

113) Define a "Quadrature Filter" for a process.

We call "Quadrature filter" a system with the following transfer function:

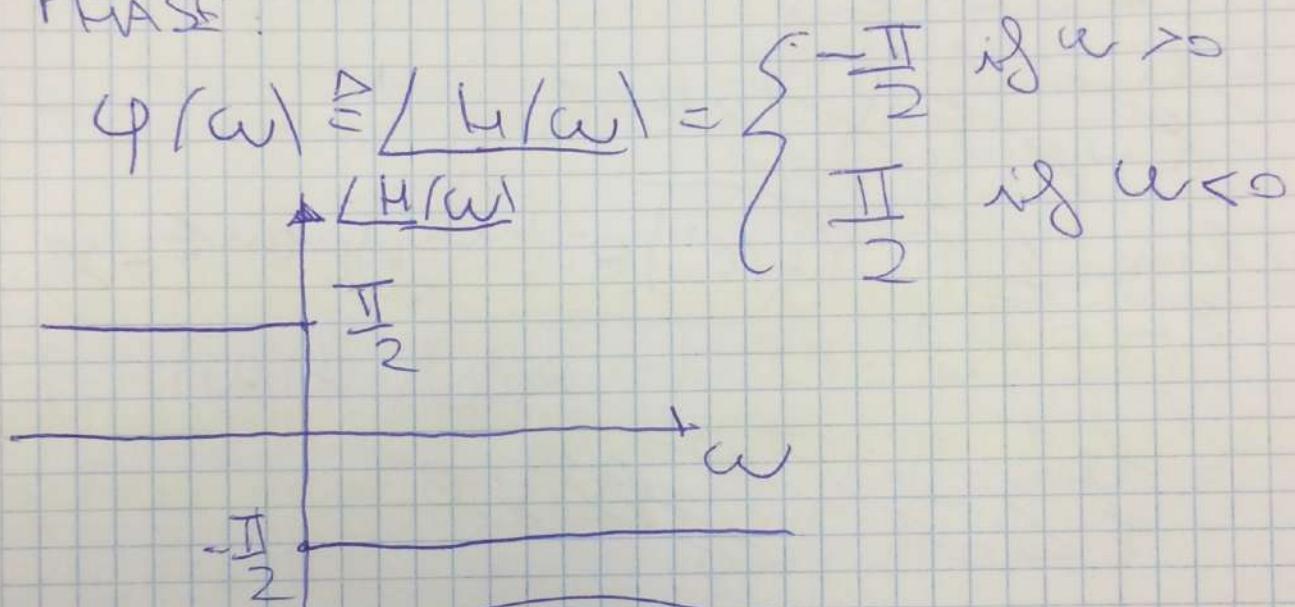
$$H(\omega) = \begin{cases} +j\omega & \text{if } \omega < 0 \\ -j\omega & \text{if } \omega > 0 \end{cases} = -j \operatorname{sign}(\omega)$$

~~H(ω) is~~

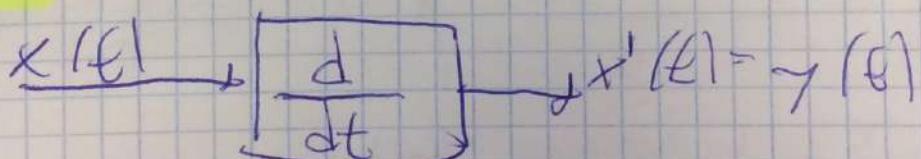
* $H(\omega) = e^{j\phi(\omega)}$ \rightarrow max of ω

Magnitude $|H(\omega)| = \Delta \quad \forall \omega$

PHASE:



111) Obtain the spectrum of the output of a differentiator when the input is a SSS process.



SPECTRUM:

$$H(\omega) = j\omega$$

Proof:

~~$$Y(\omega) = \int_{-\infty}^{+\infty} \lim_{\epsilon \rightarrow 0} \frac{x(t+\epsilon) - x(t)}{\epsilon} e^{-j\omega t} dt$$~~

$$Y(\omega) = \int_{-\infty}^{+\infty} g(\epsilon) \cdot e^{-j\omega t} dt$$

$$= \int_{-\infty}^{+\infty} \lim_{\epsilon \rightarrow 0} \left[\frac{x(t+\epsilon) - x(t)}{\epsilon} \right] e^{-j\omega t} dt$$

$$= \lim_{\epsilon \rightarrow 0} \frac{1}{\epsilon} \cdot \int_{-\infty}^{+\infty} [x(t+\epsilon) - x(t)] \cdot e^{-j\omega t} dt$$

$$\epsilon' = t + \epsilon$$

~~$$= \lim_{\epsilon \rightarrow 0} \frac{1}{\epsilon} \int_{-\infty}^{+\infty} [x(t+\epsilon) - x(t')] \cdot e^{-j\omega t'} dt'$$~~

$$\lim_{\epsilon \rightarrow 0} \frac{1}{\epsilon} \int_{-\infty}^{+\infty} x(t') e^{-j\omega t'} dt' e^{j\omega \epsilon} - x(\omega)$$

~~(def)~~ $x(\omega)$

~~$$= \lim_{\epsilon \rightarrow 0} \frac{1}{\epsilon} \int_{-\infty}^{+\infty} x(t') dt'$$~~

$$= \lim_{\epsilon \rightarrow 0} \frac{1}{\epsilon} (e^{j\omega \epsilon} - 1) x(\omega)$$

$$\lim_{\epsilon \rightarrow 0} \frac{e^{j\omega \epsilon} - 1}{\epsilon} = \frac{d}{d\omega}$$

(definitie)

By de losetac rule:

$$\lim_{\epsilon \rightarrow 0} \frac{e^{j\omega \epsilon}}{\epsilon} \cdot \frac{j\omega}{1} \cdot x(\omega) = j\omega \cdot x(\omega)$$

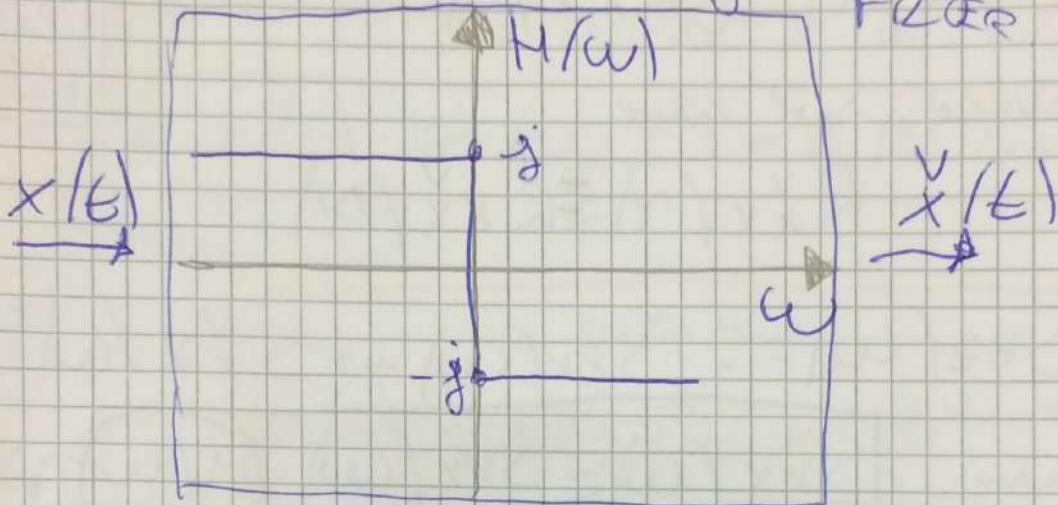
$$\Rightarrow M(\omega) = j\omega$$

113) OFFINE WELBERT TRANSFORM of a Process:

INPUT: $\overset{\text{REAL}}{\text{WSS}}$ process $X(t)$

$$\Rightarrow \overset{\circlearrowleft}{X(t)} \triangleq X(t) \oplus \frac{1}{\pi t} = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{X(\tau)}{t-\tau} d\tau$$

$\overset{\circlearrowleft}{X(t)}$ is the OUTPUT of a QUADRATURE FILTER



114) DEFINITION of "ANALYTIC SIGNAL" associated to a process $X(t)$ and DERIVE the relationship between its spectrum and that of the process $X(t)$.

DEFINITION OF ANALYTIC SIGNAL:

$X(t)$ and $\overset{\circlearrowleft}{X(t)}$ real and WSS, we form

COMPLEX PROCESS:

$$Z(t) \triangleq X(t) + \overset{\circlearrowleft}{X(t)}$$

analytic signal associated with $X(t)$.

RELATIONSHIP between SPECTRUM of $Z(t)$ and SPECTRUM of $X(t)$.

Derive expression of $S_{ZZ}(f)$. ① Compute $R_{ZZ}(f)$

$$R_{ZZ}(f) = E\{Z(f+M) \cdot Z^*(f)\}$$

$$= E\{X(f+M) \cdot X(f)\} + E\{X(f+M) \cdot X^*(f)\}$$

$$- j \cdot E\{X(f+M) \cdot X(f)\} + j \cdot E\{X(f+M) \cdot X(f)\}$$

$$= R_{XX}(f) + R_{XX}^V(f) + j[-R_{XX}^V(f) + R_{XX}^V(M)]$$

$$= 2R_{XX}(f) + jR_{XX}^V(f)$$

Since we have:

$$\boxed{R_{XX}(f) = R_{XX}^V(f)}$$

$$R_{XX}^V(f) = R_{XX}^V(M)$$

$$\Rightarrow S_{ZZ}(f) = 2[S_{XX}(f) + jS_{XX}^V(f)]$$

Since $S_{XX}^V(f) = S_{XX}(f) \cdot H(f)$

From $R_{XX}^V(f) = R_{XX}(f) \otimes h(f)$

$$S_{ZZ}(f) = \begin{cases} 2S_{XX}(f) + 2S_{XX}(f)(j)/(-j) & f > 0 \\ 2S_{XX}(f) + 2S_{XX}(f)(j)/(+j) & f < 0 \end{cases}$$

$$S_{ZZ}(f) = \begin{cases} 4S_{XX}(f) & f > 0 \\ 0 & f < 0 \end{cases}$$

\Rightarrow IN GENERAL:

$$\boxed{S_{ZZ}(f) = 4S_{XX}(f) \cdot U(f)}$$

- 4) Write the DEFINITION of RICE REPRESENTATION OF A SSS process $X(t)$.
 Give the RELATIONSHIP between its spectrum and that of its I-Q components.

DEFINITION OF RICE REPRESENTATION

Given a WSS real process $X(t)$ with ZERO MEAN, we can always write $X(t)$ as:

$$X(t) = i(t) \cdot \cos(\omega_0 t) - q(t) \cdot \sin(\omega_0 t)$$

where :

ω_0 is arbitrary

$$i(t) = \text{Real}\{z(t) \cdot e^{-j\omega_0 t}\}$$

$$q(t) = \text{Imag}\{z(t) \cdot e^{-j\omega_0 t}\}$$

$$(z(t) e^{-j\omega_0 t}) = i(t) + j q(t)$$

$z(t)$ is the ANALYTIC SIGNAL associated to $X(t)$.

RELATIONSHIP between SPECTRA:

$$\begin{aligned} S_{ii}(w) &= S_{qq}(w) = S_{xx}(w + \omega_0) \cdot U(w + \omega_0) + \\ &+ S_{xx}(w - \omega_0) \cdot U(-w + \omega_0) \end{aligned}$$

- 40) DEFINITION OF "RICE REPRESENTATION" &
 a SSS process $x(t)$. Give the relationship between its spectrum and that of ~~process~~
~~process~~ & its I-Q components.

DEFINITION OF RICE REPRESENTATION:

Given ~~a~~ a WSS Real process $x(t)$ with ~~zero mean~~. We can always write $x(t)$ as:

$$x(t) = i(t) \cos(\omega_0 t - q(t)) + q(t) \sin(\omega_0 t)$$

RELATIONSHIP:

$$\begin{aligned} R_{xx}(t) &= E\{x(t)x(t+\tau)\} = E\{i(t)\cos(\omega_0 t - q(t)) \cdot i(t+\tau)\cos(\omega_0(t+\tau) - q(t+\tau))\} \\ &= E\{\underbrace{i(t)}_{\text{REAL}} \underbrace{[\cos(\omega_0 t - q(t)) + j \sin(\omega_0 t - q(t))]}_{\text{IQ}} \cdot \underbrace{[i(t+\tau) - j q(t+\tau)]}_{\text{IQ}}\} \\ &= R_{ii}(\tau) + R_{qq}(\tau) + j R_{qi}(\tau) - j R_{iq}(\tau) \\ &= \underbrace{2R_{ii}(\tau)}_{\text{REAL}} + \underbrace{2jR_{qi}(\tau)}_{\text{IQ}} \end{aligned}$$

is arbitrary

Because:

$$\Rightarrow R_{ii}(\tau) = R_{qq}(\tau)$$

$$i(t) = \text{Real}\{z(t)\} e^{-j\omega_0 t}$$

$$q(t) = \text{Imag}\{z(t)\} e^{-j\omega_0 t}$$

$$R_{qi}(\tau) = -R_{iq}(\tau)$$

$$R_{ii}(\tau) = \frac{1}{2} \text{Real}\{R_{xx}(\tau)\}$$

$$R_{qq}(\tau) = \frac{1}{2} \text{Imaginary}\{R_{xx}(\tau)\}$$

At the end of the day:

$$\begin{aligned} S_{ii}(\omega) &= S_{qq}(\omega) = S_{xx}(\omega + \omega_0) \cdot U(\omega + \omega_0) \\ &\quad + S_{xx}(\omega - \omega_0) \cdot U(-\omega + \omega_0) \end{aligned}$$

4.3) DEFINITION OF MEAN-SQUARE PERIODIC PROCESS.

A WSS process $x(t)$ is MEAN-SQUARE (m.s.) PERIODIC if its autocorrelation $R_{xx}(\tau)$ is PERIODIC.

$$R_{xx}(\gamma + T) = R_{xx}(\gamma) \quad \forall \gamma \text{ for a certain } T$$

4.4) DEFINITION OF FOURIER EXPANSION PRESENTATION OF A SSS PROCESS $x(t)$.

Given a WSS process $x(t)$, the sum:

$$\hat{x}(t) = \sum_{n=-\infty}^{+\infty} c_n \cdot e^{jn\omega_0 t}$$

where:

$$c_n = \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t) \cdot e^{-jnw_0 t} dt$$

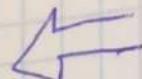
with: $\omega_0 = \frac{2\pi}{T}$

If we have T arbitrary,

$\hat{x}(t)$ is the Fourier series representation of process $x(t)$ over $(-\frac{T}{2}, \frac{T}{2})$

SOLUTION:

KARHUNEN - LOÈVE
CONTINUATION



$\varphi_n(\epsilon)$ are the EIGENFUNCTIONS of the integral equation:

SA ~~the Fourier~~ basis by

$$\boxed{\int_0^T R_{xx}(\epsilon_1, \epsilon_2) \cdot \varphi(\epsilon_2) d\epsilon_2 = \lambda \varphi(\epsilon_1)} \quad 0 < \epsilon_1 < T$$

where the solutions $\varphi_n(\epsilon)$ are orthonormal and satisfy the identity:

$$\boxed{R_{xx}(\epsilon, \epsilon) = \sum_{n=1}^{\infty} \lambda_n |\varphi_n(\epsilon)|^2} \quad 0 < \epsilon < T$$

where λ_n are the corresponding eigenvalues for each orthogonal function.

\Rightarrow This generates

$$\boxed{E \{ |x(t) - \hat{x}(t)|^2 \} = 0} \quad \begin{matrix} \text{nonzero} \\ \text{because } t \\ \text{over } [0, T] \end{matrix}$$

$$\boxed{E \{ c_n \cdot c_m^* \} = \lambda_n \cdot \delta[n-m]}$$

43) DEFINITION OF KARHUNEN-LOEVE EXPANSION.

