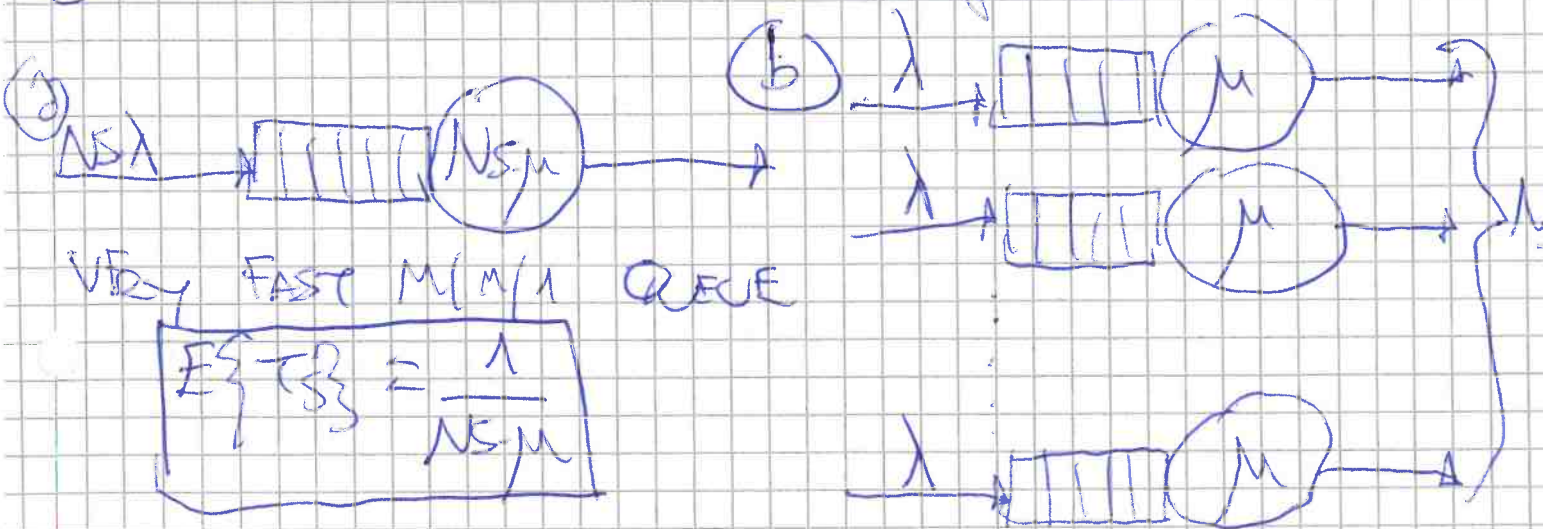
⇒ The Erlang - C formula is used to link together the traffic intensity A_0 with the probability of delay P_D .



INTERPRETATION:
 "Given the offered load, what is the # servers I need to use to obtain the desired P_D ?"
 ⇒ NO ERLANGS
 ⇒ $A_0 = 10$

4.9) PERFORMANCE COMPARISON BETWEEN:

- a) $M/M/1$, One W.L. for ~~the~~ whole are queue.
- b) N_s - many $M/M/1$ QUEUES, one W.L. per queue.
- c) $M/M/N_s$ QUEUE, One W.L. for all N_s SERVERS



b) ~~M/M/1~~ many M/M/1 queues.

$$E\{T\} = \frac{1}{\mu}$$

$N_s = \# \text{ servers}$

c) M/M/Ns queue:



One waiting line for all N_s -many servers.

$$E\{T\} = \frac{1}{\mu}$$

PERFORMANCE COMPARISON:

$$E\{T\} = \frac{1}{\mu}$$

M/M/1

$$E\{T\} = \frac{1}{\mu} + \frac{N_s \rho - \rho N_s}{(N_s \mu - \lambda)^2}$$

M/M/Ns

$E\{T^{(a)}\} = M/M/1$ with $\frac{\lambda}{N_s \mu}$ RATE

$$E\{T^{(a)}\} = \frac{1}{N_s \mu} \frac{1}{1 - \rho} = \frac{1}{N_s \mu} \frac{1}{1 - \frac{\lambda}{N_s \mu}}$$

$$\Rightarrow E\{T^{(a)}\} = \frac{1}{\lambda N_s (\mu - \lambda)} = \frac{1}{N_s (\mu - \lambda)}$$

$$\Rightarrow E\{T^{(a)}\} = \frac{1}{N_s (\mu - \lambda)}$$

$\rho < 1$
 $\lambda < N_s \mu$

$E\{T^{(b)}\}$ = For each M/M/1 queue, we have:

$$E\{T^{(b)}\} = \frac{1}{\mu - \rho} = \frac{1}{\mu - \frac{\rho}{\mu}} = \frac{1}{\mu(1 - \frac{\rho}{\mu})} = \frac{1}{\mu - \rho}$$

$$\Rightarrow E\{T^{(b)}\} = \frac{1}{\mu - \lambda}$$

ERGO, CONDITION:
 $\lambda < \mu$

$E\{T^{(c)}\}$ = M/M/NS QUEUE

$$E\{T^{(c)}\} = E\{\tau_s\} + E\{T_w\}$$

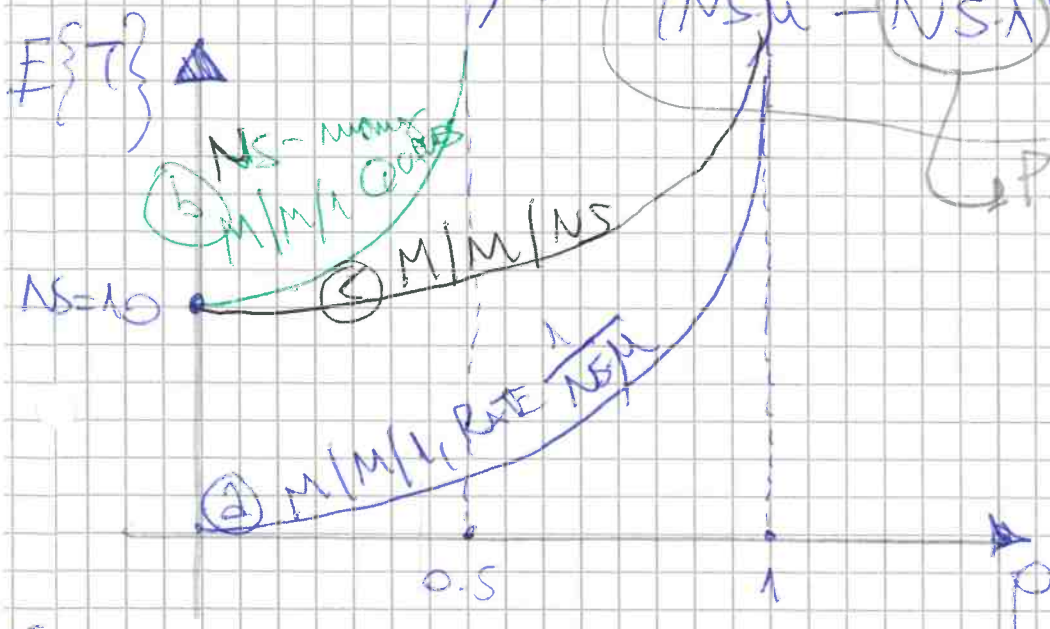
$$= \frac{1}{\mu} + \frac{NS \cdot \mu \cdot \rho NS}{(NS \mu - NS \lambda)^2}$$

Found by the PASTA property in 4.4

ERGO, CONDITION:

$$NS \lambda < NS \mu$$

Prerequisite, we had N / many servers (due to DIFFERENT)



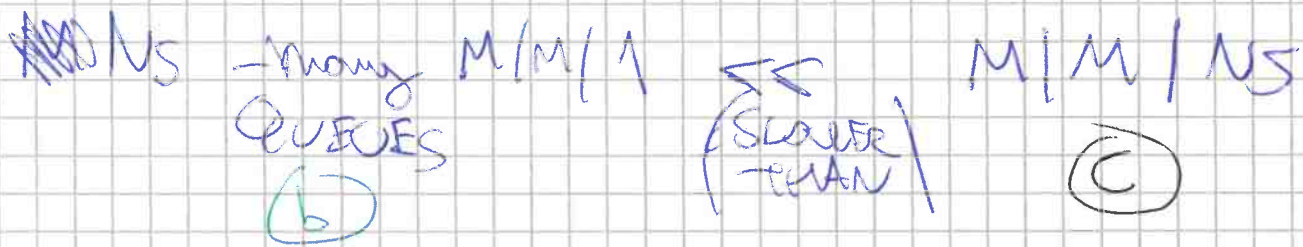
①, "SPEEDY GONZALEZ" M/M/1 QUEUE is NUMBER ONE (LIKE CHINA)

NS - many M/M/1 is NS-times SPEEDY GONZALEZ lower than M/M/1 QUEUE

UNLOADED SITUATION ($\rho \rightarrow 0$)

$$E\{T^{(b)}\} \approx E\{T^{(c)}\} \approx \frac{1}{\mu}$$

INCREASED-LOAD SITUATION:



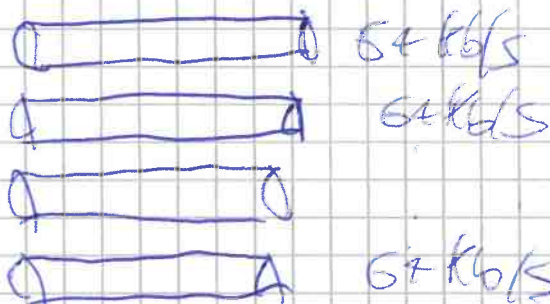
\Rightarrow Some queues & waiting lines from (b) may be idle \Rightarrow wasted ~~usable~~ SERVERS.

\Rightarrow (c) is better!

IN CONCLUSION, we prefer ECONOMY & SCALE!



Rather than 32 links at 64 kb/s, each.



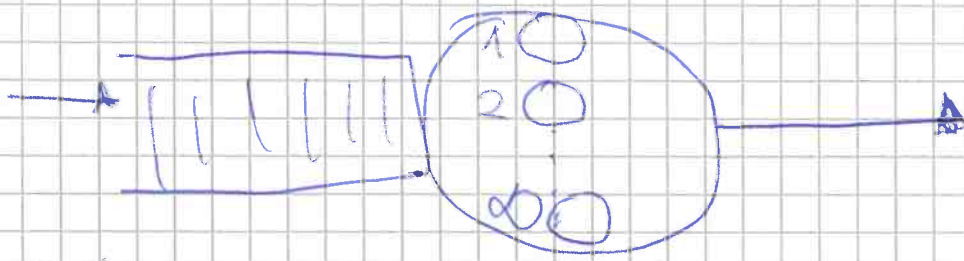
Also, we'd prefer to link one Co for many customers rather than one small Co for a few customers.

(So) M/M(∞) QUEUE, State probability P_k

~~M/M/NS~~ NS = ∞ [Infinite # SERVERS]

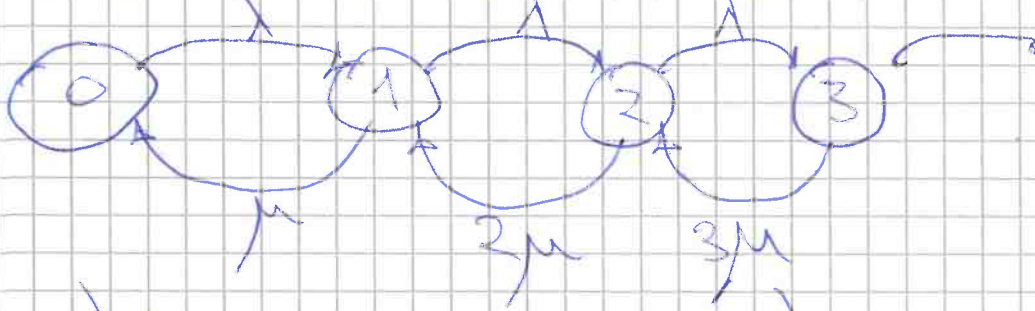
Customers always find one AVAILABLE SERVER.

\Rightarrow No waiting! $E\{TW\} = 0$



M/M/∞ QUEUE

RATE TRANSITION DIAGRAM:



$$\lambda p_0 = \mu p_1 \Rightarrow p_1 = \frac{\lambda}{\mu} p_0$$

$$\lambda p_1 = 2\mu p_2 \Rightarrow p_2 = \frac{\lambda}{2\mu} p_1 = \left(\frac{\lambda}{\mu}\right)^2 \cdot \frac{1}{2} p_0$$

$$\lambda p_2 = 3\mu p_3 \Rightarrow p_3 = \frac{\lambda}{3\mu} p_2 = \left(\frac{\lambda}{\mu}\right)^3 \cdot \frac{1}{6} p_0$$

$$\Rightarrow p_n = \left(\frac{\lambda}{\mu}\right)^n \cdot \frac{1}{n!} p_0 \quad n \geq 0$$

By the NORMALIZATION condition: $\sum_{i=0}^{\infty} p_i = 1$

$$p_0 \sum_{i=0}^{\infty} \left(\frac{\lambda}{\mu}\right)^i \cdot \frac{1}{i!} = 1 \Rightarrow p_0 = \frac{1}{\sum_{i=0}^{\infty} \left(\frac{\lambda}{\mu}\right)^i \cdot \frac{1}{i!}}$$

$$\Rightarrow p_0 = e^{-\frac{\lambda}{\mu}}$$

$$\Rightarrow p_n = \left(\frac{\lambda}{\mu}\right)^n \cdot \frac{1}{n!} \cdot e^{-\frac{\lambda}{\mu}}$$

$$\Rightarrow P_n = \frac{(\lambda)^n}{n!} \cdot e^{-\lambda}$$

POISSON DISTRIBUTION FOR A DISCRETE RV.

$$E\{T_w\} = 0$$

$$E\{T\} = \frac{1}{\mu} = E\{T_s\}$$

$$\Rightarrow E\{nw\} = 0 \Rightarrow E\{n\} = E\{n_s\} = A = \lambda \cdot E\{T_s\} = \frac{\lambda}{\mu}$$

$$\rho = \frac{E\{nw\}}{N_s} = 0$$

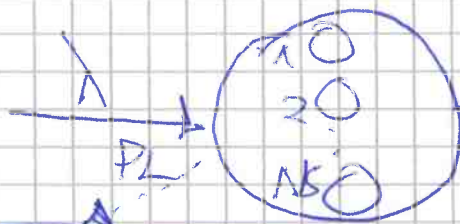
EXTREMELY LOW UTILIZATION FACTOR

3) PROOF OF ERLANG-B FORMULA, TO FIND

P_L IN AN $M/M/N_s/0$ QUEUE

Consider an $M/M/N_s/0$ QUEUE

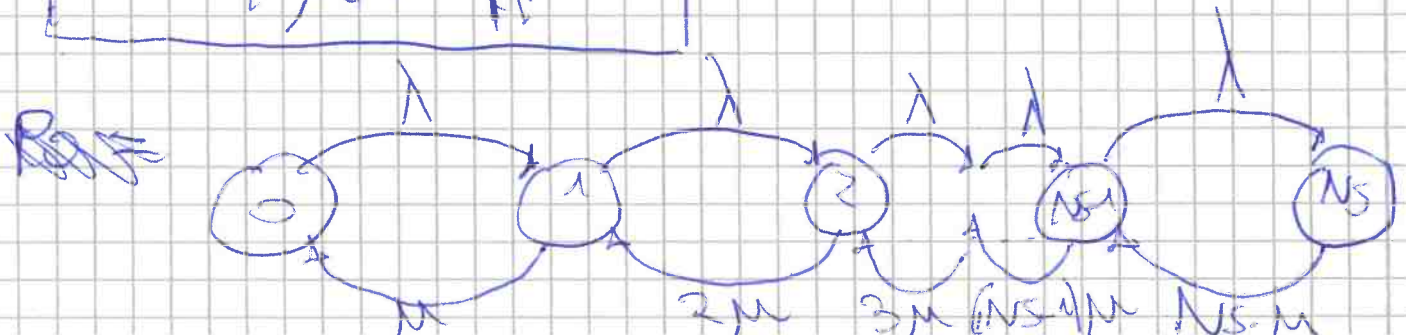
$N_s = \#$ SERVERS
 $N_w = 0$



$$\lambda L = \lambda_0 \cdot P_L$$

$$0 \leq n \leq N_s$$

$$P_n = \frac{(\lambda)^n}{n!} \cdot \frac{1}{P_0}$$



$$P_0 = \frac{1}{\sum_{n=0}^{N_S} \left(\frac{\lambda}{\mu}\right)^n \frac{1}{n!}}$$

By the NORMALIZATION CONDITION.

(After PK) was derived for M/M/1/Ns QUEUE.

$$\Rightarrow P_n = \left(\frac{\lambda}{\mu}\right)^n \frac{1}{n!}$$

$$0 \leq n \leq N_S$$

$$P_0 = \frac{1}{\sum_{n=0}^{N_S} \left(\frac{\lambda}{\mu}\right)^n \frac{1}{n!}}$$

EDWIN FORMULA of M/M-1 TYPE (B-FORMULA)

$$\Rightarrow P_L = P_B = P_{N_S} = \frac{\left(\frac{\lambda}{\mu}\right)^{N_S} \frac{1}{N_S!}}{\sum_{n=0}^{N_S} \left(\frac{\lambda}{\mu}\right)^n \frac{1}{n!}}$$

$N = N_S + N_{oc}$

Such formula is used to model circuit-switched NETWORK (i.e. the telephone).

$$\lambda = \lambda_0 (1 - P_L) = \lambda / (1 - P_{N_S}) = \Gamma$$

$$A = A_0 (1 - P_L) = \frac{\lambda}{\mu} (1 - P_{N_S}) = \{N_S\} = \{N\}$$

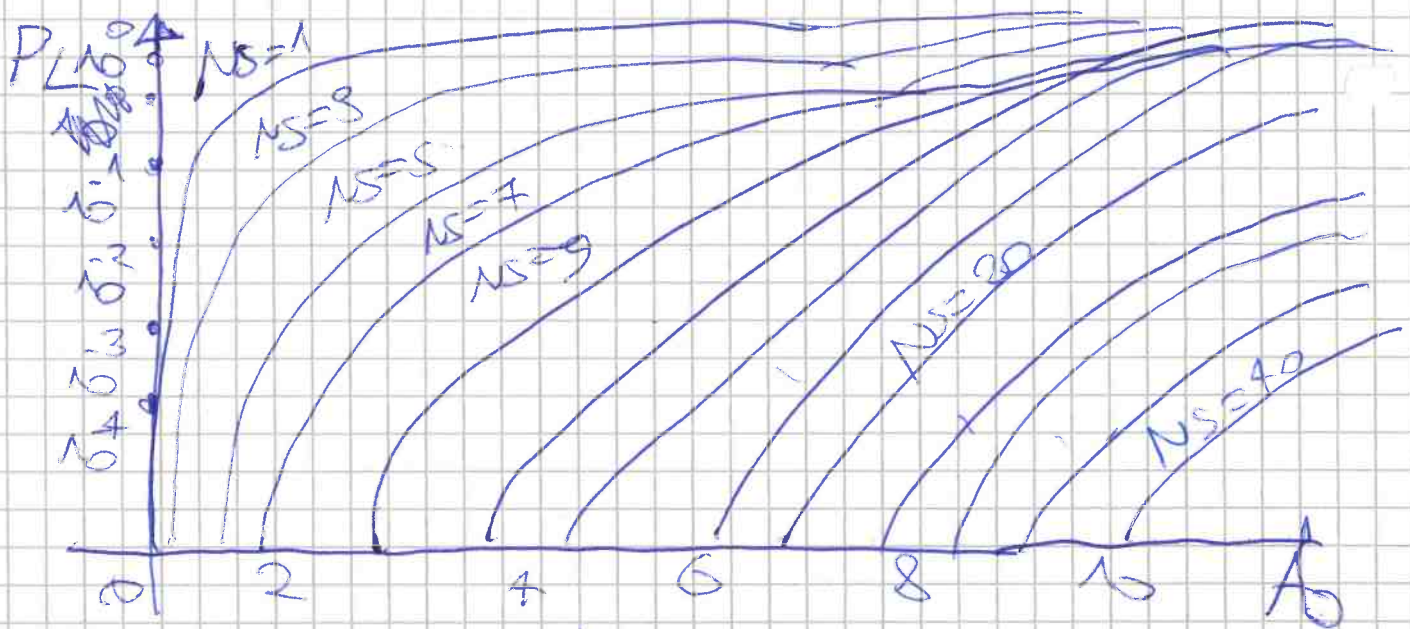
OFFERED TRAFFIC (WENTON, EDWIN'S)

$$\rho = \frac{\{N_S\}}{N_S} = \frac{A}{N_S} = \frac{\lambda (1 - P_{N_S})}{\mu \cdot N_S}$$

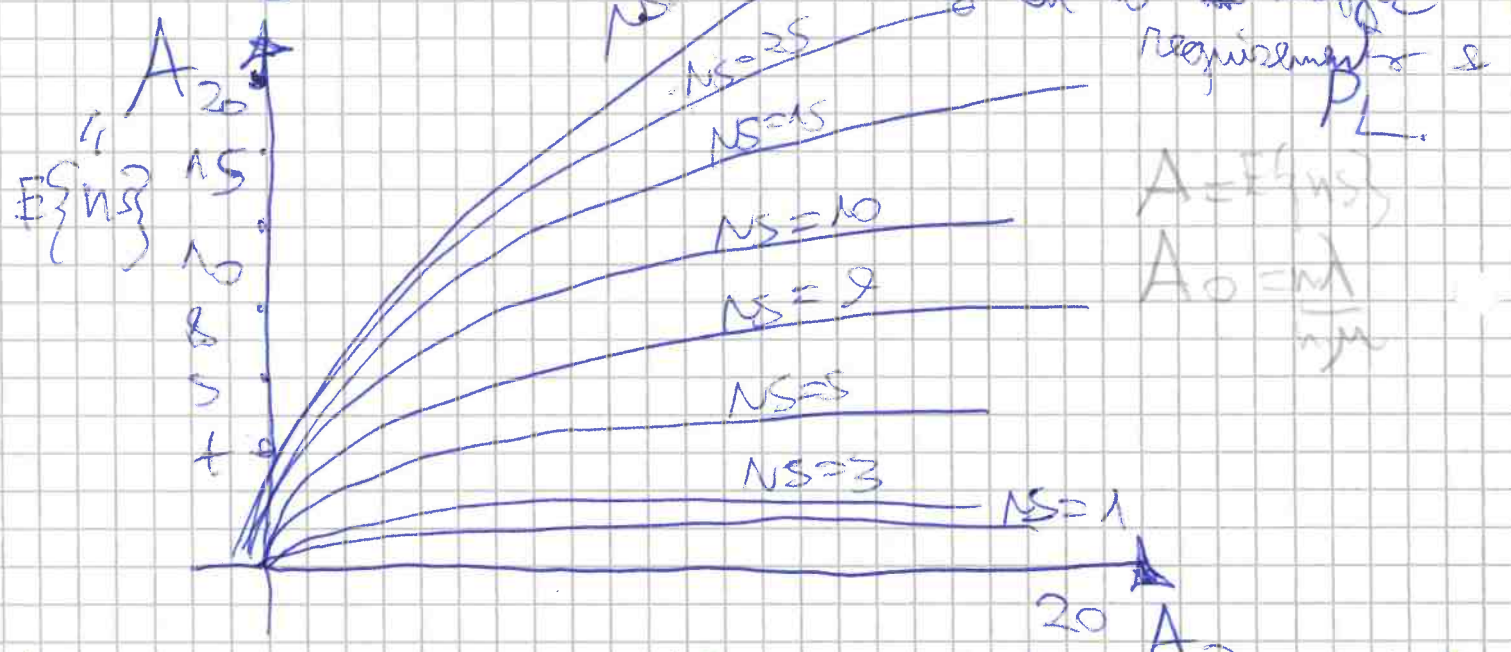
RECURSIVE EDWIN-B FORMULA

$$B_{N_S}(A_0) = \begin{cases} \frac{A_0}{A_0 + \frac{N_S}{B_{N_S-1}(A_0)}} & \text{if } N_S \geq 1 \\ 1 & \text{if } N_S = 0 \end{cases}$$

3 PLOTS :



Increasing the offered traffic intensity A_0 (Erlangs), we need to increase the # servers NS to "contain the P_L ". The P_L increases by increasing A_0 . \Rightarrow Can determine # servers NS given A_0 traffic requirements & P_L .

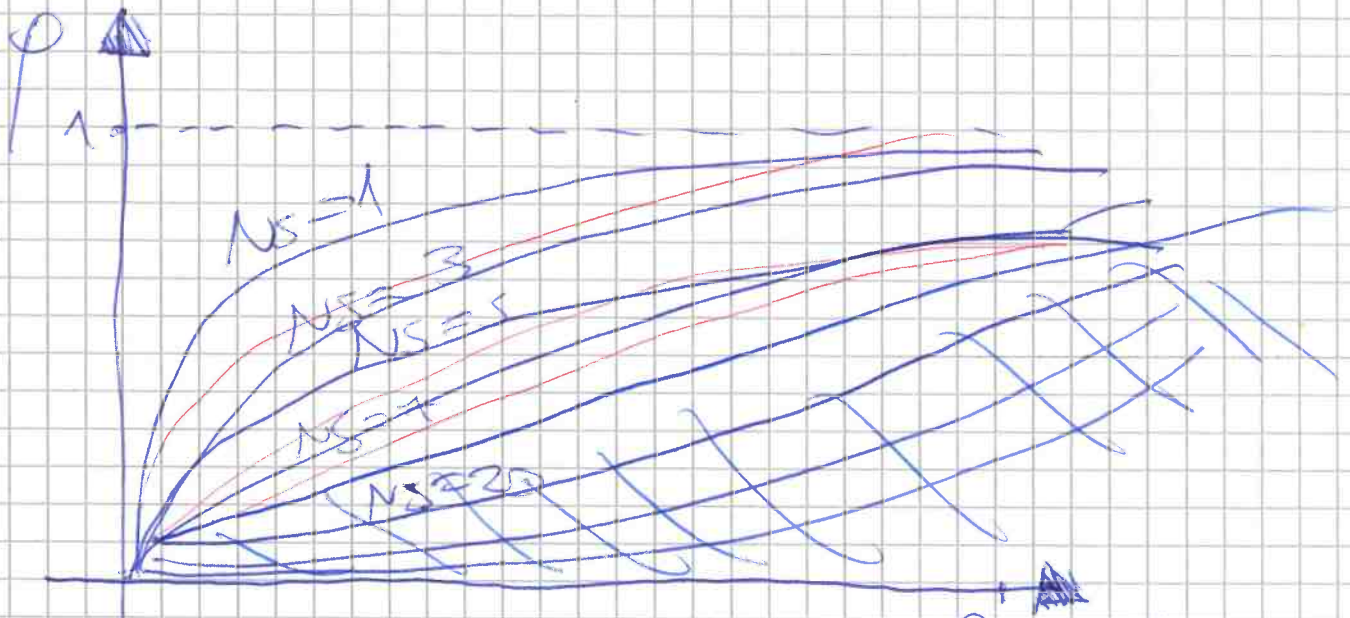


Knowing the traffic demand A_0 , we can determine the # servers NS to find the actual traffic A .

UTILIZATION COEFFICIENT ρ

VS

OFFERED TRAFFIC in M/M/1/N/S/O QUEUE



Increasing the # servers & keeping the same λ_0 , the utilization factor decreases.

~~PROPERTY FORM of Erlang~~

PROPERTY of USEFULNESS of ERLANG-B FORMULA

The formula (Erlang-B) is insensitive to the

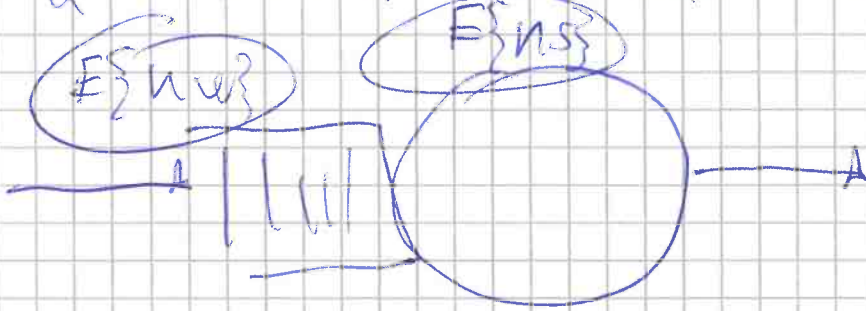
PDF of the SERVICE TIME, as long as certain hypotheses are met.