- In order to represent $X(t)$ over an interval $0 < t < T$, the Fourier Series is a special case of expansion of the more general form.

$$\hat{X}(t) = \sum_{n=1}^{+\infty} c_n \cdot \varphi_n(t) \quad \text{in } 0 < t < T$$

Where $\varphi_n(t)$ is a set of ORTHONORMAL FUNCTIONS in the interval $(0, T)$.

$$\int_0^T \varphi_n(t) \cdot \varphi_m^*(t) dt = S[n-m]$$

And coefficients c_n are given by:

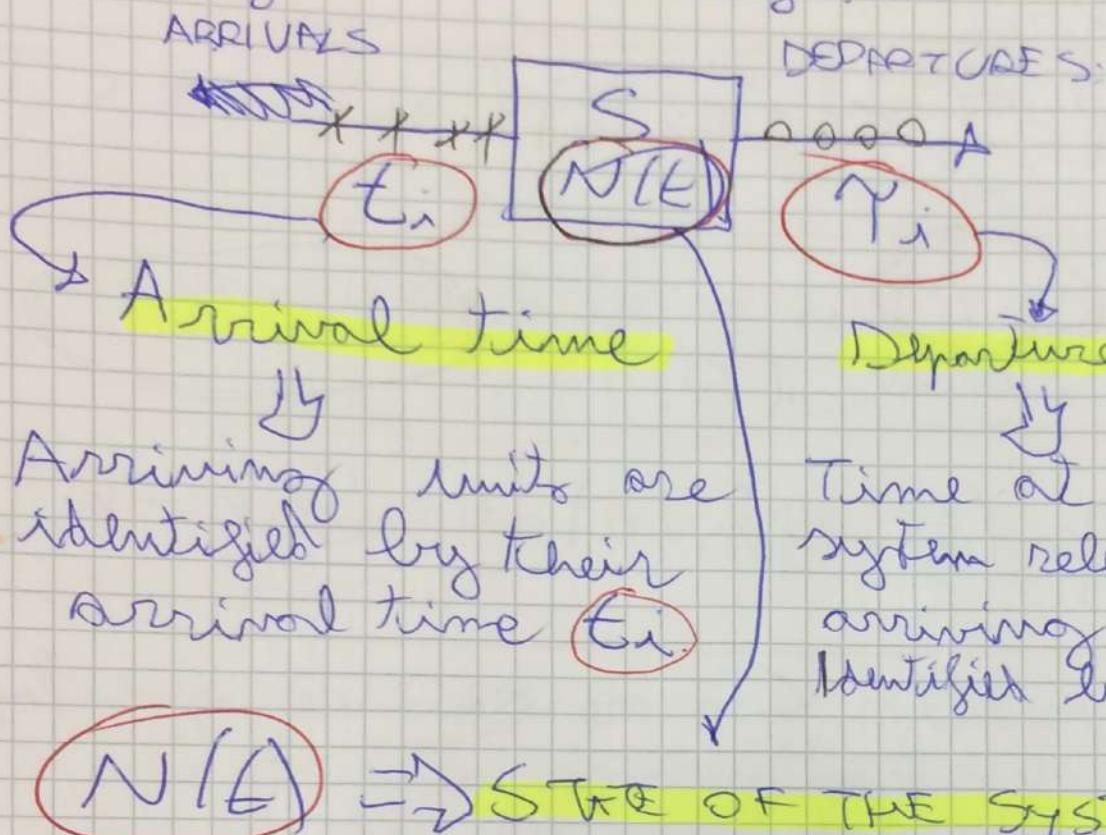
$$c_n = \int_0^T X(t) \cdot \varphi_n^*(t) dt$$

$X(t)$ very general.
Not necessarily WSS, nor M.S. random.

$$S[n-m] = \begin{cases} 1 & \text{if } n=m \\ 0 & \text{if } n \neq m \end{cases}$$

How to QUEUING THEORY - INTRODUCTION:

Queuing Theory describes a large set of phenomena concerning arrivals, waiting and servicing.



Arriving units are identified by their arrival time t_i .

Time at that the system releases a certain arriving unit. Identified by Y_i .

$N(t)$ \Rightarrow STATE OF THE SYSTEM.

It describes the # units inside the system S (being processed by S or queuing) at time t .

FUNDAMENTAL TIMES IN A SYSTEM:

- SYSTEM TIME:

a_i

time spent by the i -th unit inside the system S (how long it stays in S).

- WAITING TIME:

b_i

time spent by the i -th unit in queue before entering the system S .

$$a_i = Y_i - t_i$$

\downarrow departure

\rightarrow arrival

$$b_i = Y_{i-1} - t_i$$

\downarrow departing previous

\rightarrow arrival

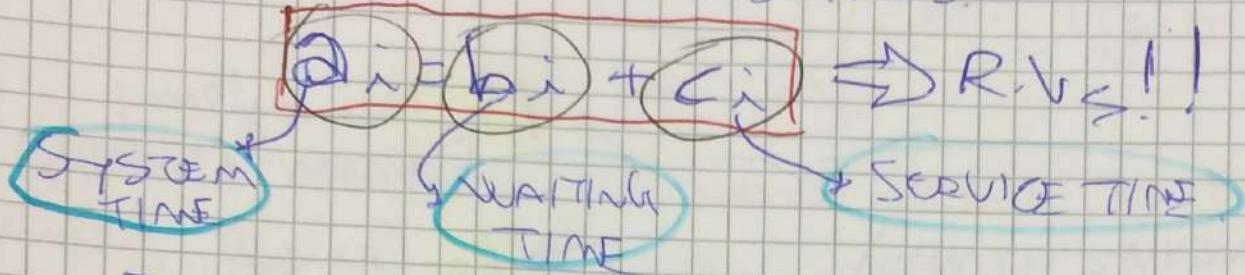
SERVICE TIME

C_i

$$C_i = Y_i - Y_{i-1}$$

Time spent by item ~~unit~~ to be processed by the system. (serviced) unit

REGULATION A manu 3 TIMES.



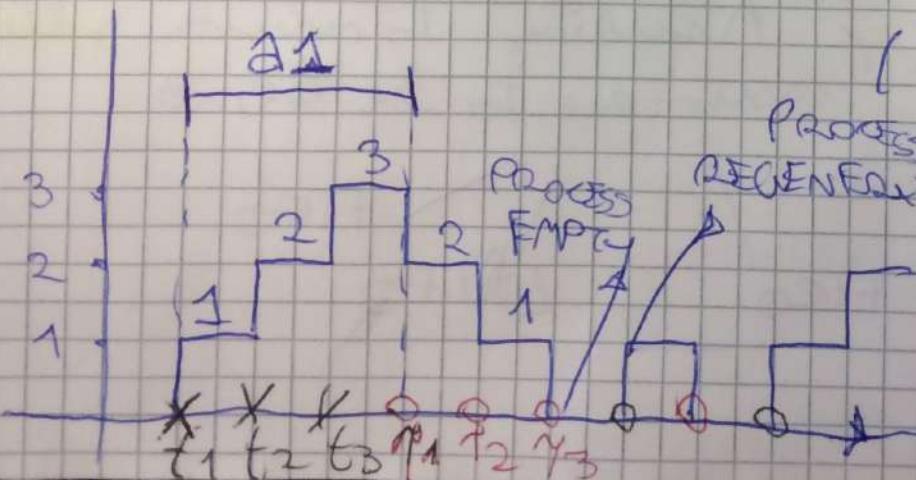
The system time is the sum of the waiting time and the service time.

REGENERATING PROCESS
(REGENERATIVE)

If $N(t)$ is the state of the system, counting the # units inside the system at time t , and if we consider a STATIONARY PROCESS $X(t)$, where a queue has already been listing,

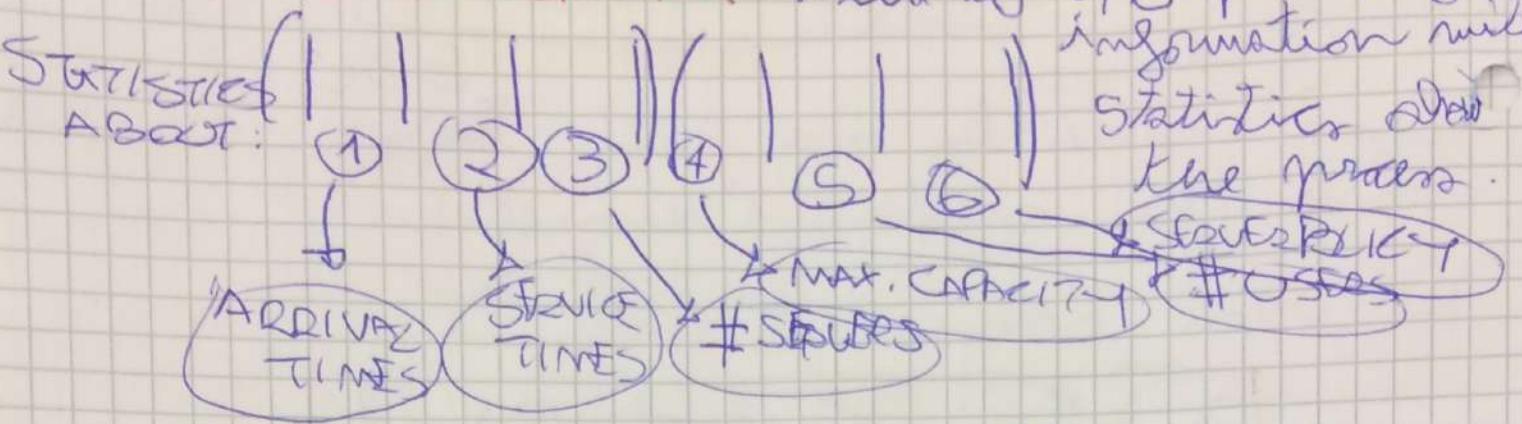
$N(t)$ is a ~~DISCRETE-STATE~~ CONTINUOUS random process:

- increasing by 1 at ϵ_i (arrival)
- decreasing by 1 at γ_i (departure)



(It gets a new process realization after REGENERATES it was empty)

KENDALL'S NOTATION: Field of 3/6 places of information with statistics about the process.



① TYPE OF INPUT PROCESS
(ARRIVAL TIMES)

M: Memoryless,
Poisson (Markov)

G: General, Arbitrary
arrival times

E: Erlang-K

② DISTRIBUTION OF SERVICE TIME

M: " "

G: " "

③ # SERVERS AVAILABLE

↑ Server

→ ∞ Servers

(immediate service)

D: Deterministic
Service time,
(No R.V.), constant

④ CAPACITY:
~~Max # users in the system~~
(How many people can wait in queue)

⑤ MAX # USERS:
(POPULATION): How many users can be served at the same time.
Capacity \rightarrow 0 users

⑥ SERVER POLICY: According to which policy users are to be served.

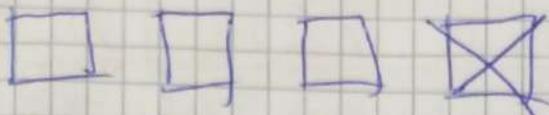
N(t)
by
STATE

FIFO

FIFO
LIFO

DEFN # units waiting
Ex: $N(t) \geq 4$ to be served (if capacity = ∞)

\Rightarrow 3 units in queue
1 unit served.



ASSUMPTIONS:

- Always consider Poisson arrival times. (Poisson Point Process), with intensity:
 $\lambda = \# \text{ units}$
- Distribution function of service time $F_C(c)$, $\forall i$.
- Arrival times and service times are INDEPENDENT R.V.s
- $N(t)$ is a ~~process~~ \rightarrow Strict-Sense Stationary.
 $\Rightarrow N(t)$ not affected by a shift of the time origin.

WRITE AND DERIVE CITTE'S FORMULA

Formula holding without any conditions about interarrival times (not joint Poisson), independently of the type of the system or properties of α_i .

IDEA: Little's Formula relates # ~~time~~ at any time with the intensity and the ~~mean~~ time.

ASSUME: SSS process $x(t)$

Suppose point processes ϵ_i and α_i are mean-ergodic.

$$\lim_{T \rightarrow \infty} \frac{E\{N(T)\}}{T} = \lambda \quad \text{INTENSITY of points over } T$$

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n \alpha_k = E\{\alpha_i\} \quad \text{SYSTEM TIME}$$

$\{ \alpha_i = b_i + c_i \}$

$$E\{N(T)\} = \lambda \cdot E\{\alpha_i\} \quad \text{LITTLE'S FORMULA}$$

PROOF: initially repeated arrival times

We will show that $N(t)$ is also mean-ergodic:

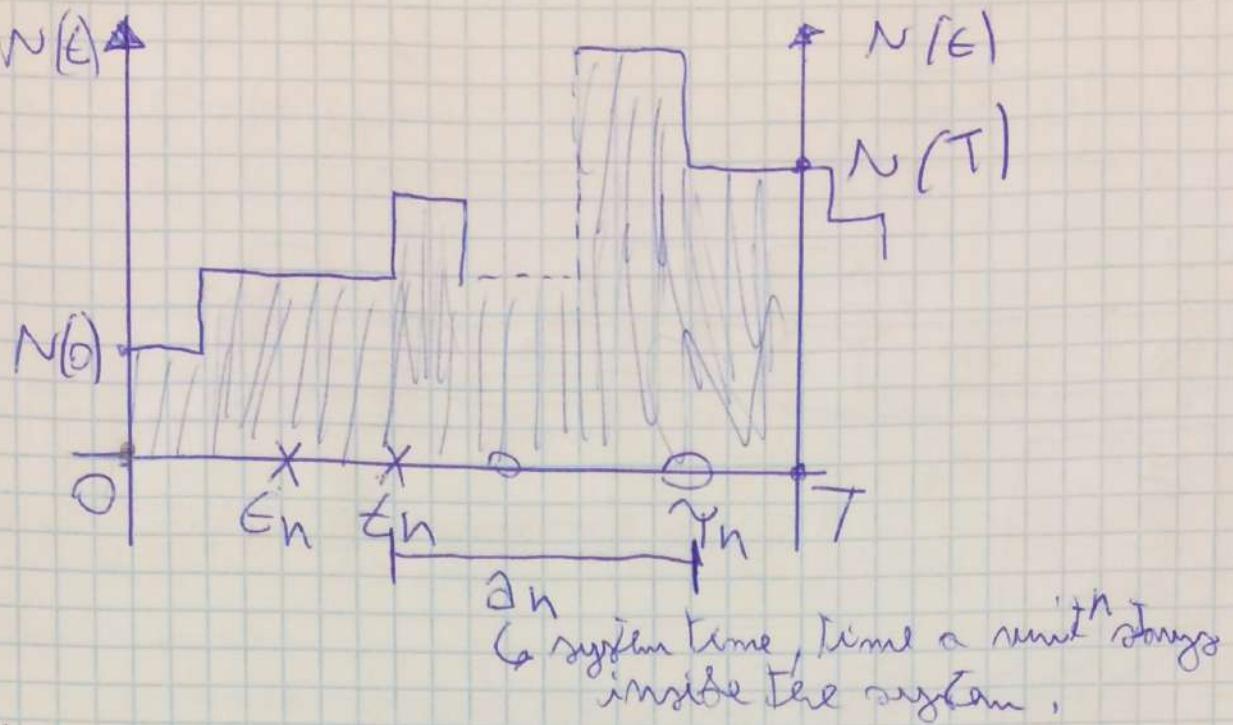
$$\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T N(t) dt = \lambda \cdot E\{\alpha_i\} = E\{N(t)\}$$

PROOF: Consider a time interval $(0, T)$:

RECALL * MEAN-ERGODICITY DEFINITION:

For a SSS $x(t)$:

$$E\{x(t)\} = \eta x$$



We have to prove that:

$$\sum_{t=1}^{NT} \Delta t \leq \int_0^T N(t) dt - \sum_{n=1}^{NT-1} \Delta n \leq \sum_{i=1}^{N(0)} \Delta i$$

point arriving in [0, T] Beginning

END $\rightarrow N(0)$

$\rightarrow N(0)$

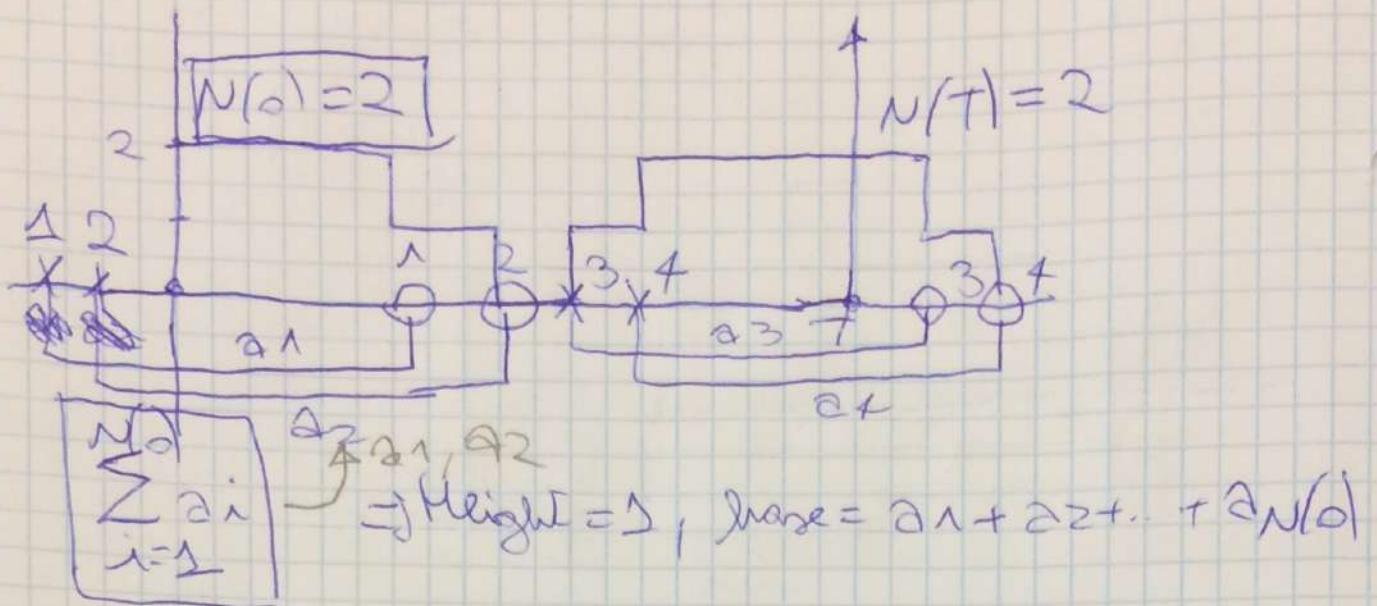
① ② ③ ④

NEGATIVE

- 1) Sum of times that $N(t)$ units still in S at $T=t$ remain in S (also beyond T).
- 2) Overall system time of units in S in time $(0, T]$
- ~~3) Sum of times that units arriving in $[0, T]$ stay in S (also beyond T)~~
- 4) Sum of times that $N(0)$ units that are in S at $t=0$ remain in S (also beyond T).

PROOF: $\sum_{i=1}^{N(0)}$

④ $\sum_{i=1}^{N(0)} \Delta i$ is an area under height 1 and base given by: $\Delta 1 + \Delta 2 + \dots + \Delta N(0)$
itself.



2-SIDES PROOF:

- (1) ~~RIGHT - HAND INEQUALITY~~
- (2) ~~LEFT - HAND INEQUALITY~~

1) RIGHT - HAND INEQUALITY

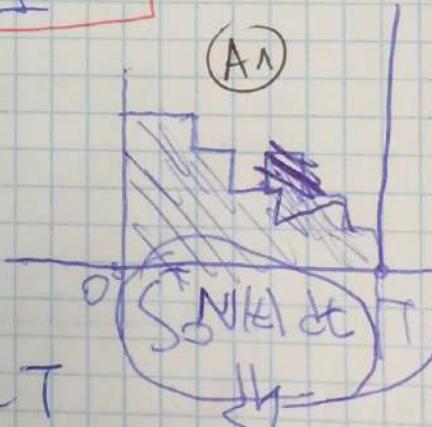
Prove that:

$$\int_0^T N(\epsilon) dt - \sum_{n=1}^{N(T)} a_n \leq \sum_{i=1}^{N(t)} a_i$$

(A)

A) No units enter (0, T)

$$\Rightarrow N(T) = 0$$



A1) All units exit S before T

\Rightarrow Surely

$$\int_0^T N(\epsilon) dt \leq \sum_{i=1}^{N(t)} a_i$$



A2) Not all units exit S before T, but some exit after T.

\Rightarrow Situation even more in favour of $\sum_{i=1}^{N(t)} a_i$.

$$\int_0^T N(\epsilon) dt \text{ is just a portion of } \sum_{i=1}^{N(t)} a_i$$

(3) If some n_T units enter S during (σ, T) .

$$\Rightarrow nT \neq 0.$$

Both (A1) and (A2) have:

$\int_0^T N(t) dt$ subtracts any positive quantity $\sum_{n=1}^{nT} a_n$

This difference is always less than or equal to $\int_0^T N(t) dt$ for $nT = 0$.

So we have proved ~~that~~ the right-hand side

$$\int_0^T N(t) dt - \sum_{n=1}^{nT} a_n \leq \sum_{i=1}^{N(\sigma)} a_i$$

muchough...

many be negative

② LEFT-HAND INEQUALITY:

We now have to prove that:

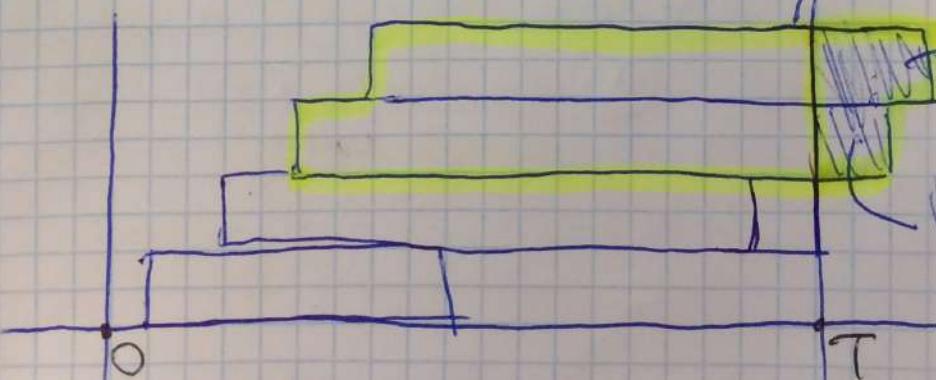
$$-\int_0^T N(t) dt + \sum_{n=1}^{nT} a_n \leq \sum_{r=1}^{N(\sigma)} a_r$$

(We ~~switched~~ will change the sign both on).

Again, we have 2 cases: (1) time $\sigma = 0$

A) Suppose that, initially, S is empty.

$$\text{at } t=0 \Rightarrow N(0)=0.$$



$$= \sum_{r=1}^{N(\sigma)} a_r$$

$$= \sum_{n=1}^{nT} a_n$$

$$= \sum_{n=1}^{nT} a_n - \int_0^T N(t) dt$$

Quantity ~~survived~~ $\sum_{n=1}^{N(T)} a_n - \int_0^T N(t) dt < \sum_{r=1}^{N(T)} a_r$

part of $\sum_{n=1}^{N(T)} a_n$ survived part

② If $N(t) \neq 0$, then $\boxed{S \text{ not empty at } t=0}$

$\sum_{n=1}^{N(T)} a_n - \int_0^T N(t) dt$ is always smaller than $\sum_{r=1}^{N(T)} a_r$ because:

$\int_0^T N(t) dt$ increases, whether n_T does not change.

$\sum_{r=1}^{N(T)} a_r$ does not change or increases (if same unit alive at $t=0$ die before T or after T).

$$\Rightarrow \sum_{n=1}^{N(T)} a_n - \int_0^T N(t) dt < \sum_{r=1}^{N(T)} a_r$$

⇒ Both the left-hand side and the right-hand side have been proved and hence:

$$-\sum_{r=1}^{N(T)} a_r \leq \int_0^T N(t) dt - \sum_{n=1}^{N(T)} a_n \leq \sum_{i=1}^{N(0)} a_i$$

Continuing with the derivation of Little's Formula from what we just proved:

$$N(t) - \sum_{k=1}^{\infty} a_k \leq \int_0^t N(\tau) d\tau - \sum_{n=1}^{N(t)} a_n \leq \sum_{i=1}^{\infty} a_i$$

We know that the random ^{SUM} at any given time instant t is,

$$E \left\{ \left(\sum_{k=1}^{N(t)} a_k \right)^2 \right\} \leq E \{ N(t)^2 \} \cdot E \{ a_k^2 \} < \infty$$

R.V. Assumed R.V. Assumed finite/limited
limited/limited

~~If the M.S. value of a R.V. is finite, then the R.V. takes the 0 value with zero probability \leftrightarrow It is a FIDR.V.~~

We want to show that this inequality holds because we do not want a limit to stay in
for an infinite time.

REASON

PROOF:

① Consider the Random Sum of X_k :

$$S = \sum_{k=1}^N X_k$$

② Suppose $X_k \geq 0$ and identically distributed with but not independent and finite mean square
value of X_k is M .

assume: $E \{ X_k^2 \} = M$

③ MEAN IS SQUARE VALUE OF S :

$$E\{S^2\} = E\left\{\left(\sum_{k=1}^n X_k\right)^2\right\} = E\left\{\sum_{k=1}^n \sum_{m=1}^n X_k X_m\right\}$$

④ Fix $n = n$

PROVED LATER

$$E\{S^2 | n = n\} = \sum_{k=1}^n \sum_{m=1}^n E\{X_k \cdot X_m\} \leq n^2 M$$

The double summation contains n terms
with $k = m$ and ~~$n^2 - n$ terms~~

$\frac{n^2}{n^2} - n$ terms with $k \neq m$ where:

$$E\{X_k \cdot X_m\} \leq M \text{ and } X_k > 0$$

\Rightarrow (5) CONCLUDE THAT:

$$E\{S^2\} = E\{E\{S^2 | n\}\} \leq E\{n^2\} \cdot E\{v_i^2\}$$

(which corresponds to what we wanted to prove)

⑤ Now PROVE last:

$$E\{X_k \cdot X_m\} \leq M$$

In our case, for $k \neq m$, we have:

$$E\{X_k \cdot X_m\} \leq E\{X_k^2\} \cdot E\{X_m^2\}$$

$\Rightarrow E\{X_k \cdot X_m\} \leq M$ Because in general:

$$E\{XY\} \leq E\{X^2\} \cdot E\{Y^2\}$$

In fact, consider the general case:

$$\text{Consider } E\{(ax - y)^2\} = a^2 E\{x^2\} - 2a E\{xy\} + E\{y^2\}$$

a
b
c

Quadratic in a and non-negative in b, c

~~$$= \cancel{a^2 E\{x^2\}}$$~~
$$a^2 - 4ac \leq 0 \quad (\text{discriminant})$$

$$\Delta \leq 0. \quad (\text{non-positive})$$

$$\Rightarrow E^2\{xy\} - E\{x^2\} \cdot E\{y^2\} \leq 0$$

Consider now again

$$\left| -\sum_{t=1}^{NT} a_t \right| \leq \int_0^T N(\epsilon) dt - \sum_{n=1}^{NT} a_n \leq \sum_{i=1}^{NT} |a_i|$$

Multiply it by $\frac{1}{T}$ with $T \rightarrow \infty$

$$\left| -\frac{1}{T} \sum_{t=1}^{NT} a_t \right| \leq \frac{1}{T} \left\{ \int_0^T N(\epsilon) dt - \frac{1}{T} \sum_{n=1}^{NT} a_n \right\} \leq \frac{1}{T} \sum_{i=1}^{NT} |a_i|$$

$$0 \leq \frac{1}{T} \left\{ \int_0^T N(\epsilon) dt - \frac{1}{T} \sum_{n=1}^{NT} a_n \right\} \leq 0$$

$$\frac{1}{T} \int_0^T N(\epsilon) dt \underset{\textcircled{2}}{\approx} \frac{1}{T} \sum_{n=1}^{NT} a_n \underset{\textcircled{1}}{\approx} 0$$

By assumption of MEAN-FREQUENCY:

$$NT \approx NT \Rightarrow \frac{1}{T} = \frac{1}{NT}$$

\Rightarrow Replace $\frac{1}{T}$ by $\frac{1}{NT}$ in $\frac{1}{T} \sum_{n=1}^{NT} a_n$

$$\cancel{\frac{1}{T} \sum_{n=1}^{NT} a_n} \approx \frac{1}{NT} \sum_{n=1}^{NT} a_n$$

① $\frac{1}{T} \sum_{n=1}^{NT} a_n \approx \frac{1}{NT} \sum_{n=1}^{NT} a_n \approx \lambda \cdot E\{a_i\}$

Now replace $\frac{1}{T}$ by $\frac{1}{NT} \int_0^T N(t) dt$.

$\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T N(t) dt = \text{R.V.} \cdot E\{a_i\} \rightarrow \text{constant}$

\Rightarrow Take $E\{ \cdot \}$ of both ~~terms~~ members \checkmark (with $N(t)$ stationary)

$$E\{N(T)\} = \lambda \cdot E\{a_i\}$$

Since both terms are equal to $\lambda \cdot E\{a_i\}$:

$$\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T N(t) dt = E\{N(t)\}$$

\Rightarrow $N(t)$ is ergodic.

4) Calculate the distribution function & the state $N(t)$ in a $M|G|\infty$ queue

We want to prove the following theorem:
 "The state $N(t)$ of a $M|G|\infty$ system is Poisson distributed:

$$P\{N(t)=k\} = e^{-\rho} \cdot \frac{\rho^k}{k!}$$

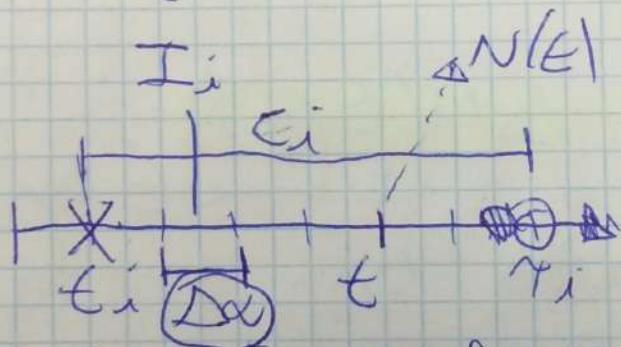
Regarding the distribution

Where ρ is the traffic intensity / offered load: \sqrt{t}

$$\rho = \lambda \cdot E\{C_n\} = \lambda \cdot \eta c$$

Amount of units arriving to service per unit time.

PROOF. Studying $N(t)$:



Because each unit can be served immediately, the service time is IMMEDIATE.

\Rightarrow In IMMEDIATE SERVICE, each service time C_i does not affect the other units.

1) ARRIVALS in I_i : The time axis preceding t is divided in small subintervals with duration $\Delta_2, \Delta_3, \dots, \Delta_n$. Δ_i is the amount of arrivals in I_i , which can be only 0 or 1 (0 units or 1 unit) and is Poisson distributed.

1.1.4 Formally

Probability of $\Delta n_i = \# \text{arrivals in } I_i$

$$P\{\Delta n_i = j\} = e^{-\lambda \cdot \Delta x} \cdot \frac{(\lambda \cdot \Delta x)^j}{j!}$$

1 unit Δx

We can have 3 cases:

- $P\{\Delta n_i = 0\} = e^{-\lambda \cdot \Delta x} \cdot \frac{(\lambda \cdot \Delta x)^0}{0!} = 1 - \lambda \Delta x$ Poisson Point in Δx
- $P\{\Delta n_i > 1\} = e^{-\lambda \cdot \Delta x} \cdot \frac{(\lambda \cdot \Delta x)^2}{2!} + e^{-\lambda \cdot \Delta x} \cdot \frac{(\lambda \cdot \Delta x)^3}{3!} + \dots \approx 0$
- $P\{\Delta n_i = 1\} = 1 - P\{\Delta n_i \geq 1\} = 1 - \lambda \Delta x$

2) Denote by $\Delta N(t, \Delta x_i)$ the contribution to the state $N(t)$ at time t due to the arrivals Δn_i in I_i (Δn_i can only be 0 or 1).

We then have:

$$N(t) = \sum_i \Delta N(t, \Delta x_i)$$

(3) Study the probability of:

$$\Delta N(t, \Delta x_i)$$

$(\Delta n_i = \# \text{arrivals in } I_i)$

Δn_i can only be 0 or 1.

$$\Delta n_i = \begin{cases} 0 \\ 1 \end{cases}$$

- If $D_{ni} = 0 \Rightarrow$ No units contribute.
- If $D_{ni} = 1$ ~~We may have a contribution depending on:~~

$$DN(t, \alpha_i) = \begin{cases} 1 & \text{Contribution} \\ 0 & \text{Depends on:} \end{cases}$$

if $D_{ni} = 1 \Rightarrow DN(t, \alpha_i) = \begin{cases} 1 & \text{if service time} \\ & [c_i > d_i] / \text{beginning} \\ & \text{duration of interval} \\ 0 & \text{if } c_i \text{ completed} \\ & \text{before } t \quad [c_i < d_i] \end{cases}$

Summing up:

* if $D_n = 1 \Rightarrow DN(t, \alpha_i) = \begin{cases} 1 & \text{if } c_i > d_i \\ 0 & \text{if } c_i \leq d_i \end{cases}$

~~Therefore the probability that there is a contribution depends on the distribution function of $c_i - d_i$~~

Therefore, the probability that there is a contribution depends on the distribution function of $c_i - d_i$

$$\underbrace{P\{DN(t, \alpha_i) = 1 | D_{ni} = 1\}}_{=} = P\{c_i > d_i\} = 1 - F(d_i)$$

By the TOTAL PROBABILITY THEOREM:

$$P\{DN(t, \alpha_i) = 1\} = P\{DN(t, \alpha_i) = 1 | D_{ni} = 1\} \cdot P\{D_{ni} = 1\}$$

$$P\{D_{ni} = 1\} + \textcircled{O}$$

Other case: zero contribution

$$P\{DN(t, \alpha_i) = 0 | D_{ni} = 0\} = 0$$

$$= [1 - F_c(d_i)] \cdot \Delta \alpha$$

(Poisson counts over non-overlapping intervals)

\Rightarrow r.v. $DN(t, \alpha_i)$ are i.i.d and independent because r.v. D_{ni} are independent.

4) Now studying $N(\epsilon) = \sum DN(\epsilon, x_i)$ as a sum of $n-1$ R.V.s. We need the following theorem:

THEOREM

Suppose R.V.s. x_i are independent and each one takes on the values 1 and 0

$$\boxed{0-1 \text{ R.V.}} \rightarrow P_i = P\{x_i=1\} \quad q_i = P\{x_i=0\} = 1 - p_i$$

if $Z = x_1 + x_2 + \dots + x_n$, then: (we want Z to be Poisson distributed)

WHAT
WE
WANT.

$$P\{Z=k\} = \frac{\lambda^k}{k!} \cdot e^{-\lambda} \quad \text{for } n \rightarrow \infty,$$

with

$$\lambda = p_1 + p_2 + \dots + p_n$$

$$\Rightarrow p_i \rightarrow 0 \quad \text{as } n \rightarrow \infty$$

PROOF:

① Consider the characteristic function of x_i .

$$\begin{aligned} \Phi_{x_i}(\omega) &= E\{e^{j\omega x_i}\} = p_i \cdot e^{j\omega \cdot 1} + q_i \cdot e^{j\omega \cdot 0} \\ &= p_i \cdot e^{j\omega} + q_i = \cancel{e^{j\omega - p_i}} \cdot e^{j\omega} + (1 - p_i). \\ &= 1 + p_i \cdot (e^{j\omega} - 1) \end{aligned}$$

For $Z = x_1 + x_2 + \dots + x_n$, we have the sum of n independent R.V.s.