REQUIRED HYPOTHESES

- (A) POISSON ARRIVALS
- (B) FINITE NUMBER of SERVICE-TIME DISTRIBUTION
 - ↳ heavy-tail distribution $\Rightarrow \text{VAR}\{X\} = \infty$
- (C) EXPONENTIAL INTERARRIVAL TIMES
(& INDEPENDENT)

(52) LITTLE'S FORMULA PROOF

We want to show that, at STEADY-STATE, for a CONSERVATIVE SYSTEM we have.



$$E\{n\} = \lambda \cdot E\{T\}$$

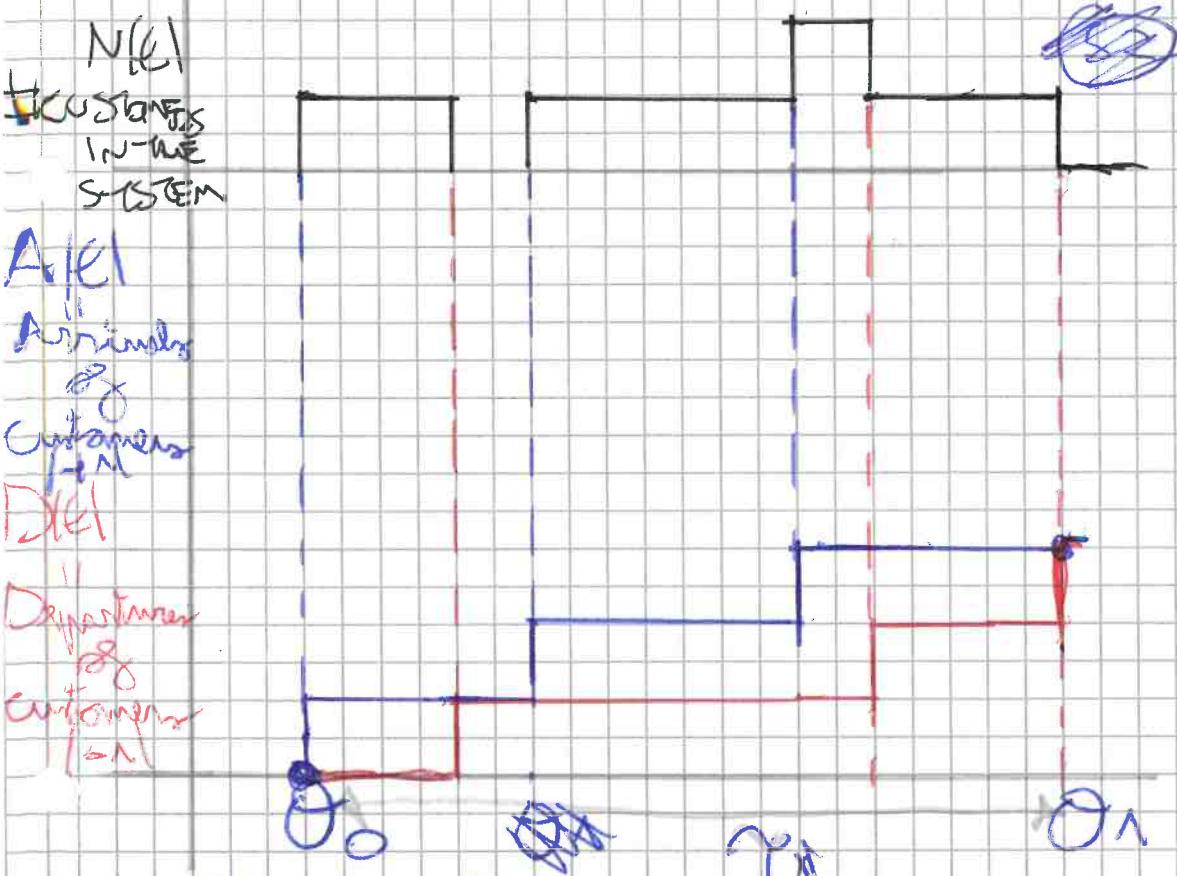
$$E\{nw\} = \lambda \cdot E\{Tw\}$$

$$E\{ns\} = \lambda \cdot E\{Ts\}$$

λ ACCEPTED TRAFFIC INTENSITY

Where $E\{n\} = E\{nw\} + E\{ns\}$

Proof:



$\theta_0 - \theta_1 = \gamma$ (in time)
 REGENERATIVE POINTS = Points with NO CUSTOMERS in the SYSTEM.

$A(t) = \#$ ARRIVED CUSTOMERS $m / (\theta_0, \theta_0 + t)$

$D(t) = \#$ DEPARTED CUSTOMERS $m / (\theta_0, \theta_0 + t)$

$A(\theta_0) = D(\theta_0)$ $A(\theta_1) = D(\theta_1)$ EMPTY SYSTEM

$N(t) = \#$ CUSTOMERS at time t .

$N(t) = A(t) - D(t)$ in the queue

REGENERATIVE POINTS:

$N(\theta_0) = 0, \quad N(\theta_1) = 0$

INITIALLY, we have an empty SYSTEM, and we have,

$\gamma = \theta_1 - \theta_0$

RECALL what LITTLE'S FORMULA relates:

① # CUSTOMERS in the system $\{N\}$

② AVERAGE RATE of ARRIVALS λ

③ AVERAGE time spent in the system $\{T\}$

$$E\{N\} = \lambda E\{T\}$$

① $E\{N\} \rightarrow \bar{n} = \frac{\lambda}{\mu} \int_0^{\infty} N(x) dx$

② $E\{T\} \rightarrow \bar{w} = \frac{\lambda}{A(x)} \sum_{j=1}^{\infty} w_j$

ARRIVED CUSTOMERS

AVERAGE time spent in the queue by all customers

② $\lambda \rightarrow \bar{\lambda} = \frac{A(x)}{T} \Rightarrow A(x) = \bar{\lambda} \cdot T$

ARRIVALS in T

T = Interval duration

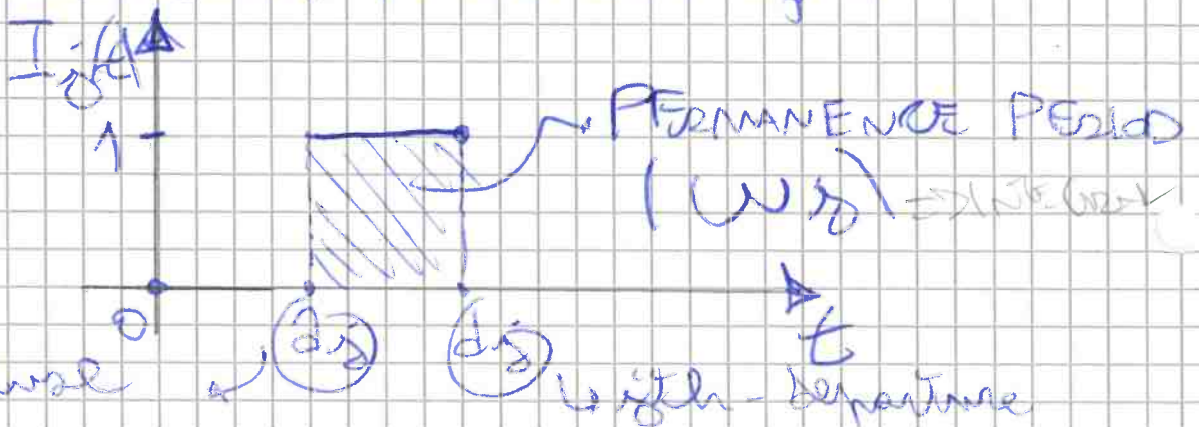
Now putting these concepts together:
 p.p.: $A(x)$ into \bar{w}

③: $\bar{w}' = \frac{\lambda}{A(x)} \sum_{j=1}^{\infty} w_j$

$A(x) = \bar{\lambda} \cdot T$

Now consider the CHARACTERISTIC FUNCTION

has value (1) only if there is a customer INSIDE the queue.



CHARACTERISTIC FUNCTION $I_j(t)$

$$I_j(t) = \begin{cases} 1 & 0 \leq t \leq d_j \\ 0 & \text{elsewhere} \end{cases}$$

Sum of the CDF
Function of all servers

⇒ MAKE PERIOD

OVERALL

$$N(t) = \sum_{j=1}^{A(t)} I_j(t) = \sum_{j=1}^{A(t)} I_j(t)$$

Overall # customers in the system

$$w_j = \int_{\theta_0}^{\theta_1} I_j(t) dt$$

$I_j(t) = 0$
when no customers are present

$$\textcircled{1} \bar{n} = \frac{1}{T} \int_{\theta_0}^{\theta_1} \sum_{j=1}^{A(t)} I_j(t) dt$$

$$\textcircled{2} \bar{w} = \frac{1}{T} \sum_{j=1}^{A(t)} w_j$$

$$\bar{n} = \lambda \cdot \bar{w} = \frac{1}{T} \sum_{j=1}^{A(t)} \int_{\theta_0}^{\theta_1} I_j(t) dt$$

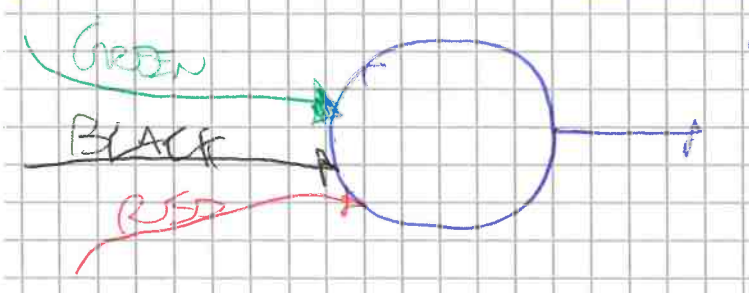
⇒ We can hence conclude that:

$$\lambda \cdot \bar{w} = \bar{n} \quad (\text{LITTLE'S FORMULA})$$

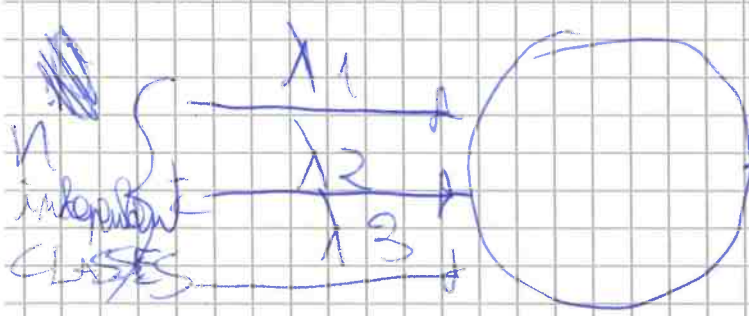
$$\Rightarrow \boxed{E\{n\} = \lambda \cdot E\{T\}}$$

~~53~~ DEFINITION of ~~INDEPENDENT~~ (MUTUAL EXCLUSIVE) PART of FCNN.

55 DEFINITION of LOCAL $E\{T_{s_i}\}$, $E\{N_{s_i}\}$, $E\{N_{s_i}\}$, $E\{N_{s_i}\}$, NO PRIORITY ~~AND~~ BUT MULTIPLE USER CLASSES



3 different user classes, yet all of them have the same PRIORITY.



LOCAL \rightarrow For one class
GLOBAL \rightarrow For all classes

$\lambda = \sum_i \lambda_i$ One class is independent from the other ones.

$E\{T_s\} = \frac{1}{\lambda} \cdot \sum_{i=1}^n \lambda_i \cdot E\{T_{s_i}\}$ GLOBAL PDF of the SERVICE PDF.

$E\{T_s\} = \frac{1}{\lambda} \cdot \sum_{i=1}^n \lambda_i \cdot E\{T_{s_i}\}$ GLOBAL $E\{T_s\}$

$\rho = \frac{E\{N_{s_i}\}}{1} = \lambda \cdot E\{T_{s_i}\} = \lambda \cdot \frac{1}{\lambda} \sum_{i=1}^n \lambda_i E\{T_{s_i}\}$
 $= \sum_{i=1}^n \lambda_i \cdot E\{T_{s_i}\} = \rho_i = \sum_{i=1}^n \rho_i$

$$\rho = \sum_{i=1}^N \rho_i$$

$$\Rightarrow \rho < 1$$

GLOBAL UTILIZATION FACTOR & STABILITY CONDITION

$$E\{T_w\} = \lambda \cdot \frac{E\{T_s^2\}}{2(1-\rho)} = \lambda \frac{\sum_{i=1}^N \lambda_i E\{T_{s_i}^2\}}{2(1-\sum_{i=1}^N \rho_i)}$$

Big Line P-K FORMULA

$$= \frac{\sum_{i=1}^N \lambda_i \cdot E\{T_{s_i}^2\}}{2(1-\sum_{i=1}^N \rho_i)}$$

Need to consider all the user classes for each class $E\{T_{w_i}\}$

$$\Rightarrow E\{T_{w_i}\} = E\{T_w\}$$

GLOBAL $E\{T_w\}$

LOCAL $E\{T_{w_i}\}$

LOCAL QUEUEING TIME

GLOBAL QUEUEING TIME

$$E\{T_i\} = E\{T_w\} + E\{T_{s_i}\}$$

$$E\{T\} = E\{T_w\} + E\{T_s\}$$

$$E\{T\} = \frac{1}{\lambda} \sum_{i=1}^N \lambda_i \cdot E\{T_i\}$$

AVERAGE # CUSTOMERS ($E\{n_w\}, E\{n\}, E\{n_s\}$)
 ↳ Cumulative Metric!

$$E\{n_{w_i}\} = \lambda_i \cdot E\{T_{w_i}\} = \lambda_i \cdot E\{T_w\}$$

$$E\{n_w\} = \sum_{i=1}^N E\{n_{w_i}\}$$

GLOBAL # CUSTOMERS IN WAITING LINE

~~$$E\{n_i\} = \lambda \cdot E\{T_i\}$$~~

$$E\{n\} = \sum_{i=1}^n E\{n_i\} = \lambda \cdot E\{T\} = \frac{\lambda^2 \cdot E\{T_s\}}{2(1-\rho)}$$

$$E\{n_i\} = \lambda_i \cdot E\{T_i\} = \underbrace{E\{n_{s_i}\}}_{\rho_i} + E\{n_{w_i}\}$$

$$\Rightarrow E\{n_i\} = \rho_i + E\{n_{w_i}\}$$

PER-CLASS
GLOBAL # CUSTOMERS

$$E\{n\} = \sum_{i=1}^n E\{n_i\} = \rho + E\{n_w\}$$

GLOBAL
CUSTOMERS
in all
CLASSES

$$E\{n\} = \rho + \frac{\lambda^2 \cdot E\{T_s\}^2}{2(1-\rho)}$$

§6 DEFINITION & VIRTUAL & RESIDUAL TIME
with NO PRIORITY CLASSES, with USE CLASSES!!

$$E\{T_w\} = E\{T_v\} + E\{T_r\}$$

VIRTUAL TIME
(Service time of all customers before me in the waiting line)

RESIDUAL SERVICE TIME
Remaining service time of the customer being served or I arrive.
[Non-Markovian nature of the queue]

$$E\{T_V\} = \sum_{i=1}^K E\{T_{s_i}\} = E\{T_{s_i(1)}\} + E\{T_{s_i(2)}\} + \dots + E\{T_{s_i(K)}\}$$

$$E\{T_V\} = K \cdot E\{T_S\}$$

of servers in the waiting line

$$E\{E\{T_{s_i(1)} + T_{s_i(2)} + \dots + T_{s_i(K)} \mid N_{s_i} = K_i\}\}$$

$$\Rightarrow E\{T_V\} = \sum_{i=1}^N E\{N_{s_i}\} \cdot E\{T_{s_i}\}$$

~~$$= \sum_{i=1}^N E\{N_{s_i}\} \cdot E\{T_{s_i}\}$$

$$= \sum_{i=1}^N \lambda_i E\{T_{s_i}\} \rho_i$$~~

$$\Rightarrow E\{T_V\} = \sum_{i=1}^N (\lambda_i \cdot E\{T_{s_i}\}) \cdot E\{T_{s_i}\} = \rho_i$$

$$= \sum_{i=1}^N \rho_i \cdot E\{T_{s_i}\}$$

VIRTUAL TIME

$$\Rightarrow E\{T_V\} = \rho \cdot E\{T_W\} = \sum_{i=1}^N \rho_i \cdot E\{T_{s_i}\}$$

By the P-K FORMULA:

$$E\{T_V\} = \frac{\lambda \cdot E\{T_S^2\}}{2(1-\rho)} \cdot \rho$$

\Rightarrow Now we can find $E\{T_E\} = E\{T_W\} - E\{T_V\}$

$$E\{T_R\} = E\{T_W\} - E\{T_V\}$$

$$= E\{T_W\} - \rho \cdot E\{T_W\}$$

$$\Rightarrow E\{T_R\} = E\{T_W\}(1 - \rho)$$

Use Lemma 1

$$\Rightarrow E\{T_W\} = \frac{\lambda \cdot E\{T_S^2\}}{2(\mu - \rho)}$$

$$\Rightarrow E\{T_R\} = \frac{\lambda \cdot E\{T_S^2\}}{2(\mu - \rho)} \cdot (1 - \rho)$$

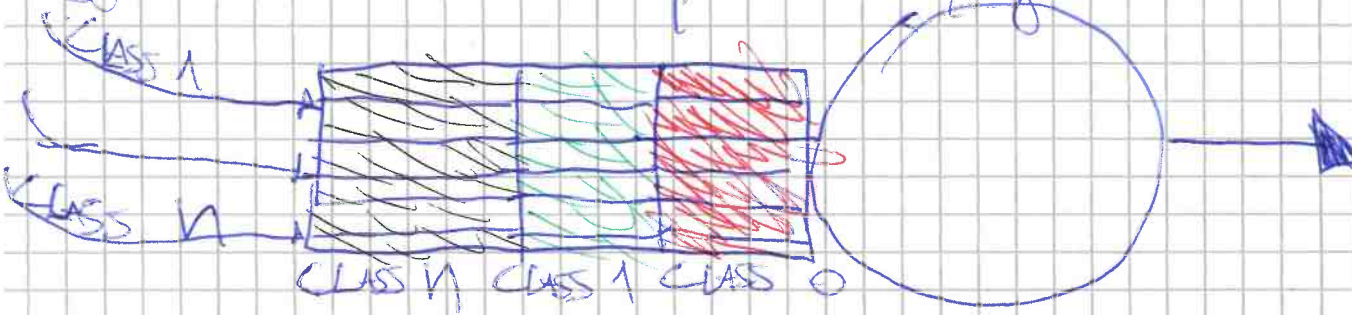
RESIDUAL TIME

$$\Rightarrow E\{T_R\} = \frac{\lambda \cdot E\{T_S^2\}}{2}$$

NON-INTERCEPTABLE RESIDUAL TIME!

b) M/G/1 QUEUE WITH PRIORITIES for USER CLASSES \rightarrow VIRTUAL & RESIDUAL TIME

There exist different waiting lines for the different user classes (a priority for each one).



PRIORITY INDEX = Inversely proportional to the PRIORITY itself

$\left. \begin{array}{l} 0 = \text{TOP PRIORITY} \\ n = \text{LOWEST PRIORITY} \end{array} \right\} \Rightarrow \text{QoS, deterministic BEHAVIOUR.}$

STARVATION in PACKET SWITCHING is BAD!
 (Ex: If ~~Gold~~ Gold packets keep arriving & Bronze packets are waiting in line, STARVATION of Bronze packets would occur).

Now, we are interested in determining $E\{T_{wi}\}$ for the i-th user class [Now also considering PRIORITIES!]

$$E\{T_{wi}\} = \sum_{j=1}^i E\{T_{ij}\} + \sum_{j=1}^{i-1} E\{T_{ij}'\} + E\{T_R\}$$

(USE CLASS C)

Where: $\sum_{j=1}^i E\{T_{ij}\} =$ TIME to wait for customers already in the waiting line to be SERVED.

$\sum_{j=1}^{i-1} E\{T_{ij}'\} =$ TIME to wait for customer with priority lower than mine to be SERVED, hence "superseding" me in the waiting line.
 \Rightarrow Customers with lower priority arriving while I wait.



$E\{T_{Rj}\} =$ ORIGINAL SERVICE TIME of the customer in the service center as I arrive to the queue.

$$E\{T_{ij}\} = E\{N_{wi}\} \cdot E\{T_{Rj}\}$$

$$= \lambda_j \cdot E\{T_{wi}\} \cdot E\{T_{Rj}\}$$

$$= \rho_j \cdot E\{T_{wi}\}$$

Lower PRIORITY CLASS
 \downarrow
 Actually should be of other ones!

$$E\{T_{ij}^*\} = E\{W_{ij}^*\} \cdot E\{T_{Sj}\}$$

$$= \lambda_j \cdot E\{T_{W_{ij}}\} \cdot E\{T_{Sj}\}$$

$$= \rho_j \cdot E\{T_{W_{ij}}\}$$

Customers in waiting line with priority lower than mine.

$$E\{T_{eS}\} = \frac{\lambda}{2} E\{T_S^2\}$$

Because of NO PREEMPTION!

Putting it all together we now have:

$$E\{T_{W_{i1}}\} = \sum_{j=1}^{i-1} E\{T_{ij}^*\} + \sum_{j=1}^{i-1} E\{T_{ij}^*\} + E\{T_{eS}\}$$

$$= \sum_{j=1}^{i-1} \rho_j \cdot E\{T_{W_{ij}}\} + \sum_{j=1}^{i-1} \rho_j \cdot E\{T_{W_{ij}}\} + \frac{\lambda}{2} \cdot E\{T_S^2\}$$

$$= \sum_{j=1}^{i-1} \rho_j \cdot E\{T_{W_{ij}}\} + \rho_i \cdot E\{T_{W_{i1}}\} + \sum_{j=1}^{i-1} \rho_j \cdot E\{T_{W_{ij}}\} + \frac{\lambda}{2} \cdot E\{T_S^2\}$$

$$= \sum_{j=1}^{i-1} \rho_j \cdot E\{T_{W_{ij}}\} + \rho_i \cdot E\{T_{W_{i1}}\} + E\{T_{W_{i1}}\} \sum_{j=1}^{i-1} \rho_j + \frac{\lambda}{2} \cdot E\{T_S^2\}$$

$$E\{T_{W_{i1}}\} \cdot \left(1 - \sum_{j=1}^{i-1} \rho_j - \rho_i\right) = \sum_{j=1}^{i-1} \rho_j \cdot E\{T_{W_{ij}}\} + \frac{\lambda}{2} \cdot E\{T_S^2\}$$

$$\Rightarrow E\{T_{W_{i1}}\} \left(1 - \sum_{j=1}^i \rho_j\right) = \sum_{j=1}^{i-1} \rho_j \cdot E\{T_{W_{ij}}\} + \frac{\lambda}{2} \cdot E\{T_S^2\}$$

$$\Rightarrow E\{T_{w_i}\} = \frac{\sum_{j=1}^{i-1} p_j \cdot E\{T_{w_j}\} + \frac{\lambda}{2} \cdot E\{\tau_s^2\}}{1 - \sum_{j=1}^{i-1} p_j}$$

WAITING TIME WITH PRIORITY!

Now set:

$$R_i = \sum_{j=1}^i p_j$$

$$R_0 = 0$$

For $i=1$, $E\{T_{w_1}\} = ?$ [TOP PRIORITY, GOLD]

$$E\{T_{w_1}\} = \frac{\sum_{j=1}^0 p_j \cdot E\{T_{w_j}\} + \frac{\lambda}{2} E\{\tau_s^2\}}{1 - \sum_{j=1}^0 p_j}$$

$$\Rightarrow E\{T_{w_1}\} = \frac{\frac{\lambda}{2} \cdot E\{\tau_s^2\}}{1 - \cancel{p_1}}$$

For $i=2$ $p_1 \cdot E\{T_{w_1}\}$

$$E\{T_{w_2}\} = \frac{\sum_{j=1}^1 p_j E\{T_{w_j}\} + \frac{\lambda}{2} \cdot E\{\tau_s^2\}}{1 - \sum_{j=1}^1 p_j}$$

$$\Rightarrow E\{TW_2\} = \frac{\lambda}{2} \cdot E\{TS^2\} + \rho_1 \cdot E\{TW_1\}$$

$$\lambda - \rho_1 - \rho_2$$

~~$E\{TW_2\}$~~ For $i=3$:

$$E\{TW_3\} = \sum_{j=1}^3 \rho_j \cdot E\{TW_j\} + \frac{\lambda}{2} \cdot E\{TS^2\}$$

$$\lambda - \rho_1 - \rho_2 - \rho_3$$

$$E\{TW_3\} = \rho_1 \cdot E\{TW_1\} + \rho_2 \cdot E\{TW_2\} + \frac{\lambda}{2} E\{TS^2\}$$

$$\lambda - \rho_1 - \rho_2 - \rho_3$$

Substitute $E\{TW_1\}$ into $E\{TW_2\}$

$$E\{TW_2\} = \rho_1 \cdot E\{TW_1\} + \frac{\lambda}{2} \cdot E\{TS^2\}$$

$$\lambda - \rho_1 - \rho_2$$

$$\Rightarrow E\{TW_2\} = \rho_1 \cdot \frac{\lambda}{2} \cdot E\{TS^2\} + \frac{\lambda}{2} \cdot E\{TS^2\}$$

$$\lambda - \rho_1$$

$$\lambda - \rho_1 - \rho_2$$

$$= \frac{\lambda}{2} \cdot E\{TS^2\} \cdot \left(\frac{\rho_1}{\lambda - \rho_1} + 1 \right)$$

$$= \frac{\lambda}{2} \cdot E\{TS^2\} \cdot \left(\frac{\rho_1 + \lambda - \rho_1}{\lambda - \rho_1} \right)$$

$$\lambda - \rho_1 - \rho_2$$

$$\Rightarrow E\{TW_2\} = \frac{\frac{\lambda}{2} \cdot E\{TS^2\}}{(1-p_1) \cdot (1-p_1-p_2)}$$

\Rightarrow In GENERAL:

$$E\{TW_i\} = \frac{\frac{\lambda}{2} \cdot E\{TS^2\}}{(1-R_{i-1}) \cdot (1-R_i)}$$

WAITING TIME for the i th-USER CLASS
M/G/1 WITH PRIORITIES

$$E\{TW_i\} = \frac{E\{TS\}}{(1-R_{i-1}) \cdot (1-R_i)}$$

NB: WAITING TIME WITHOUT PRIORITIES

$$E\{TW\} = E\{TW_i\} = E\{TS\}$$

$$E\{TW\} = \frac{\lambda \cdot E\{TS^2\}}{2(1-\rho)}$$

$$R_i = \sum_{j=1}^i p_j$$

$$R_{i-1} = \sum_{j=1}^{i-1} p_j$$

FORMULAS' SUMMARY: - NO PRIORITY

PFR CLASS:

$$E\{T_i\} = E\{T_{wi}\} + E\{T_{si}\}$$

$$E\{N_{wi}\} = \lambda_i \cdot E\{T_{wi}\}$$

$$E\{N_i\} = \lambda_i \cdot E\{T_i\} = \rho_i + E\{N_{wi}\}$$

$\underbrace{\hspace{10em}}_{E\{N_{si}\}}$

GLOBAL:

$$E\{T_w\} = \frac{1}{\lambda} \cdot \sum_{i=1}^n \lambda_i \cdot E\{T_{wi}\}$$

NOT
COMPULSIVE

$$E\{T\} = \frac{1}{\lambda} \sum_{i=1}^n \lambda_i \cdot E\{T_i\} = E\{T_s\} + E\{T_w\}$$

\triangleq L.F.

$$E\{N_w\} = \sum_{i=1}^n E\{N_{wi}\} = \sum_{i=1}^n \lambda_i \cdot E\{T_{wi}\}$$

$$E\{N\} = \sum_{i=1}^n E\{N_i\} = \rho + E\{N_w\}$$

NB: $E\{T_{wi}\} = E\{T_w\}$

only if there is NO
priority!

[i.e. NO PRIORITY
CLASSES]

M/G/1 λ INVARIANCE TO USER CLASS considered!
 QUEUE WITH MULTIPLE CLASSES: (PROOF ~~skipped~~)
~~WITHOUT PRIORITIES~~ $E\{T_w\}$ ~~WITHOUT PRIORITIES~~ $E\{T_w\} = E\{T_w\}$

$$E\{T_w\} = \frac{\lambda}{2} \cdot E\{T_s^2\}$$

$\lambda = \rho$

$$E\{T_w\} = \frac{\lambda}{2} \cdot E\{T_s^2\}$$

$(1-R_{i-1}) / (1-R_i)$

$$E\{T_v\}$$

WITHOUT PRIORITIES (Priority classes)

$$E\{T_v\} = \frac{\lambda}{2} \cdot E\{T_s^2\} \cdot \rho$$

$\lambda = \rho$

$$\Rightarrow E\{T_v\} = \rho \cdot E\{T_w\}$$

PROVE $E\{T_v\} = \rho \cdot E\{T_w\}$!
 WITH PRIORITY NO PRIORITY

WITH PRIORITIES (Priority classes)

$$E\{T_v\} = \sum_{i=1}^n E\{w_{w_i}\} \cdot E\{T_{s_i}\}$$

[All customers in other user classes] ~~with priority~~

$$= \sum_{i=1}^n \lambda_i \cdot E\{T_{w_i}\} \cdot E\{T_{s_i}\}$$

$$= \sum_{i=1}^n \rho_i \cdot E\{T_{w_i}\}$$

Because it's M/G/1 with priority

~~$$\frac{\lambda}{2} \cdot E\{T_s^2\} \cdot \sum_{i=1}^n \rho_i$$~~
~~$$(1-R_{i-1}) / (1-R_i)$$~~

$$= \sum_{i=1}^n p_i \cdot E\{T_{S^2}\}$$

$$= \sum_{i=1}^n p_i \cdot \frac{\lambda}{2} \cdot E\{T_{S^2}\} \frac{1}{(1-R_{i-1})(1-R_i)}$$

$$= \frac{\lambda}{2} \cdot E\{T_{S^2}\} \cdot \sum_{i=1}^n \frac{p_i}{(1-R_{i-1})(1-R_i)}$$

Consider $(1-R_{i-1}) - (1-R_i) = R_i - R_{i-1} = \sum_{j=1}^i p_j - \sum_{j=1}^{i-1} p_j = p_i$

$$(1-R_{i-1}) - (1-R_i) = (1 - \sum_{j=1}^{i-1} p_j) - (1 - \sum_{j=1}^i p_j)$$

$$= (1 - p_1 - p_2 - p_3 - \dots - p_{i-1}) - (1 - p_1 - p_2 - \dots - p_i)$$

$\Rightarrow p_i$ is the only survivor.

$$\Rightarrow (1-R_{i-1}) - (1-R_i) = p_i$$

$$\Rightarrow E\{T_{S^2}\} = \frac{\lambda}{2} \cdot E\{T_{S^2}\} \cdot \sum_{i=1}^n \frac{(1-R_{i-1}) - (1-R_i)}{(1-R_{i-1})(1-R_i)}$$

Remember: $R_0 = 0$ & BREAK the fractions:

$$\Rightarrow \frac{\lambda}{2} E\{T_{S^2}\} \left[\sum_{i=1}^n \frac{1}{1-R_i} - \sum_{i=1}^n \frac{1}{1-R_{i-1}} \right]$$

$$= \left(\frac{1}{1-R_1} + \frac{1}{1-R_2} + \dots + \frac{1}{1-R_n} \right) - \left(\frac{1}{1-R_0} + \frac{1}{1-R_1} + \dots + \frac{1}{1-R_{n-1}} \right)$$

$\Rightarrow \lambda < 1$ and $\frac{\lambda}{1-Rn}$ are true only **SURVIVORS.**

$$\Rightarrow E\{T_V\} = \frac{\lambda}{2} \cdot E\{T_S^2\} \left[\frac{1}{1-Rn} - 1 \right]$$

$$\Rightarrow E\{T_V\} = \frac{\lambda}{2} \cdot E\{T_S^2\} \cdot \left(\frac{\lambda - \lambda + Rn}{1 - Rn} \right) \quad \text{" } \rho$$

$$\Rightarrow E\{T_V\} = \frac{\lambda}{2} \cdot E\{T_S^2\} \cdot \frac{\rho}{1-\rho} = \rho \cdot E\{T_W\}$$

VIRTUAL TIME WITHOUT PRIORITIES is **INVARIANT** to the **USER CLASS** considered!