② Char. function: $\Phi_Z(\omega) = E\{e^{j\omega(x_1 + x_2 + \dots + x_n)}\}$

$$= \Phi_{x_1}(\omega) \cdot \Phi_{x_2}(\omega) \cdot \dots \cdot \Phi_{x_n}(\omega)$$

$$\Rightarrow \Phi_Z(\omega) = [1 + p_1(e^{j\omega} - 1)] \cdot \dots \cdot [1 + p_n(e^{j\omega} - 1)]$$

Now take the TAYLOR EXPANSION:

③

TAYLOR EXPANSION:

$$e^x = \frac{x^0}{0!} + \frac{x^1}{1!} + \frac{x^2}{2!} + \dots$$

$$\text{Set } x = \lambda e^{i\omega u}$$

$$\Rightarrow e^{P_i(e^{i\omega u}-1)}$$

(recall:

$$\lambda + p_1 + p_2 + \dots + p_n$$

$$\text{for } p_i \rightarrow 0$$

$$\approx \phi_{x_i(\omega)} = 1 + p_i(e^{i\omega u} - 1)$$

for $p_i \ll 1$ (truncated to linear term)

~~Now consider two cases~~

⇒ The product of $\phi_{x_1(\omega)}, \dots, \phi_{x_n(\omega)}$ (product of exponentials) is approximately $\phi_z(\omega)$. Formally: ④

$$\phi_z(\omega) = e^{p_1(e^{i\omega u} - 1)} \cdot e^{p_2(e^{i\omega u} - 1)} \cdots e^{p_n(e^{i\omega u} - 1)}$$

If $p_i \rightarrow 0, p_1 + p_2 + \dots + p_n \rightarrow 0, n \rightarrow \infty$

$$\phi_z(\omega) = e^{\lambda \cdot (e^{i\omega u} - 1)}$$

Since this is the characteristic function of a Poisson-distributed R.V., the R.V. Z is Poisson distributed.

$$P\{Z=k\} = \frac{\lambda^k}{k!} e^{-\lambda} \text{ with } Z = x_1 + x_2 + \dots + x_n$$

Therefore the R.V.

$$N(t) = \sum_i D_N(t, \alpha_i) \text{ is Poisson distributed}$$

with parameter λ , where λ is distributed

PROVED is Poisson-distributed

A Poisson + Distributions:

$$\lambda = \lim_{\Delta x \rightarrow 0} \sum_{i=1}^{+\infty} P\{DN(t_i, \Delta x) = i\}$$

Consider only intervals with continuations

$$= \lim_{\Delta x \rightarrow 0} \sum_{i=1}^{+\infty} [1 - F_C(x_i)] \cdot \lambda \cdot \Delta x$$

$$= \lambda \cdot \int_0^{+\infty} [1 - F_C(x)] dx$$

THEOREM: Since we want to show that:

$$E\{N(t)\} = \lambda, E\{C\} = \alpha$$

$$\int_0^{+\infty} [1 - F_C(x)] dx = E\{C\} \text{ with } C > 0$$

PROOF: In general we have, for $x \geq 0$:

$$\int_0^{+\infty} [1 - F_X(x)] dx = \int_0^{+\infty} P\{X \geq x\} dx = E\{X\}$$

because:

$$\int_0^{+\infty} P\{X \geq x\} dx = \int_0^{+\infty} \left(\int_x^{+\infty} f_X(u) du \right) dx$$

$$= \int_0^{+\infty} \left(\int_0^x f_X(u) du \right) dx = \int_0^{+\infty} f_X(u) \int_0^u dx du$$

$$= \int_0^{+\infty} f_X(u) u du = E\{X\}$$

Poisson Parameter

$$\Rightarrow \lambda = \lambda \cdot E\{C\} = \lambda \cdot \alpha$$

by definition of Mean value of $N(t)$.

$$\lambda = \lambda \cdot E\{c\} = \lambda \cdot \eta c$$

This consider with Little's Formula.

$$E\{N(t)\} = \lambda = \lambda \cdot \eta c = \rho$$

$$P\{N(t) < k\} = e^{-\rho} \frac{\rho^k}{k!}$$

\Rightarrow Distribution of units form M/G/ ∞ system.

(1) Write the definition of a Marks off process and specify it be a continuous-time discrete-state Marks off chain.

DEFINITION OF MARKOFF PROCESS:

A Marks off process is a stochastic process $X(t)$ where the past has no influence on the future if its present is specified.

$$P\{X(t_n) \leq x | X(t_{n-1}) = x(t_{n-1}) \text{ given past}\}$$

where time has continuous values.

ANALYTIC DEFINITION FOR CONTINUOUS-TIME (CT) DISCRETE-STATE Marks off Chain.

A continuous-Time Marks off Chain is defined as:

~~Continuous-Time Markoff Chain definition~~

Continuous-Time (CT) Markoff Chain definition.

$$\begin{aligned} & P\{X(t_{n+1})=x_{n+1} | X(t_n)=x_n, \dots, X(t_1)=x_1\} \\ & = P\{X(t_{n+1})=x_{n+1} | X(t_n)=x_n\} \end{aligned}$$

where ~~$\{x_n\}$~~ belong to the set of DISCRETE VALUES

$\{z_1, z_2, \dots, z_N\}$ and $t_1 < t_2 < \dots < t_n < t_{n+1}$ are
GENERIC INSTANTS

(2). Definition and properties of the transition probability for a Continuous Time Discrete State Markoff Chain

NOT VERSION
transition probability DEFINITION for CT - DSCV

(from i -th state at time t_1 to j -th state at time t_2)

$$\Pi_{ij}(t_1, t_2) \triangleq P\{X(t_2)=z_j | X(t_1)=z_i\}$$

PROPERTIES.

STATE PROBABILITIES:

$$P_i(t) \triangleq P\{X(t)=z_i\}$$

1) NORMALIZATION:

$$\sum_j \Pi_{ij}(t_1, t_2) = 1$$

2) TOTAL PROBABILITY THEOREM:

$$\sum_i P_i(t_1) \Pi_{ij}(t_1, t_2) = P_j(t_2)$$

(12) Give the definition & properties of the transition probability rates for a Continuous-Time Discrete-State Markov Chain

We know that $\Pi(\gamma)$ is the transition probability matrix and it satisfies the differential equation:

$$\boxed{\Pi'(\gamma) = \Pi(\gamma) \wedge}$$

$\Rightarrow \Pi(\gamma)$ can be determined as:

$$\boxed{\Pi(\gamma) = e^{\Lambda\gamma} \Rightarrow \text{KOLMOGOROV EQUATION}}$$

In matrix form, $\boxed{\Lambda = \Pi'(0^+)}$

$$\boxed{\Lambda = \Pi'(0^+) = \begin{bmatrix} \lambda_{11} & \dots & \lambda_{1N} \\ \vdots & \ddots & \vdots \\ \lambda_{N1} & \dots & \lambda_{NN} \end{bmatrix}}$$

Matrix of numbers

where the elements λ_{ij} (numbers are):

$$\boxed{\lambda_{ij} = \Pi'_{ij}(0^+) = \frac{d}{d\gamma} \Pi_{ij}(\gamma) \Big|_{\gamma=0^+}}$$

derivative from the right of Π_{ij} at 0^+ .

(Assuming Π_{ij} differentiable in 0^+)

↳ holds if transition probability Π_{ij} from s_i to s_j is the probability of s_i over small interval $d\gamma$ is in the order of $d\gamma$.

So, we must have: condition.

$$\boxed{\Pi_{ij}/d\gamma = P\{X(\gamma + d\gamma) = s_j | X(\gamma) = s_i\} = \lambda_{ij}}$$

$\lambda_{ij} \cdot d\gamma$ is $d\gamma$ if $s_j = s_i$

So, at $\gamma = 0$,
 we consider $\Pi(0) = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$
 how elements
~~of Π~~ change,
 when you start moving forward in time
 from:

$$\boxed{\gamma = 0 \rightarrow \gamma = 0^+}$$

$$\boxed{\frac{d}{d\gamma} \Pi(\gamma) \Big|_{\gamma=0} = \frac{d}{d\gamma} \Pi(\gamma) \Big|_{\gamma=0^+}}$$

\Rightarrow Derivatives ignore the transition PROBABILITIES
 but RATES of $\lambda(i)$.

$\Rightarrow \lambda_{ij}$ is the rate at which the proba
 deports from z_i to z_j , because:

$\lambda_{ij} D t = P\{ \text{a system at time } \gamma \text{ is in state } z_i \text{ transitions to any other state } z_j \} \text{ during a small interval } (\gamma, \gamma + Dt)$

PROPERTIES:

$$\sum_j \lambda_{ij} = 0 \quad \sum_i \lambda_{ij} = 1$$

$$-\lambda_{ii} = \sum_j \lambda_{ij} \Rightarrow \lambda_{ii} \text{ negative missing term for } i$$

For $i = 0$

$$\lambda_{i0} = \frac{d \Pi_{i0}(\gamma)}{d\gamma} \Big|_0 \leq 0$$

3) CHAPMAN-KOLMOGOROV EQUATION:

$$\boxed{\Pi_{ij}(t_1, t_3) = \sum_{t_2} \Pi_{ij}(t_1, t_2) \cdot \Pi_{jj}(t_2, t_3)}$$

$$\Pi_{ij}[t_1, t_3] = \Pi_{ij}[t_1, t_2] \cdot \Pi_{jj}[t_2, t_3]$$

with ~~$t_1 < t_2 < t_3$~~

→ Assumption $x(t)$ is homogeneous
 → Transition probability depends on difference $t_2 - t_1$

$$\Pi_{ij}(t_1, t_2) = \Pi_{ij}(t_2 - t_1) = \Pi_{ij}/\gamma$$

$$= P\{x(t + \gamma) = j | x(t) = i\}$$

CHAPMAN-KOLMOGOROV EQUATION FOR CT MARKOFF CHAINS.

$$\boxed{\Pi(\gamma + \alpha) = \Pi(\gamma) \cdot \Pi(\alpha)}$$

where

$\Pi(\gamma)$ is the transition matrix with elements $\Pi_{ij}(\gamma)$, function of γ .

$$\Pi[n_1, n_2] = \begin{bmatrix} \Pi_{11}[n_1, n_2] & \Pi_{12}[n_1, n_2] & \dots \\ \vdots & \vdots & \ddots \\ \Pi_{N1}[n_1, n_2] & \Pi_{N2}[n_1, n_2] & \dots & \Pi_{NN}[n_1, n_2] \end{bmatrix}$$

$\Pi_{ii}(\gamma)$ DERIVATIVE in γ
 is either negative or zero
 NEGATIVE.

$$-\lambda_{ii} = \sum_j \lambda_{ij} \geq 0$$



(Q3) Describe the Birth-Death Process and give its transition probability matrix.

BIRTH-DEATH PROCESS

Suppose a CT homogeneous Markoff chain takes on values $0, 1, 2, \dots$ and only transitions equal to $+1$ or -1 are allowed.

$\Rightarrow X(t)$ is called a BIRTH-DEATH process.

~~Markovian~~

A Birth-Death process is a Markoff process

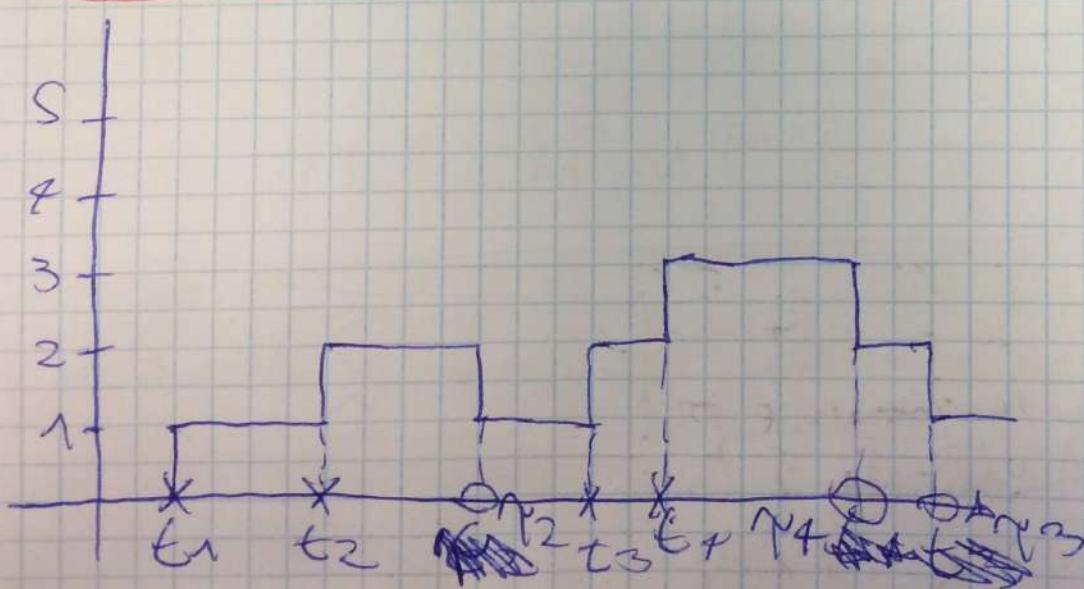
POSSIBLE TRANSITION RATES

~~only up or down~~
list of
~~only up or down~~
ONCE IF

$i = j$ or (STEADY)
 $i = j - 1$ or (DOWN)
 $i = j + 1$ (UP)

only changes of value allowed

- \Rightarrow Only corresponding transitions from t to $t + \Delta t$ are allowed [can only go UP or DOWN at transition times], but can also remain steady.
- \Rightarrow Intertransition times are exponential.



For two generic Time instants t and $t + \Delta t$,
there can be 3 cases for transition rates.

(1)

$$n \rightarrow n$$

(2)

$$n \rightarrow n+1$$

(3)

$$n \rightarrow n-1$$

→ TRI-DIAGONAL MATRIX

$\lambda =$
(big
lambda)

λ_1	λ_{12}	\dots	0
λ_{12}	λ_{23}	\dots	0
0	λ_{23}	λ_{34}	\dots
\vdots	\ddots	\ddots	\ddots
0	\dots	λ_{n-1n}	λ_{nn}

Where we may have

$$\text{UP } d_i \geq \lambda_i(i+1)$$

Transition rate increases by Δt

$$\text{Down } B_i \leq \lambda_i(i-1)$$

Transition rate decreases by Δt

MAIN PRINCIPLE:

$$\begin{cases} -\lambda_{ii} = d_i + B_i \\ \lambda_{ii} = -(d_i + B_i) \end{cases}$$

(with zero sum)

$\lambda =$

λ_1	λ_{12}	\dots	0
λ_{12}	λ_{23}	\dots	0
0	λ_{23}	λ_{34}	\dots
\vdots	\ddots	\ddots	\ddots
0	\dots	λ_{n-1n}	λ_{nn}

TRANSITION PROBABILITY
RATES MATRIX

We know that TRANSITION PROBABILITIES are

$$P\{X(t+\Delta t) = a_j | X(t) = a_i\}$$

$$= \begin{cases} 1 + \lambda_{ii} \Delta t & \text{if } i=j \\ \lambda_{ij} \Delta t & \text{if } i \neq j \end{cases}$$

⇒ BIRTH-DEATH EQUATIONS.

$$P\{X(t+\Delta t) = n | X(t) = n-1\} = \alpha_{n-1} \cdot \Delta t$$

$$P\{X(t+\Delta t) = n | X(t) = n\} = 1 - (\alpha_n + \beta_n) \Delta t$$

$$P\{X(t+\Delta t) = n | X(t) = n+1\} = \beta_{n+1} \Delta t$$

14 Determine relationship between STATE PROBABILITIES and TRANSITION PROBABILITIES (EQUILIBRIUM EQUATION) for a BIRTH-DEATH PROCESS:

Given the BIRTH-DEATH EQUATIONS

$$\text{① } P\{x(t+DT) = n \mid x(t) = n-1\} = \alpha_{n-1} DT \quad \text{DOWN}$$

$$\text{② } P\{x(t+DT) = n \mid x(t) = n\} = 1 - (\alpha_n + \beta_n) DT \quad \text{STAY}$$

$$\text{③ } P\{x(t+DT) = n \mid x(t) = n+1\} = \beta_{n+1} DT \quad \text{UP}$$

Birth-Death equations describe all possible behaviours of the CUE-JE.

⇒ To Obtain the EQUILIBRIUM EQUATION:

Suppose: $x(6)$ is STATIONARY

$$\exists P\{x(E+\Delta E)=n\} = P\{x(E)=n\} \triangleq \boxed{p_n} \quad n=0,1,2,\dots$$

→ We can apply the TOTAL PROBABILITY & ST. THEOREM to Pm

For $n > 0$,

$$\text{① } P\{N = P \} = P \{ X(t+dt) = n \} \times \{ |t| = n-1 \} \cdot P \{ X(|t| = n-1) \}$$

$$+ P\{x(t+\Delta t) = n \mid x(t) = n\} \cdot P\{x(t) = n\}$$

$$+ P \{ x(t+\Delta t) = n | x(t) = n+1 \} \cdot P \{ x(t) = n+1 \}$$

\Rightarrow By (1)(2), (3) equations :

$$P_n = \underbrace{\alpha_{n-1} \Delta t \cdot P_{n-1}}_{\textcircled{1}} + \left[1 - (\alpha_n + \beta_n) \Delta t \right] \cdot P_n + \underbrace{\beta_n + 1}_{\textcircled{2}} \Delta t \cdot P_{n+1}$$

Buy Bayes Formula in the application of the
TOTAL PROBABILITY THEOREM:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

$$P_n = P\{x(t) = n | x(t+DT) = n\} = P\{x(t+DT) = n | x(t) = n\}$$

$$= P\{x(t) = n | x(t+DT) = n\} \cdot P\{x(t+DT) = n | x(t) = n\}$$

$$+ P\{x(t) = n+1 | x(t+DT) = n\} \cdot P\{x(t+DT) = n | x(t) = n+1\}$$

$$+ P\{x(t) = n-1 | x(t+DT) = n\} \cdot P\{x(t+DT) = n | x(t) = n-1\}$$

→ This is a BACKWARDS MOVEMENT:

* = backwards movement.
We hence have: $P(x(t) = n | x(t+DT) = n) = P(x(t+DT) = n | x(t) = n)$

$$P\{x(t) = n-1 | x(t+DT) = n\} = \beta_n^* DT$$

$$P\{x(t) = n+1 | x(t+DT) = n\} = \alpha_n^* DT$$

$$P\{x(t) = n | x(t+DT) = n\} = 1 - (\alpha_n^* + \beta_n^*) DT$$

And P_n is now, by substituting in

$$P_n = \beta_n^* DT \cdot P_n + [1 - (\alpha_n^* + \beta_n^*)] P_n + \alpha_n^* DT P_n$$

Since by stationarity we have that:

$$P_n = P\{x(t) = n\} = P\{x(t+DT) = n\}$$

→ By BAYES Formula:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

$$P\{x(t) = n | x(t+DT) = n\} = P\{x(t+DT) = n | x(t) = n\}$$

$$\times \frac{P(x(t) = n)}{1 - \alpha_n^* - \beta_n^* DT} = P\{x(t+DT) = n | x(t) = n\}$$

Now we want to get α_n^* and β_n^* :
From the Birth-Death Equations:

$$P\{x(t+DE) = n | x(t) = n+1\} < \beta_{n+1} \cdot DE \quad (A)$$

and from the backwards equation:

$$P\{x(t) = n+1 | x(t+DE) = n\} < \alpha_n^* \cdot DE \quad (B)$$

\Rightarrow Bayes' Theorem:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

$$\beta_{n+1} \cdot DE$$

$$\alpha_n^* \cdot DE$$

$$p_n$$

$$P\{x(t+DE) = n\}$$

$$\frac{\beta_{n+1} \cdot DE}{P\{x(t) = n+1 | x(t+DE) = n\}} \cdot p_n = P\{x(t) = n+1\}$$

$$\Rightarrow \beta_{n+1} \cdot DE = \alpha_n^* \cdot DE \cdot \frac{p_n}{p_{n+1}}$$

$$\Rightarrow \alpha_n^* = \beta_{n+1} \cdot \frac{p_{n+1}}{p_n}$$

Repeating the procedure:

$$P\{x(t+DE) = n | x(t) = n-1\} = \alpha_{n-1} \cdot DE$$

$$P\{x(t) = n-1 | x(t+DE) = n\} = \beta_n^* \cdot DE$$

$$\Rightarrow P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

~~$\alpha_{n-1} \cdot DE = \beta_n^* \cdot DE$~~

~~$\alpha_{n-1} \cdot DE = \beta_n^* \cdot DE \cdot \frac{p_n}{p_{n-1}}$~~

$$\alpha_{n-1} \cdot DE = \beta_n^* \cdot DE \cdot \frac{p_n}{p_{n-1}}$$

$$\Rightarrow \beta_{n^*} = d_{n-1} \cdot \frac{p_{n-1}}{p_n}$$

We can now substitute d_{n^*} and β_{n^*} in:

$$d_n + \beta_{n^*} = d_n + \beta_n$$

After simplification:

$$\Rightarrow \beta_{n+1} \cdot \frac{p_{n+1}}{p_n} + d_{n-1} \cdot \frac{p_{n-1}}{p_n} = d_n + \beta_n$$

$$\beta_{n+1} \cdot p_{n+1} + d_{n-1} \cdot p_{n-1} = d_n + \beta_n$$

$$\beta_{n+1} \cdot p_{n+1} + d_{n-1} \cdot p_{n-1} = (d_n + \beta_n) \cdot p_n$$

BIRTH-DEATH EQUILIBRIUM EQUATION
for $n \geq 2$

$\text{if } n=2$

$$\Rightarrow \beta_1 \cdot p_1 - d_0 \cdot p_0 = 0$$

15) Prove that conservative transitions in a M|M|1 queue are exponentially spaced.

We want to show that:

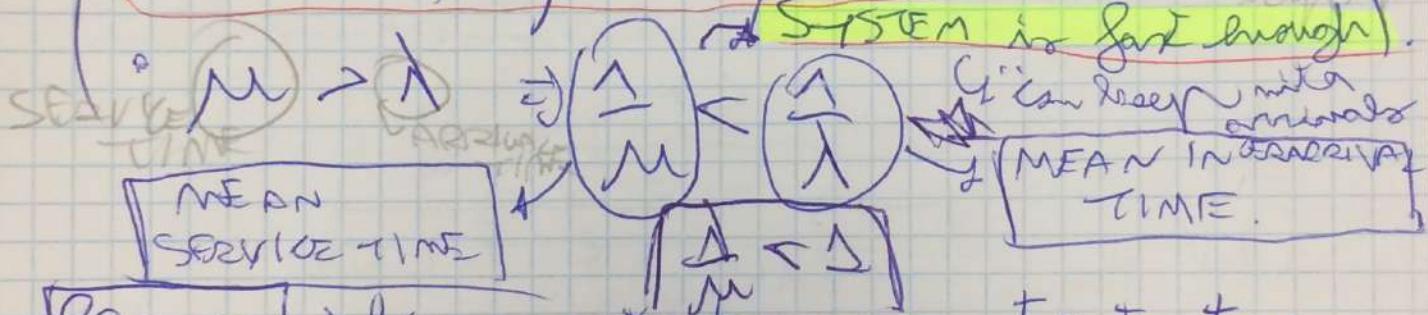
Conservative transitions in a M|M|1 queue are exponentially spaced

Assume:

- Arrival times t_i are PPP with intensity λ .

- Service time c_i is exponentially distributed and independent of arrival times t_i :

$$f_{c_i}(c) = \mu \cdot e^{-\mu c} \cdot u(c)$$



Pass: We want to show that the Birth-Death equations are satisfied and I am able to find p_n , $P\{X(t) = n\}$

- Assume first in DG , only one transition can occur (multiple transitions have probability of infinitesimal order).

- By the PPP property, the probability that one unit arrives in $(t, t+Dt)$ is:

$$\lambda \cdot Dt.$$

$$\Rightarrow P\{1 \text{ unit in } (t, t+Dt)\} = \lambda \cdot Dt.$$

So, the UP transition would be,

$$P\{N(t+DT) = n+1 | N(t) = n\} = \lambda \cdot DT$$

We want to show that, for a DOWN transition

$$P\{N(t+DT) = n-1 | N(t) = n\} = \mu \cdot DT \quad \forall t$$

↳ We want to find probability that service ζ_i will be such that:

~~first departure in
[t, t+DT] is ζ_{i-1}~~ ~~last departure in
[t, t+DT] is ζ_i~~

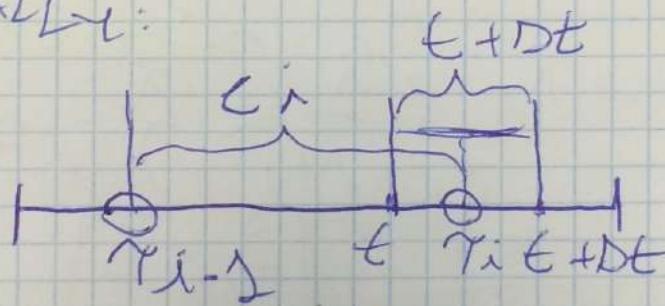
$$P\{(\zeta_i \text{ starts } \zeta_i < t+DT | \zeta_{i-1} < \zeta_t)\} \quad [t, t+DT]$$

↳ service for inter-unit \rightarrow first departure after t \rightarrow last departure before $t+DT$.

GRAPH CALL:

↳

Use a



FAILURE APPROXIMATION: Probability that inter-unit fails in $(t, t+DT)$ when we know it is still alive at t :

(THESIS) $P\{\text{inter-unit fails in } (t, t+DT) | \text{ is alive at } t\}$

↳ When

↳ Life Z_i of inter-unit is known to be exponentially distributed, the probability of failure in $(t, t+DT)$ does not depend on t when ζ_i is still alive.

PROOF: Some 'failure' probability at any time when ζ_i is alive.

~~PROOF that "Probability of failure does not depend on t, when unit is no fault alive."~~

SYSTEM FAILURE PROOF:

Let t_f = time of failure of S

R.V. $X = t_f$, where ~~t_f~~ is the random time of failure of S.

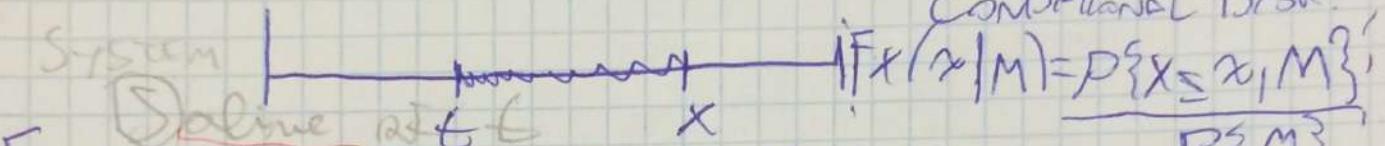
$P\{S \text{ failure before } t\}$

$$= P\{X \leq t\} = F_x(t)$$

$P\{S \text{ alive at } t\}$ [surviving after t].

$$= P\{X > t\} = 1 - F_x(t)$$

RECALL: CONDITIONAL DISTR:



For $M = \{X > t\}$, we know:

Conditional distribution of S alive at t:

$$F_x(x|X > t) = \frac{P\{X \leq x, X > t\}}{P\{X > t\}} = \begin{cases} \frac{F_x(x) - F_t(t)}{1 - F_x(t)} & \text{if } x \geq t \\ 0 & \text{if } x < t \end{cases}$$

$$g_x(x|X > t) = \begin{cases} \frac{f_x(x)}{1 - F_x(t)} & \text{if } x \geq t \\ 0 & \text{if } x < t \end{cases}$$

$$g_x(x|X > t) = \begin{cases} \frac{f_x(x)}{\int_t^{\infty} g_x(x) dx} & \text{if } x \geq t \\ 0 & \text{if } x < t \end{cases}$$

$$P\{x < X \leq x + dx | X > t\} = g_x(x|X > t)dx$$

For $x = t$, consider:

CONDITIONAL FAILURE RATE (CFR)

$\beta(t) dt =$ Prob. that system fails in the interval $(t, t+dt)$ assuming it did NOT fail prior to t .

$$\beta(t) dt \triangleq P\{\text{failure in } (t, t+dt) | \text{alive at } t\}$$

$$= P\{t < X \leq t + dt | X > t\}$$

$$\boxed{\beta(t) dt = g_x(t|X > t) dt}$$

NB: $\beta(t)$ is a function of time.

FOR EXPONENTIAL CASE (our case)

$$g_x(x) = \mu \cdot e^{-\mu x} \cdot U(x)$$

$$\Rightarrow \beta(t) = \frac{\mu \cdot e^{-\mu t}}{1 - (1 - e^{-\mu t})} = \mu = g_x(0)$$

(Probability that one fails in t does not depend on t).

~~Prob. one fails in t~~ can conclude that:

~~P one unit departs in $(t, t+dt)$~~
P ex. $t < T_i \leq t + dt$ $\forall i < t$

~~P one unit fails in $[t, t+dt]$ $\forall t$~~
~~P $T_i < t + dt$ $\forall i < t$~~
 ~~$\sum_{i=1}^n P(T_i < t + dt) = n - P(T_1 > t + dt) = n - P(T_1 > t)$~~

Conclusion:

\Rightarrow We can conclude that.

[ite
rative
stage]

$P\{$ one unit departs in $(t, t+Dt)\}$

$$\Leftarrow P\{c_i : t < \gamma_i < t + Dt \mid \gamma_{i-1} \leq t\}$$

and

$$= P\{ \text{ith unit } \cancel{\text{joins}} \text{ in } (t, t+Dt) \\ \text{ith unit still alive in } t \}$$

$$\Leftarrow P\{t' < c_i < t' + Dt \mid c_i \geq t'\}$$

$$\Rightarrow = P\{N(t+Dt) = n-1 \mid N(t) = n\} \quad (\text{why?})$$

We also know that:

$$P(t) = f_X(t \mid X > t) = \mu$$

$$= P\{t < X \leq t+Dt \mid X > t\}$$

So, we can conclude that:

Dt

$$P\{t < c_i < t + Dt \mid c_i \geq t\} = f_{c_i}(t \mid c_i \geq t)$$

$$= \beta(t) \cdot Dt$$

$$= \mu \cdot Dt$$

\Rightarrow For exponential PDF of c_i , finally:

$$P\{N(t+Dt) = n-1 \mid N(t) = n\} = \mu \cdot Dt$$

We have hence shown that: Q.E.D $\forall r$

$$P\{N(t+Dt) = n \mid N(t) = n-1\} = \lambda \cdot Dt \quad \forall t$$

$$P\{N(t+Dt) = n-1 \mid N(t) = n\} = \mu \cdot Dt.$$

$$\Rightarrow \text{Since } B(E) = P\{E \leq t + dt | X > 0\}$$

$$\Rightarrow \text{Then: } = Sx_i(t+dt | X > 0)$$

$$P\{E \leq t + dt | X_i \geq t\} = Sx_i(t | X_i \geq t) dt$$

$$\Rightarrow B(E) dt = \mu dt$$

~~Finally for exponential PDF of X_i :~~

$$P\{N(6+dt) = n-1 | N(t) = n\} = \mu dt.$$

~~We have shown what we wanted to prove Q.E.D.~~

⑩ Calculate the probability of "EMPTY SYSTEM" in a $M/M/1$ queue.

In a $M/M/1$ queue, we have:

$$\lambda \text{ (arrival rate)} \quad \mu \text{ (service rate)}$$

$$\alpha_n = \lambda \quad B_n = \mu$$

The **EQUILIBRIUM EQUATION** to be solved becomes:

$$\text{From: } \alpha_{n-1} p_{n-1} + B_{n+1} p_{n+1} = (B_n - \alpha_n) p_n$$

$$\text{To: } 1 \cdot p_{n-1} + \mu \cdot p_{n+1} = (\lambda + \mu) p_n$$

Difference Equation

$$\text{From: } p_n = p_0 \prod_{k=1}^n \frac{\alpha_{k-1}}{B_k}$$

STATE PROBABILITY,
(Prob. that queue length is n)

$$\Rightarrow p_n = P\{N(t) = n\} = p_0 \cdot \left(\frac{1}{\mu}\right)^n$$

where p_0 Probability of empty system.

where $p_0 = p_0$. We want to obtain it.
We know $p_n \neq 1$.
System seems to keep up with arrivals

$$0 \leq p \leq \frac{\lambda}{\mu} < 1$$

Since $\sum_{n=0}^{+\infty} x^n = \frac{1}{1-x}$

From Normalization:

$$\cancel{P_n = p_0 \cdot \sum_{n=0}^{+\infty} \left(\frac{\lambda}{\mu}\right)^n} \Rightarrow \text{Because: } \sum_{n=0}^{+\infty} x^n = \frac{1}{1-x}$$

$$\Rightarrow \cancel{\sum_n p_n = p_0 \cdot \frac{1}{1-\cancel{\left(\frac{\lambda}{\mu}\right)}}} = \textcircled{1} \rightarrow \frac{\lambda}{\mu} < 1$$

We can then get p_0 :

$$p_0 = 1 - \frac{\lambda}{\mu} = 1 - p$$

(1) Calculate the mean number of units in the server, the mean system time and the mean waiting time in a $M/M/1$ queue.