& it is equal to the **VIRTUAL TIME** without **PRIORITIES**:

$$E\{T_W\} = \frac{\lambda}{2} E\{T_S^2\} \cdot \frac{\rho}{1-\rho} = \rho \cdot E\{T_W\}$$

~~WITH PRIORITY~~
 $E\{T_V\}$

WITHOUT PRIORITY:

$$E\{T_V\} = \rho \cdot E\{T_W\}$$

WITH PRIORITY:

$$E\{T_V\} = \sum_{i=1}^n \rho_i \cdot E\{T_{W_i}\}$$

$$\Rightarrow E\{T_V\} = \rho \cdot E\{T_W\} = \sum_{i=1}^n \rho_i \cdot E\{T_{W_i}\}$$

⇒ CONSERVATION LAW: E{TV}

$$E\{TV\} = E\{TW\} = \frac{1}{\rho} \sum_{i=1}^n \rho_i \cdot E\{TW_i\}$$

No priority
WITH PRIORITY

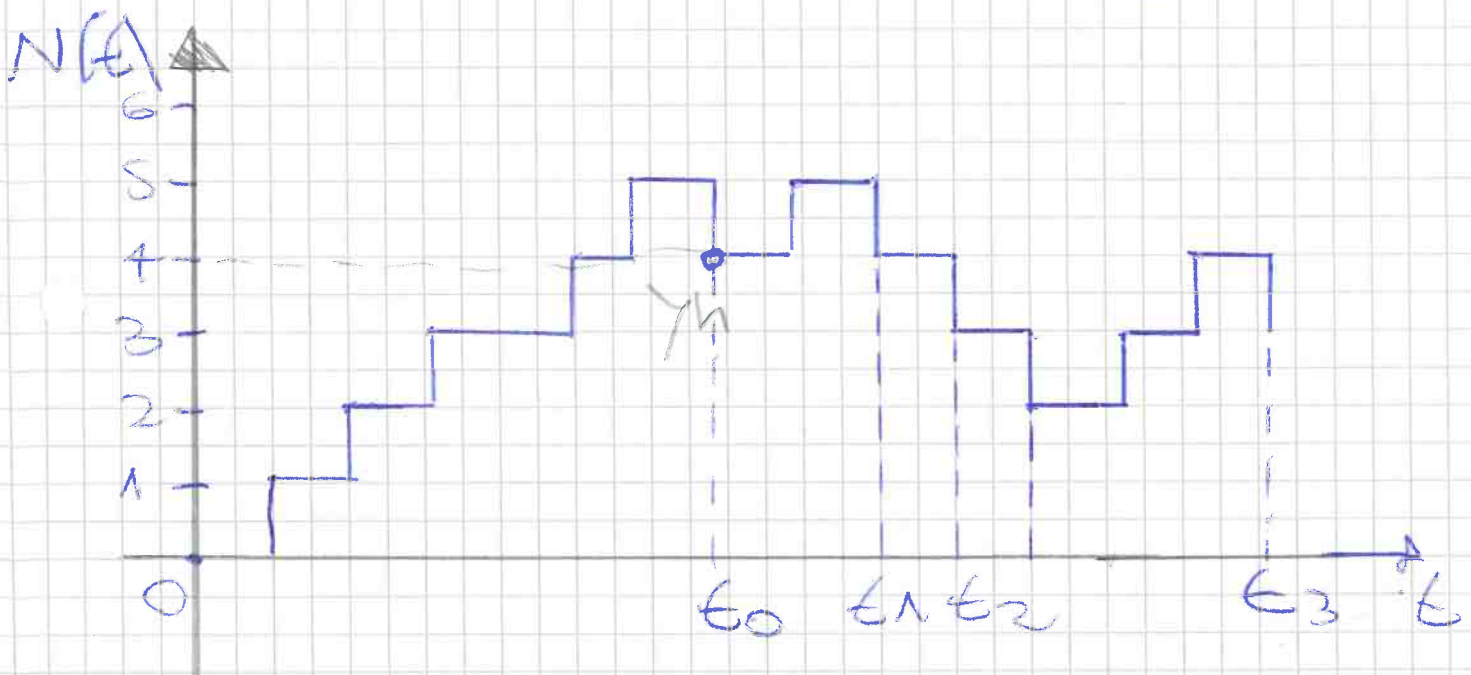
⇒ If having some classes with lower priority than others, there will be other classes with decreased performance.

⇒ BALANCE COEFFICIENTS!
 mean introducing priority
 ↳ worse service with high priority
 ↳ Better service with lower priority
 ↳ WAITING TIME in line!

~~[Essentially, ...]~~
 ⇒ Remaining somewhere!]

53) EMBEDDED MARKOV CHAIN APPROACH (DTMC) for M/G/1 QUEUES

We would like the STATE of the chain to be characterized uniquely by the # CUSTOMERS in the system.



⇒ Now consider the following two R.V.s:

$\{Y_n\}$ = # CUSTOMERS left in the system ^{C/D/E/C/E} by the n th-DEPARTURE SERVICE ~~CUSTOMERS~~ (What I see when "turning" my back after leaving the system)

$\{Z_n\}$ = # CUSTOMERS arriving to the queue ^{at next time} during the n th-SERVICE

customers going into the waiting line while I'm being served
 QUESTION: Could $\{Y_n\}$ be a DTMC?

ARRIVAL # CUSTOMERS AND DEPARTURE

$$Y_{N+1} = \begin{cases} (1) & Y_N + Z_{n+1} - 1 & Y_N > 0 \\ (2) & 1 + Z_{n+1} - 1 & Y_N = 0 \end{cases}$$

$(N-1)$ NEW CUSTOMERS ARRIVAL
 NEW CUSTOMERS ARRIVAL
 $(N-1)$ CUSTOMERS DEPARTURE
 (QUEUE NOT empty)
 (QUEUE NOT empty)
 (QUEUE NOT empty)
 (QUEUE NOT empty)
 (QUEUE NOT empty)
 (QUEUE NOT empty)

$Y_N > 0$

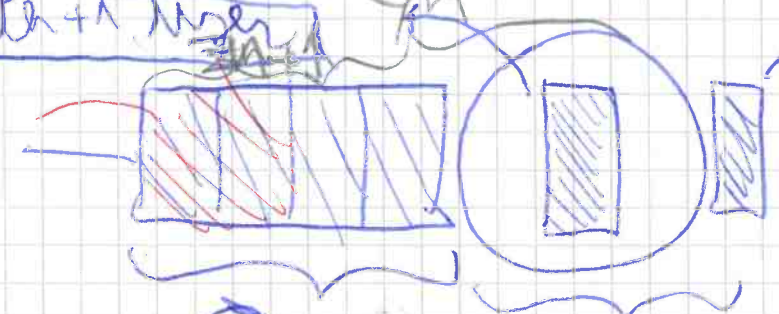
(WAITING LINE)

(1) Someone in the QUEUE - & in SERVICE CENTER

$n+1$ user

n user

Z_{n+1}



(new # customers)

Y_{n+1}

Y_N

$Y_N = 0$

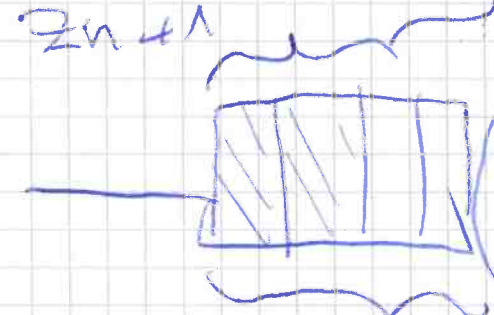
(WAITING LINE)

(2) Nobody in the QUEUE - & nobody in the SERVICE CENTER

Z_{n+1}

$Y_N = 0$

$n+1$ user



Y_{n+1}

⇒ If we now define:

$$n(z) = \begin{cases} 1 & \text{if } Y_N > 0 \\ 0 & \text{if } Y_N = 0 \end{cases}$$

⇒ We can then express Y_{n+1} as:

$$Y_{n+1} = Y_n + Z_{n+1} - (\mu(Y_n))$$

And if Y_n were a Markov Chain, then we would have that:

$$h_{ij} = P\{Y_{n+1} = j | Y_n = i\}$$

"Is this true"? Do we have a DTMC instance?

"If we look at certain time intervals of the M/G/1 QUEUE ~~is it a DTMC~~"

do we have a DTMC? ⇒ EXIT ONLY (leave queue) customers

↳ Spoiler: Yes, but only upon departure from the system. NON-MARKOVIAN

⇒ A DTMC found in an M/G/1 QUEUE is known as a HIDDEN MARKOV CHAIN.

By DO SUBSTITUTE VARIABLES (EMBEDDED) $h_{ij} = P\{Y_{n+1} = j | Y_n = i\} ⇒$ check if this holds true

$$h_{ij} = P\{Z_{n+1} - \mu(Y_n) = j - i\}$$

Where:

$i = Y_n = 0$ [First row of the matrix] ⇒ $P\{Z_{n+1} = j\}$ ONE-STEP TRANS. PROB. MATRIX

$i = Y_n > 0$ [NEXT rows of the matrix] ⇒ $P\{Z_{n+1} = j\}$ PMF

⇒ We now want to find:

$P\{Z_n = k\}$ ⇒ Apply **TOT. PROB. THEOREM**
 in **CONTINUOUS CASE**

↳ # CUSTOMERS arriving during the ~~field~~ **service** **ALL CONTRI**
 $P\{Z_n = k\} = \int_0^{\infty} P\{Z_n = k | \theta\} g(\theta) d\theta$
 (PPF of θ has been chosen)

By **WOLFE** ⇒ **POISSON** process in θ ⇒ **POISSON** ARRIVALS (like a **MARKOV CHAIN**)
 $= \int_0^{\infty} \frac{\lambda \theta}{k!} e^{-\lambda \theta} g(\theta) d\theta$

$P\{Z_n = k\} = P_k$

[Provided that **QUEUE** is **ERGODIC / STABLE**]

$\lambda \cdot E\{S\} < 1$

We have have a $A < 1$ **HIDDEN MARKOV CHAIN** **ACCESSES**
 i.e: All the **server** **is** **accessed**

⇒ We now write the **MATRIX** of **TRANSITION PROBABILITIES**.

Let $H = \begin{bmatrix} p_0 & p_1 & p_2 & \dots & p_k \\ p_0 & p_1 & p_2 & \dots & p_k \\ 0 & p_0 & p_1 & \dots & p_{k-1} \\ 0 & 0 & p_0 & p_1 & \dots & p_{k-2} \end{bmatrix}$ $\left. \begin{array}{l} h_{ij} = p_j \text{ if } i=0 \\ h_{ij} = p_{j-1} \text{ if } i > 0 \end{array} \right\}$

⇒ We have a **HOMOGENEUS DTMC** and we can evaluate its **STEADY-STATE** probabilities

$\pi^d \cdot \mu = \pi^d$ (in ERGODIC CONDITIONS)
 STEADY-STATE PROBABILITY - - - - - **ARBITRARY** VARIATIONS ONLY (PAST)

$\Rightarrow \pi_j^d = \pi_j^d = \pi_j^d$

What you see at the DEPARTURE = what you see at the ARRIVAL (What a random observer sees)

where $\pi_j^d = P\{Y_n = j\}$

Evaluate the STATIONARY PROBABILITY

\Rightarrow We hence have a **WOTMC** upon CUSTOMER DEPARTURE (i.e. the state is only given by the # of CUSTOMERS in the system)

S4 MEAN VALUE ANALYSIS - PROOF of P-K FORMULA
 (on the way to P-K FORMULA)

Recall: $Y_{n+1} = Y_n + Z_{n+1} - \mu(Y_n)$

all terms: $\Rightarrow E\{Y_{n+1}\} = E\{Y_n\} + E\{Z_{n+1}\} - E\{\mu(Y_n)\}$

with $\lambda \cdot E\{S\} < 1$ (ERGODICITY CONDITION)

~~BE~~

Because of **ERGODICITY**, a **STEADY-STATE** exists.

$\lim_{n \rightarrow \infty} E\{Y_{n+1}\} = E\{Y_n\} = E\{Y\}$

$\lim_{n \rightarrow \infty} E\{\mu(Y_n)\} = E\{\mu(Y)\}$

$\lim_{n \rightarrow \infty} E\{Z_n\} = E\{Z_{n+1}\} = E\{Z\}$

$\Rightarrow E\{Y_{n+1}\} = E\{Y_N\} + E\{Z_{n+1}\} - E\{\mu/Y_n\}$
 For
 lim
 $n \rightarrow \infty$: $E\{Y_N\}$ $E\{Y\}$ $E\{Z\}$

~~$\Rightarrow E\{Y\} = E\{Y\} + E\{Z\} - E\{\mu/Y_N\}$~~

$\Rightarrow E\{\mu/Y_N\} = E\{Z\}$

$\mu/Y = \begin{cases} 0 & \text{if the queue is empty} \\ 1 & \text{if the queue is not empty} \end{cases}$
 $Y_N = 0$ if the queue is empty
 $Y_N = 1$ if the queue is not empty

$\Rightarrow E\{\mu/Y\} = \frac{E\{N\}}{N_S} = \frac{E\{N\}}{1} = \rho$

$\Rightarrow E\{Z\} = \rho$

P-K FORMULA PROOF

We know that:

GOAL: Find $E\{Y\}$

$Y_{n+1} = Y_n + Z_{n+1} - \mu/Y_n$

Square all terms!

~~$Y_{n+1}^2 = Y_n^2 + Z_{n+1}^2 - 2Y_n Z_{n+1} + \mu^2/Y_n^2 - 2\mu Y_n/Y_n + \mu^2/Y_n^2$~~

SOURCE the LEFT & RIGHT-HAND SIDE:

$$|y_{n+1}|^2 = |y_n|^2 + |z_{n+1}|^2 + \mu |y_n| + 2y_n z_{n+1} - 2y_n \mu |y_n| - 2z_{n+1} \mu |y_n|$$

$$\mu |y_n| = y_n \quad \& \quad E \{ \mu |y_n| \} = E \{ z \}$$

Take $E \{ \cdot \}$ of all terms

$|z_{n+1}|, |y_n|$ & $|z_{n+1}|, \mu |y_n|$ INDEPENDENT

$$E \{ |y_{n+1}|^2 \} = E \{ |y_n|^2 \} + E \{ |z_{n+1}|^2 \} + E \{ \mu |y_n| \} + 2 E \{ y_n \} \cdot E \{ z_{n+1} \} - 2 E \{ y_n \} \mu - 2 E \{ z_{n+1} \} \mu$$

$$\Rightarrow = E \{ z^2 \} + E \{ z \} + 2 E \{ y \} \cdot E \{ z \} - 2 E \{ y \} - 2 (E \{ z \})$$

~~2E~~ We are interested in finding $E \{ y \}$

$$-2 E \{ y \} \cdot E \{ z \} + 2 E \{ y \} = E \{ z^2 \} + E \{ z \} - 2 (E \{ z \})$$

$$2 E \{ y \} (1 - E \{ z \}) = E \{ z^2 \} + E \{ z \} + E \{ z \} - E \{ z \} - 2 E \{ z \}$$

$$2 E \{ y \} (1 - E \{ z \}) = E \{ z^2 \} + 2 E \{ z \} - 2 E \{ z \} - E \{ z \}$$

$$2 E \{ y \} (1 - E \{ z \}) = 2 E \{ z \} [1 - E \{ z \}]$$

$$\Rightarrow 2 E \{ y \} (1 - E \{ z \}) = E \{ z^2 \} - E \{ z \} + 2 E \{ z \} [1 - E \{ z \}]$$

$$\Rightarrow E \{ y \} = \frac{E \{ z^2 \} - E \{ z \}}{2(1 - E \{ z \})} + \frac{2 E \{ z \} [1 - E \{ z \}]}{2(1 - E \{ z \})}$$

$$\Rightarrow E\{Y\} = \underbrace{E\{Z\}}_p + \frac{E\{Z^2\} - E\{Z\}}{2[1 - E\{Z\}]}$$

$$\Rightarrow E\{Y\} = p + \frac{E\{Z^2\} - p}{2 \cdot (1 - p)}$$

Where $E\{Z^2\}$ is: POISSON-DISTRIBUTION

$$E\{Z^2\} = \sum_{k=1}^{+\infty} k^2 \cdot P\{Z=k\} = \sum_{k=1}^{+\infty} k^2 \cdot \int_0^{+\infty} \frac{(\lambda\theta)^k}{k!} \cdot e^{-\lambda\theta} \delta_s(\theta) d\theta$$

$$= \int_0^{+\infty} \sum_{k=1}^{+\infty} k^2 \cdot \frac{(\lambda\theta)^k}{k!} \cdot e^{-\lambda\theta} \delta_s(\theta) d\theta = E\{Z^2\}$$

Consider the **POISSON DISTRIBUTION**.

$E\{X\} \leftarrow$ The AVERAGE # ARRIVALS $\lambda \theta (0, \theta) = \lambda\theta$

$\text{VAR}\{X\} \Rightarrow$ The VARIANCE is also $\lambda\theta$

\Rightarrow Take the VARIANCE FORMULA:

$$\text{VAR}\{Z\} = E\{Z^2\} - E\{Z\}^2$$

$$E\{Z^2\} = (E\{Z\})^2 + \text{VAR}\{Z\}$$

$$E\{Z^2\} = E\{Z\}^2 + \text{VAR}\{Z\}$$

$$E\{Z^2\} = \lambda^2 \theta^2 + \lambda\theta$$

$$\Rightarrow E\{Z^2\} = \int_0^{+\infty} (\lambda^2 \theta^2 + \lambda\theta) \cdot \delta_s(\theta) d\theta$$

$$= \lambda^2 \int_0^{+\infty} \theta^2 \cdot \delta_s(\theta) d\theta + \lambda \int_0^{+\infty} \theta \cdot \delta_s(\theta) d\theta$$

BREAK IT!

$$\Rightarrow \lambda^2 \int_0^{\infty} \theta^2 \cdot f_S(\theta) d\theta + \lambda \int_0^{\infty} \theta f_S(\theta) d\theta$$

$$= \lambda^2 \cdot E\{S^2\} + \lambda \cdot E\{S\}$$

$E\{S^2\} = \frac{E\{S^2\}}{\lambda^2} \cdot \lambda = \frac{E\{S^2\}}{\lambda}$

$$\Rightarrow E\{N\} = E\{Y\} = \rho + \frac{\lambda^2 \cdot E\{S^2\} + \lambda E\{S\}}{2 \cdot (1 - \rho)}$$

$$\Rightarrow E\{N\} = \rho + \frac{\lambda^2 \cdot E\{S^2\}}{2(1-\rho)}$$

P-R FORMULA, provided that:
 $\lambda \cdot E\{S\} < 1$

$$C_S = \frac{\theta_S}{E\{S\}} \Rightarrow C_S^2 = \frac{\theta_S^2}{E\{S\}^2} = \frac{E\{S^2\} - E\{S\}^2}{E\{S\}^2}$$

VARIANCE

$$E\{S^2\} \cdot C_S^2 = E\{S^2\} - E\{S\}^2$$

$$\Rightarrow E\{S^2\} \cdot (1 + C_S^2) = E\{S^2\}$$

$$E\{N\} = \rho + \frac{\lambda^2 \cdot E\{S^2\} \cdot (1 + C_S^2)}{2(1-\rho)}$$

By the above is EXPONENTIAL
 (i.e. like an M/M/1 QUEUE)

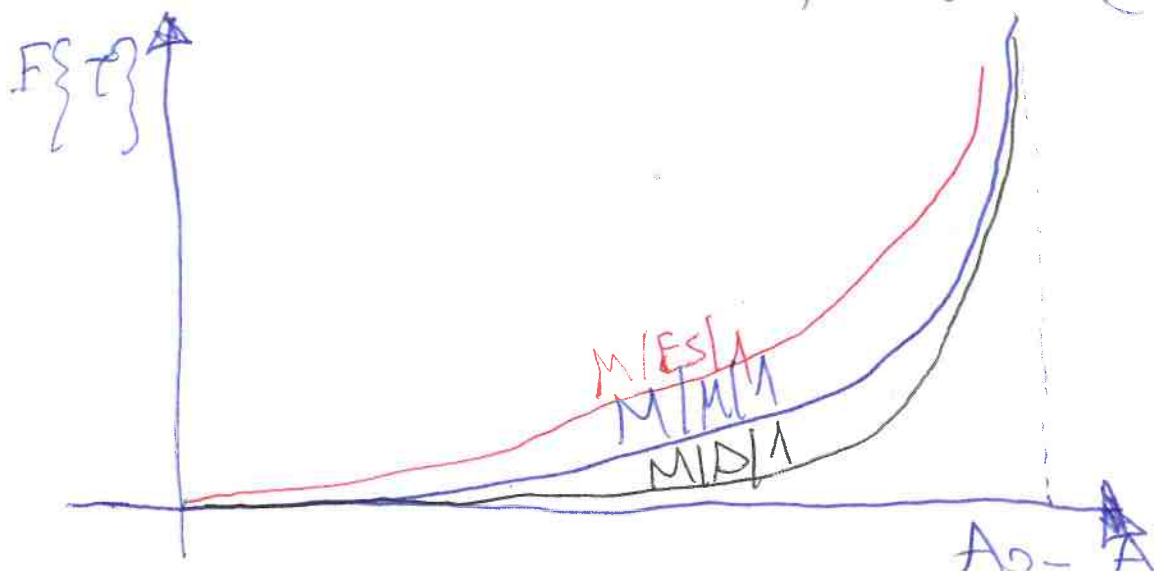
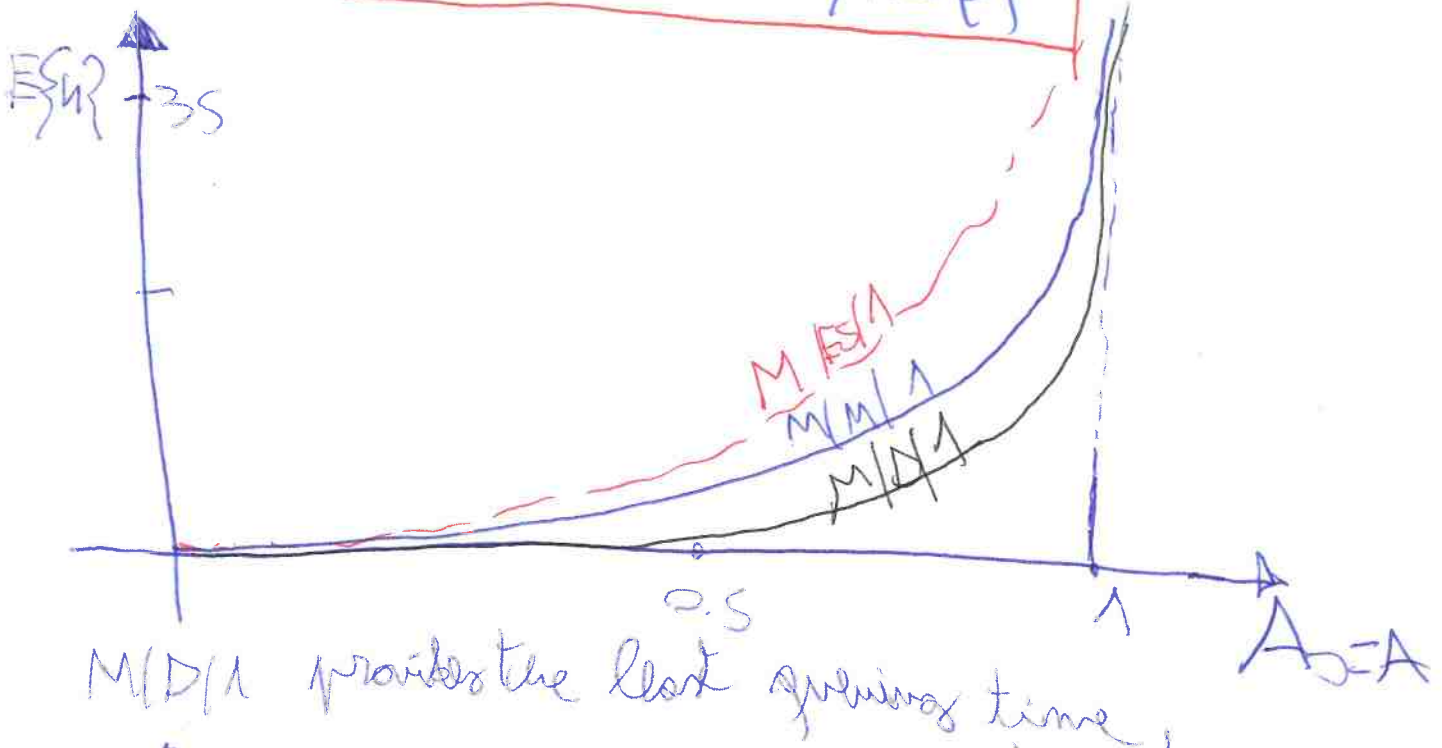
$$\Rightarrow E\{N\} = \rho + \frac{\rho^2}{1-\rho} = \rho + \frac{\rho + \rho^2}{1-\rho} = \frac{\rho^2}{1-\rho}$$

AVERAGE QUEUEING TIMES IN M/G/1 QUEUES.

$$E\{\tau\} = \frac{E\{n\}}{\lambda} = \frac{E\{N\}}{\lambda}$$

$$E\{\tau\} = E\{S\} + \frac{\lambda \cdot E\{S^2\}}{2(\lambda - \rho)} = \underbrace{E\{S\}}_{E\{\tau\}} + \underbrace{\frac{\lambda E\{S^2\}}{2(\lambda - \rho)}}_{E\{\tau_w\}}$$

$$\Rightarrow E\{\tau_w\} = \frac{\lambda \cdot E\{S^2\}}{2(\lambda - \rho)}$$



PERCENTILES in M/M/1 - M/M/1/∞ QUEUE

Don't limit ourselves to the analysis of mean values, but consider the DISTRIBUTION as well ⇒ stronger distribution can get all MOMENTUMS.

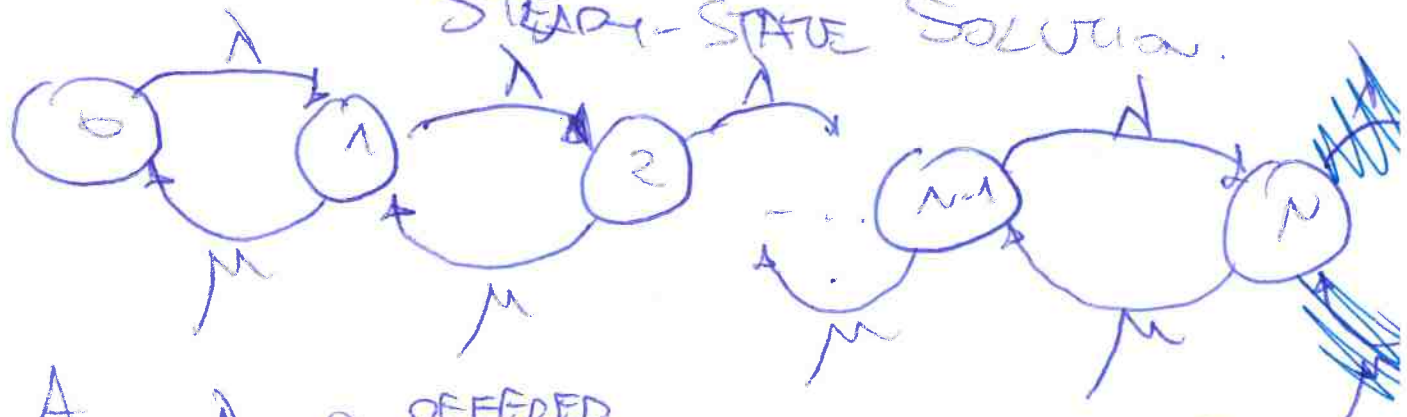
PERCENTILES IN QUEUES

Especially useful in DATA-driven analysis
 ⇒ Similar approach to CONFIDENCE INTERVAL

⇒ Consider M/M/1/NW QUEUE

$N = N_w + 1$ [FINITE-SIZE queue].

FINITE # STATES
 ⇒ APERIODIC ⇒ Also have a STEADY-STATE SOLUTION.



$A_0 = \frac{\lambda}{\mu}$ [OFFERED TRAFFIC INTENSITY] $\neq A$ [ACCEPTED TRAFFIC INTENSITY]

~~$\sum_{k=0}^{\infty} P_k = 1$~~

Find p_n :

$$\lambda p_0 = \mu p_1 \Rightarrow p_1 = \frac{\lambda}{\mu} p_0$$

$$\lambda p_1 = \mu p_2 \Rightarrow p_2 = \frac{\lambda}{\mu} p_1 = \frac{\lambda}{\mu} \cdot \frac{\lambda}{\mu} p_0 = \left(\frac{\lambda}{\mu}\right)^2 p_0$$

$$\lambda p_2 = \mu p_3 \Rightarrow p_3 = \frac{\lambda}{\mu} p_2 = \frac{\lambda}{\mu} \cdot \frac{\lambda}{\mu} \cdot \frac{\lambda}{\mu} p_0 = \left(\frac{\lambda}{\mu}\right)^3 p_0$$

$$\Rightarrow p_n = \left(\frac{\lambda}{\mu}\right)^n p_0$$

$$A_0 = \frac{\lambda}{\mu} \Rightarrow p_n = (A_0)^n p_0$$

\Rightarrow Find p_0 by applying $\sum_{k=0}^N p_k = 1$

$$\sum_{n=0}^N (A_0)^n p_0 = 1$$

$$\Rightarrow p_0 = \frac{1}{\sum_{n=0}^N (A_0)^n}$$

$$= \frac{1 - A_0}{1 - A_0^{N+1}} \quad 0 \leq n \leq N$$

\Rightarrow Use can then substitute p_0 into p_n :

$$p_n = (A_0)^n \cdot \frac{1 - A_0}{1 - A_0^{N+1}}$$

$$\sum_{i=0}^N (d)^i = \frac{1 - d^{N+1}}{1 - d}$$

Presently, we are interested in:

$$P_L = P_B$$

(because homogeneous process)

$$P_L = P_B = A_0^N \cdot (1 - A_0) / (1 - A_0^{N+1})$$

$$E\{N_B\} = A = A_0 (1 - P_L)$$



~~OFFERED~~ ACCEPTED TRAFFIC INTENSITY
(AVG. # BUSY SERVERS)

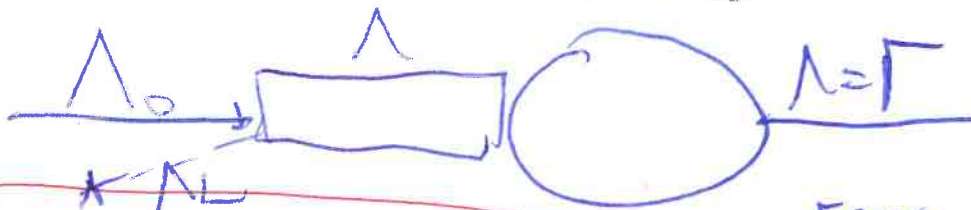
$$A_L = P_L \cdot A_0$$

REJECTED

TRAFFIC INTENSITY
(When saturated queue)

~~THROUGHPUT~~ THROUGHPUT

⇒ INTENSITY of exiting customers from the queue.



$$\Gamma = \Lambda = A_0 (1 - P_L)$$

FREQUENCY of exiting customers

$$\Lambda_L = \Lambda_0 \cdot P_L$$

FREQUENCY of accepted customers

↳ FREQUENCY of REJECTED (lost) customers

$$P_n = A_0^n \cdot \frac{1 - A_0}{1 - A_0^{N+1}} \quad 0 \leq n \leq N$$

$$\begin{aligned} \Rightarrow E\{n\} &= \sum_{k=0}^N k P_k = \frac{1 - A_0}{1 - A_0^{N+1}} \sum_{k=0}^N k A_0^k \\ &= \frac{1 - A_0}{1 - A_0^{N+1}} \sum_{k=0}^N k \cdot A_0^{k-1} \end{aligned}$$

Not considering BLOCKING CASE

(1) way: Use known series' formula

(2) way: Make the DERIVATIVE

$$\sum_{k=0}^N k \cdot A_0^{k-1} = \frac{d}{dA_0} \frac{1 - A_0^{N+1}}{1 - A_0}$$

~~$$E\{n\} = \frac{A_0}{1 - A_0} \cdot (1 + N)$$~~

$$= \frac{[(1 - A_0)^{N+1}]' \cdot (1 - A_0) - (1 - A_0^{N+1}) \cdot (1 - A_0)'}{(1 - A_0) \cdot (1 - A_0)^{N+1}}$$

$$E\{n\} = \frac{A_0}{1 - A_0} \frac{1 + N \cdot A_0^N - (N+1) \cdot A_0^N}{1 - A_0^{N+1}}$$

$$\Rightarrow E\{\tau\} = \frac{E\{n\}}{\Lambda} \quad \text{where } \Lambda = \Gamma = \lambda(1 - P_L)$$

$$\sum_{n=0}^N n \cdot A^{n-1} = \frac{d}{dA_0} \frac{1 - A_0^{N+1}}{1 - A_0}$$

$$\Lambda_L = \lambda \cdot PL$$

$$E\{n\} = \frac{A_0}{1 - A_0} \frac{1 + N \cdot A_0^N - (N+1) \cdot A_0^{N+1}}{1 - A_0^{N+1}}$$

$$\Rightarrow E\{\tau\} = \frac{E\{n\}}{\lambda}$$

SO FAR, we've only considered mean values.

Now:

Not only interested in mean value, but also in the distribution of the values.

Ex: VOICE DELAY ≤ 150 ms
 (MAXIMUM is relevant for ~~for~~ QoS)
 DETERMINISTIC STRICT GUARANTEE!

Worst-case analysis \rightarrow NETWORK CALCULUS

Theory for crossing logs (Bound)
 Performance of packet-switched networks with QoS & scheduling.

PERCENTILES



PERCENTILE [Consider ~~at~~ probability out of 1-100]

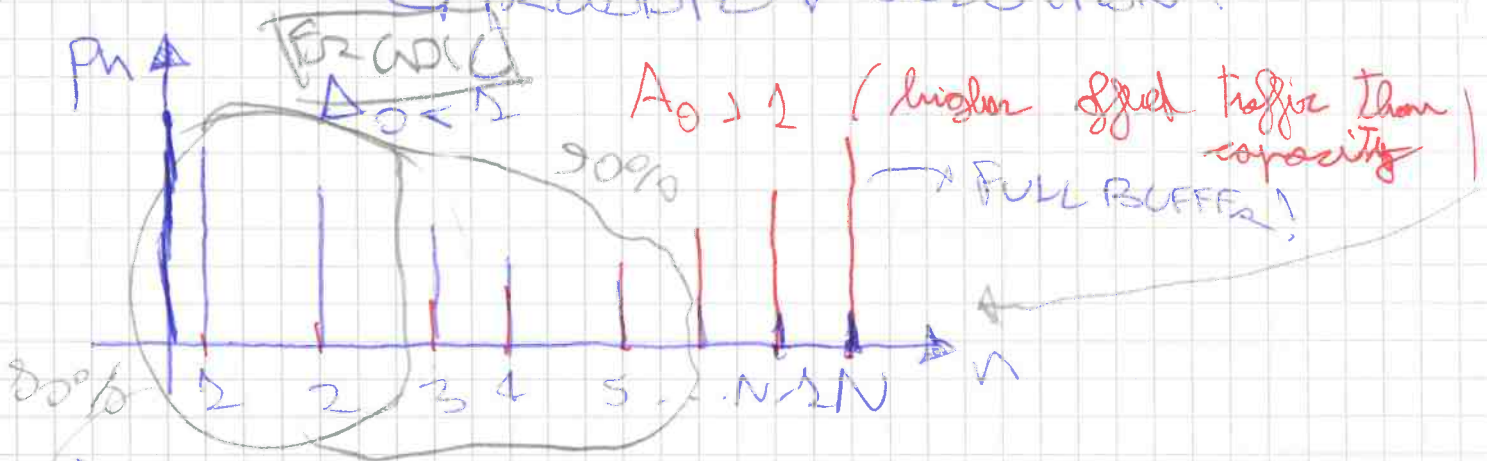
Value that does not surpass a certain threshold with a certain ~~percentage~~ (ϵ)

$$P\{n \leq N(\epsilon)\} = \epsilon$$

Annotations: $N(\epsilon)$ is VALUE (THRESHOLD), ϵ is PROBABILITY.

EX: 50% PERCENTILE \rightarrow Value (not being surpassed with 50% probability)

For an M/M/2/NW \hookrightarrow FRACIDIC SOLUTION!



Ex. Alpha \rightarrow losses with BUFFER.

$\lg \epsilon = 0.8 \Rightarrow N_{0.8} = 2$ (80%)

$\lg \epsilon = 0.9 \Rightarrow N_{0.9} = 6$ (90%)

Discrete DISTRIBUTION

DECILES (10 - 20 - 30 - ... - 100)

1st DECILE \Rightarrow 10% PERCENTILE

2ND DECILE \Rightarrow 20% PERCENTILE

QUANTILES [0-25]

1st QUANTILE \Rightarrow 25% 2ND QUANTILE [25-50%

8) PERCENTILE FOR M/M/1/NW QUEUES

1) FINDING PERCENTILE VALUE

PERCENTILE VALUE \rightarrow want to find this

$$P\{N \leq N_c\} = \sum_{n=0}^{N_c} P_n = \epsilon \Rightarrow \text{PERCENTILE'S VALUE}$$

GOAL:

Find N_c

Sum all Pns of the distributions up to the desired value (N_c)

We know:

$$P_n = (A_0)^n \cdot \frac{(1-A_0)}{1-A_0^{N+1}}$$

$$\Rightarrow \epsilon = \frac{(1-A_0)}{1-A_0^{N+1}}$$

$\sum_{n=0}^{N_c} A_0^n$
GOAL: Find N_c

$$= \frac{(1-A_0)}{1-A_0^{N+1}} \cdot \frac{1-A_0^{(N_c)+1}}{1-A_0}$$

$$\epsilon = \frac{1-A_0^{(N_c)+1}}{1-A_0^{N+1}}$$

$$\Rightarrow \epsilon (1-A_0^{N+1}) = 1-A_0^{(N_c)+1}$$

$$\Rightarrow A_0^{(N_c)+1} = 1 - \epsilon (1-A_0^{N+1})$$

~~$\log A_0^{(N_c)+1} = \log [1 - \epsilon (1-A_0^{N+1})]$~~
 ~~$\log A_0^{N_c+1} = \log A_0 + \log A_0^{N_c} = \log [1 - \epsilon (1-A_0^{N+1})]$~~

$$\Rightarrow N_{\Sigma} = \frac{\log[1 - \Sigma(1 - A_0)^{N+1}]}{\log A_0}$$

$$\Rightarrow N_{\Sigma} = \frac{\log[1 - \Sigma(1 - A_0)^{N+1}]}{\log A_0} - 1$$

By the LOGARITHMS' RULES:

$$\log_b(M^k) = k \cdot \log_b M$$

$$\log(A_0^{N_{\Sigma}+1}) = \log[1 - \Sigma(1 - A_0)^{N+1}]$$

$$(N_{\Sigma}+1) \log(A_0) = \log[1 - \Sigma(1 - A_0)^{N+1}]$$

$$\Rightarrow N_{\Sigma} + 1 = \frac{\log[1 - \Sigma(1 - A_0)^{N+1}]}{\log A_0}$$

$$\Rightarrow N_{\Sigma} = \frac{\log[1 - \Sigma(1 - A_0)^{N+1}]}{\log A_0} - 1$$

5) FINDING

PERCENTIVE VALUE

$0 \leq \Sigma \leq 1 \Rightarrow$ Not-integer N_{Σ}
 Write a proper Σ , can find a DISCRETE Σ

We know:

$$P_n = A_0^n \cdot (1 - A_0)$$

FOR $M/M/N/D$ QUEUE:
 $P_n = (1 - \rho) \rho^n$
 $A_0 < 1$

$$\Sigma = \sum_{n=0}^{N_{\Sigma}} P_n = (1 - A_0) \cdot \sum_{n=0}^{N_{\Sigma}} A_0^n$$

$$\Rightarrow \Sigma = (1 - A_0) \cdot \frac{(1 - A_0)^{N_{\Sigma}+1}}{(1 - A_0)}$$

Again, we are interested in $N\varepsilon$.

$$\varepsilon = 1 - A_0^{N\varepsilon+1}$$

$$\Rightarrow A_0^{N\varepsilon+1} = 1 - \varepsilon$$

$$\log(A_0^{N\varepsilon+1}) = 1 - \varepsilon$$

$$\Rightarrow (N\varepsilon+1) \cdot \log(A_0) = \log(1 - \varepsilon)$$

$$\Rightarrow N\varepsilon = \frac{\log(1 - \varepsilon)}{\log(A_0)} - 1$$

for $M/M/1/\infty$

Where if N

$$\varepsilon \approx \varepsilon \cdot A_0^{N+1}$$

$$\Rightarrow M/M/1 \approx M/M/1/N$$

(Similar approximation of INFINITE BUFFER with FINITE BUFFER)

$N \ll \infty$ $N \ll N$

$$\text{if } N\varepsilon \approx \varepsilon \cdot A_0^{N+1}$$

$\Rightarrow M/M/1/N$ is a GOOD APPROXIMATION of an $M/M/1/\infty$ queue

PDF of WAITING TIME in M/M/1

We know that in steady state: $\{T_w\}$ EXP. DISTRIBUTION

$$P_n = (1-\rho) \cdot \rho^n, \quad \rho = \frac{\lambda}{\mu}$$

We would like to find:

$$f_{T_w}(t) \Rightarrow \text{PDF of the WAITING TIME.}$$

IDEA.

Find $f_{T_w}(t|n)$, i.e.: PDF of waiting time based on the # CUSTOMERS you see upon arriving to the queue.

$$f_{T_w}(t|n) = \begin{cases} \delta(t) & n=0 \\ \frac{\mu}{n!} \frac{t^{n-1}}{(n-1)!} e^{-\mu t} & n \geq 1 \end{cases}$$

PDF of R.V. that has a no customers in queue line

- ① CUSTOMER: \Rightarrow Erlang-1 = exponential R.V. Exponential service \Rightarrow ^{RESIDUAL} wait (whole SERVICE) EXPONENTIAL
- ② CUSTOMERS:

~~RES~~ wait: RESIDUAL + Exponential service
exponential service

\Rightarrow Erlang-2 R.V. **IN GENERAL**

$$\textcircled{n} \text{ CUSTOMERS } \Rightarrow \text{ Erlang-}n \text{ R.V.}$$

~~IN GENERAL~~

⇒ We can put everything together to find $f_{TW}(t)$ considering all possible / combinations to cases.

⇒ $f_{TW}(t) = \sum_{n=0}^{\infty} f_{TW}(t|n) \cdot p_n$ (arr) WEIGHT

because POISSON ARRIVALS ⇒ entrance are same as random times

~~FAST~~

$= \sum_{n=0}^{\infty} f_{TW}(t|n) \cdot p_n$

⇒ $f_{TW}(t) = \underbrace{(1-p) \cdot \delta(t)}_{n=0} + \sum_{n=1}^{\infty} \underbrace{(1-p) \cdot p^n}_{n-1=k} \cdot \frac{\mu^n / n! \cdot e^{-\mu t}}{\mu}$

$= (1-p) \cdot \delta(t) + \mu(1-p) \cdot e^{-\mu t} \cdot p \sum_{n=1}^{\infty} \frac{p^{n-1} \cdot \mu^{n-1} / (n-1)!}{(n-1)!}$

$= (1-p) \cdot \delta(t) + \mu p (1-p) e^{-\mu t} \sum_{k=0}^{\infty} \frac{(\mu p)^k}{k!}$

$\sum_{k=0}^{\infty} \frac{x^k}{k!} = e^x$ IT IS EXP. DISTRIBUTION!

$= (1-p) \cdot \delta(t) + p \cdot \mu(1-p) \cdot e^{-\mu t} \cdot e^{\mu p t}$

$E\{NW\} = \frac{p}{1-p}$ BECAUSE OF EXP. DISTRIBUTION ⇒ in M/M/1 QUEUE

$E\{TW\} = 0 + p \cdot \frac{1}{\mu(1-p)}$

PDF OF WAITING TIME IS EXP. DISTRIBUTED

⇒ We can conclude that:

$E\{TW\} = \frac{1}{\mu} \cdot \frac{p}{1-p}$

* \Rightarrow LAST FEW STEPS EXPLAINED:

$$S_{\text{stuff}} = (1-p) \cdot \delta(x) + p \cdot \underbrace{\mu/(1-p)} \cdot e^{-\mu/(1-p)t}$$

$$\delta(x) = \begin{cases} +\infty & x=0 \\ 0 & x \neq 0 \end{cases}$$

PDF of an EXPONENTIAL RV

$$\lambda e^{-\lambda x}$$

$$E\{x\} = \frac{1}{\lambda}$$

\Rightarrow In this case

$$E\{x\} = \frac{1}{\mu/(1-p)}$$

$$\int_{-\infty}^{+\infty} \delta(x) dx = 1$$

$$\Rightarrow E\{\tau_w\} = 0 + \frac{p}{\mu/(1-p)}$$

for $t \neq 0$

$$\Rightarrow E\{\tau_w\} = \frac{p}{\mu(1-p)}$$

And the PDF of the WAITING TIME is EXPONENTIALLY DISTRIBUTED.

$$g(\epsilon) \otimes \delta(\epsilon) = g(\epsilon) \quad \Rightarrow$$

PDF of the QUEUING TIME IN M/M/1 QUEUES:

⇒ Now need to consider 2 R.V.'s PDF:

- 1) WAITING TIME'S PDF
- 2) SERVICE TIME'S PDF (Found before)

PDF of the WAITING TIME

$$f_{t|t} = [(1-p) \delta(t) + \mu(1-p) \cdot \rho \cdot e^{-\mu(1-p)t} \cdot \mu(t)]$$

$$\otimes [\mu \cdot e^{-\mu t} \cdot \mu(t)]$$

$$f_{t|t} = f_{t|t} \otimes f_{t|t}$$

$E\{T\} = E\{T\} + E\{T\}$

PDF of SERVICE TIME

$$= \mu(1-p) e^{-\mu t} \cdot \mu(t) + \mu^2 \cdot (1-p) \cdot \rho [e^{-\mu t} \cdot \mu(t)]$$

$$\otimes [e^{-\mu t} \cdot \mu(t)]$$

⇒ Again, apply ~~the~~ L-Transform to the convolved part. MULTIPLICATION would get a ~~...~~.

~~$$= \mu(1-p) \left[\frac{1}{s+\mu} + \mu \rho \frac{1}{s+\mu(1-p)} \cdot \frac{1}{s+\mu} \right]$$~~

$$f_{t|t} = \frac{\mu(1-p)}{s+\mu} + \frac{\mu^2 \cdot (1-p) \cdot \rho}{(s+\mu(1-p)) \cdot (s+\mu)}$$

$$= \mu(1-p) \cdot \left[\frac{1}{s+\mu} + \frac{\mu \rho}{(s+\mu(1-p)) \cdot (s+\mu)} \right]$$

$$= \mu(1-\rho) \cdot \frac{1}{s+\mu} \left[1 + \frac{\mu\rho}{s+\mu(1-\rho)} \right]$$

$$= \frac{\mu(1-\rho)}{s+\mu} \cdot \left[\frac{\cancel{s+\mu} - \mu\rho + \mu\rho}{s+\mu(1-\rho)} \right]$$

$$= \frac{\mu(1-\rho)}{s+\mu(1-\rho)}$$

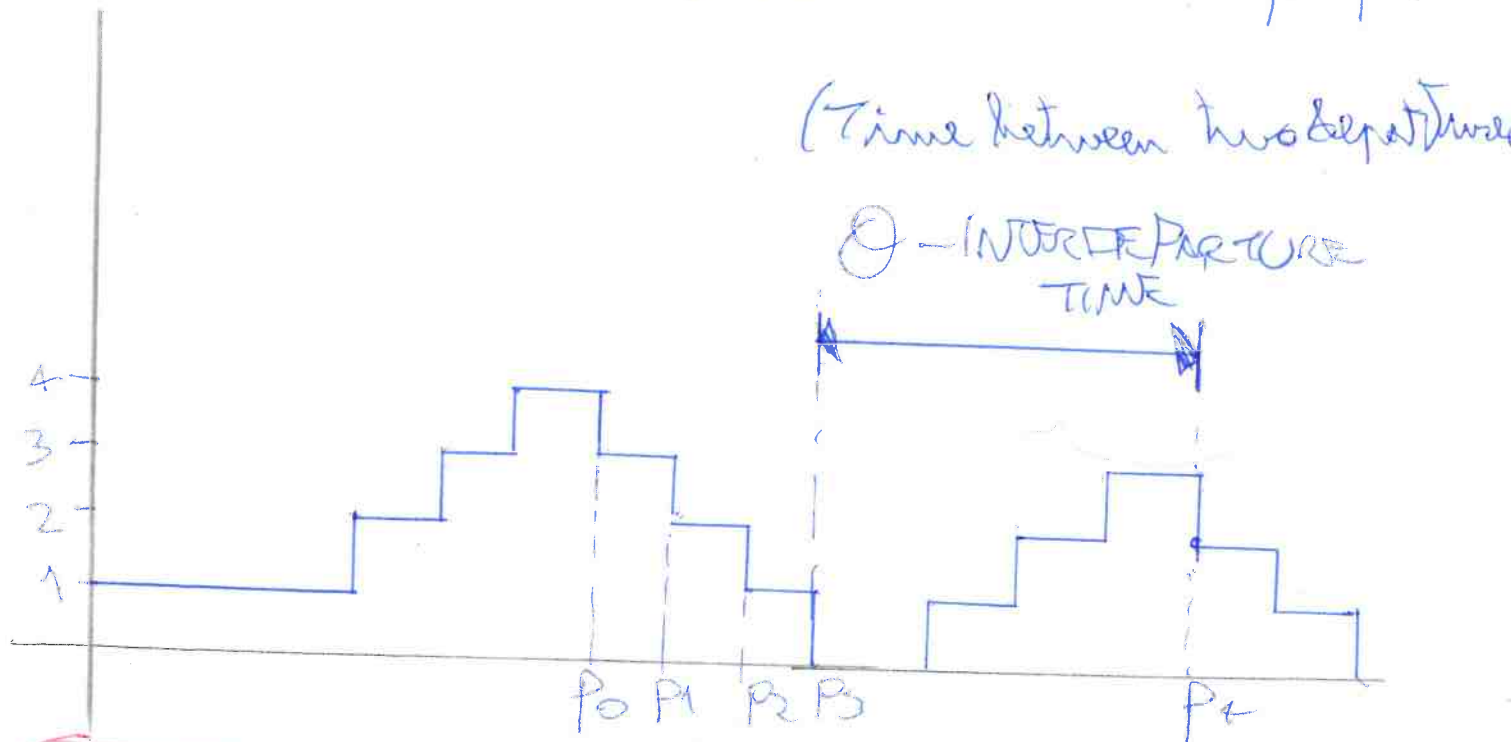
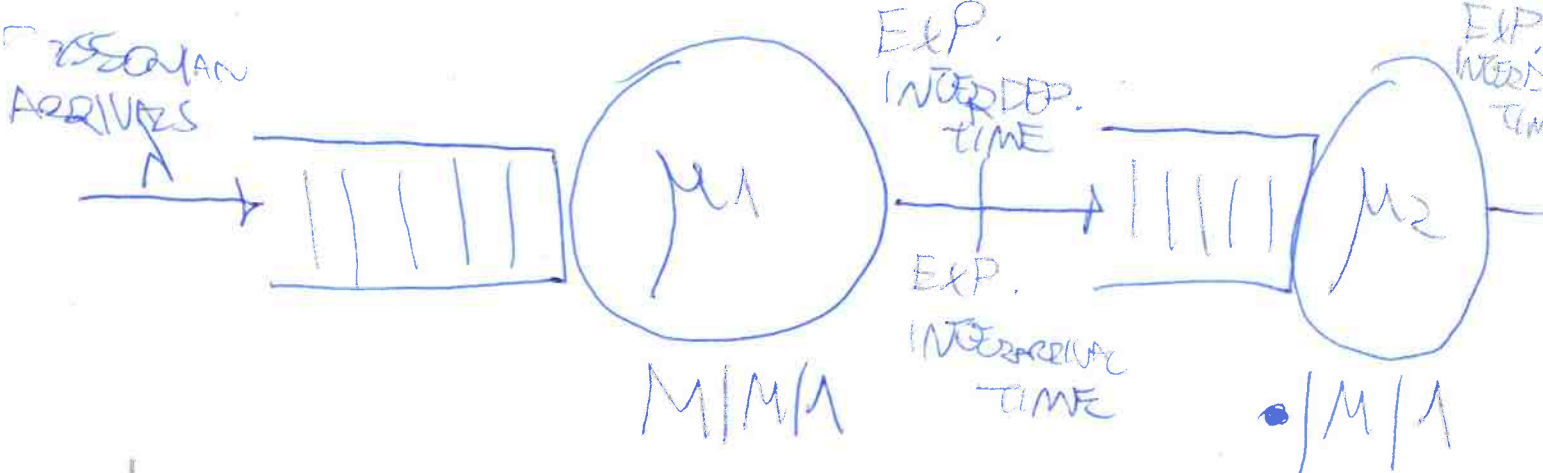
$$\mathcal{L}^{-1} \Rightarrow \boxed{f_T(t) = \mu(1-\rho) \cdot e^{-\mu(1-\rho)t} \cdot \mu(1-\rho)}$$

\Rightarrow The PDF of the **QUEUEING TIME** in **M/M/1** **QUEUES** is **EXPONENTIALLY DISTRIBUTED**.

$$\Rightarrow E\{W\} = \frac{\rho}{1-\rho}$$

$$E\{T\} = \frac{1}{\mu} \cdot \frac{1}{1-\rho} = \frac{\hat{\lambda}}{\mu(1-\rho)}$$

GA) NETWORKS of QUEUES - BURKE THEOREM



BURKE THEOREM'S THESIS:

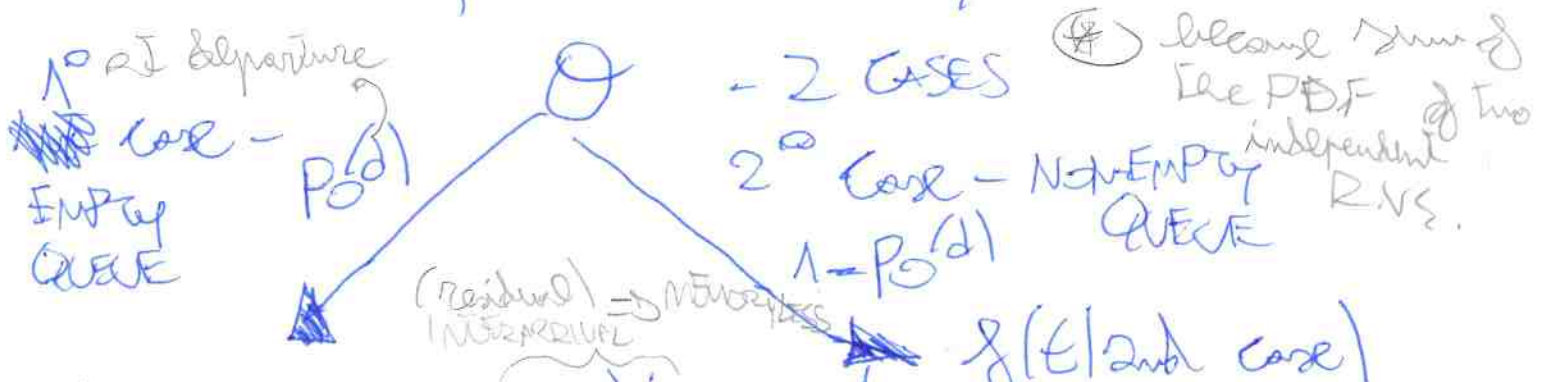
In $M/M/NS$ queues at steady-state, the departure process is still Poisson and is independent from the input one.

PROOF of BURKE THEOREM (not what I need to!)

We would need to show that, having Poisson arrivals, the interdeparture time is exponentially distributed and independent from the input one, in an $M/M/NS$ queue.

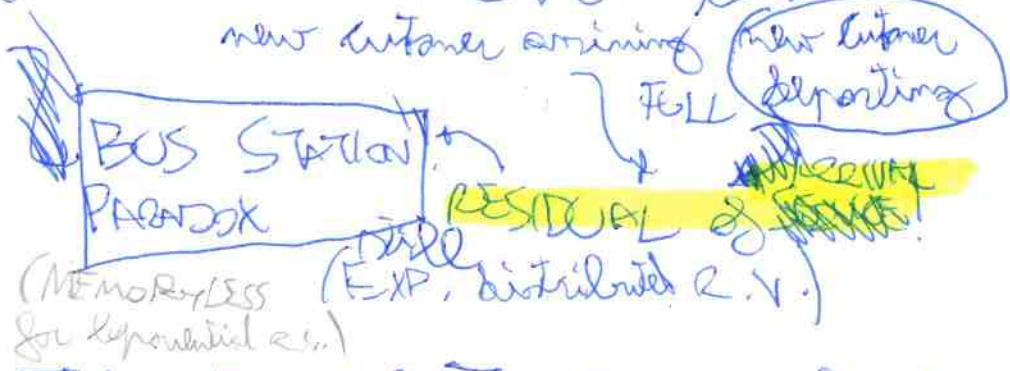
OUR POINT: In our case, we just show that, (\neq BURKE THEOREM!) showing POISSONIAN ARRIVALS, The departure process is still in an M/M/1 QUEUE.

$\Theta = R.V.$ corresponding to the interdeparture times in M/M/1 queues at STEADY STATE.



$f(t) \text{ 1st case} = \lambda e^{-\lambda t} \mu e^{-\mu t}$

$f(t) \text{ 2nd case} = \mu e^{-\mu t}$
 [SERVICE-TIME]
 finishing since
 finishing dep.