MEAN NUMBER OF UNITS IN S. at a time:

~~$$E\{N\} = \sum_{k=0}^{+\infty} k \cdot p_k = (1-p) \sum_{k=0}^{+\infty} \textcircled{k} \cdot p_k$$~~
~~$$E\{N\} = (1-p) \cdot p^n = p_n = (1-p)^p$$~~

$$E\{N\} = \sum_{n=0}^{+\infty} n \cdot \textcircled{p_n} = \sum_{n=0}^{+\infty} n \cdot (1-p) \cdot p^n$$

$$= (1-p) \sum_{n=0}^{+\infty} n \cdot p^n = (1-p) \cdot p \cdot \sum_{n=0}^{+\infty} \textcircled{n} \cdot p^n$$

$$= (1-p) \cdot p \frac{d}{dp} \sum_{n=0}^{+\infty} p^n$$

We know that:

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

$$\Rightarrow (1-\rho) \cdot \frac{\rho \frac{1}{1-\rho}}{\rho(1-\rho)} = (1-\rho) \cdot \frac{\rho}{(1-\rho)^2}$$

$$\Rightarrow E\{N(E)\} = \frac{\rho}{1-\rho}$$

$$\left(\frac{1}{1-\rho}\right)' = \frac{1 \cdot 1 - 1 \cdot (-1)}{(1-\rho)^2} = \frac{2}{(1-\rho)^2}$$

MEAN SYSTEM TIME

Avg. length of queue at time t :

$$E\{N(E)\} = 1 = \frac{\rho}{1-\rho} - 1 = \frac{\rho - 1 + \rho}{1-\rho} = \frac{2\rho - 1}{1-\rho}$$

From Little's Formula:

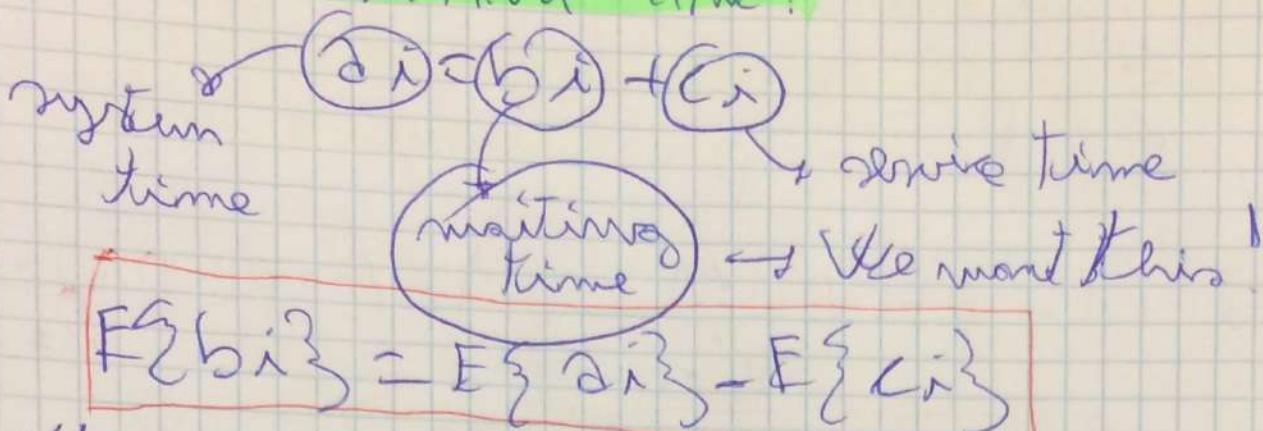
$$E\{N(E)\} = \lambda \cdot E\{a_i\} \quad E\{a_i\} = E\{N(E)\}$$

$$E\{a_i\} = \frac{1}{\lambda} \cdot \frac{\rho}{1-\rho} = \frac{\rho}{\lambda(1-\rho)} \quad \text{Mean interarrival time.}$$

$$\Rightarrow E\{N(E)\} = \lambda \cdot \frac{\rho}{\lambda(1-\rho)} = \frac{1}{1-\rho} \quad \text{MEAN SYSTEM TIME}$$

$$= \frac{1}{\mu - \lambda} = \frac{1}{\mu(1-\frac{\lambda}{\mu})} = \frac{1}{\mu(1-\frac{\lambda}{\mu})} = \frac{1}{\mu(1-\frac{\lambda}{\mu})}$$

MEAN WAITING TIME:



We know that:

$$\text{MEAN SYSTEM TIME} \quad E\{a_i\} = \frac{1}{\mu \cdot (1-\rho)}$$

And we know:

$$E\{c_i\} = \frac{1}{\mu}$$

$$E\{b_i\} = \frac{1}{\mu \cdot (1-\rho)} - \frac{1}{\mu} = \frac{\lambda - \mu - \rho}{\mu \cdot (1-\rho)}$$

$$= \frac{\rho}{\mu \cdot (1-\rho)} = E\{c_i\} \cdot E\{N(E)\} = \frac{\rho}{\mu \cdot (1-\rho)}$$

$$\Rightarrow E\{b_i\} = E\{c_i\} \cdot E\{N(E)\}$$

$$\text{MEAN SERVICE TIME} = \frac{1}{\mu} \cdot \frac{\rho}{1-\rho}$$

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

BEGINNING OF (13):

$$q_i \equiv N(\gamma_i) < n_{2,i}$$

~~W_i = N(γ_i)~~ # units in S after i-th arrival

12) Determine the ONE-STEP TRANSITION MATRIX
for the embedded Markov Chain in Q
M/G/1 queue.

Denote by n_t the # arrivals in $[0, t]$:

$$n_t = n(t) = n_t(0, t)$$

Denote by $N(t)$ the # units in S at time t

\Rightarrow Assume at $t=0$, no units

$$n_0 = N(0) = 0$$

Service times by ~~units~~ (units)

Units: $1, 2, 3, \dots, N, \dots$

↳

Service times: $(c_1, c_2, c_3, \dots, c_n, \dots)$

are Q.V.S

that are i.i.d with ~~fixed distribution~~ and $E\{c_i\} = \gamma_c$ KNOWN.

Now, we know

$$q_{ii} = N(\gamma_c +) = \# \text{ units in SV after } i\text{-th-unit has left.}$$

THEOREM

R.V.s. $\{q_{ii}\}$, $i \geq 1$ are a Markov Chain with one-step transition matrix $\Pi[1] = \Pi$.

$$\Pi = \begin{bmatrix} \pi_{00}[1] & \pi_{01}[1] & \dots \\ \pi_{10}[1] & \pi_{11}[1] & \dots \\ \pi_{20}[1] & \pi_{21}[1] & \dots \\ \vdots & \vdots & \ddots \end{bmatrix} = \begin{bmatrix} d_{00} & d_{01} & d_{02} & \dots \\ d_{10} & d_{11} & d_{12} & \dots \\ 0 & d_{21} & d_{22} & \dots \\ 0 & 0 & d_{32} & \dots \end{bmatrix}$$

FIRST-ORDER

TRANSITIONS from $s_i \rightarrow s_j$

~~PROOF OF DIFFERENTIATION PROPERTY~~

Where : $\alpha_{\delta, \delta+k} = P\{q_{i+1} = \delta + k \mid q_i = \delta\}$

~~PROOF OF DIFFERENTIATION PROPERTY~~

$$\alpha_{\delta, \delta+k} = \left\{ \begin{array}{l} \alpha_{\delta, \delta+k} = \int_0^{+\infty} e^{-\lambda u} \cdot (\lambda u)^{k+1} \cdot g(u) du \\ \text{TRANSITION} \\ \text{PROBABILITY} \end{array} \right.$$

$$\alpha_{0, k} = \int_0^{+\infty} e^{-\lambda u} \cdot (\lambda u)^k \cdot g(u) du$$

PROOF BY TRANSITIONS.

$$P\{q_{i+1} = \delta \mid q_i, q_{i-1}, \dots, 0\} = P\{q_{i+1} = \delta \mid q_i\}$$

Because $\{q_i\}$ is a SUBSEQUENCE of Markov
embeded Chain.

~~PROOF BY TRANSITIONS~~ \square JUSTIFICATION:

Certain elements of Π are $\sigma(\pi_{2,0}^{\text{like}}[1])$ because
we cannot have a decrease by 2 - among
consecutive elements, but only a
decrease by 1.

PROOF of $\alpha_{\delta, \delta+k}$:

Assuming a HOMOGENEOUS chain, we know.

$$q_i = N / \gamma_i$$

$$q_{i+1} = N / \gamma_{i+1}$$

$$\Rightarrow \alpha_{\delta, \delta+k} = P\{q_{i+1} = \delta + k \mid q_i = \delta\}$$

$$\alpha_{0, k} = P\{q_{i+1} = k \mid q_i = 0\} \quad \rightarrow \delta = 0$$

\Rightarrow For consecutive transitions.

$$\begin{cases} C_{i+1} = \gamma_{i+1}^+ - \gamma_i & \text{if } q_i \geq 1 \\ C_{i+1} = \gamma_{i+1}^+ - t_{i+1} & \text{if } q_i = 0 \end{cases}$$

(Time before next unit arrives)
(Time unit stays)

$$\Rightarrow \begin{cases} q_{i+1} = q_i - 1 + h_{C_{i+1}} & \text{for } q_i \geq 1 \\ q_{i+1} = q_i + n_{C_{i+1}} & \text{for } q_i = 0 \end{cases}$$

What you get at γ_{i+1}^+ = what you get at $\gamma_i^+ +$ what arrives.

So, for $j \geq 1$.

$$d\delta_j \delta_{j+k} = P\{n_{C_{j+k}} = k+1\}$$

By TOT Prob.

$$\Rightarrow d\delta_j \delta_{j+k} = \int_0^{+\infty} P\{n_{C_{j+k}} = k+1 | C_{j+k} = c\} g(c) dc$$

$$d\delta_j \delta_{j+k} = \int_0^{+\infty} e^{-\lambda c} \frac{(\lambda c)^{k+1}}{(k+1)!} \cdot g(c) dc$$

For $j=0$

$$d\delta_j \delta_{j+k} = \int_0^{+\infty} e^{-\lambda c} \cdot \frac{(\lambda c)^k}{k!} \cdot g(c) dc$$

C.Q.E.D.

(One-step transition matrix, Embedded Markov chain, one-step transition probability).

~~DEATH rates between q_i and q_{i+1}~~ .

INITIAL SITUATION SKETCH

① if $N(\gamma_{i-1}^+) \geq 2$

$$N(\gamma_{i-1}^-)$$

$$q_{i-1} \geq 2$$

$$N(\gamma_i^-)$$

$$N(\gamma_{i-1}^+)$$

arrived

$$n_{ci}$$

$$= N(\gamma_{i-1}^+) + n_{ci}$$

$$\gamma_{i-1}$$

$$\gamma_i$$

$$c_i \quad (\text{ith-unit right site})$$

$$\Rightarrow N(\gamma_i^+) = N(\gamma_{i-1}^+) + n_{ci}$$

Since the statistics n_{ci} do not depend on i ,

$$q_i^n = q_{i-1} + n_{ci} \quad \text{for } q_{i-1} \geq 2$$

② if $N(\gamma_{i-1}^+) = 0$

$$q_{i-1} = 0$$

$$N(\gamma_{i-1}^-)$$

empty set

$$N(\gamma_i^+) = n_{ci}$$

$$\gamma_{i-1}$$

$$c_i \quad \gamma_i$$

$$N(\gamma_i^+) = n_{ci}$$

or:

$$q_i = n_{ci} \quad \text{for } q_{i-1} = 0$$

ERLANG PDF:

$$\frac{c^n \cdot z^{n-s} \cdot e^{-cz}}{(n-s)!} \cdot U(z)$$

parameter c

(Q8) Obtain the Probability Density Function (PDF) of system time in a M/M/1 queue.

We know that the MEAN WAITING TIME is:

$$E\{b_i\} = E\left\{ \sum_{i=1}^{N+1} c_i \right\}$$

$$E\{b_i\} = E\{c_i\} \cdot E\{N(\ell)\}$$

Now consider the PDF of system time (Q8):

→ After a new arrival, there are $n+1$ units in S.

→ $\beta_i = \text{sum of } n+1 \text{ RNS.}$ for $n \geq 1$

$$\beta_i = \underbrace{S_0}_{C_i \text{ if } n=0} + C_{i-(n-1)} + C_{i-(n-2)} + \dots + C_{i-1} + C_i$$

↳ residual service time of customer served at arrival instant.

↳ exponential PDF with parameter $\mu_{\text{SYSTEM FAILURE}}$

C_i independent and exponential PDF.

⇒ $\beta_i = \text{sum of } n+1 \text{ independent exponential R.N.}$

⇒ $P\{\# \text{ units in S at i-th arrival} = n\}$

= STATE EQUIILIBRIUM PROBABILITY.

$$P(N(\ell)=n) \Rightarrow P_n = (1-p) \cdot p^n$$

$n+1$ times

$$\Rightarrow f_{\beta_i}(t) = \sum_{n=0}^{+\infty} (1-p) p^n \cdot [f_{S_0}(t) \otimes f_{C_1}(t) \otimes \dots \otimes f_{C_i}(t)]$$

where $f_{C_i}(t) = \mu \cdot e^{-\mu t}, t > 0$

$t > 0$

⇒ $n+1$ convolution $\Rightarrow n+1$ Erlang PDF with mean λ

\Rightarrow Erlang - PDF mit parameter μ

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

(we substituted
number $n+2$ in
Erlang formula)

$$\Rightarrow g_{\text{air}}(t) = \sum_{n=0}^{+\infty} (1-\rho) \cdot \rho^n \cdot \mu \cdot e^{\mu t} \cdot \frac{(\mu t)^n}{n!}$$

$$\Rightarrow g_{\text{air}}(t) = (1-\rho) \cdot \mu \cdot e^{\mu t} \cdot \sum_{n=0}^{+\infty} \frac{(\rho \mu t)^n}{n!}$$

$\rho = \frac{\lambda}{\mu}$

$$g_{\text{air}}(t) = (1 - \frac{\lambda}{\mu}) \cdot \mu \cdot e^{-\mu t} \cdot \sum_{n=0}^{+\infty} \frac{(\lambda \cdot \mu t)^n}{n!}$$

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

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

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

$$\boxed{g_{\text{air}}(t) = (\mu - \lambda) \cdot e^{-(\mu - \lambda)t}}$$

$t \geq 0$

(λt is exponential R.V. with parameter $(\mu - \lambda)$)
 PROBABILITY DENSITY FUNCTION OF

WAITING TIME:

$$\boxed{a_i = b_i + c_i} \quad (c_i \text{ independent of } b_i)$$

\Rightarrow Take CHARACTERISTIC FUNCTION for all terms:

$$\boxed{\phi_{\text{air}}(\omega) = \phi_{b_i}(\omega) \cdot \phi_{c_i}(\omega)}$$

We know that:

- a_i exponential with parameter $\mu - 1$

$$\Rightarrow \boxed{\Phi_{a_i}(\omega) = \frac{\mu \cdot (1-\rho)}{\mu \cdot (1-\rho) - j\omega}}$$

- c_i exponential with parameter μ :

$$\boxed{\Phi_{c_i}(\omega) = \frac{\mu}{\mu - j\omega}}$$

~~$$\begin{aligned} \Phi_{b_i}(\omega) &= \Phi_{a_i}(\omega) \cdot \Phi_{c_i}(\omega) \\ \Phi_{b_i}(\omega) &= \frac{\mu \cdot (1-\rho)}{\mu \cdot (1-\rho) - j\omega} \cdot \frac{\mu}{\mu - j\omega} \end{aligned}$$~~

$$= a_i = b_i + c_i$$

$$\Rightarrow \boxed{\Phi_{a_i}(\omega) = \Phi_{b_i}(\omega) \cdot \Phi_{c_i}(\omega)}$$

$$\Rightarrow \boxed{\Phi_{b_i}(\omega) = \frac{\Phi_{a_i}(\omega)}{\Phi_{c_i}(\omega)}}$$

$$\Rightarrow \Phi_{b_i}(\omega) = \frac{\mu \cdot (1-\rho)}{\mu \cdot (1-\rho) - j\omega} \cdot \frac{(\mu - j\omega)}{\mu}$$

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

because:

$$\frac{\mu \cdot (1-\rho)}{\mu \cdot (1-\rho) - j\omega} \cdot \frac{(\mu - j\omega)}{\mu}$$

$$\begin{aligned}
 & \frac{\mu(1-p)}{n} \cdot \frac{\delta w - \mu}{\delta w - \mu(1-p)} \\
 &= \frac{\mu(1-p)}{n} \cdot \frac{\delta w - \mu(1-p) + \mu(1-p) - \mu}{\delta w - \mu(1-p)} \\
 &= \frac{\mu(1-p)}{n} \cdot \left[\frac{\cancel{\delta w - \mu(1-p)}}{\cancel{\delta w - \mu(1-p)}} + \frac{\mu(1-p) - \mu}{\delta w - \mu(1-p)} \right] \\
 &= \frac{\mu(1-p)}{n} \cdot \left[1 + \frac{\mu(1-p) - \mu}{\delta w - \mu(1-p)} \right] \\
 &= \frac{\mu(1-p)}{n} + \frac{[\mu(1-p)][\mu(1-p) - \mu]}{n \cdot [\delta w - \mu(1-p)]} \\
 &= (1-p) + \frac{[\mu(1-p)][-\mu p]}{n \cdot [\delta w - \mu(1-p)]} \\
 &= (1-p) + \frac{(1-p)(-\mu p)}{\delta w - \mu(1-p)} \\
 &= (1-p) + p \frac{(1-p) \cdot \mu}{\delta w - \mu(1-p)}
 \end{aligned}$$

$\epsilon \geq 0$

$$f_{bi}(t) = \begin{cases} (1-p) + p \frac{(1-p) \cdot \mu}{\delta w - \mu(1-p)} & \text{if } t \geq 0 \\ 0 & \text{if } t < 0 \end{cases}$$

\Rightarrow bin is of mixed type

PROBABILITY DENSITY FUNCTION OF WAITING TIME

ϵ in units $R = 1 - p$

$\Rightarrow f_{bi}(t) = \begin{cases} (1-p) \cdot \delta t & \text{if } t = 0 \\ p \cdot \mu(1-p) \cdot e^{-\mu(1-p)t} & \text{if } t > 0 \end{cases}$

EXP. DISTRIBUTION
WITH PROB. DENSITY

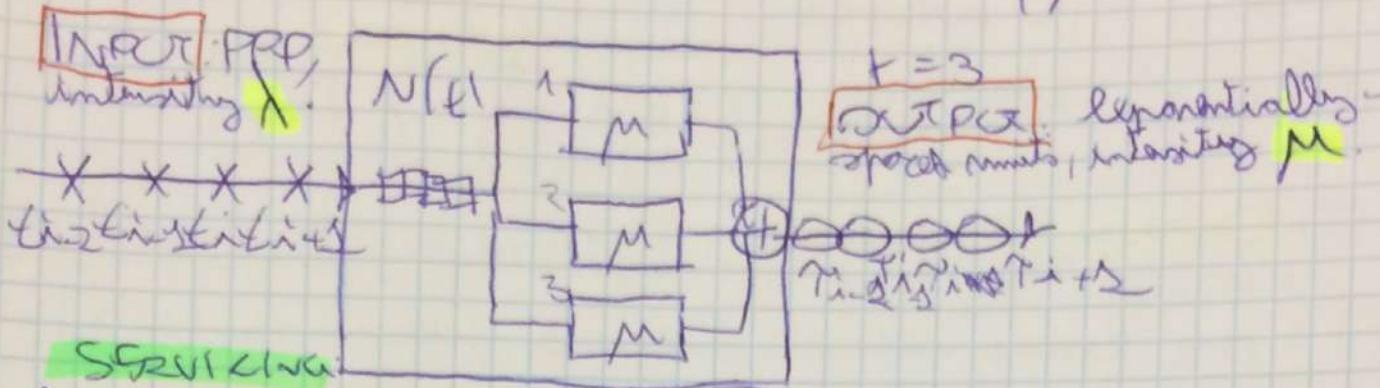
$\delta b_i(\epsilon) \Rightarrow$ Using here ~~the~~ reverse transform
of $\phi b_i(w)$, we get:

$$\delta b_i(t) = \cancel{(1-p) \cdot \delta(\epsilon)} + \cancel{p \cdot \mu \cdot (1-p) \cdot \mu} \\ \cancel{p \cdot (1-p) \cdot \delta w} \\ \delta b_i(\epsilon) = \underbrace{(1-p) \cdot \delta(\epsilon)}_{t \geq 0} + \underbrace{p \cdot \mu \cdot (1-p) \cdot e^{-\mu(1-p)t}}_{t > 0}$$

$$\Rightarrow \boxed{\delta b_i(t) = \begin{cases} (1-p) \cdot \delta(\epsilon) & \text{if } t=0 \\ p \cdot \mu \cdot (1-p) \cdot e^{-\mu(1-p)t} & \text{if } t>0 \end{cases}}$$

② Describe an M/M/r queue.