Take the L transform of case (1) and (2)

$$F(s) = P_0^{(d)} \frac{\lambda}{s+\lambda} \frac{\mu}{s+\mu} + (1-P_0^{(d)}) \frac{\mu}{s+\mu}$$

$P_0^{(d)} = P_0$ since the queue has UNITARY VARIATIONS. (as in M/M/1)

$P_0^{(d)} = P_0$ ~~for~~ ^{for} random order ~~to~~ ^{thanks to} PASTA PROPERTY. (POISSON ARRIVALS!)

$$P_0^{(d)} = P_0 = 1 - \rho = 1 - \frac{\lambda}{\mu}$$

$$1 - P_0^{(d)} = \lambda - \lambda(1 - \rho) = \rho = \frac{\lambda}{\mu}$$

$$\Rightarrow f(s) = \left[1 - \frac{\lambda}{\mu}\right] \frac{\lambda \cdot \mu}{(s + \lambda)(s + \mu)} + \frac{\lambda}{s + \mu}$$

$$= \frac{\mu - \lambda}{\mu} \frac{\lambda \cdot \mu}{(s + \lambda)(s + \mu)} + \frac{\lambda}{s + \mu}$$

$$= \frac{\lambda}{s + \mu} \left[\frac{\mu - \lambda}{s + \lambda} + 1 \right]$$

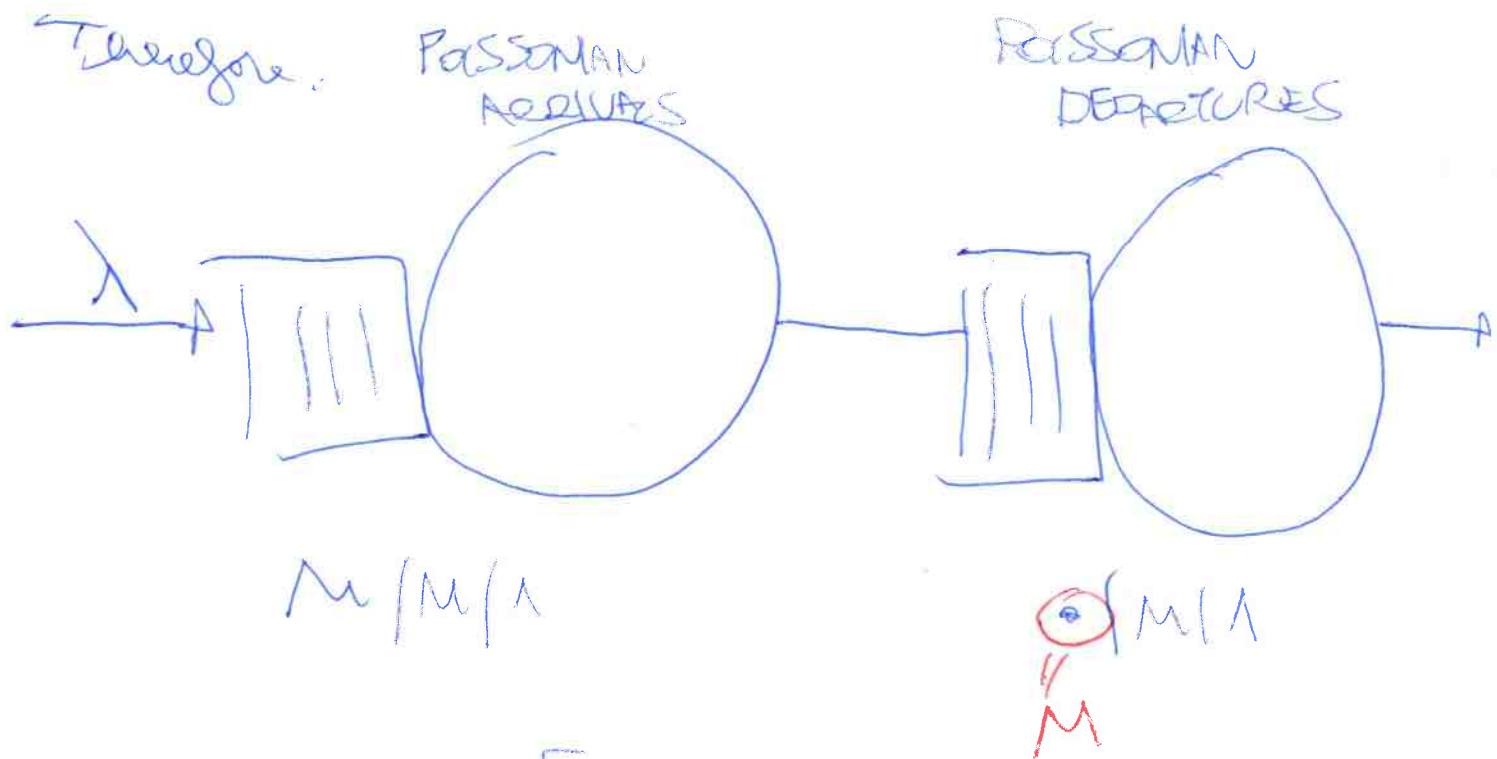
$$= \frac{\lambda}{s + \mu} \left[\frac{\mu - \lambda + s + \lambda}{s + \lambda} \right]$$

$$= \frac{\lambda}{s + \mu} \frac{s + \mu}{s + \lambda}$$

$$= \frac{\lambda}{s + \lambda}$$

$$\Rightarrow g(t) = \lambda \cdot e^{-t} \cdot \mu t e^{\lambda t}$$

\Rightarrow INTER DEPARTURE TIME is indeed
EXP. DISTRIBUTED!



Also, knowing: [NO FEEDBACK!]

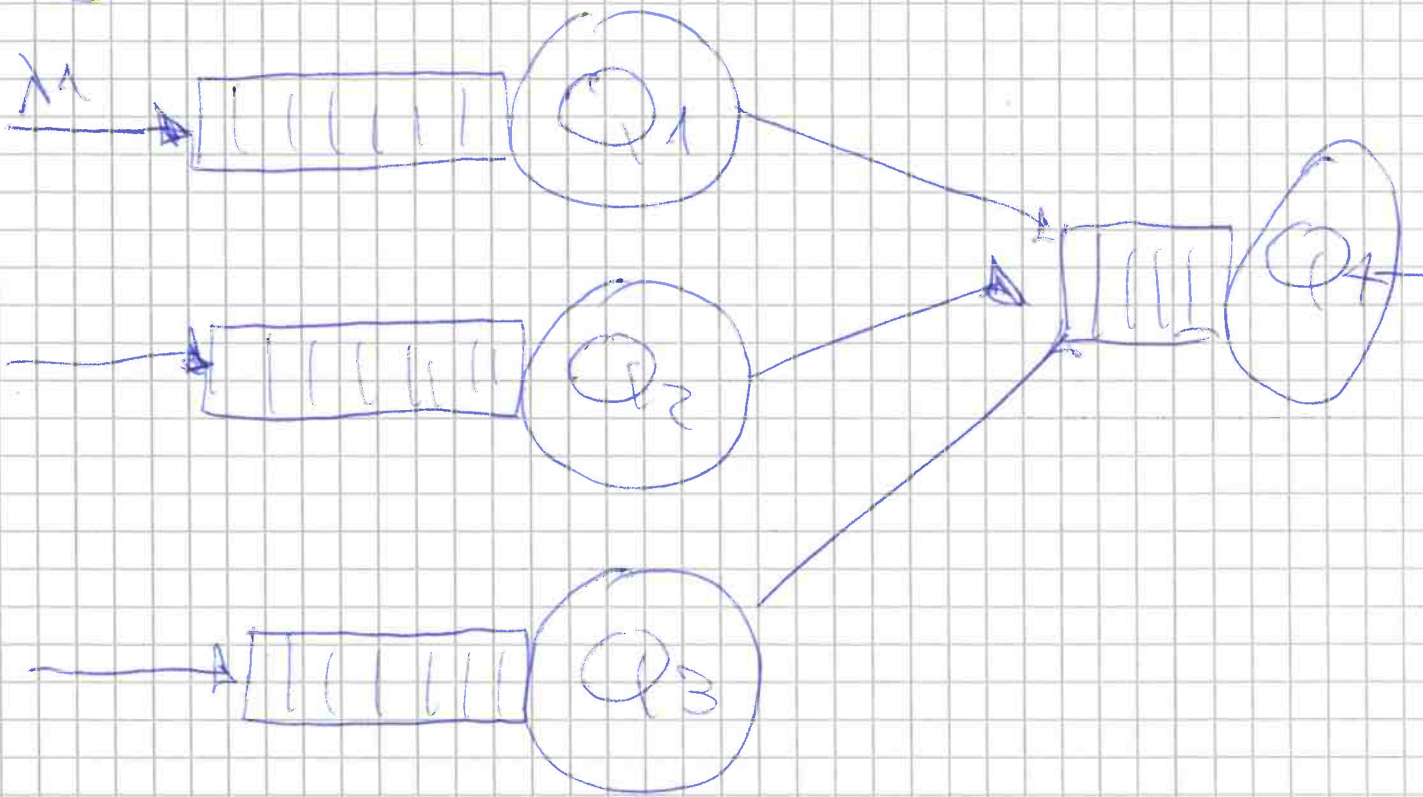
- STATISTICAL DECOMPOSITION of a POISSON process into (n) POISSON PROCESSES
- COMPOSITION of (n) POISSON PROCESSES to still a POISSON PROCESS
- BURKE THEOREM

\Downarrow

We can only study OPEN MARKOVIAN NETWORKS of queues without feedback.

If we have the result of Jackson THEOREM, we can study OPEN MARKOVIAN NETWORKS of queues with feedback. (i.e. treat non-Markovian queues as if they were Markovian!).

62 DEFINITION of OPEN MARKOVIAN NETWORKS of QUEUES.



OPEN NETWORK of QUEUES: Networks where we have customers coming in from the "External world" and going out to the external world (i.e. entering & leaving the queue).

STATE $N = (n_1, n_2, n_3, n_4)$

- a) STATE
 - ↳ # of CS in every single queue of the network
 - ↳ $n_i = \# \text{ of CS in queue } i$
 - ↳ $n = \# \text{ of CS in the network}$

NB. The STATE EVOLUTION process of a Markovian network of QUEUES is a Markov Chain (B&D in a dimension)

b) STATE PROBABILITY of a NETWORK: It is given by the PRODUCT-FORM SECTION.

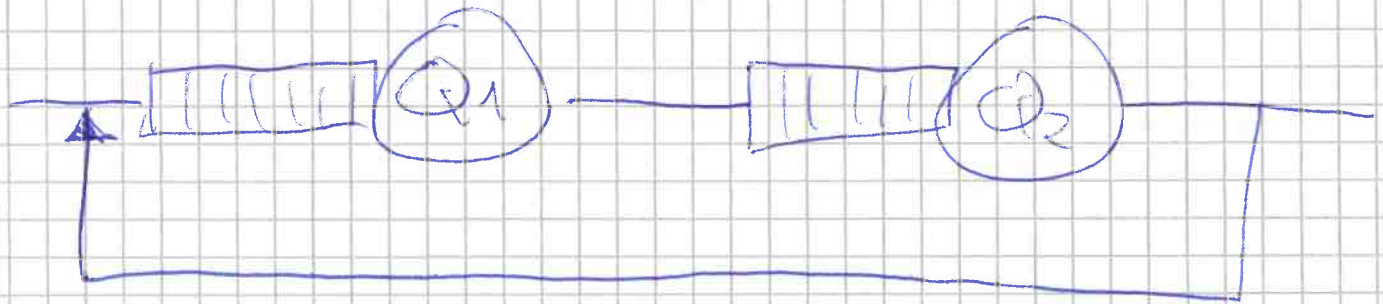
$$P_{k_1, k_2, \dots, k_n} = P_{k_1} P_{k_2} \dots P_{k_n}$$

STATE PROBABILITY

EXAMPLE:

M/M/1

M/M/1



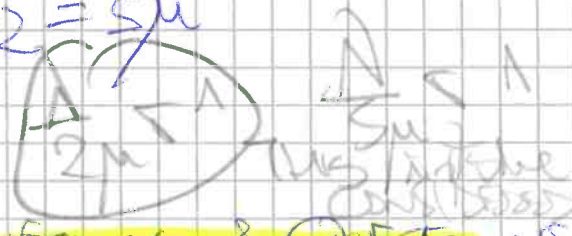
$$P_{k_1, k_2} = \left(1 - \frac{\lambda}{\mu_1}\right) \left(\frac{\lambda}{\mu_1}\right)^{k_1} \left(1 - \frac{\lambda}{\mu_2}\right) \left(\frac{\lambda}{\mu_2}\right)^{k_2}$$

ERGODICITY CONDITION of an Open Markovian Network of QUEUES.

$$\lambda < \min(\mu_1, \mu_2) \quad \text{[Feed-Back network]}$$

Ex: $\mu_1 = 2\mu, \mu_2 = 5\mu$

$$\Rightarrow \lambda < 2\mu$$



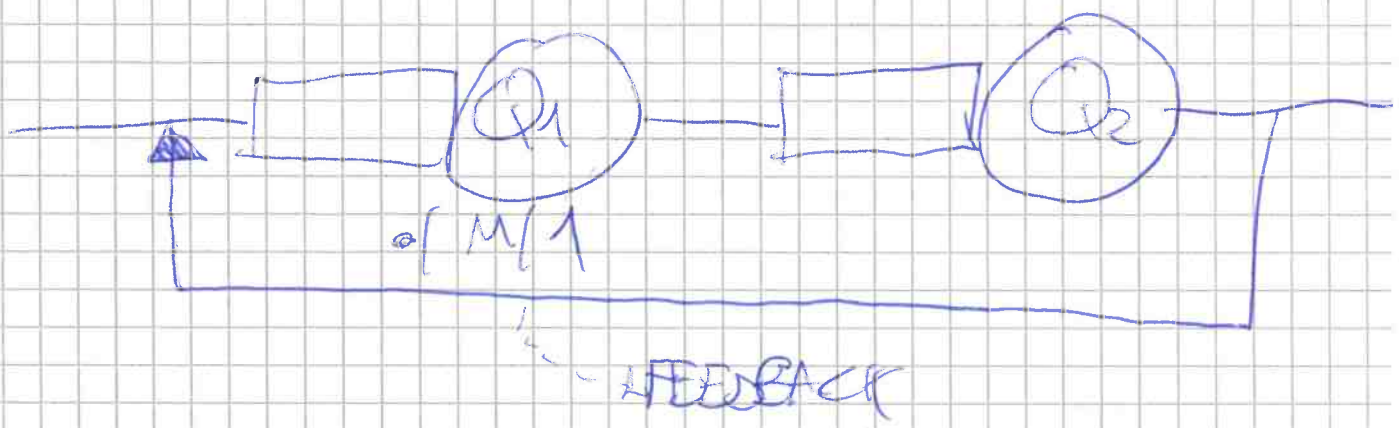
OPEN MARKOVIAN NETWORK of QUEUES VS NETWORK of QUEUES

63) An Open Markovian Network of Queues is an open network of queues only if every queue is MARKOVIAN (i.e. This only occurs if all the Markovian queues are without FEEDBACK).

FEEDBACK VS NO FEEDBACK

A network of QUEUES with feedback has queues with "ARBITRARY" service times in the feedback...

⇒ EXAMPLE: 1 TAP



However, this presents the Markovian nature from existing ⇒ NON-MARKOVIAN QUEUE!

⇒ the STATE no longer depends only on the current # CUSTOMERS, but also on the current "PHASE".

⇒ No independent arrivals!

We still have an OPEN MARKOVIAN NETWORK of QUEUES / with FEEDBACK [EVEN if the single queues are NOT MARKOVIAN and INDEPENDENT]

In this case,

⇒ We do have a: [THANKS TO JACKSON!]

OPEN MARKOVIAN NETWORK of QUEUES, but not an:

OPEN NETWORK of MARKOVIAN QUEUES

The SACKSON

THEOREM tells us that

we can study ~~any~~ ~~networks~~

NON-MARKOVIAN QUEUES / ~~with~~ NETWORKS of
or if ~~these~~ queues were MARKOVIAN!

57 RESULT OF JACKSON THEOREM:

↳ TRAFFIC EQUATIONS!

They are valid in STEADY-STATE and are used to solve the PRODUCT FORM SOLUTION of form ^{FOR MARKOVIAN} ~~NON-MARKOVIAN~~ QUEUES

$$P_{k_1 k_2} = \left(1 - \frac{\lambda_1}{\mu_1}\right) \cdot \left(1 - \frac{\lambda_2}{\mu_2}\right) \cdot \left(\frac{\lambda_1}{\mu_1}\right)^{k_1} \cdot \left(\frac{\lambda_2}{\mu_2}\right)^{k_2}$$

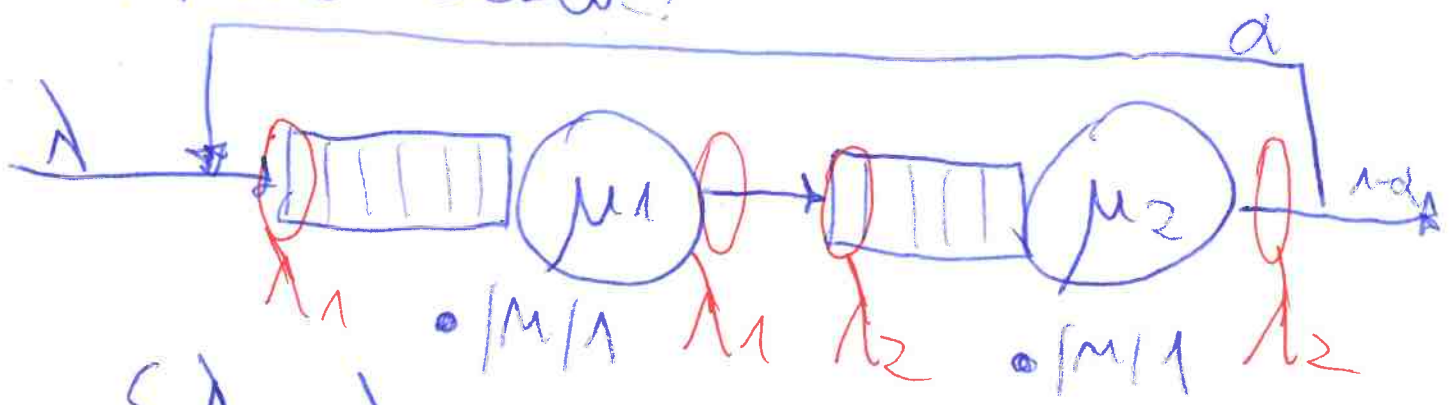
TRAFFIC / FREQUENCY EQUATIONS:

INPUT frequency of arrivals [AT STEADY STATE]

OUTPUT frequency of departure.

⇒ They allow us to find λ_1, λ_2 (as a function of λ/λ).

EXAMPLE USAGE:



$$\begin{cases} \lambda_1 = \lambda_2 \\ \lambda_1 = \lambda + \alpha \lambda_2 \end{cases}$$

[In exercises, we're using λ_1, λ_2 though]

$$\begin{aligned} \Rightarrow \lambda_1 &= \lambda + \alpha \lambda_1 \\ \Rightarrow \lambda_1 / (1 - \alpha) &= \lambda \end{aligned}$$

$$\Rightarrow \lambda_1 = \frac{\lambda}{1 - \alpha} = \lambda_2$$

⇒ We can then use the found λ_1, λ_2 to solve the ~~PRODUCT-FORM EQUATIONS~~ PRODUCT-FORM SOLUTION

INTERESTING RESULT of JACKSON'S

THEOREM:

[As one ~~is~~ ^{is} ~~was~~ ^{was} considering the queues ~~as~~ ^{as} MARKOVIAN & independent]

⇒ The PRODUCT-FORM ~~is~~ ^{holds} for ^{non} MARKOVIAN QUEUES ~~too~~ (the ones with feedback)

6.4 REQUIREMENTS of the JACKSON THEOREM

It can be applied to OPEN MARKOVIAN NETWORKS OF QUEUES

OPEN MARKOVIAN NETWORKS OF QUEUES (NO FEEDBACK)

OPEN MARKOVIAN NETWORKS OF QUEUES (WITH FEEDBACK)

↓
Queues are Markovian

↓
As if queues were Markovian

Some PRODUCT-FORM STRUCTURE & TRAFFIC EQUATIONS

REQUIREMENTS for a JACKSON NETWORK of QUEUES

If an Open Markovian Network of Queues Represents the following properties, then it is said to be a JACKSON NETWORK of QUEUES:

- Single class of users
- Infinite WAITING LINE, $M_i = \infty$ (Ex: $M/M/1/\infty$)
- Generic # QUEUES in the Network = Q
- Multiple servers N_{s_i} in each queue Q_i .
 $\Rightarrow M/M/m_i$ for Q_i .
- EXPONENTIAL SERVICE TIME in each queue Q_i .
 $E\{T_{s_i}\} = \frac{1}{\mu_i}$ in Q_i .
- POISSON ARRIVALS from external world.
 λ_i
- FCFS SCHEDULING / SERVING POLICY.
- $k_{ij} \Rightarrow$ Routing probability from Q_i to Q_j .

\Rightarrow JACKSON NETWORK of QUEUES if all the requirements are satisfied.

PROBABILITY to "Go out":

$$r_{i0} = 1 - \sum_{k=1}^Q r_{ik}$$

TRAFFIC EQUATIONS' FORM:

$$\frac{\lambda_i}{\lambda_i} = \delta_i + \sum_{j=1}^Q \lambda_j \cdot r_{ji} \quad \forall i, i \in [1, Q]$$

everything entering queue (i) from other queues (j)

everything entering queue (i) from the external world

~~not~~ ERGODICITY (STEADY-STATE CONDITION):

The network will be in STEADY-STATE only if every queue is ERGODIC.

$$\lambda_i < m_i \cdot \mu_i \quad \forall i, i \in [1, Q]$$

$$\Rightarrow \frac{\lambda_i}{\mu_i} < m_i$$

$$\rho_i = \frac{E\{n_{si}\}}{N_{si}} = \frac{\lambda_i}{\mu_i \cdot m_i} < 1$$

$$\rho < N_s$$

$$\Rightarrow \lambda < \min(\mu_1, \mu_2, \dots, \mu_n)$$

② How to operate with the JACKSON THEOREM:

STEP ①:

- a) Lay out the TRAFFIC EQUATIONS
- b) Solve the TRAFFIC EQUATIONS
- c) Verify that every queue is ERODOK.

STEP ②:

Consider each queue as an $M/M/m_i$ QUEUE [TRUE if NO feedback, not TRUE if NO feedback].

For an $M/M/N_i$ QUEUE:

$$P_{n_i} = \begin{cases} \left(\frac{\lambda_i}{\mu_i}\right)^n \cdot \frac{1}{n!} \cdot \rho_0 & n \leq N_i \\ \left(\frac{\lambda_i}{\mu_i}\right)^n \cdot \frac{1}{N_i!} \cdot \frac{1}{N_i^{n-N_i}} \rho_0 & n > N_i \end{cases}$$

SIMPLE DEFINITION of ρ_i

$$\rho_i = \frac{\lambda_i}{\mu_i \cdot m_i} \Rightarrow \frac{\lambda_i}{\mu_i} = \rho_i \cdot m_i$$

$$P_i(k_i) = \begin{cases} \rho_i(0) \cdot \frac{(\rho_i \cdot m_i)^{k_i}}{k_i!} & k_i \leq m_i \\ \rho_i(0) \cdot \frac{(\rho_i \cdot m_i)^{k_i}}{m_i!} \cdot \left(\frac{m_i}{N_i}\right)^{k_i - m_i} & k_i > m_i \end{cases}$$

$$\rho_i = \left(\frac{\lambda_i}{\mu_i \cdot N_i}\right)^n \cdot \frac{(\rho_i \cdot m_i)^{k_i}}{m_i^{k_i}}$$

STEP (3):

with no p₀ 4

Multiply the STATE PROBABILITY P_N with one another to obtain P_N (PRODUCT-FORM SOLUTION)

$$P_N = \prod_{i=1}^N p_i$$

$$\forall i \in [1, N]$$

b) FINDING OF PROOF OF JACKSON THEOREM

We want to obtain:

$$P(N) = P_{K1} P_{K2} \dots P_{KN}$$

Instead of building a complex multi-dimensional STATE TRANSITION DIAGRAM, we only consider a CONFIGURATION of jobs and then take the possible TRANSITIONS between them.

∴ We hence consider the following cases:

1. Someone enters the NETWORK of QUEUES from the EXTERNAL WORLD
2. Someone leaves the NETWORK of QUEUES and goes to the EXTERNAL WORLD
3. Someone moves within the NETWORK of QUEUES / i.e. internal transition

JACKSON'S THEOREM DEMONSTRATION:

[of the PRODUCT-FORM

~~$P_N = P_{K_1} P_{K_2} \dots P_{K_N}$~~ SOLUTION

Result of JACKSON'S THEOREM

$P_N = P_{K_1, k_1, \dots, k_i, \dots, k_j, \dots, k_N}$

1st-queue, i-th-queue, j-th-queue

VECTOR containing the #CUSTOMERS in each one of these N queues.

IDEA: Jackson, instead of trying to build a STATE TRANSITION DIAGRAM [MULTI-DIMENSIONAL] for a general open Markovian Network of queues, he considered only some GENERIC CONFIGURATIONS & STATES

~~states~~ ⇒ Only certain transitions are indeed possible!

3 POSSIBLE TRANSITIONS are possible within a NETWORK ⇒ Take 4 Configurations

Someone coming to states corresponding to these situations:

1. INITIAL SITUATION:

$N = C(k_1, \dots, k_i, \dots, k_j, \dots, k_N)$

2. SOMEONE ARRIVING TO QUEUE i FROM EXTERNAL

$N = i+1 = (k_1, \dots, k_i+1, \dots, k_j, \dots, k_N)$

(starts from 0 to 1)

3. SOMEONE LEAVING FROM QUEUE j TO EXTERNAL

$$N_{0,j} = (k_1, \dots, k_i, \dots, k_{j-1}, \dots, k_n)$$

4. SOMEONE (INTERNALLY) TRANSFERRING FROM QUEUE j TO QUEUE i

$$N_{i,j} = (k_1, \dots, k_{i+1}, \dots, k_{j-1}, \dots, k_n)$$

$k_{j-1} > 0$

TRANSITION TYPES:

1) ENTERING TRANSITION:

① $N_{0,j} \rightarrow N$
 $k_{j-1} \rightarrow k_j$
 SOMEONE (A CUSTOMER) ENTERS FROM EXTERNAL TO QUEUE j .
 Poisson process λ_j
 entering intensity λ_j

② $N \rightarrow N_{i,0}$
 $k_i \rightarrow k_{i+1}$

SOMEONE ENTERS FROM EXTERNAL TO QUEUE i .
 Poisson process λ_i
 entering intensity λ_i

2) EXITING TRANSITION:

② $N_{i,0} \rightarrow N$
 $k_{i+1} \rightarrow k_i$
 SOMEONE (A CUSTOMER) EXITS FROM THE NETWORK.
 (FROM QUEUE i TO THE EXTERNAL)

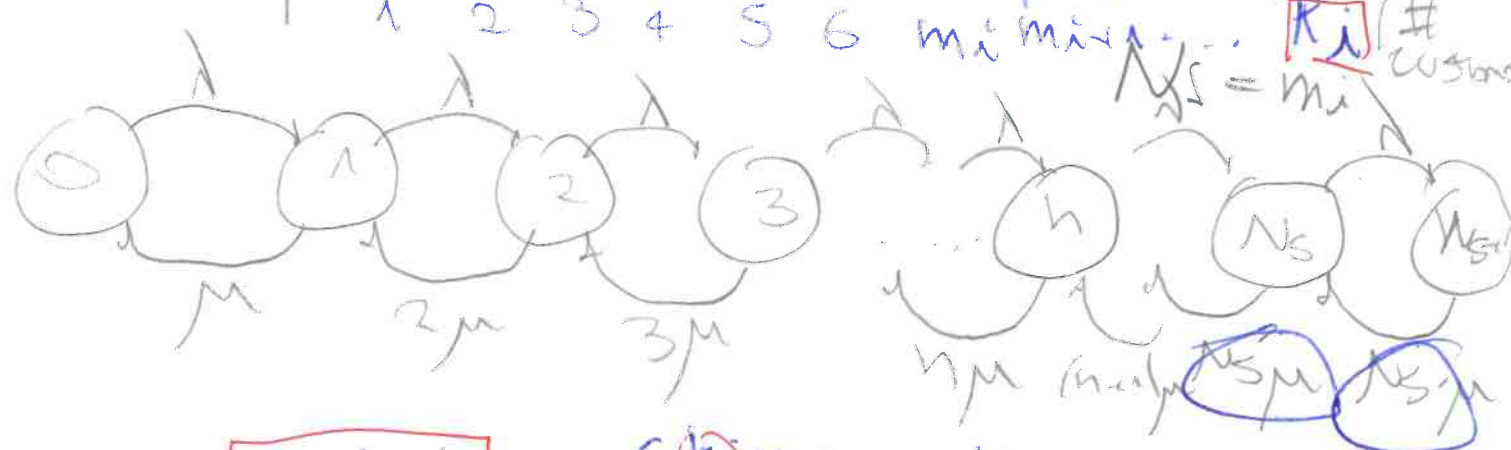
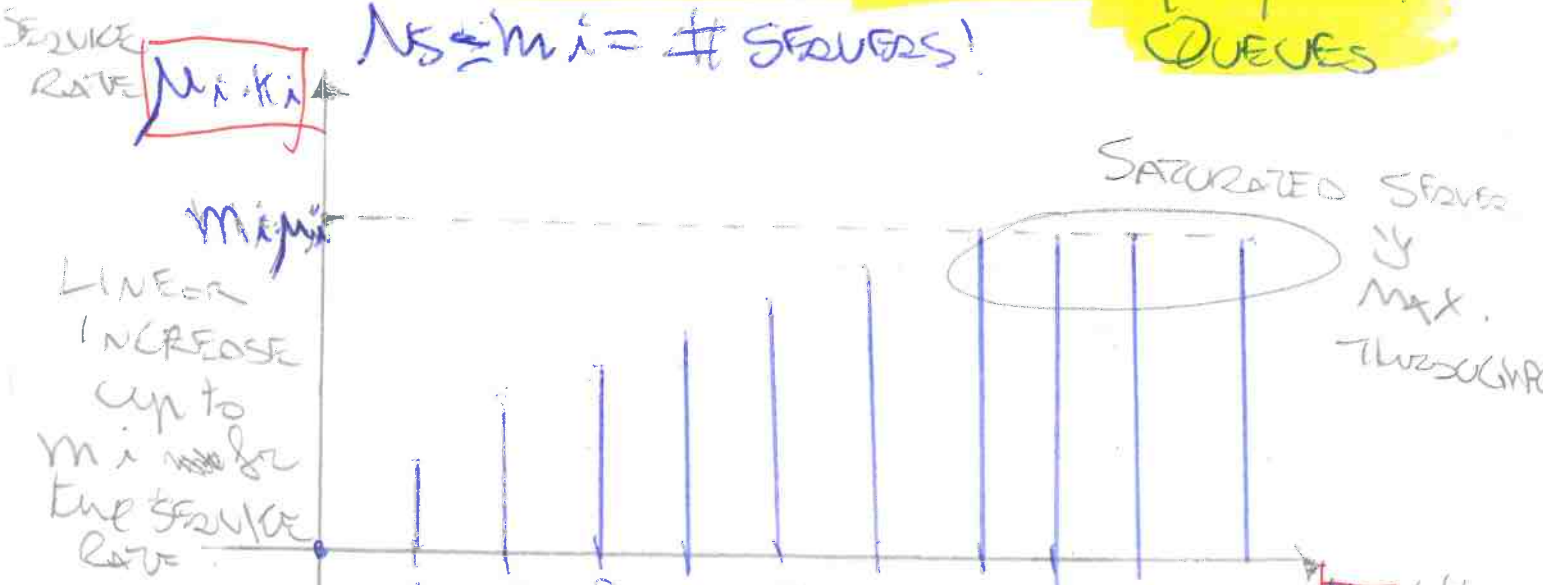
② $N \rightarrow N_{0,j}$
 $k_j \rightarrow k_{j-1}$

FROM QUEUE j TO THE EXTERNAL

EXITING from QUEUE i / QUEUE i is due to CUSTOMER SERVICING. \Rightarrow (2) and 2

\Downarrow

Consider SERVICE RATE μ_i M/M/M/1 QUEUES
 $N_s = m_i = \#$ SERVERS!



$$\mu_i(k_i) = \begin{cases} k_i \mu_i & k_i \leq m_i \text{ LINEAR INCREASE} \\ m_i \mu_i & k_i > m_i \text{ SATURATED SERVERS} \end{cases}$$

\Rightarrow Consider hence: $d_i(k_i) = \min(k_i, m_i)$ the COEFFICIENT of the rate



NB: In case of transition (2) before making there are $k_i + 1$ CUSTOMERS in QUEUE Q_i .

(2)

EXITING PROBABILITY = $\alpha_i (k_i + 1) \mu_i \delta_i$
 (from the network)

(2)

$\alpha_j (k_j) \mu_j \delta_j$

Where $\delta_i = 1 - \sum_{j=1}^Q \alpha_j \mu_j$

(3) INTERNAL MOVEMENT

(Same # customers in the system)

(3) $N_{i,j} \rightarrow N$

$k_{i+1}, k_{j-1} \rightarrow k_i, k_j$

SOMEONE (1 customer) MOVES FROM QUEUE i TO QUEUE j .

Probability of INTERNAL MOVEMENT =

$$\alpha_i (k_i + 1) \mu_i \delta_i$$

(3)

$N \rightarrow N_{i,j}$

$k_i, k_j \rightarrow k_{i+1}, k_{j-1}$

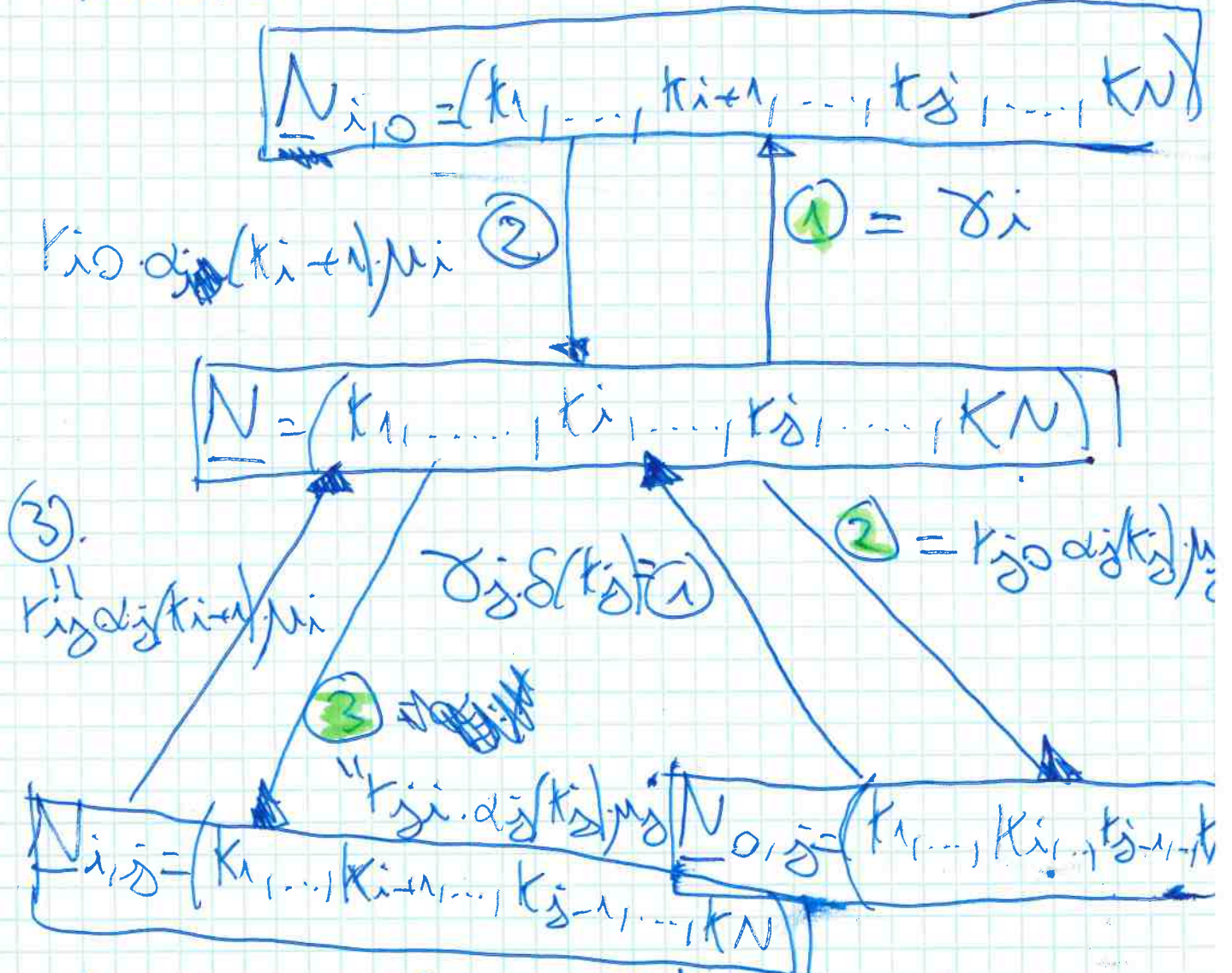
CUSTOMER MOVING FROM QUEUE j TO QUEUE i

Where $\delta(k_i) = \begin{cases} 1 & \text{if } k_i \geq 1 \\ 0 & \text{otherwise} \end{cases}$
 (moving leaving)

DELTA of KRONDELTA

(Can never have less than 1 customer!)

⇒ We can then modelise such transitions:



$$\Rightarrow \delta(k_j) = \begin{cases} 1 & \text{if } k_j \geq 1 \\ 0 & \text{otherwise} \end{cases}$$

→ DELTA of KRONECKER.

⇒ JACKSON'S SMART IDEA: We can now apply the FCP to P_N for the EXIT FLOW

$$P_N \left[\sum_{i=1}^N \delta_i + \sum_{j=1}^N \left[\sum_{i=1}^N k_{ji} \alpha_j / \mu_j + \alpha_j / \mu_j \right] \right]$$

(1) → from EXTERNAL ARRIVALS to i
 (3) INTERNAL FROM OTHER STATES i to j
 (2) EXTERNAL FROM j to exit

Because of POISSONIAN INPUTS from the EXTERNAL WORLD, we would have INFINITELY many states!

→ bezieht sich nur auf den ersten Teil!

$$P_N \left[\sum_{i=1}^N \delta_i + \sum_{j=1}^N \left[\sum_{i=1}^N \alpha_{ij}(k_{ij}) \mu_j \cdot r_{ji} + \alpha_{ij}(k_{ij}) \mu_j \cdot r_{j0} \right] \right]$$

$$P_N \left[\sum_{i=1}^N \delta_i + \sum_{j=1}^N \alpha_{ij}(k_{ij}) \mu_j \left[\sum_{i=1}^N r_{ji} + r_{j0} \right] \right]$$

$$\Rightarrow \underline{P_N} \left[\sum_{i=1}^N \delta_i + \sum_{j=1}^N \alpha_{ij}(k_{ij}) \mu_j \right] \sum_{i=1}^N r_{ji} = 1$$

EXIT FLOW FROM P_N

⇒ Now consider the INPUT FLOW ①/②/③ INTO P_N

$$\sum_{i=1}^N P_{N, i, 0} \alpha_{i, i+1}(k_{i+1}) \mu_i \cdot k_{i0} + \sum_{j=1}^N P_{N, 0, i, j} \delta_j \cdot \delta(k_{ij})$$

$$+ \sum_{i=1}^N \sum_{j=1}^N P_{N, i, j} \alpha_{i, i+1}(k_{i+1}) \mu_i \cdot k_{ij}$$

Solution:

$$\Gamma_N \text{ EXIT FLOW} = \Gamma_N \text{ INPUT FLOW}$$

⇒ We can then obtain the PRODUCT-FORM SOLUTION from these GLOBAL BALANCE EQUATIONS for an OPEN MARKOVIAN NETWORK of QUEUES with NO FEEDBACK & 20 MARKS & COMPUTATIONS!!

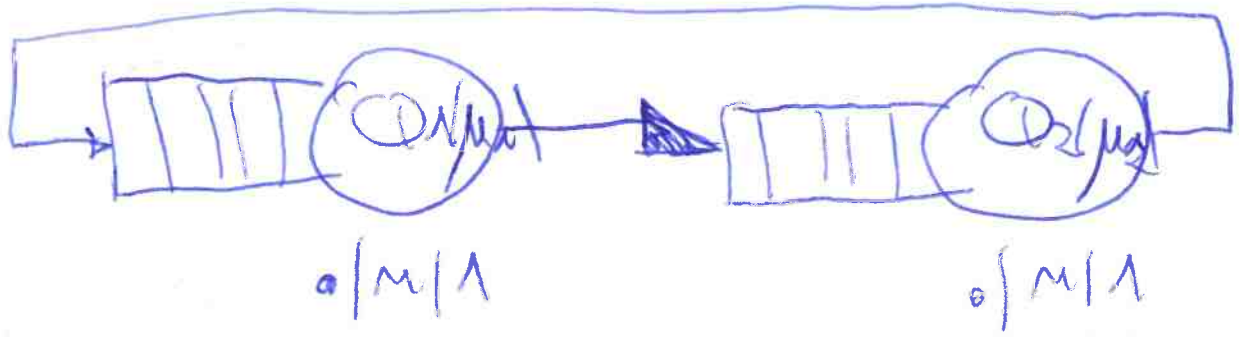
CLOSED MARKOVIAN NETWORK OF

QUEUES:

CLOSED:

CONSTANT (same) # CUSTOMERS in the SYSTEM. (no INPUT (output) leaving customers)

OPEN: We do have INPUT ARRIVALS / customers leaving the system

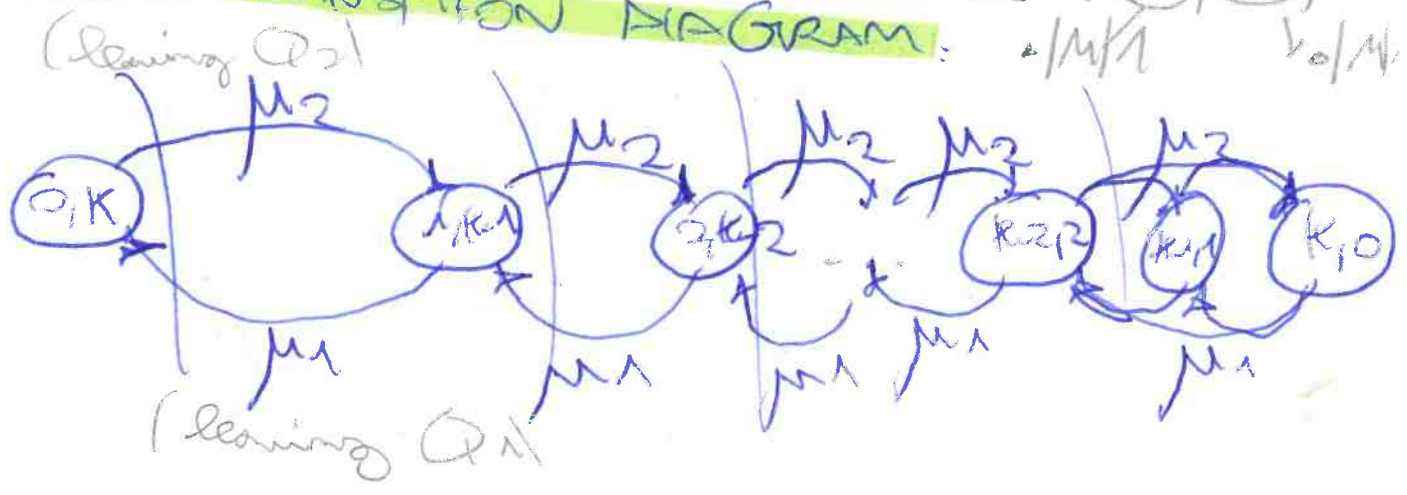


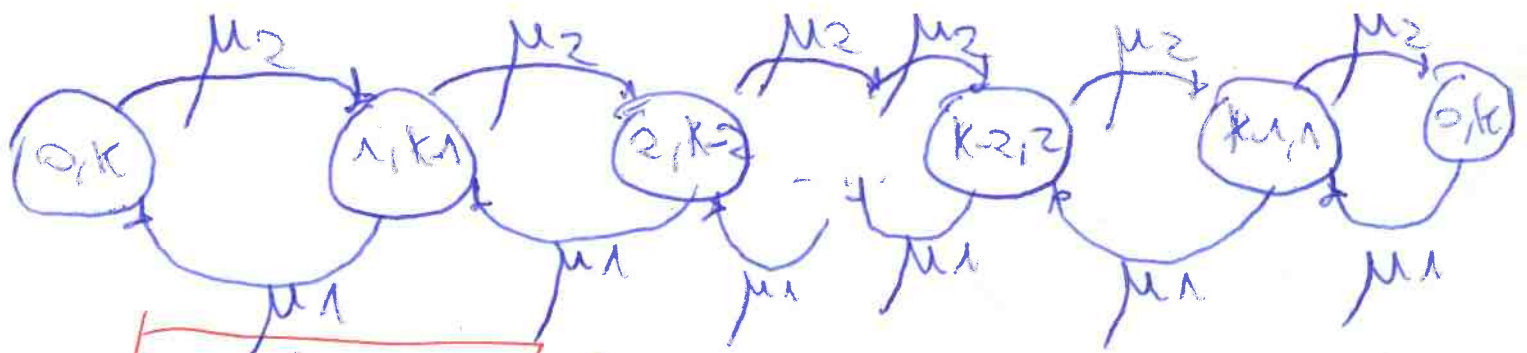
STATE = K ⇒ MARKOVIAN network of queues. ⇒ So, the state is ONLY characterized by the # CUSTOMERS in the system.

#customers in Q_1 \rightarrow n_1, n_2 #customers in Q_2

Also need EXPONENTIAL DISTRIBUTION of the SERVICE CENTER to have a MARKOVIAN network of queues.

STATE TRANSITION DIAGRAM: $\lambda = (\mu_1, \mu_2)$





$\mu_1 + \mu_2 = k$ (constant # customers in the queue)

⇒ Apply FCP to find the STATE PROBABILITY

$$\Gamma_0: \mu_2 \cdot P_{0,k} = \mu_1 \cdot P_{1,k-1} \Rightarrow P_{1,k-1} = \frac{\mu_2}{\mu_1} \cdot P_{0,k}$$

$$\Gamma_1: \mu_2 \cdot P_{1,k-1} = \mu_1 \cdot P_{2,k-2} \Rightarrow P_{2,k-2} = \frac{\mu_2}{\mu_1} \cdot P_{1,k-1} = \left(\frac{\mu_2}{\mu_1}\right)^2 P_{0,k}$$

$$\Gamma_2: \mu_2 \cdot P_{2,k-2} = \mu_1 \cdot P_{3,k-3} \Rightarrow P_{3,k-3} = \frac{\mu_2}{\mu_1} P_{2,k-2} = \left(\frac{\mu_2}{\mu_1}\right)^3 P_{0,k}$$

$$\Rightarrow P_{i, k-i} = \left(\frac{\mu_2}{\mu_1}\right)^i \cdot P_{0,k} \quad 0 \leq i \leq k$$

⇒ Apply the NORMALIZATION CONDITION:

$$\sum_{i=0}^k P_{i, k-i} = 1$$

$$\Rightarrow \sum_{i=0}^k \left(\frac{\mu_2}{\mu_1}\right)^i \cdot P_{0,k} = 1$$

$$\Rightarrow P_{0,k} = \frac{1}{\sum_{i=0}^k \left(\frac{\mu_2}{\mu_1}\right)^i} = \frac{1 - \frac{\mu_2}{\mu_1}}{1 - \left(\frac{\mu_2}{\mu_1}\right)^{k+1}}$$

⇒ STATE PROBABILITY in terms:

$$P_i, k-1 = \frac{1 - \frac{\mu_2}{\mu_1}}{1 - \left(\frac{\mu_2}{\mu_1}\right)^{k+1}} \cdot \left(\frac{\mu_2}{\mu_1}\right)^i \quad 0 \leq i \leq k$$

[Under finite # customers in the WAITING LINE]
 × Some STATE PROBABILITY of an M/M/1/N_W

⇒ State set N_W = k-1

⇒ STRONG SIMILARITY to M/M/1

$$\boxed{\lambda = \mu_2} \quad \boxed{\mu = \mu_1}$$

~~⇒ P_{i, k-1}~~

⇒ k = N_W + 1

$$P_i, N_W = \frac{1 - \frac{\lambda}{\mu}}{1 - \left(\frac{\lambda}{\mu}\right)^{N_W+2}} \cdot \left(\frac{\lambda}{\mu}\right)^i$$

⇒ How can we actually solve the PRODUCT-FORM SOLUTION & find the STATE PROBABILITY?



GORDON-NEVELL THEOREM!

GORDON-NEWELL THEOREM

of CLOSED Markovian Networks of QUEUES in STEADY-STATE.

PRODUCT-FORM!

[JACKSON \Rightarrow Traffic EQUATIONS]

EXAMPLE - M/M/1,

$$P_i(n) = (1 - \rho_i) \cdot \rho_i^{n_i}$$

\Rightarrow GORDON-NEWELL THEOREM

\neq

JACKSON THEOREM:

In ~~two~~ case of GORDON-NEWELL:

$$P_{k_1 k_2} = \frac{1}{G} \left(\frac{\lambda_1}{\mu_1} \right)^{k_1} \left(\frac{\lambda_2}{\mu_2} \right)^{k_2}$$

P.O. \Rightarrow No longer NORMALIZATION condition!

JACKSON THEOREM (Open Markovian Networks of QUEUES)

$\sum \# \text{QUEUES} = [0, \infty)$

$\sum \# \text{STATE PER QUEUE} = [0, \infty)$
 $\sum \# \text{CUSTOMERS PER QUEUE} = [0, \infty)$

\Rightarrow P.O.s

Because they coming in from EXTERNAL or NORMALIZATION COEFFICIENT.

→ LOPE'S
→ Po in the Product-Form Solution

GORDON-NEWELL CLOSED MARKOVIAN NETWORK OF QUEUES:

→ STATE per QUEUE (When showing k customers in the network of queues.)

$$\Rightarrow \text{STATE} = [0, k_1]$$

→ P_0^i only if going from 0 to 0 or

NORMALIZATION COEFFICIENT (JACKSON \Rightarrow Multiplication)
 \Rightarrow Need a different NORMALIZATION.

\Rightarrow Yet, some shape of DECAY (GEOMETRIC)

(JACKSON \Rightarrow "Simple" multiplication)
G-N \Rightarrow Need a P_0^i NORMALIZATION COEFF. \Rightarrow different NORMALIZATION COEFFICIENT based on the # CUSTOMERS.



GORDON-NEWELL THEOREM - DEMONSTRATION:

We are interested in the STATE EVOLUTION
of the GORDON-NEWELL MARKOVIAN

CLOSED NETWORKS OF QUEUES \Rightarrow Only

\Rightarrow Similar approach to JACKSON THEOREM's
PROOF, though we are now only considering
one type of transition (3) and (3) **(3)**
~~INTERNAL~~ INTERNAL MOVEMENT.

⇒ Because we are dealing with **CLOSED** MARKOVIAN NETWORKS of queues, we are only ~~interested~~ concerned with **INTERNAL-STATE TRANSITIONS**. (3) (3)

$$N = (k_1, \dots, k_i, \dots, k_j, \dots, k_N) \quad \Gamma_N$$

TRANS. RATE OF SOURCE
 $\lambda_{ij} = \lambda_j / \mu_j$
 (FROM Q_j TO Q_i)

$\lambda_{ji} = \lambda_i / \mu_i$
 (FROM Q_i TO Q_j)

$$N_{-ij} = (k_1, \dots, k_{i-1}, \dots, k_{j-1}, \dots, k_N)$$

$\alpha_i(k_i) = \min(k_i, m_i) \Rightarrow$ COEFFICIENT OF THE RATE

FINITE # STATES \Rightarrow Always Ergodic in CLOSED NETWORK (MUT. K. #) \Downarrow Analyze Steady-State!

Jackson's \Rightarrow Not always Ergodic!

(FINITE # STATES!)

$$\lambda_i < m_i \cdot \mu_i$$

$$\Gamma_N: N = \# \text{ QUEUES}$$

$$\sum_{i=1}^N k_i = K \quad \text{CONSTANT}$$

$$K = \# \text{ customers in the network.}$$

$$\Gamma_N: P_N \sum_{j=1}^N \sum_{i=1}^N \lambda_{ji} \alpha_j(k_j) \mu_j =$$

Flow in possible trans.

$$= \sum_{i=1}^N \sum_{j=1}^N P_{nij} \cdot r_{ij} \cdot \mu_i / (k_i + 1) \cdot \mu_i$$

ENTERING FLOW

$$\Rightarrow P_N \left[\sum_{j=1}^N \mu_j (k_j) \mu_j \sum_{i=1}^N r_{ji} \right]$$

EXIT FLOW

$$= \sum_{i=1}^N \sum_{j=1}^N P_{nij} \cdot r_{ij} \cdot \mu_i / (k_i + 1) \cdot \mu_i$$

PRODUCT-FORM SOLUTION

(STEPS to come to it!)

↳ STEPS to come to a

PRODUCT-FORM SOLUTION.

$$P_N = \frac{1}{G} \prod_{i=1}^N h_i(k_i)$$

[of this form]

$h_i(k_i)$ are the expressions of the STATE PROBABILITIES of the M/M/1's (M/M/1_i) QUEUES without $P_i(0)$.

$$\Rightarrow \sum_N P_N = 1$$

$$n_1 + n_2 + \dots + n_N = k$$

$n_1, n_2, \dots, n_N \geq 0$

$P_N = P(\text{be in a certain state } N)$

NORMALIZATION CONDITION:

(Sum of all possible STATE PROBABILITIES configurations, given that we have a fixed # CUSTOMERS (k)).

$$\sum_{N=1}^{\infty} \prod_{i=1}^N h_i(k_i) = 1$$

Sum of all possible state probabilities configurations

$$\Rightarrow G = \sum_{N=1}^{\infty} \prod_{i=1}^N h_i(k_i)$$

b

HOW TO OPERATE WITH THE GORDON-NEVELL THEOREM:

[CLOSED MARKOVIAN NETWORKS OF QUEUES]

1) WRITE THE TRAFFIC EQUATIONS.

$$\lambda_i = \sum_j \lambda_j \cdot \tau_{ji} + \nu_i$$

$N = \# \text{ QUEUES}$

ENTERING INTO QUEUE i.

$$\det = \phi$$

⇒ We can tie down a LINEAR HOMOGENEOUS SYSTEM of EQUATIONS, where the SPACE of solutions is given by

$$\Lambda = (\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_N) \quad \lambda_i = \frac{\lambda_i}{\lambda_1}$$

NORMALIZED COMPONENT

⇒ Any multiple of one solution is still a solution [fixing the topology]

2) MULTIPLY $h_i(k_i)$ of M/M/M_i type (without p_i(d)). in the Product-Form solution (lay out Product-Form & the different factors)

3) Evaluate G , normalising the STATE PROBABILITIES on all the possible states of the closed network of queues with K customers inside

$$\sum_N P_N = 1$$

$$G = \sum_N \prod_{i=1}^N h_i / k_i$$

4) Evaluate the true A_i from the MARGINAL PROBABILITIES of each queue and their Γ_i THROUGHPUT of queue

$$\Gamma_i = A_i \cdot \mu_i \quad \left(\frac{1}{\mu_i} = 1 - P_i(0) \right)$$

\Rightarrow true STATE PROBABILITY of NETWORK of QUEUES

\downarrow

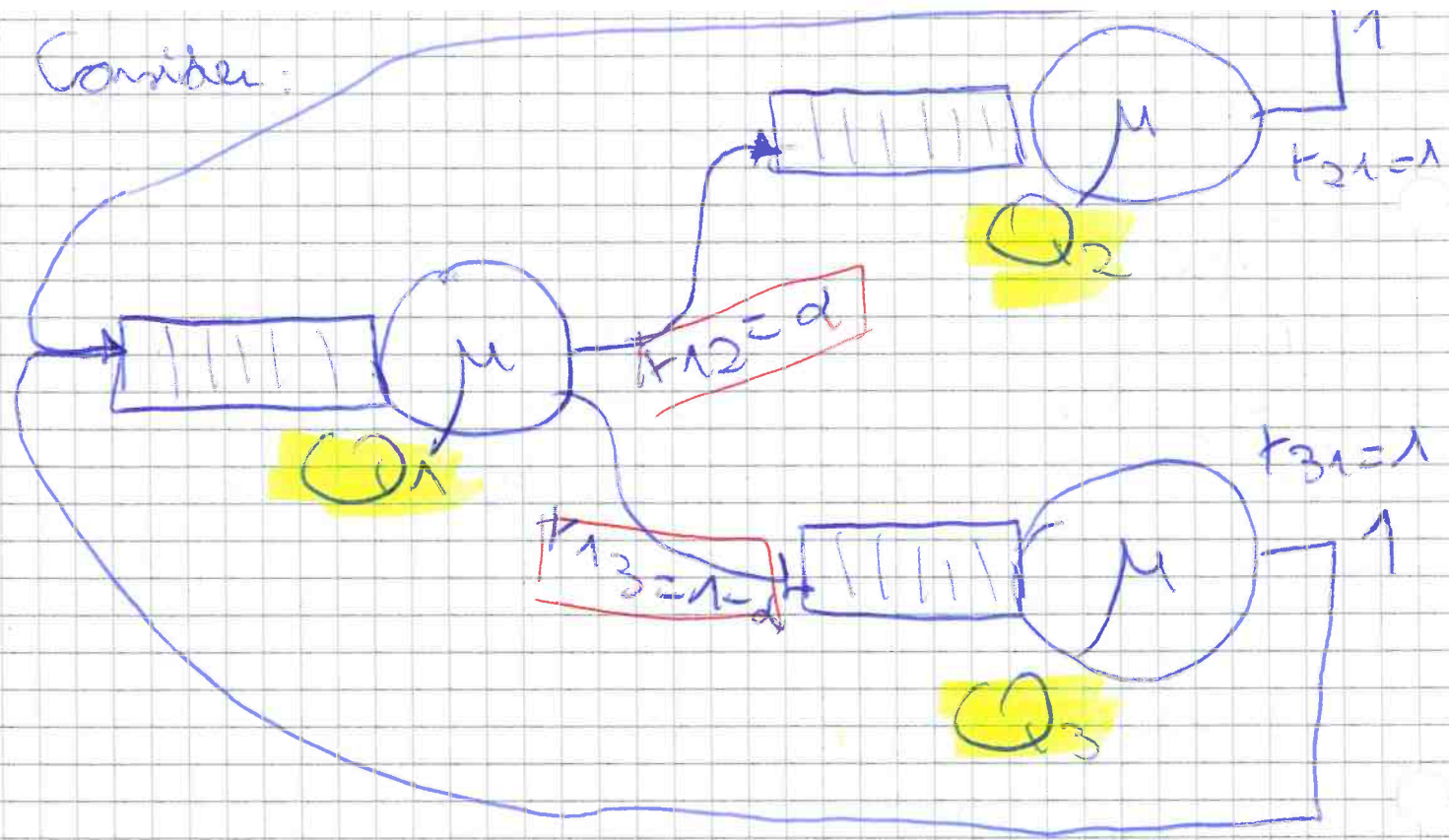
STATE PROBABILITY of each queue

ANALYSIS OF A CLOSED MARKOVIAN NETWORK OF QUEUES (USING G. THE GORDON-NEWELL THEOREM)

All the servers are EXPONENTIAL, CLOSED NETWORK of QUEUES.



Consider:



$$r_{12} = \alpha \quad r_{13} = 1 - \alpha$$

$$r_{21} = 1 \quad r_{31} = 1$$

$\Rightarrow N_{S_i} = m_i = 1$ [A server in local queue]

$\alpha = \frac{1}{2}$ \Rightarrow All the possible combinations of states.

$$\# \text{ STATES} = N_{\text{STATES}} = \binom{Q + N_U - 1}{Q - 1}$$

$Q = \# \text{ QUEUES in the network}$
 $N_U = \# \text{ USERS}$

\Rightarrow Presently: $Q = 3$ (# QUEUES)
 $N_U = 3$ (3 users)

$$\Rightarrow N_{\text{STATES}} = \binom{3+3-1}{2} = \frac{5!}{2! 3! 3!} = \frac{5 \cdot 4 \cdot 3 \cdot 2 \cdot 1}{2 \cdot 3 \cdot 3 \cdot 2 \cdot 1}$$

$$\Rightarrow N_{\text{STATES}} = \frac{5 \cdot 4 \cdot 3}{3 \cdot 2} = 10$$

We know we are analyzing with M/M/1 QUEUES.