An M/M/r queue containing r identical servers operating in parallel with i.i.d. exponential service times (μ parameter).



A unit arriving in (t_i) is served if there is at least one free server (or a busy server gets freed) $m = \# \text{ busy servers}$. $r = \# \text{ servers}$.

if $m < r \Rightarrow$ immediate service
 if $m = r \Rightarrow$ queue is formed

DEPARTURE:

Each server releases units exponentially spaced in time with intensity μ .

⇒ Departure process is generated by merging independent PFS, each with intensity μ .

if $m < r \Rightarrow$ intensity = $m \cdot \mu$

if $m = r \Rightarrow$ intensity = $r \cdot \mu$

Time between completions has parameter $m \mu$.
 $m \neq r$.

TRANSITIONS:

Study the transition probabilities for $N(t)$
 $m \leq r \Rightarrow$ Birth-death equations.

$$\textcircled{1} P\{N(t+\Delta t) = n \mid N(t) = n-1\} = ?$$

$$\textcircled{2} P\{N(t+\Delta t) = n \mid N(t) = n+1\} = ?$$

① In a small interval Δt (assuming 2 transitions have negligible probability because PPP arrives):

$$P\{N(t+\Delta t) = n \mid N(t) = n-1\} = \lambda \cdot \Delta t \quad (\text{UP TRANSITION})$$

② DOWN TRANSITION: (because of PPP departures)

$P\{ \text{one busy server becomes free in } [t, t+\Delta t] \} = \mu \cdot \Delta t$

(→ reduces value of $N(t)$ by 1.)

$$\Rightarrow P\{ \text{busy server gets free in } [t, t+\Delta t] \} = (1 - \mu \cdot \Delta t)^m$$

$$\Rightarrow P\{ \text{at least one server gets free in } [t, t+\Delta t] \} = 1 - (1 - \mu \Delta t)^m$$

(Don't consider ~~multiple~~ max. one server gets free).

because $\Rightarrow P\{ \text{multiple servers get free in } [t, t+\Delta t] \}$ is negligible.

DOWN TRANSITION

$$\Rightarrow P\{N(t+\Delta t) = n \mid N(t) = n+1\} = 1 - (1 - \mu \Delta t)^m$$

$$\Rightarrow P\{N(t+\Delta t) < n \mid N(t) = n+1\} \approx m \cdot \mu \cdot \Delta t \quad (\text{MSR})$$

$\Rightarrow N(t)$ is a birth-death process with constant birth (arrival) rate and departure based on S (# active servers in $[t, t+\Delta t]$) $\rightarrow m$.

$$\alpha_{n-1} = \lambda \quad \left\{ \begin{array}{l} m \cdot \mu \text{ if } m < t, m = n \\ 0 \text{ if } m = t \end{array} \right.$$

$$\beta_{n+1} = \left\{ \begin{array}{l} \mu \text{ if } m = t \\ 0 \text{ if } m < t \end{array} \right.$$

19) Calculate the Probability of empty system in a M/G/1 queue.

$$\boxed{q_i = N(\gamma_{i+})} \leftarrow \begin{array}{l} \# \text{ points in } S \text{ after } i\text{-th unit} \\ \text{has left } S \end{array}$$

$$\left| \begin{array}{l} \text{① } q_i = q_{i-1} + n_c - 1 \quad \text{for } q_{i-1} \geq 1 \\ \text{② } q_i = n_c \quad \text{for } q_{i-1} = 0 \end{array} \right)$$

In compact form:

$$\Rightarrow \boxed{q_i = \bar{q}_{i-1} + n_c} \text{ for MARKOVIAN EMBEDDED CHAIN}$$

Where: $\bar{q}_i = \begin{cases} q_{i-1} & \text{if } q_{i-1} \geq 1 \\ 0 & \text{if } q_{i-1} = 0 \end{cases}$

$$\boxed{P_k = P\{N(\gamma_{i+}) = k\} = P\{q_i = k\}}$$

\rightarrow Probability that S contains k units at γ_{i+} , where $q_i = N(\gamma_{i+}) = k$ units in S when the unit has just left.

\rightarrow We are interested in empty system $P\{K=0\} \Rightarrow$ Find P . for $K=0$.

$$P_0 = P\{S \text{ empty at } \gamma_{i+}\}$$

$$\boxed{P_0 = P\{N(\gamma_{i+}) = 0\} = P\{q_i = 0\}}$$

We know that:

$$q_i = \bar{q}_{i-1} + n_c = \# \text{ points in random interval (nonrandom)} \quad \text{in random time}$$

\Rightarrow Take $E(\cdot)$:

$$\boxed{E\{q_i\} = E\{\bar{q}_{i-1}\} + E\{n_c\}}$$

By stationarity of \bar{q}_i :

$$E\{\bar{q}_i\} = E\{\bar{q}_{i-1}\}$$

$$E\{\bar{q}_i\} = \sum_{k=0}^{+\infty} (k-1) \cdot p_k$$

⇒ So:

$$E\{q_i\} = E\{\bar{q}_i\} + E\{n_c\}$$

We know that: ~~Probabilities~~

~~Probabilities~~: By definition of $E\{q_i\}$

$$E\{\bar{q}_{i-1}\} = E\{\bar{q}_i\} = 0 \cdot P\{q_i=0\} + \sum_{k=1}^{+\infty} (k-1) \cdot p_k$$

By definition of $E\{q_i\}$:

$$E\{q_i\} = \eta_q \sum_{k=0}^{+\infty} k \cdot p_k = \sum_{k=1}^{+\infty} k \cdot p_k -$$

$$\Rightarrow E\{q_i\} = \eta_q - (1 - p_0)$$

~~Now~~

Since $\bar{q}_i = \begin{cases} q_i & q_i \geq 1 \\ 0 & \text{else} \end{cases}$

Then:

$$\Rightarrow E\{\bar{q}_{i-1}\} = \sum_{k=1}^{+\infty} k \cdot p_k = 1 - p_0$$

$$\Rightarrow E\{\bar{q}_i\} = \eta_q - (1 - p_0)$$

⇒ Now we have:

$$E\{q_i\} = E\{\bar{q}_{i-1}\} + E\{n_c\} \quad \text{And } p_0 = p$$

$$\Rightarrow \eta_q = \eta_q - (1 - p_0) + \lambda \cdot \eta_c \quad p$$

$$\Rightarrow p_0 = 1 - p_0 + \lambda \cdot \eta_c \quad p$$

Then, we know from:

$$E\{\bar{q}_i - 1\} = E\{q_i\} - E\{q_i^*\}$$

$$= \eta_q - (\lambda \eta_c)$$

$$= \eta_q - \rho$$

$$= \eta_q - (1-p_0)$$

and from

$$\bar{q}_i = \begin{cases} q_i - 1 & q_i \geq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\Rightarrow E\{\bar{q}_i - 1\} = \eta_q - (1-p_0) \quad \boxed{E\{q_i\} - 1 - p_0}$$

"E\{\bar{q}_i\}"

~~$\sum_{k=1}^{10} k \cdot p_k$~~

From:

$$E\{q_i\} = E\{\bar{q}_i - 1\} + E\{n_c\}$$

η_q $\eta_q - (1-p_0)$ $\lambda \cdot \eta_c$

$$\Rightarrow \cancel{\eta_q} = \cancel{\eta_q} - (1-p_0) + \lambda \cdot n_c$$

$$0 = -1 + p_0 + \lambda n_c$$

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

where

$$\rho = \lambda \cdot \eta_c$$

$$\text{and } \lambda \cdot \eta_c < 1$$

$$\Rightarrow \eta_c < \frac{1}{\lambda}$$

20) Demonstrate the Pollaczek - Kinchin formula for the M/G/1 queue \Rightarrow

We know that:

$$\bar{q}_i = \begin{cases} q_i - 1 & \text{if } q_i \geq 1 \\ 0 & \text{if } q_i = 0 \end{cases}$$

at least 1 arrival before γ_i and after t_i)

(no arrivals after t_i and before γ_i).

~~$\bar{q}_i = \bar{q}_{i-1} + n_{ci}$~~

Where:

- q_i = new units in (t_i, γ_i) of duration α_i
- \bar{q}_{i-1} = new units in b_{i-1} waiting time (queued)
- n_{ci} = new units in C_i service time.

①

Now take the MEAN SQUARE value of \bar{q}_i

From $\rightarrow \bar{q}_i = \bar{q}_{i-1} + n_{ci}$

and $\bar{q}_i = \begin{cases} q_{i-1} - 1 & \text{if } q_{i-1} \geq 1 \\ 0 & \text{if } q_{i-1} = 0 \end{cases}$

We want to show

$$\Rightarrow E\{\bar{q}_i^2\} = E\{\bar{q}_{i-1}^2\} + E\{n_{ci}^2\} + 2E\{\bar{q}_{i-1}\} \cdot E\{n_{ci}\}$$

PROOF:

$$E\{\bar{q}_i^2\} = E\{(\bar{q}_{i-1} + n_{ci})^2\}$$

~~DEFINITION~~

$$\text{From } q_i = \begin{cases} q_{i-1} - 1 + n_{ci} & \text{if } q_{i-1} \geq 1 \\ n_{ci} & \text{if } q_{i-1} = 0 \end{cases}$$

$$\Rightarrow q_i = \bar{q}_{i-1} + n_{ci}$$

BEGINNING OF Eq :

We are now interested in finding:

$$\eta_q = E\{N(\gamma_i^+)\} \quad (\text{length of queue at } \gamma_i^+)$$

\Rightarrow Derive POLLAK-ZEKE-KINCHIN FORMULA

By independence and stationarity, then:

$$E\{\bar{q}_i^2\} = E\{\bar{q}_i^2\} + E\{n_{c,i}^2\} + 2E\{\bar{q}_i\} E\{n_c\}$$

② Now take the ~~MEAN SQUARE VALUE~~ of

$$\bar{q}_i.$$

$$\text{From: } \bar{q}_i = \begin{cases} q_i - 1 & \text{if } q_i \geq 1 \\ 0 & \text{if } q_i = 0 \end{cases}$$

\Rightarrow We want to show that:

$$E\{\bar{q}_i^2\} = E\{q_i^2\} - 2\eta_q + p$$

$$\text{PROOF: } E\{\bar{q}_i^2\} = \sum_{k=0}^{+\infty} (k-1)^2 \cdot P_k$$

$$\Rightarrow E\{\bar{q}_i^2\} = \sum_{k=0}^{+\infty} (k-1)^2 \cdot P_k \quad p = P\{q_i = k\}$$

$$= \sum_{k=1}^{+\infty} P_k \cdot (k-1)^2 + P_0 = \sum_{k=1}^{+\infty} P\{q_i = k\} + \cancel{\sum_{k=0}^{+\infty} P\{q_i = 0\}}$$

$$= \sum_{k=1}^{+\infty} P_k \cdot (k^2 - 2k + 1) = \cancel{\sum_{k=1}^{+\infty} P_k \cdot k^2} + \cancel{\sum_{k=1}^{+\infty} P_k \cdot 2k} - \cancel{\sum_{k=1}^{+\infty} P_k}$$

$$= \sum_{k=0}^{+\infty} k^2 \cdot P_k - \cancel{\sum_{k=0}^{+\infty} k \cdot P_k} + \cancel{\sum_{k=1}^{+\infty} P_k} = 1 - P_0$$

$$\therefore E\{q_i^2\} = E\{\bar{q}_i^2\} + 2\eta_q + 1$$

⇒ We know:

$$E\{q_i^2\} = E\{\bar{q}_i^2\} + E\{n_{ci}^2\} + 2E\{q_i\} \cdot E\{n_{ci}\}$$

and we have found that: and $E\{\bar{q}_i\} = \eta q - \frac{(1-p)}{p}$

$$E\{\bar{q}_i^2\} = E\{q_i^2\} - 2\eta q + 1 - p$$

⇒ ~~We have equation $E\{q_i^2\} = E\{q_i\}$~~

If we substitute $E\{\bar{q}_i^2\}$ in the first equation:

$$\begin{aligned} E\{q_i^2\} &= E\{q_i^2\} - 2\eta q + 1 - p + E\{n_{ci}^2\} + \\ &\quad + 2E\{\bar{q}_i\} E\{n_{ci}\} \end{aligned}$$

$$\begin{aligned} 0 &= -2\eta q + 1 - p + E\{n_{ci}^2\} + \\ &\quad + 2 \cdot [\eta q - (1-p)] \cdot E\{n_{ci}\} \end{aligned}$$

where $1-p = p$

$$0 = -2\eta q + p + E\{n_{ci}^2\} + 2[\eta q - p] E\{n_{ci}\}$$

We know: $E\{n_{ci}\} = 1 \cdot \eta c = p$

⇒ ~~$E\{n_{ci}^2\} = \lambda \eta c + \lambda^2 \cdot E\{c^2\}$~~

$$\Rightarrow E\{n_{ci}^2\} = p + \lambda^2 \cdot E\{c^2\}$$

$$\Rightarrow 0 = -2\eta q + p + p + \lambda^2 \cdot E\{c^2\} + 2[\eta q \cdot p - p^2]$$

$$0 = -2\eta q + 2p + \lambda^2 \cdot E\{c^2\} + 2\eta q \cdot p - 2p^2$$

$$0 = -\eta q \cdot [2 - 2p] + 2p + \lambda^2 \cdot E\{c^2\} - 2p^2$$

$$\eta q = \frac{2p \cdot (1-p) + \lambda^2 \cdot E\{c^2\}}{2 \cdot (1-p)} \Rightarrow \text{Simplifiz.}$$

$$\Rightarrow \gamma_q = \frac{2p(1-p) + \lambda^2 E\{C^2\}}{2(1-p) - 2(1-p)}$$

$$\boxed{\gamma_q = p + \frac{\lambda^2 E\{C^2\}}{2(1-p)} \quad \boxed{E\{N(\gamma_i + 1)\}}}$$

POLLACZEK-KINCHIN FORMULA.

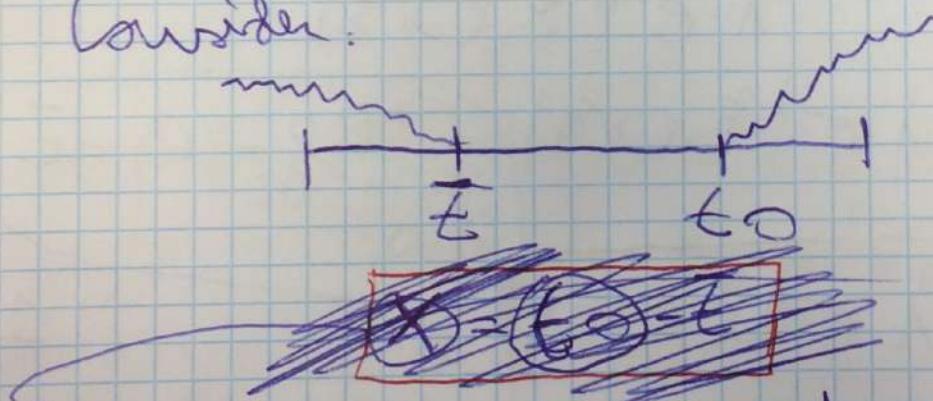
- (2) Demonstrate that the waiting time (empty server) in a M/G/1 queue is exponentially spaced.

EMPTY PERIOD DEFINITION:

A period of time ~~when~~ is called EMPTY PERIOD of S when $N(t) = 0$.