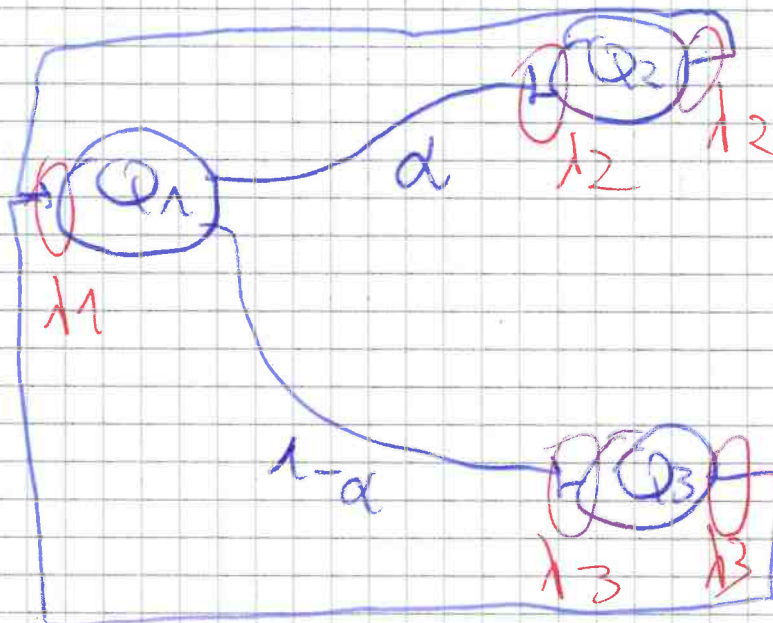
$$P_n(A_n) = (1 - \rho_n) \cdot \rho_n^{n_i}$$

$$n_i / k_n = \left(\frac{\lambda_i}{\mu_i} \right)^{k_i}$$

\Rightarrow The PRODUCT-FORM solution has Form

$$P_{k_1, k_2, k_3} = \frac{1}{G} \cdot \prod_{i=1}^3 n_i / k_i$$

Where $k_1 + k_2 + k_3 = N_C = 3$



EXAMPLE
[No theory]

1) STEP: SOLVE TRAFFIC EQUATIONS:

$$\begin{cases} \lambda_2 = \alpha \lambda_1 \\ \lambda_3 = (1 - \alpha) \lambda_1 \\ \lambda_1 = \lambda_2 + \lambda_3 \end{cases}$$

We could choose any other possible value.

\Rightarrow If we set $\lambda_1 = 1$ (and we know $\alpha = \frac{1}{4}$)

$$\Rightarrow \lambda_2 = \alpha = \frac{1}{4} \Rightarrow \lambda_1 = \lambda_2 = \frac{1}{\frac{1}{4}} = 1$$

$$\Rightarrow \lambda_3 = \lambda_1 - \lambda_2 = 1 - \frac{1}{4} = \frac{3}{4}$$

$$\Rightarrow \underline{\lambda} = \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{pmatrix} = \begin{pmatrix} 1 \\ \frac{1}{4} \\ \frac{3}{4} \end{pmatrix} \quad \text{VECTOR SPACE SOLUTION!}$$

\Rightarrow If we set $\lambda_1 = \lambda$

$$\Rightarrow \lambda = \begin{pmatrix} \lambda \\ \frac{\lambda}{4} \\ \frac{3\lambda}{4} \end{pmatrix}$$

STILL A SOLUTION!

68 BCMP NETWORK

Boadjet

Chandry

Moody

Palacios-Gomez

RESULT of NETWORK:

Once again, a PRODUCT-FORM SOLUTION to find the state PROBABILITY.

CHARACTERIZATION:

- Multiple classes of CUSTOMERS (i.e.: different T-SWERS customers can wear).
- Multiple queuing disciplines (i.e.: FCFS, LCFS).
- More general distribution of the service time (No longer just EXPONENTIAL DISTRIBUTION).

IMPORTANCE & USAGE:

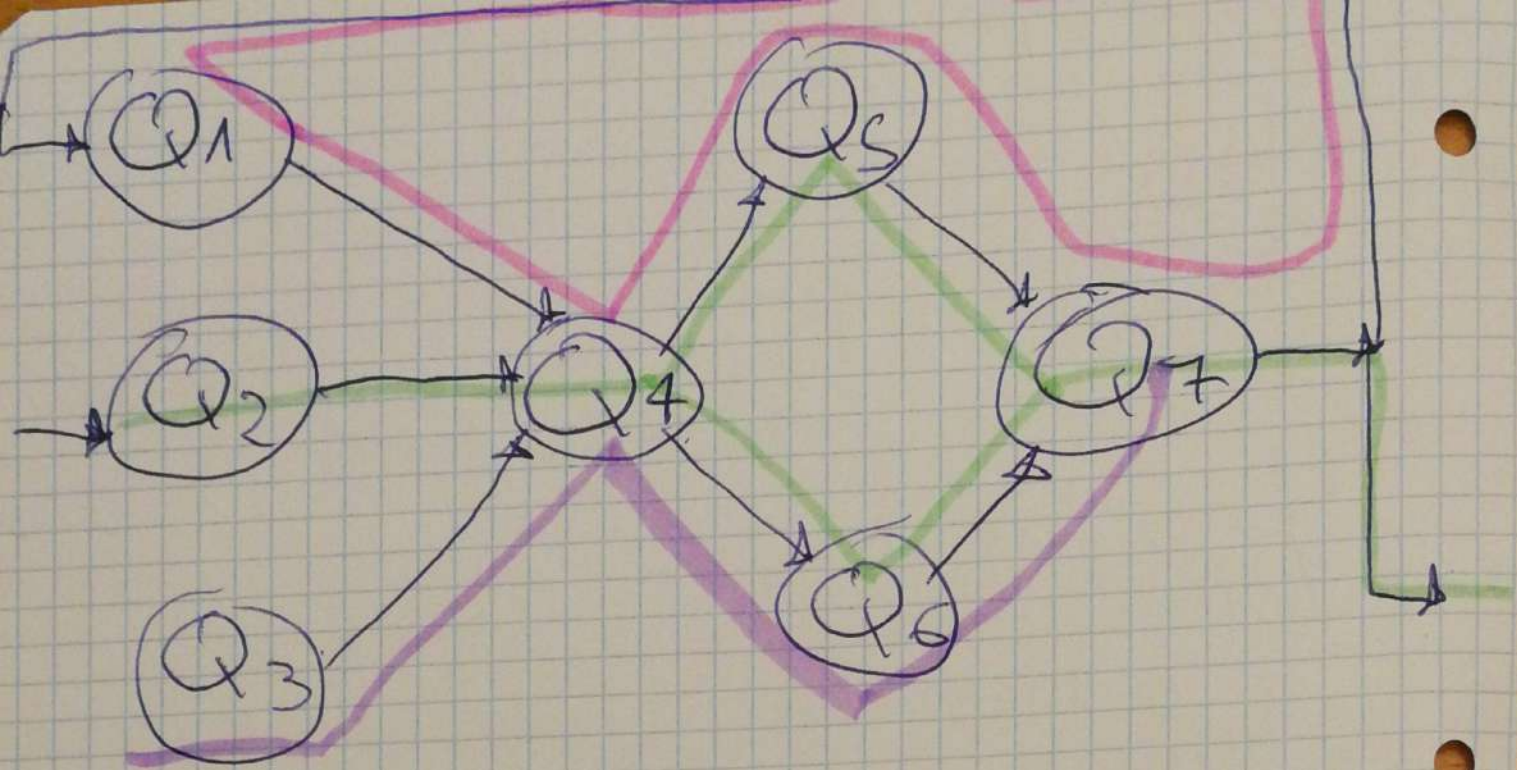
Used for SCHEDULING (i.e.: Virtualization of a physical device into multiple logical ones).

⇒ Synchronization/Control of class is possible!

[OPEN/CLOSED/HYBRID CLASS]

M QUEUES, R CLASSES

are possible.



OPEN CLASS

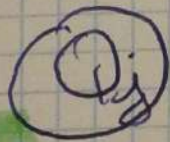
Switching class / change to state

CLOSED CLASS

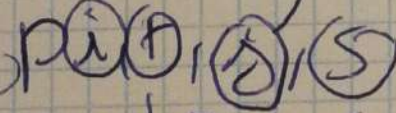
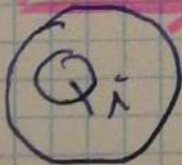
REVERSE PROBABILITY (old + is)

P. to transition

S CLASS



R CLASS



From QUEUE TO QUEUE
 | From CLASS | To CLASS

Behind the reverse & change of class probability, I can recognize a MARKOV CHAIN!

Generally, in fact:

digits is a ~~MARKOV~~ REDUCIBLE MARKOV CHAIN.

↓
We can then identify a set of IRREDUCIBLE SUBSETS of STATES
(Become different classes)
& separate groups of STATES

If we can assume to avoid PERIODIC STATES
& that the # STATES in each subset is
FINITE \Rightarrow We have ERGODIC
SUBSETS

(each one APERIODIC, IRREDUCIBLE, FINITE
STATES)

~~There~~ ERGODIC SUBSETS are then called:

E_1, E_2, \dots, E_N

$N = \# \text{ ERGODIC SUBSETS}$

$R = \# \text{ CLASSES}$

If we have R classes and NO change of
class: Δ as many ergodic subsets as
classes

$$N = R$$

(# ERGODIC SUBSETS = # CLASSES)

If we can change class: Δ as fewer than

$$N < R \quad (\# \text{ ERGODIC SUBSETS})$$

[Aggregate some subsets] \uparrow
CLASSES

For each queue, we can now define a new state N_i (mult. to the different classes).

$$N_i = (N_{i1}, N_{i2}, \dots, N_{iR})$$

STATE of QUEUE (one row)

Customers of Class 1
(# customers of class in queue i)

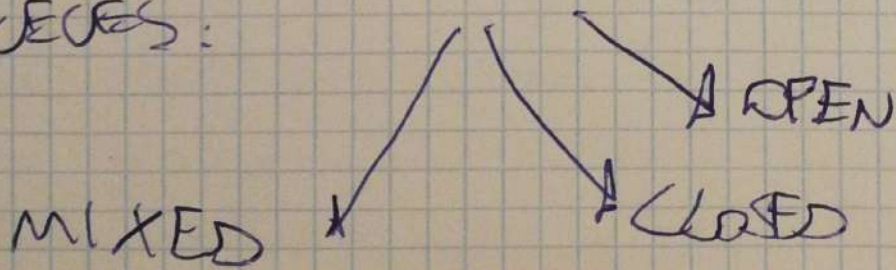
Class 2

Class R

N_i = MATRIX of the STATE of the SYSTEM (not a vector)
(# CUSTOMERS of class j in queue i)

STATE CHARACTERIZATION: # CUSTOMERS of class j in Queue i
 N_{ij}

TYPES of USER CLASSES for BCMP NETWORKS of QUEUES:



If some classes are CLOSED, then for them

$$\sum_{j=1}^M \sum_{i \in \text{CLOSED}} N_{ij} = N_C$$

(Constant # customers in the closed classes). Subsets corresponding to CLOSED CLASSES

BCMP ANALYSIS:

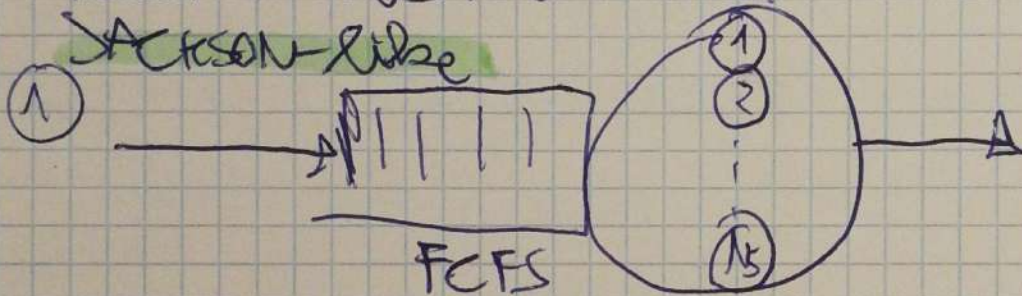
EXTERNAL ARRIVALS:

↳ POISSONIAN WITH FIXED RATE
(UDP / Fixed-rate UDP)

↳ POISSONIAN WITH RATE depending on the STATE of the QUEUE.

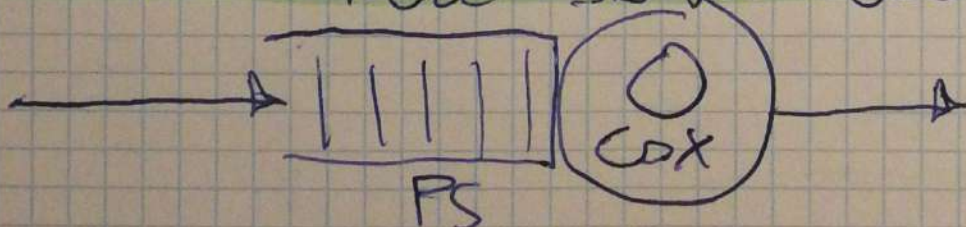
Ex: TCP - Changes packet ^{transmission} rate based on the network bandwidth.

TYPES of QUEUES we can use in BCMP NETWORKS:



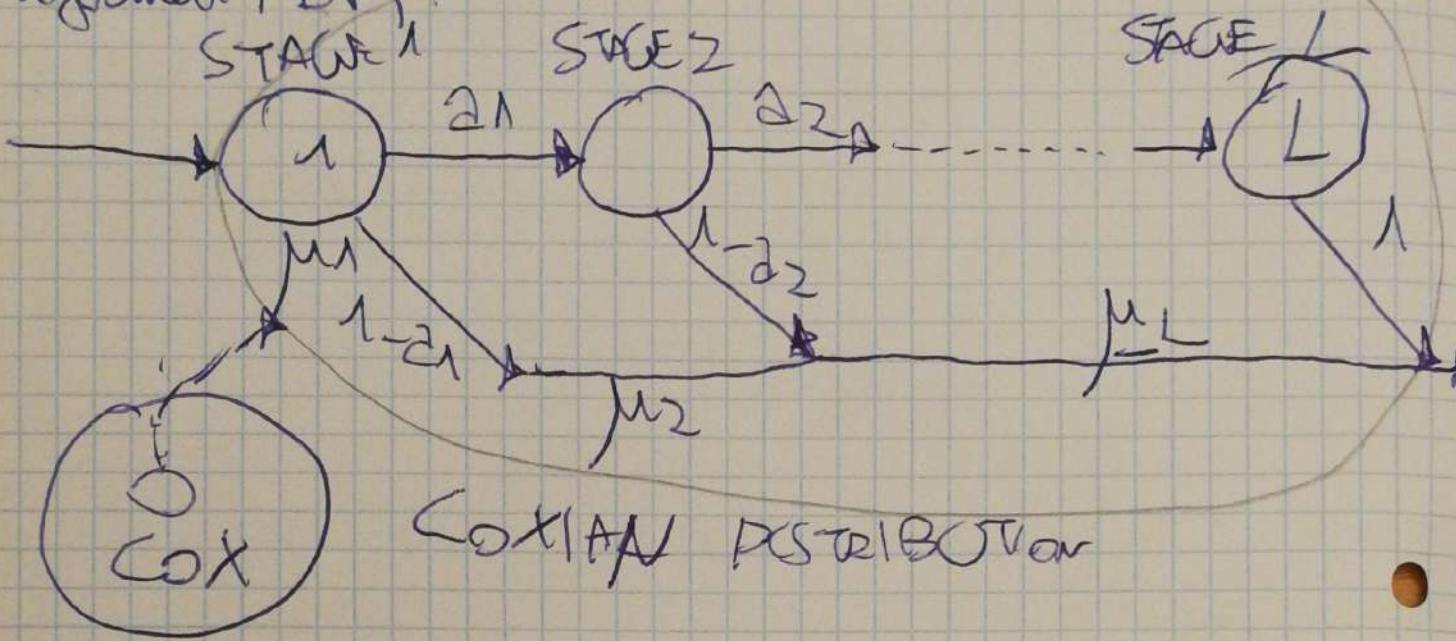
- FCFS ^{STANDING POLICY} • $N = \infty$ • MULTIPLE SERVERS
 - EXP. DISTRIBUTION of SERVICE TIME
 - SAME $E\{T\}$ for ALL CLASSES
 - SERVICE TIME depends on the # customers in the queue. (adaptive)
- Increasing # customers → Server's behaviour changes & can be analysed.

② COXIAN - SINGLE - SERVER QUEUE (IDEAL)



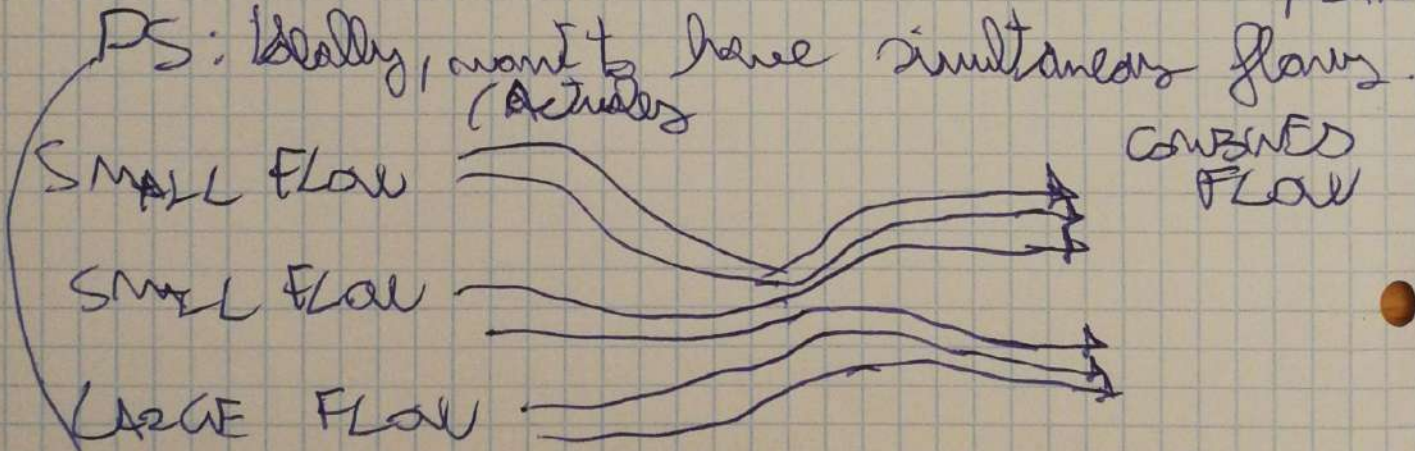
- PS ^{STANDING POLICY} (Processor Sharing)

Very General PDF having a fractional form of its transform PDF



COXIAN DISTRIBUTION

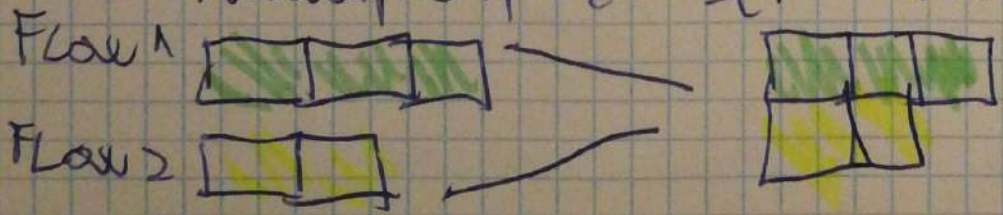
- $NS=1$ (Single-server)
- DIFFERENT job class
- COXIAN DISTRIBUTION
- PS - QUEUEING DISCIPLINE



EX. ~~...~~

ROUND-ROBIN over DE (Infinitesimal service time). $\Delta t \rightarrow 0$

SIMULATE the simultaneous execution of multiple programs (APPROXIMATION)



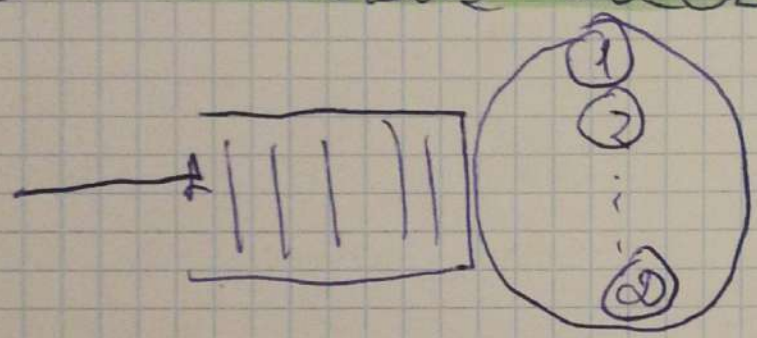
③



Cox-LQFS

- $N_S = 1$
- EXPONENTIAL DISTRIBUTION
- DIFFERENT for each class
- LQFS queueing discipline

④ INFINITE SERVER QUEUE (DELAY MODEL)



- $N_S = \infty$
- EXPONENTIAL DISTRIBUTION
- $E\{M} = \infty$

(Used to emulate the processing delay in a processor / TRANSMISSION DELAY in a system).
DETERMINISTIC

BCMP NETWORK'S IDEA:

~~State~~ STATE of the NETWORK = Vector of vectors (MATRIX)
(simple definition)
↳ #customers in each queue for each class.
BCMP NETWORK'S THEOREM.
↓
PRODUCT-FORM SOLUTION.

$$P(N) = \frac{1}{G} \prod_{i=1}^N g_i(N_i)$$

$\underbrace{P(N)}_{\text{MATRIX}}$ $\underbrace{N}_{\text{# QUEUES}}$ $\underbrace{g_i(N_i)}_{\text{VECTOR}}$
 NORMALIZATION COEFFICIENT

How to operate with the BCMP NETWORKS.

1. Solve the TRAFFIC EQUATIONS:

$$\lambda_{i,t} = \gamma_{i,t} + \sum_{j=1}^M \sum_{s=1}^Q \lambda_{j,s} P_{j,s \rightarrow i,t}$$

$\underbrace{\lambda_{i,t}}_{\text{is OPEN NETWORK (arrivals from the external)}} \quad i=1, \dots, M \text{ # QUEUES}$
 $t=1, \dots, Q \text{ # CLASSES}$

2. Check the ERGONOMY CONDITION:

$$\sum_{k=1}^Q \frac{\lambda_{i,t}^*}{\mu_{i,t}^*} < 1$$

$\underbrace{Q}_{\text{# OPEN CLASSES}}$

$$\left. \begin{array}{l} \lambda_{i,t}^* \\ \mu_{i,t}^* \end{array} \right\} \begin{array}{l} \lambda_{i,t}^* = \lim_{j \rightarrow \infty} \lambda_{i,t}(j) \\ \mu_{i,t}^* = \lim_{j \rightarrow \infty} \mu_{i,t}(j) \end{array} \left. \vphantom{\begin{array}{l} \lambda_{i,t}^* \\ \mu_{i,t}^* \end{array}} \right\} \begin{array}{l} \text{NOT dependent} \\ \text{on the} \\ \text{\# processes} \\ \text{in the network} \end{array}$$

Dependent on the # processes in the network

In case of BCMP NETWORKS, where:

- ① USERS can't change classes
- ② FREQUENCIES λ_i, μ_i do not depend on the # processes in the network.

"JACKSON-LIKE" (1) $N_{\lambda}! \prod_{r=1}^R \left(\frac{1}{N_{\lambda r}!} \right) \left(\frac{V_{\lambda r}}{N_{\lambda}} \right)^{N_{\lambda r}}$

$Z_{\lambda}(N_{\lambda}) =$

(1) $\frac{(N_{\lambda})!}{\mu_{\lambda} N_{\lambda}} \prod_{r=1}^R \frac{V_{\lambda r}^{N_{\lambda r}}}{N_{\lambda r}!}$

PS-COXIAN

(2) $N_{\lambda}! \prod_{r=1}^R \left(\frac{1}{N_{\lambda r}!} \right) \left(\frac{V_{\lambda r}}{M_{\lambda r}} \right)^{N_{\lambda r}}$

LEFS-COXIAN (3)

NS=∞ COXIAN (4)

(4) $\prod_{r=1}^R \frac{1}{N_{\lambda r}!} \left(\frac{V_{\lambda r}}{M_{\lambda r}} \right)^{N_{\lambda r}}$

$V_{\lambda r} = \begin{cases} \frac{\lambda_{\lambda r}}{M_{\lambda r}} & \text{if } r \text{ is CLOSED CLASS} \\ \lambda_{\lambda r} & \text{if } r \text{ is OPEN CLASS} \end{cases}$

$N_{\lambda} = \sum_{r=1}^R N_{\lambda r}$

(NORMALIZATION) CONDITION over all orders of one queue (i)

② Write here **PRODUCT Form**.

$$P_{k_1 k_2 k_3} = \frac{\Lambda}{G} \cdot \binom{\Lambda_1}{\mu}^{k_1} \binom{\Lambda_2}{\mu_2}^{k_2} \binom{\Lambda_3}{\mu_3}^{k_3}$$

SUBSTITUTE OBTAINED VALUES WITH THE TRAFFIC EQUATIONS

$$= \frac{\Lambda}{G} \cdot \left(\frac{\Lambda_1}{\mu}\right)^{k_1} \cdot \left(\frac{\Lambda_1}{4\mu}\right)^{k_2} \cdot \left(\frac{3\Lambda_1}{4\mu}\right)^{k_3}$$

$$= \frac{\Lambda}{G} \cdot \binom{\Lambda_1}{\mu}^{k_1 + k_2 + k_3}$$

$$= \frac{\Lambda}{G} \cdot \binom{\Lambda}{\mu}^{k_1} \cdot \left(\frac{\Lambda}{4}\right)^{k_2} \cdot \left(\frac{3}{4}\right)^{k_3}$$

[Use Lemma:]

③ Evaluate **G** (G) ⇒ EXHAUSTIVE ANALYSIS of all possible STATES

We found that: $N_{STATES} \binom{Q + N_U - 1}{Q - 1} = 10$

~~Exhaustive~~ All possible states are, with $N_U = 3$

- (3, 0, 0); (0, 3, 0); (0, 0, 3); (2, 1, 0); (0, 1, 2)
- (2, 0, 1); (0, 2, 1); (1, 1, 1); (1, 0, 2); (1, 2, 0)

$$P_{k_1, k_2, k_3} = k \cdot 1^{k_1} \cdot \left(\frac{1}{4}\right)^{k_2} \cdot \left(\frac{3}{4}\right)^{k_3}$$

$$P(3, 0, 0) = 1^3 = 1 \cdot k$$

$$P(0, 3, 0) = \left(\frac{1}{4}\right)^3 \cdot k$$

$$P(0, 0, 3) = \left(\frac{3}{4}\right)^3 \cdot k$$

$$P(2, 1, 0) = \frac{1}{4} \cdot k$$

$$P(2, 0, 1) = \frac{3}{4} \cdot k$$

$$P(1, 2, 0) = \left(\frac{1}{4}\right)^2 \cdot k$$

$$P(0, 2, 1) = \left(\frac{1}{4}\right)^2 \cdot \frac{3}{4} \cdot k$$

$$P(1, 0, 2) = \left(\frac{3}{4}\right)^2 \cdot k$$

$$P(0, 1, 2) = \frac{1}{4} \cdot \left(\frac{3}{4}\right)^2 \cdot k$$

$$P(1, 1, 1) = \frac{1}{4} \cdot \left(\frac{3}{4}\right) \cdot k$$

$$\sum_{k_1, k_2, k_3} P_{k_1, k_2, k_3} = 1$$

$$\Rightarrow k = \frac{16}{55} \Rightarrow \frac{1}{55}$$

NB: We demand the **NORMALIZATION CONDITION**

$$\sum_{k_1, k_2, k_3} P_{k_1, k_2, k_3} = 1$$

\Rightarrow We sum all the **MARGINAL PROBABILITIES** and get the result

$\frac{1}{55}$

~~like that that: We have that~~

~~$$k = \frac{SS}{16} = \frac{1}{G}$$~~

$$k = \frac{16}{SS} = \frac{1}{G}$$

~~We have hence found that~~

And knowing that the PERIOD FORM solution is:

$$P_{k_1 k_2 k_3} = \frac{1}{G} \cdot \left(\frac{1}{4}\right)^{k_1} \cdot \left(\frac{1}{4}\right)^{k_2} \cdot \left(\frac{3}{4}\right)^{k_3}$$

$$\Rightarrow P_{k_1 k_2 k_3} = \frac{16}{SS} \cdot \left(\frac{1}{4}\right)^{k_1} \cdot \left(\frac{1}{4}\right)^{k_2} \cdot \left(\frac{3}{4}\right)^{k_3}$$

$$P_{k_1 k_2 k_3} = \frac{16}{SS} \cdot \left(\frac{1}{4}\right)^{k_2} \cdot \left(\frac{3}{4}\right)^{k_3}$$

(4) Find the REAL (TRUE) λ_i from the STATE PROBABILITIES of the NETWORK. We can then evaluate the MARGINAL STATE PROBABILITIES of each QUEUE.

MARGINAL

STATE PROBABILITY $\pi_{i,j} \Rightarrow$ j customers in Q_i

(~~Evaluate~~ ^{Sum} all the different possibilities to have such situation).

\Rightarrow Probabilities of a certain SUBSET

$$\pi_{1,0} = p_{0,3,0} + p_{0,0,3} + p_{0,2,1} + p_{0,1,2}$$

$$\pi_{1,1} = p_{1,2,0} + p_{1,0,2} + p_{1,1,1}$$

$$\pi_{1,2} = p_{2,1,0} + p_{2,0,1}$$

$$\pi_{1,3} = p_{3,0,0}$$

AVERAGE # CUSTOMERS
IN QUEUE 1:

If we have the MARGINAL PROBABILITIES,
we can evaluate ~~evaluate~~ $E\{n_1\}$

$$E\{n_1\} = \sum_{i=1}^3 i \cdot \pi_{1,i} \quad \left[\text{or } E\{n\} = \sum_{n=0}^{\infty} n \cdot p_n \right]$$

$$\Rightarrow E\{n_1\} = \sum_{i=1}^3 i \cdot \pi_{1,i} = 1 \cdot \pi_{1,1} + 2 \pi_{2,1} + 3 \pi_{3,1}$$

THROUGHPUT of QUEUE 1

$$\Gamma_1 = \sum_{i=1}^3 \mu_i \cdot \pi_{1,i} = \sum_{i=1}^3 \mu \cdot \pi_{1,i}$$

$\mu_i = \mu$ [BECAUSE single server
QUEUE]

$$\Gamma_1 = \mu \cdot [\pi_{1,1} + \pi_{1,2} + \pi_{1,3}]$$

$$= \mu [1 - \pi_{1,0}]$$

\Rightarrow For M/M/1:

$$\Gamma_1 = \lambda$$

If you have λ , you
have all other λ 's too!

All customers
with at
least one
customer
in the
QUEUE
waiting for
the server.

$$NB: E\{n_1\} + E\{n_2\} + E\{n_3\} = N_U$$

~~$$E\{n_1\} = \lambda$$~~

1
3

4) EVALUATION of TRUE λ_i from the THROUGHPUT of each queue.

Use formula (for M/M/1 queue). FREQUENCY of ACCEPTED CUSTOMERS

$$P_{x1} \cdot P_{x2} \cdot P_{x3} = \prod \lambda_i K \Rightarrow \Gamma_i = \Lambda_i = \lambda_i$$

$$\Gamma_{int} = \mu (1 - \pi_{1,0}) = \lambda_1$$

$$\Gamma_1 = \mu (1 - p_{030} - p_{003} - p_{021} - p_{012}) = \mu \frac{9}{11} = \lambda_1$$

$$\Rightarrow \Gamma_1 = \mu \cdot \frac{9}{11} = \lambda_1 = \lambda_1$$

Use Renewal Test:

Substituting in

$\Lambda =$	λ_1	$\frac{9}{11} \mu$
	$\frac{1}{4} \lambda_1$	$\frac{9}{44} \mu$
	$\frac{3}{4} \lambda_1$	$\frac{9}{44} \mu$
		$\frac{27}{44} \mu$

$$\lambda_2 = \frac{9}{11} \mu$$

\Rightarrow We can then evaluate the AVERAGE THROUGHPUT based on the MARGINAL PROBABILITIES

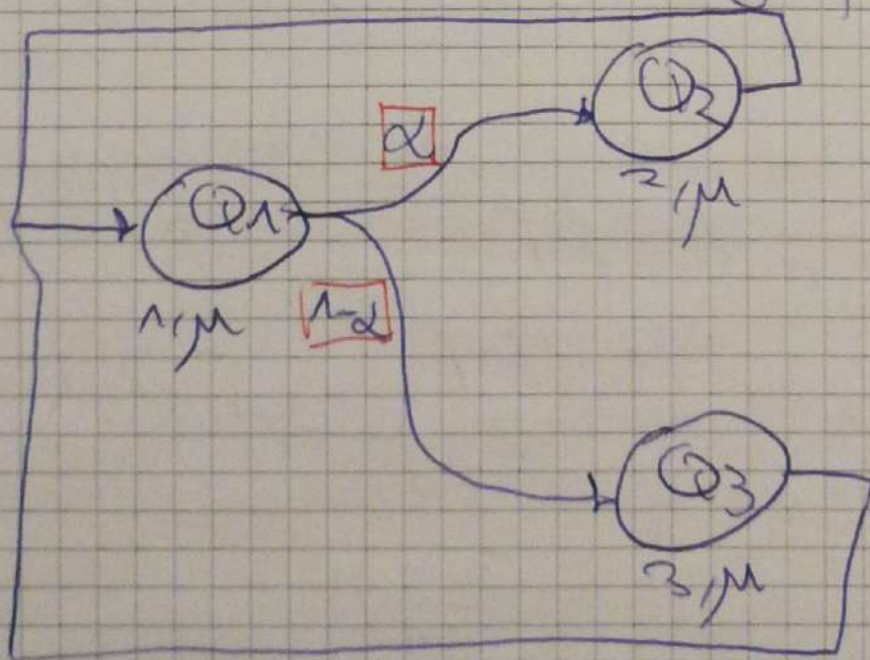
$$E\{n_n\} = \sum_{i=1}^3 i \pi_i = 1 \cdot \pi_1 + 2 \pi_2 + 3 \pi_3$$

$$\Rightarrow E\{n_j\} = \sum_{i=1}^{\infty} i \cdot \pi_{ji}$$

AVERAGE TIME SPENT IN EACH QUEUE

[IN A CLOSED NETWORK OF QUEUES]

\Rightarrow We want to apply LITTLE'S THEOREM to our ~~open~~ network of queues.



$$\Rightarrow E\{n_j\} = \lambda \cdot E\{T_j\}$$

$$\Rightarrow E\{T_j\} = \frac{E\{n_j\}}{\lambda_j}$$

AVG. TIME SPENT IN "Q_j" QUEUE λ

ALTERNATIVELY:

Use Little's Formula.

$$E\{N\} \cdot \lambda = E\{T\} = 3$$

$$\Rightarrow E\{T\} = \frac{3}{\lambda_1} = \frac{3}{\lambda_1} = \frac{3}{\frac{9}{\mu}} = \frac{11}{3} \cdot \frac{1}{\mu}$$

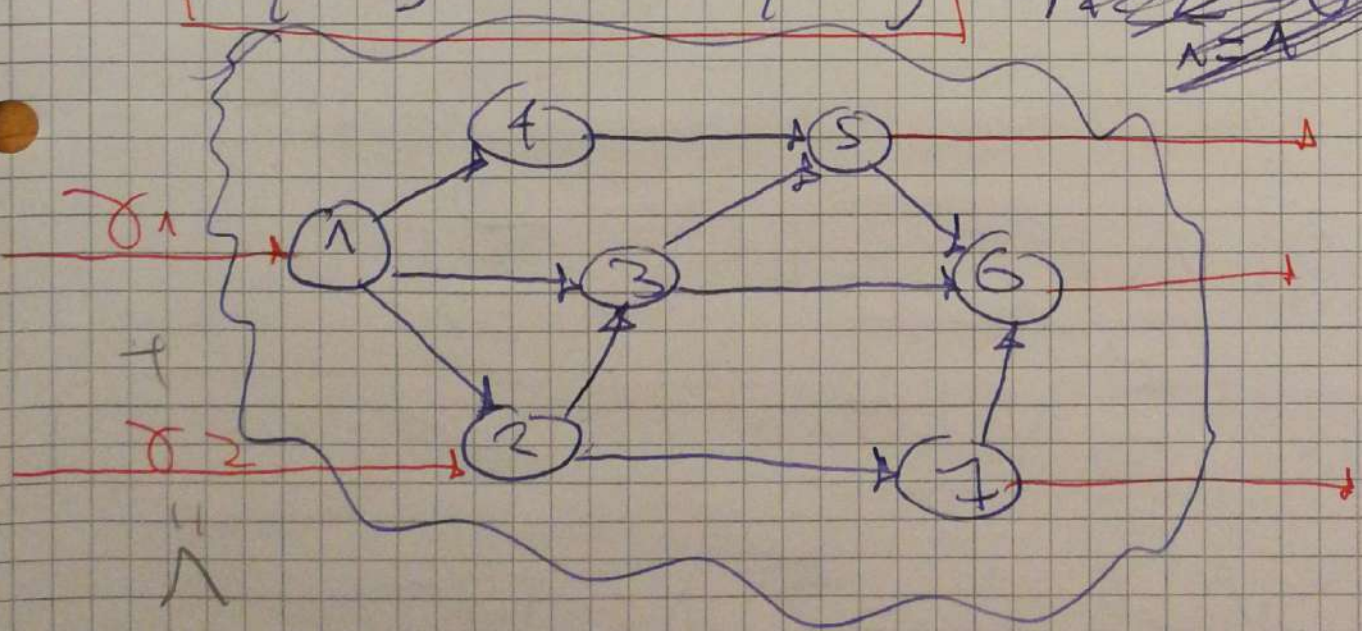
67

TRANSIT TIME IN AN OPEN NET WORK OF QUEUES

Our course is specifically aimed at evaluating the CROSSING TIME of OPEN NETWORK of QUEUES / A QUEUE.

$$E\{N\} = \lambda \cdot E\{T\}$$

~~As per NSA~~



$$\lambda = \sum_{i=1}^P \gamma_i$$

$E\{T\}$

P # QUEUES with an INPUT from the external.

$$E\{N\} = \Lambda \cdot E\{\tau\}$$

$$\Lambda = \sum_{i=1}^P \lambda_i$$

$P = \#$ QUEUES
with EXTERNAL
INPUT.

ALSO: TOTAL # CUSTOMERS in NETWORK,
(All QUEUES) //

Sum of # CUSTOMERS in each QUEUE
of the NETWORK.

$$E\{N\} = \sum_{i=1}^P E\{N_i\}$$

~~ALSO~~ # CUSTOMERS in QUEUE i :

$$E\{N_i\} = \lambda_i \cdot E\{\tau_i\}$$

\Rightarrow Put these 2 things together:

$$\Lambda \cdot E\{\tau\} = E\{N\} = \sum_{i=1}^P E\{N_i\}$$

$$= \sum_{i=1}^P \lambda_i \cdot E\{\tau_i\}$$

$$\Rightarrow \Lambda \cdot E\{\tau\} = \sum_{i=1}^P \lambda_i \cdot E\{\tau_i\}$$

\Rightarrow AVERAGE TRAVERSAL TIME.

$$E\{\tau\} = \sum_{i=1}^P \frac{\lambda_i}{\Lambda} \cdot E\{\tau_i\}$$

AVERAGE TRAVERSAL TIME:

$$E\{T\} = \sum_{i=1}^Q \left(\frac{\lambda_i}{\lambda} \right) E\{T_i\}$$

Time spent in the queue

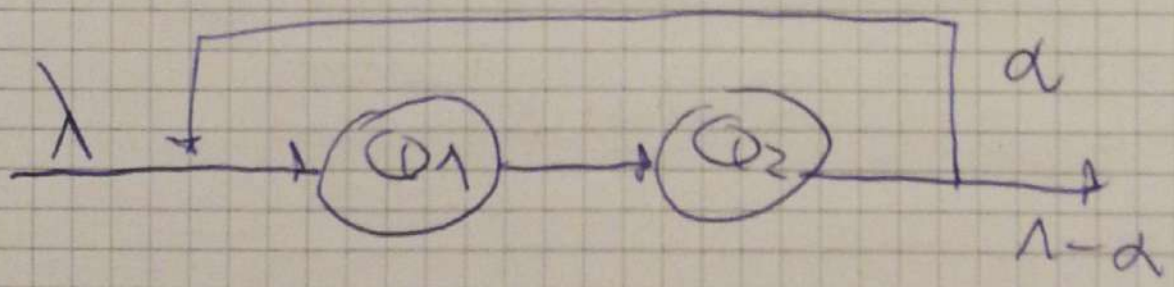
$E\{T_i\}$ = # traverses through Q_i .
 COEFFICIENT corresponding to the # TIMES of passing through / visiting the queue

$$\lambda = \sum_{i=1}^P \lambda_i$$

(coming from external)

EXAMPLES OF TOPOLOGIES OF OPEN NETWORKS & QUEUES

CASE ①: TOPOLOGICAL APPROACH



For $d < \lambda$, $E\{T_1\}$, $E\{T_2\}$

QUEUING TIME Q_1 QUEUING TIME Q_2

$$P\{n \text{ transmits through } Q_1 \text{ \& } Q_2\} = \begin{cases} (1-d) & n=1 \\ d(1-d) & n=2 \\ d^2(1-d) & n=3 \end{cases}$$

$$\Rightarrow P\{n \text{ transmits}\} = d^{n-1} (1-d) \quad n \geq 1$$

$$E\{\# \text{TRANSITS}\} = \sum_{i=1}^{\infty} i \cdot (\lambda \cdot \alpha)^{i-1}$$

$$\Rightarrow E\{\# \text{TRANSITS}\} = \frac{\lambda}{\lambda - \alpha} = \frac{\lambda}{\lambda - \alpha}$$

~~ALTERNATIVELY~~

$$\Rightarrow E\{T\} = \frac{\lambda}{\lambda - \alpha} \cdot E\{T_1\} + \frac{\lambda}{\lambda - \alpha} \cdot E\{T_2\}$$

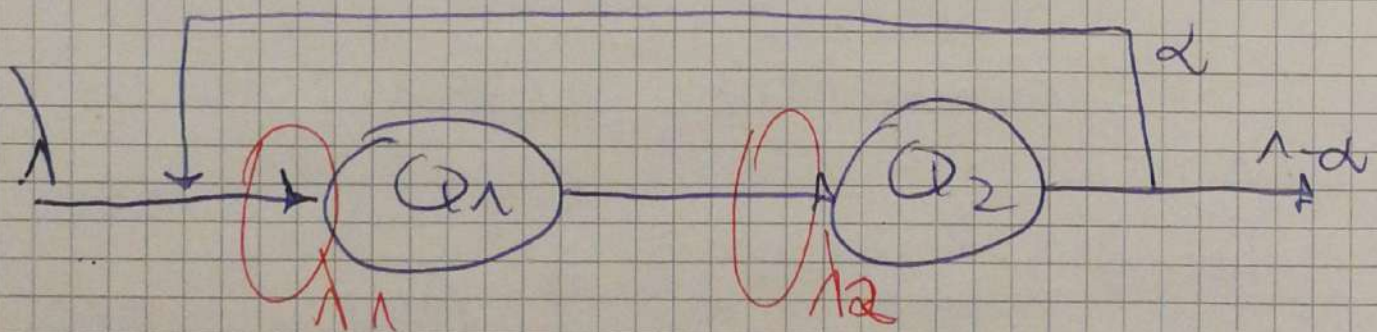
$$E\{T\} = \frac{E\{T_1\} + E\{T_2\}}{\lambda - \alpha}$$

ALTERNATIVE APPROACH (TRAFFIC EQUATIONS)

\Rightarrow want to find λ_1, λ_2 for:

$$E\{T\} = \sum_{i=1}^{\infty} \frac{\lambda_i}{\lambda} E\{T_i\}$$

\Rightarrow Lay out TRAFFIC EQUATIONS:



$$\begin{cases} \lambda_1 = \lambda_2 \\ \lambda = \lambda_2 / (1 - \alpha) \end{cases} \Rightarrow \lambda_1 = \frac{\lambda}{1 - \alpha}$$

$$\lambda_2 = \frac{\lambda}{1 - \alpha}$$

Global INPUT Global OUTPUT

$$E\{T\} = \frac{\lambda_1}{\lambda} \cdot E\{T_1\} + \frac{\lambda_2}{\lambda} \cdot E\{T_2\}$$

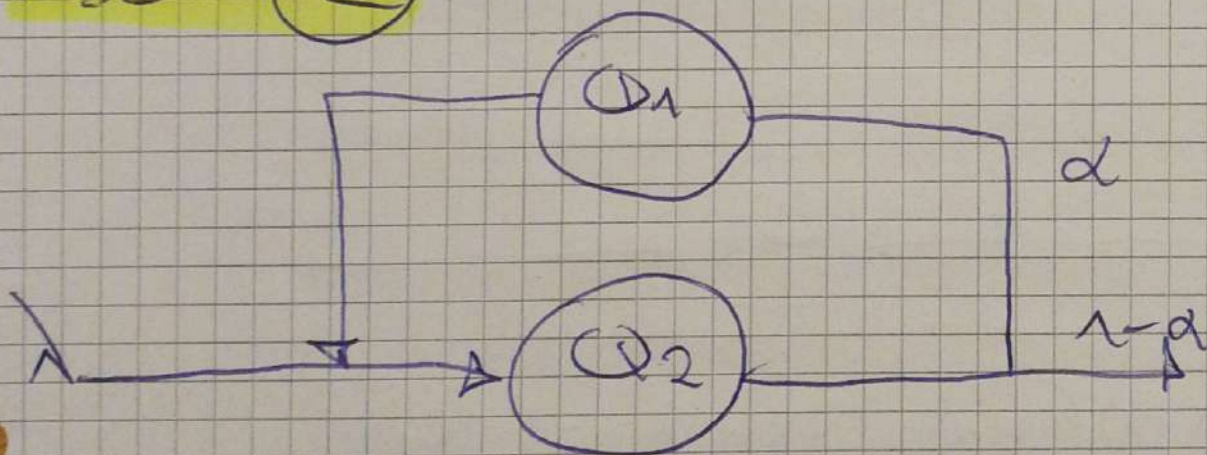
λ
(what goes in)

$$= \frac{\lambda_1}{\lambda} \cdot E\{T_1\} + \frac{\lambda_2}{\lambda} \cdot E\{T_2\}$$

$$= \frac{\lambda}{\lambda - \alpha} E\{T_1\} + \frac{\lambda}{\lambda - \alpha} \cdot E\{T_2\}$$

$$= \frac{E\{T_1\} + E\{T_2\}}{\lambda - \alpha}$$

CASE ②



$$\alpha < \lambda \quad [E\{G\} = 1], \quad E\{T_1\}, \quad E\{T_2\}$$

$$P\{N \text{ traversals through } Q_1 \text{ \& } Q_2\} = \frac{\alpha}{\lambda} \cdot \frac{\lambda - \alpha}{\lambda - \alpha}$$

$$E\{\# \text{ traversals through } Q_2\} = \frac{\lambda}{\lambda - \alpha}$$

(same situation as ①)

$$E\{\# \text{ traversals through } Q_1\} = \frac{\lambda}{\lambda - \alpha} - \frac{\alpha}{\lambda - \alpha}$$

$$= \frac{\lambda - \alpha}{\lambda - \alpha}$$

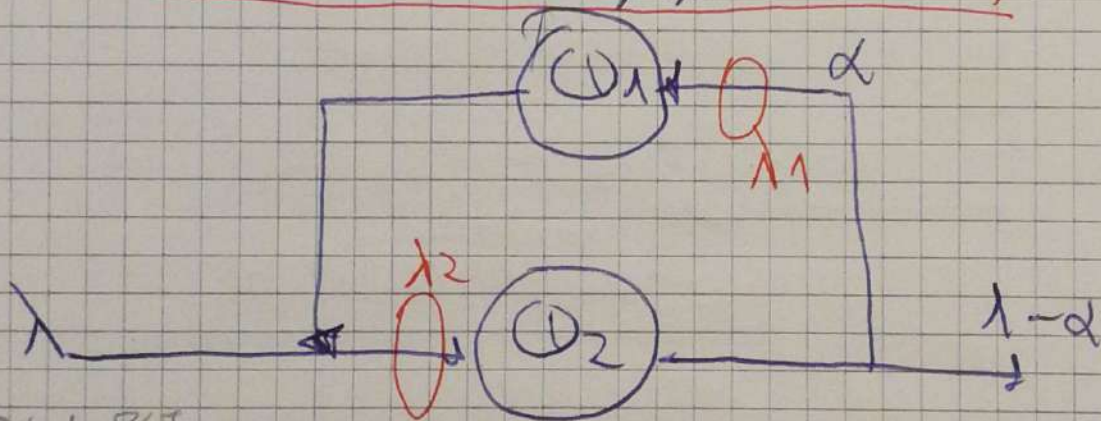
$$\Rightarrow E\{\tau\} = \frac{\alpha}{1-\alpha} E\{\tau_1\} + \frac{E\{\tau_2\}}{1-\alpha}$$

$$= \frac{\alpha E\{\tau_1\} + E\{\tau_2\}}{1-\alpha}$$

ALTERNATIVE APPROACH: \Rightarrow

Write the TRAFFIC EQUATIONS

$$E\{\tau\} = \sum_{i=1}^n \frac{\lambda_i}{\lambda} E\{\tau_i\}$$



GLOBAL INPUT

$$\lambda = \lambda_2 \cdot (1-d)$$

$$\Rightarrow \lambda_2 = \frac{\lambda}{1-d}$$

$$\lambda_1 = \alpha \lambda_2$$

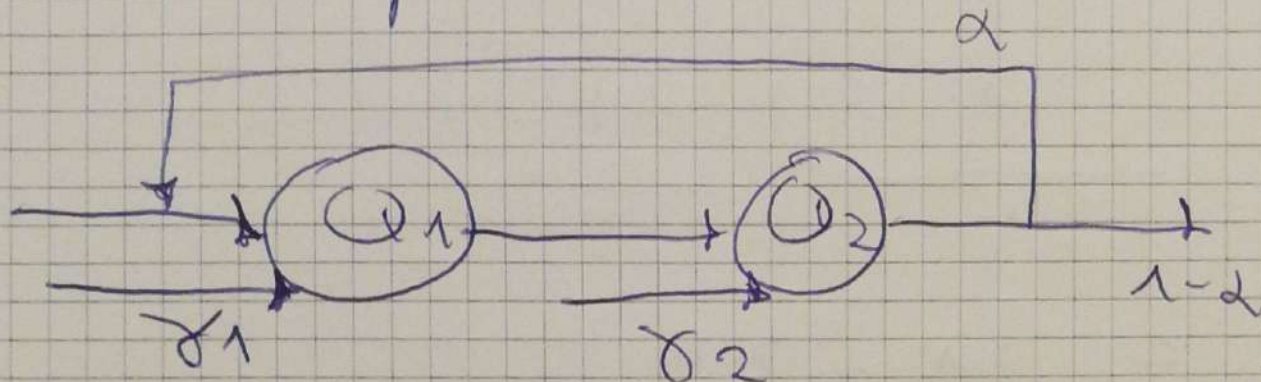
$$\lambda_1 = \frac{\alpha \lambda}{1-d}$$

$$\Rightarrow E\{\tau\} = \frac{\alpha}{1-\alpha} E\{\tau_1\} + \frac{\lambda}{\lambda} E\{\tau_2\}$$

$$= \frac{\alpha E\{\tau_1\} + E\{\tau_2\}}{1-\alpha}$$

CASE ③ $\Lambda = \delta_1 + \delta_2$

Customers can enter from input 1 & from input 2 (δ_1, δ_2)



INPUT 1 (δ_1) \Rightarrow CASE ①

INPUT 2 (δ_2) \Rightarrow CASE ②

$$\textcircled{1} = E\{\tau\} = \frac{E\{\tau_1\} + E\{\tau_2\}}{\lambda - \alpha} \left(\frac{\delta_1}{\delta_1 + \delta_2} \right)$$

$$\textcircled{2} = E\{\tau\} = \frac{\alpha E\{\tau_1\} + E\{\tau_2\}}{\lambda - \alpha} \left(\frac{\delta_2}{\delta_1 + \delta_2} \right)$$

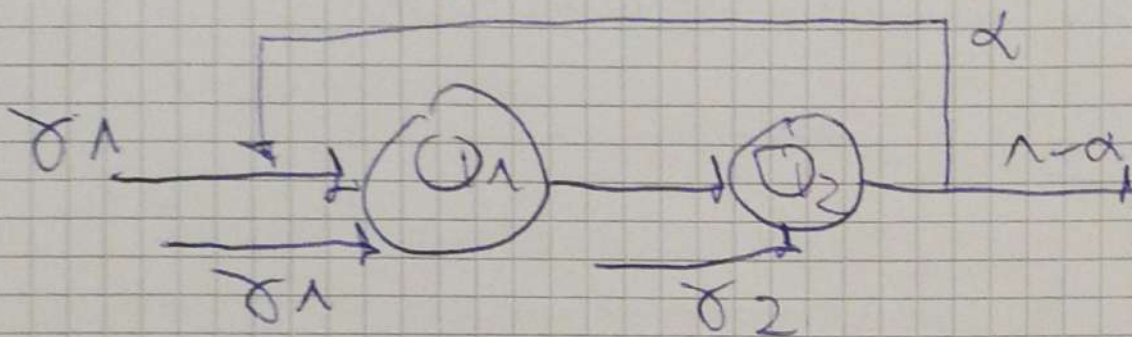
\Rightarrow We now need to WEIGHT the two different cases!

$$\Rightarrow E\{\tau\} = \frac{\delta_1}{\delta_1 + \delta_2} \frac{E\{\tau_1\} + E\{\tau_2\}}{\lambda - \alpha} + \frac{\delta_2 \alpha}{\delta_1 + \delta_2} \frac{E\{\tau_1\} + E\{\tau_2\}}{\lambda - \alpha}$$

$$\Rightarrow E\{\tau\} = \frac{E\{\tau_1\} \cdot (\delta_1 + \alpha \delta_2)}{(\lambda - \alpha)(\delta_1 + \delta_2)} + \frac{E\{\tau_2\}}{(\lambda - \alpha) \cdot (\delta_1 + \delta_2)}$$

ALTERNATIVE APPROACH

~~write down~~ \Rightarrow write down TRAFFIC EQUATIONS



$$\lambda = \lambda_1 + \lambda_2$$

GLOBAL INPUT GLOBAL OUTPUT

$$\left\{ \begin{array}{l} \lambda_1 + \lambda_2 = \lambda_2 (1 - \alpha) \\ \lambda_1 = \lambda_1 + \alpha \lambda_2 \end{array} \right.$$

$$\lambda_1 = \lambda_1 + \alpha \lambda_2$$

$$\lambda_2 = \lambda_1 + \alpha \lambda_2 \quad \text{[ALTERNATIVE APPROACH]}$$

$$\Rightarrow \lambda_2 = \frac{\lambda_1 + \alpha \lambda_2}{1 - \alpha}$$

$$\Rightarrow \lambda_1 = \frac{\lambda_1 + \alpha (\lambda_1 + \alpha \lambda_2)}{1 - \alpha}$$

$$= \frac{\lambda_1 (1 - \alpha) + \alpha \lambda_1 + \alpha^2 \lambda_2}{1 - \alpha}$$

$$= \frac{\lambda_1 - \alpha \lambda_1 + \alpha \lambda_1 + \alpha^2 \lambda_2}{1 - \alpha}$$

$$\lambda_1 = \frac{\lambda_1 + \alpha \lambda_2}{1 - \alpha}$$

~~$\Rightarrow \lambda_1 = \frac{\lambda_1 + \alpha \lambda_2}{1 - \alpha}$~~

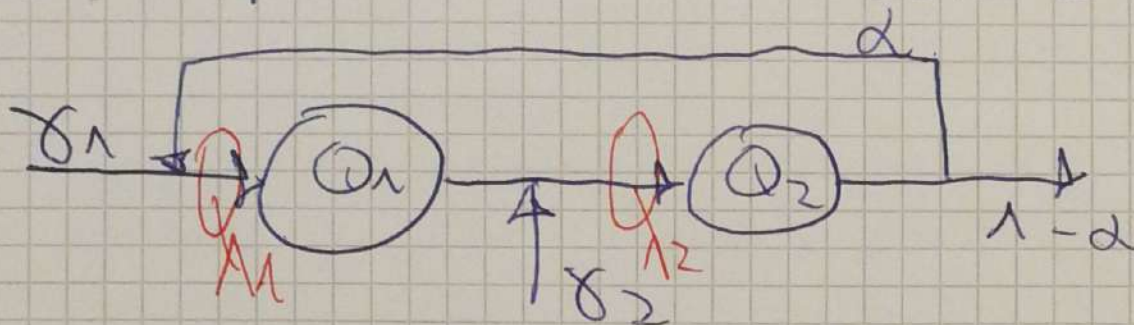
$$E\{\tau\} = \sum_{i=1}^Q \frac{\lambda_i}{\lambda} \cdot E\{\tau_i\}$$

$$= \frac{\lambda_1}{\lambda} \cdot E\{\tau_1\} + \frac{\lambda_2}{\lambda} \cdot E\{\tau_2\}$$

$$= \frac{\alpha_1 + \alpha_2 \alpha_2}{(1-\alpha_1) \cdot (\alpha_1 + \alpha_2)} E\{\tau_1\} + \frac{(\alpha_1 + \alpha_2) \cdot E\{\tau_2\}}{(1-\alpha_1) \cdot (\alpha_1 + \alpha_2)}$$

$$= \frac{(\alpha_1 + \alpha_2 \alpha_2)}{(1-\alpha_1) \cdot (\alpha_1 + \alpha_2)} E\{\tau_1\} + \frac{E\{\tau_2\}}{(1-\alpha_1)}$$

→ Now express this via the GENERAL FORMULA:



$$\lambda = \delta_1 + \delta_2$$

(could do the same thing:
 $\lambda_1 + \delta_2 = \lambda_2$)

$$\begin{cases} \delta_1 + \delta_2 = \lambda_2 / (1 - \alpha) \\ \delta_1 + \alpha \lambda_2 = \lambda_1 \end{cases}$$

$$\Rightarrow \lambda_2 = \frac{\delta_1 + \delta_2}{1 - \alpha}$$

$$\lambda_1 = \delta_1 + \alpha \frac{\delta_1 + \delta_2}{1 - \alpha} = \delta_1 + \frac{\alpha \delta_1 + \alpha \delta_2}{1 - \alpha}$$

$$\lambda_1 = \frac{\delta_1 + \alpha \delta_2}{1 - \alpha}$$

$$\Rightarrow E\{T\} = \frac{\delta_1 + \alpha \delta_2}{(1 - \alpha)(\delta_1 + \delta_2)} \cdot E\{T\} + \frac{(\delta_1 + \delta_2) \cdot E\{T\}}{(1 - \alpha)(\delta_1 + \delta_2)}$$

(No need to know probabilities!)

DIFFERENCE WITH REALITY:

Lengths not exponential (random)

↳ Same length of packet over network
 & same service time over all routers

↳ By mathematical models, different service time at different routers