The EMPTY PERIOD is a R.V. *

Consider:



x = duration of empty period

t_0 = time of first arrival

E = First origin (beginning of empty period)

We know: x exp. distributed when origin E is fixed

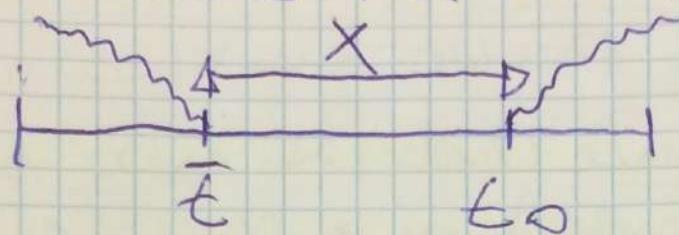
$$f_x(x|t \text{ given}) = \lambda \cdot e^{-\lambda x} \cdot (1/x)$$

time instant at
that the empty
period begins.

EXPLANATION

It is the distance of first Poisson point from a given point \bar{t} .

\Rightarrow If starting point \bar{t} of an empty period is a R.V. (departure time of last run in S), this R.V. depends on what happened before \bar{t} and is independent of first arrival beyond \bar{t} .
 \Rightarrow Non-adjacent intervals!



$$\Rightarrow X = t_0 - \bar{t}$$

So, for any $f_{\bar{t}}(\bar{t})$, By the total probability theorem:

$$f_X(x) = \int_{-\infty}^{+\infty} f_X(x | \bar{t} = \bar{t}) \cdot f_{\bar{t}}(\bar{t}) d\bar{t}$$

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

$$\Rightarrow f_X(x) = \lambda \cdot e^{-\lambda \bar{t}} \cdot \nu(x) \left(\int_{-\infty}^{+\infty} f_{\bar{t}}(\bar{t}) d\bar{t} \right)$$

$$\Rightarrow f_X(x) = \lambda \cdot e^{-\lambda x} \cdot \nu(x)$$

\Rightarrow We have shown that the time interval X of first animal after an empty period has EXPONENTIAL PDF with parameter λ even for \bar{t} random.

$$\Rightarrow \eta_X = \frac{1}{\lambda} \quad (\text{MEAN EMPTY TIME})$$

~~2)~~ Calculate the "mean - system time and "mean waiting time" in a $M/G/1$ queue.

~~MEAN - SYSTEM TIME~~

We defined:

$$q_{it} \in N_{ai}$$

$$\mathbb{E}\{q_{it}\} \triangleq \mathbb{E}\{N_{ai}\} = \lambda \cdot \mathbb{E}\{\tau_i\} = \text{MEAN}$$

points
 in random
 interval
 Δt

From Pollaczek formula:

$$N_q = F\{q_i\} = p + \frac{\lambda \cdot \mathbb{E}\{\epsilon_i^2\}}{\mathbb{E}\{N_{ai}\}^2 - 1}$$

$\Rightarrow \mathbb{E}\{\tau_i\}$, dividing Pollaczek Formula by λ
 because of Little's Formula:

~~LENKELZ~~ ~~REAPER~~

$$\mathbb{E}\{N_{ai}\} = \lambda \cdot \mathbb{E}\{\tau_i\}$$

$$\Rightarrow \mathbb{E}\{\tau_i\} = \mathbb{E}\{N_{ai}\} \cdot \frac{1}{\lambda}$$

POLLAZEK'S FORMULA.

$$\mathbb{E}\{\tau_i\} = p + \frac{\lambda \cdot \mathbb{E}\{\epsilon_i^2\}}{\lambda \cdot 2 \cdot (1-p)}$$

$$\Rightarrow \mathbb{E}\{\tau_i\} = \frac{p}{\lambda} + \frac{\lambda \cdot \mathbb{E}\{\epsilon_i^2\}}{2 \cdot p_0}$$

where $p_0 = 1 - p$

MEAN WAITING TIME:

$$\bar{a}_i = b_i + c_i$$

$$\Rightarrow E\{b_i\} = E\{\bar{a}_i\} - E\{c_i\}$$

$$\Rightarrow E\{b\} = E\{\bar{a}\} - E\{c\} \quad \rho = \lambda \cdot nc$$

We know that:

$$E\{c\} = nc$$

$$E\{\bar{a}\} = nc + \frac{\lambda \cdot E\{c^2\}}{2 \cdot (1 - \lambda \cdot nc)}$$

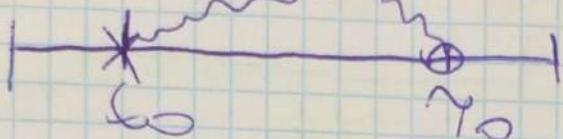
$$\Rightarrow E\{b\} = nc + \frac{\lambda \cdot E\{c^2\}}{2 \cdot (1 - \lambda \cdot nc)} = nc$$

$$\Rightarrow E\{b\} = \frac{\lambda \cdot E\{c^2\}}{2 \cdot (1 - \lambda \cdot nc)}$$

Q3 Calculate the "mean busy time" and the "mean number of units served" in a $\text{M}/\text{G}/1$ queue.

~~QUESTION~~ MEAN BUSY TIME (γ)

Consider a Busy Period: γ : Want to find $E\{\gamma\}$



$$\text{C}_0 = \gamma_0 - L_0 = \text{SERVICE TIME}$$

~~Service Interval~~ $N_C =$ # arrivals in interval $(t_0, t_0 + \gamma_0)$ of duration C_0

$\gamma = \text{BUSY PERIOD} =$ Internal where we have
at least 1 unit in S
from first arr.

$$N(t_0^+) = 1$$

(first arrival in empty queue)

$$N(t_0 + \gamma)^+ = N_C$$

(all arrivals until end)



$$N(t_0^+) = 1$$

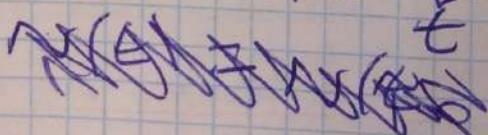
(first arrival).

$$N(t_0 + \gamma)^+ = N_C$$

(END of AARRV last departure)

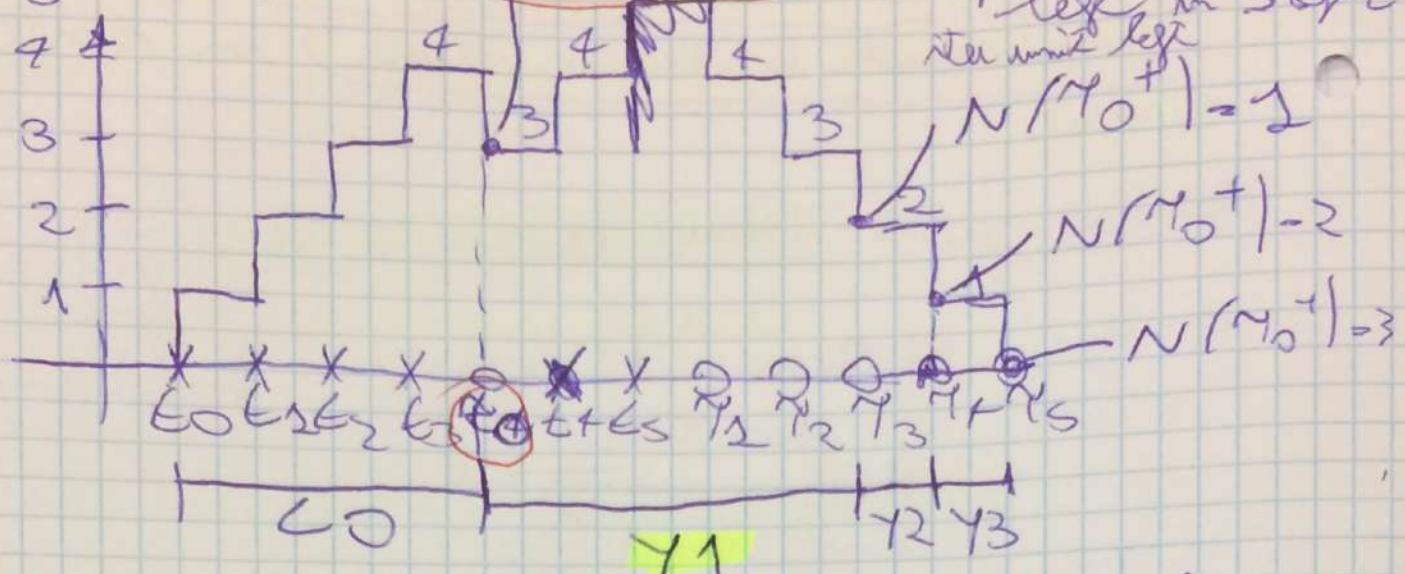
Busy Period γ goes from:

$(t_0, t_{0+\gamma})$ where:



$$N(t) = N(t_0^+) - 1 =$$

Consider:



γ_1 = Interval from t_0 to a new γ , where

$$N(\gamma^+) = N(t_0) - 1$$

$(N(t)$ has decreased by 1 for the first time

Sub-Busy Periods

at γ_1^+
→ (emptying the server with $N(t)$)

Only one unit present \rightarrow NC at (t_0, γ_0) .

If n_C units arrive in (t_0, γ_0)

$\Rightarrow N(t) = 0$ if it decreased by 1 n_C times.

NB: Sub-busy periods will be shown to have some behaviors as busy periods.

Busy Periods

$$\Gamma = C_0 + \gamma_1 + \gamma_2 + \dots + \gamma_{n_C}$$

If $N(\gamma_0^+) \geq 1$, the time γ_1 does not depend on $N(\gamma_0^+)$ (initial value), but only on the sequence of arrivals and departures after γ_0^+ .

$\Rightarrow \gamma_1, \gamma_2, \dots, \gamma_N$ are independent because events occurring in non-overlapping intervals.

Each sub-busy period behaves as a busy period

departures = # arrivals + 1

(3) Sub-busy periods y_i and the busy period γ are identically distributed.

$$\boxed{\gamma = c_0 + y_1 + y_2 + \dots + y_{nc}}$$

\downarrow TOTAL Busy Period

\Rightarrow Take $E\{y_i\}$ out of all components to compute MEAN Busy TIME. (γ_y)

$$\gamma_y = E\{y\} = E\{c\} + E\left\{\sum_{i=1}^{nc} y_i\right\}$$

We know that:

$$E\left\{\sum_{i=1}^{nc} y_i\right\} = (E\{n_c\}) \cdot \gamma_y - \lambda \cdot n_c$$

$$\Rightarrow E\left\{\sum_{i=1}^{nc} y_i\right\} = \lambda \cdot n_c \cdot \gamma_y$$

\Rightarrow onto that: $E\{y\} = \gamma_y$, $E\{c\} = \eta_c$

\Rightarrow Substituting in initial equation.

$$\gamma_y = \eta_c + E\{n_c\} \cdot \gamma_y$$

and we know $E\{n_c\} = \lambda \cdot \eta_c$

$$\Rightarrow \gamma_y = \eta_c + (\lambda \cdot \eta_c) \gamma_y$$

$$0 = \gamma_y + \eta_c + (\lambda \eta_c) \gamma_y$$

$$\Rightarrow -\gamma_y \cdot (1 + \lambda \eta_c) + \eta_c$$

$$\Rightarrow \eta Y = \frac{\eta c}{1-\lambda \eta c}$$

Egys

for $p = \lambda \eta c$

$$\Rightarrow \eta Y = \frac{\eta c}{1-p}$$

MEAN NUMBER OF UNITS SERVED: (during busy) time

MEAN # UNITS SERVED IN A Busy TIME γ

MEAN # ARRIVALS IN RANDOM INTERVAL γ

Want: $E\{\eta Y\}$

(All units arriving in busy time must be served)

$$\Rightarrow E\{\eta Y\} = \lambda \cdot E\{Y\} = \lambda \cdot \eta Y$$

And we know:

$$E\{\eta Y\} = \frac{\eta c}{1-\lambda \eta c}$$

$$\Rightarrow E\{\eta Y\} = \frac{\lambda \cdot \eta c}{1-p} = \frac{p}{1-p} = \frac{p}{p_0}$$

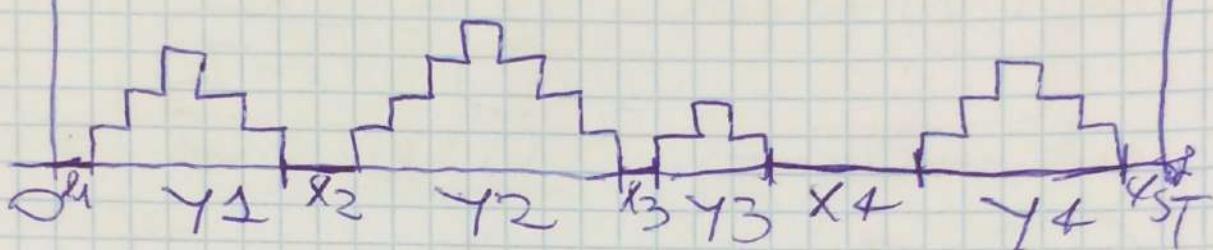
$$\Rightarrow E\{\eta Y\} = \cancel{\frac{\lambda \eta c}{1-\lambda \eta c}}$$

~~• Z_i is exponential with parameter $(\mu - \lambda)$~~
~~• Z_i is exponential with λ~~

- ② (28) ~~Q~~ Obtain the probability of empty system at time T :

Consider an interval $(0, T)$, where there are both empty periods and busy periods:

$X = \text{empty period}$ $y = \text{busy period}$



~~T_x~~ $\boxed{T_x} = \text{Time spent in all empty periods in } (0, T)$

~~T_y~~ $\boxed{T_y} = \text{Time spent in all busy periods in } (0, T)$

$$\boxed{T = T_x + T_y} \quad \text{MEAN OF}$$

$$\boxed{n_x = E\{X_i\}} = \text{MEAN OF empty periods } X_i$$

$$\boxed{n_y = E\{Y_i\}} = \text{MEAN OF busy periods } Y_i$$

Assuming T is large and $n_x = \# \text{ empty periods}$ $n_y = \# \text{ busy periods}$

$$n = n_x + n_y = \# \text{ intervals overall in } (0, T).$$

\Rightarrow By MEAN-FREQUENCY:

$$\boxed{n_x \approx \frac{T_x}{n}}$$

$$\boxed{n_y \approx \frac{T_y}{n}}$$

And assuming:

$$\boxed{P\{N(t)=0\} = \frac{I_x}{T}}$$

P.S.

Supply system < Time spent in empty periods

And also assuming that:

overall time

$$\eta_x \approx \eta_y$$

∴ We want to find $P\{N(t)=0\}$

$$\Rightarrow P\{N(t)=0\} = \frac{I_x}{T} = \frac{I_x}{T_x + T_y}$$

and we know:

↳ We know: $T = T_x + T_y$

$$\eta_x \approx \frac{T_x}{n_x} \quad \eta_y = \frac{T_y}{n_y}$$

$$\Rightarrow \boxed{T_x = \eta_x \cdot n_x} \quad \boxed{T_y = \eta_y \cdot n_y}$$

$$\Rightarrow P\{N(t)=0\} = \underline{\eta_x \cdot n_x}$$

$$\eta_x \cdot n_x + \eta_y \cdot n_y$$

We know that:

$$\cancel{\boxed{\eta_x \approx \eta_y}} \Rightarrow \cancel{\frac{n_x \cdot n_x}{\eta_x \cdot (n_x + n_y)}} = \cancel{\frac{n_x}{n_x + n_y}}$$

We also know that:

$$\cancel{\eta_x = p} \quad \text{and} \quad \cancel{\eta_y = \frac{nc}{1-p}}$$

∴

We know that:

$$nx = ny$$

$$\Rightarrow P\{N(t=0)\} = \frac{nx \cdot nx}{nx \cdot nx + ny \cdot ny} = \frac{nx \cdot nx}{nx \cdot nx + ny \cdot ny}$$

$$\Rightarrow \frac{nx}{nx + ny}$$

and we know that:

$$nx = \lambda t$$

and

$$ny = \frac{\lambda c}{1-p}$$

$$\Rightarrow \frac{t}{t + \frac{\lambda c}{1-p}}$$

$$= \frac{t}{t + \frac{\lambda c}{1-p}}$$

$$= \frac{t}{t + \frac{\lambda \cdot (t + \frac{\lambda c}{1-p})}{1-p}} = \frac{t}{t + \frac{t + \lambda c}{1-p}} = \frac{t}{1 + \frac{\lambda c}{1-p}}$$

$$= \frac{t}{(1 + \frac{\lambda c}{1-p})} = \frac{t}{1 + \frac{\lambda c}{1-p}}$$

$$= \frac{t}{t + \frac{\lambda c}{1-p}} = \frac{t}{1 + \frac{\lambda c}{1-p}}$$

$$= \frac{t}{1 + \frac{\lambda c}{1-p}} = \frac{t}{1 - p} = 1 - p$$

$$= 1 - p \text{ DEPENDS}$$

$$\Rightarrow P\{N(\gamma_i^+) = 0\} = 1 - p.$$

$$\Rightarrow 1 - p = P\{N(\gamma_i^+) = 0\} = P_0.$$

We also want to have that:

$$E\{N(t)\} = E\{N(\gamma_i^+)\}$$

~~Knowing:~~

$$N(\gamma_i^+) = n_{2i}$$

$$\Rightarrow E\{N(\gamma_i^+)\} = E\{n_{2i}\}$$

And we know: $E\{N(\tau_i^+)\} = E\{\text{hai}\}$

$$E\{\text{hai}\} = E\{a_i\} \cdot \lambda$$

$$\Rightarrow E\{N(\tau_i^+)\} = E\{a_i\} \cdot \lambda$$

By LITTLE'S FORMULA:

$$E\{N(t)\} = \lambda \cdot E\{a_i\}$$

$$\Rightarrow E\{N(t)\} = E\{N(\tau_i^+)\}$$

O.F.O