INSTITUTE OF AERONAUTICAL ENGINEERING

(Autonomous)

Dundigal, Hyderabad - 500 043

ELECTRONICS AND COMMUNICATION ENGINEERING

DEFINITIONS AND TERMINOLOGY QUESTION BANK

Course Name	:	**PROBABILTY THOERY AND STOCHASTIC PROCESS**
Course Code	:	**AECB08**
Program	:	**B.Tech**
Semester	:	**THREE**
Branch	:	**Electronics and Communication Engineering**
Section	:	**A, B, C, D**
Academic Year	:	**2020 - 2021**
Course Faculty	:	**Dr. M V Krishna Rao, Professor** **Ms. G Ajitha, Assistant Professor**

COURSE OBJECTIVES:

The students will try to learn:	
I	The fundamental concepts of the 1-dimensional and 2-dimensional random variables and their characterization in probability space.
II	The stationary random process, its framework and application for analysing random signals and noises.
III	The characteristics of 1-dimensional stationary random signals in time and frequency domains.
IV	Analysis of the response of a linear time invariant (LTI) system driven by 1-dimensional stationary random signals useful for subsequent design and analysis of communication systems.

COURSE OUTCOMES:

After successful completion of the course, students will be able to:		
Course Outcomes		**Knowledge Level (Bloom's Taxonomy)**
CO 1	**Infer** the concepts of the random experiment, event probability, joint event probability, and conditional event probability for proving the Bayes theorem and for computing complex event probabilities and independence of multiple events.	Understand
CO 2	**Explain** the concept of random variable, the probability distribution function (PDF), probability density function (pdf), joint and conditional probability density function (cpdf), and demonstrate the differences among various density functions such as Gaussian, Rayleigh, Poisson, Binomial etc.	Understand

CO 3	**Explain** the transformation of random variables, the Expectation operator on functions of random variables to formulate the definition of moments and demonstrate the use of the characteristic and moment generating functions to analytically derive the standard moments.	Understand
CO 4	**Interpret** the vector random variables as the extension of scalar random variables to characterize their joint, marginal, and conditional density/ distribution functions.	Understand
CO 5	**Derive** the density function of sum of random variables for demonstrating the central limit theorem and its physical significance.	Apply
CO 6	**Explain** the Expectation operator on functions of vector random variables to formulate the definition of joint moments (e.g. Correlation and Covariance) and demonstrate the use of the joint characteristic and joint moment generating functions to alternatively derive the joint standard moments.	Understand
CO 7	**Develop** the framework for linear transformation of vector gaussian random variables using the properties of jointly gaussian variables.	Apply
CO 8	**Extend** the random variable concept to random process and its sample functions for demonstrating the time domain characteristics such as stationarity, independence, and ergodicity of a random process.	Understand
CO 9	**Relate** the correlation and covariance functions and their properties for the time domain classification of random processes.	Understand
CO 10	**Develop** analytically the auto-power and cross- power spectral densities to solve the related problems of random processes using correlation functions and the Fourier transform.	Apply
CO 11	**Analyze** the response of a linear time invariant (LTI) system driven by stationary random processes using the time domain description of random processes.	Analyze
CO 12	**Discover** the frequency domain characteristics of of a linear time invariant (LTI) system response driven by stationary random processes using the relationship between correlation functions and power density spectra.	Analyze

DEFINITIONS AND TERMINOLOGY QUESTION BANK

S.No	Question	Answer	Blooms Taxonomy Level	Course Outcome
		MODULE-I		
1	Define an experiment.	An operation which can produce some well-defined outcomes is called an experiment. Each outcome is called an event.	Remember	CO 1
2	Define random experiment.	In an experiment where all possible outcomes are known and in advance if the exact outcome cannot be predicted, is called a random experiment.	Remember	CO 1
3	Define outcome.	The possible results of an event. For example, when a die is rolled, the possible outcomes are 1, 2, 3, 4, 5, and 6.	Remember	CO 1
4	Define sample space.	A sample space of an experiment is the set of all possible outcomes of that random experiment.	Remember	CO 1
5	Define discrete sample space.	A discrete sample space is one that is listable; it can be either finite or infinite. Examples. {H, T}, {1, 2, 3}, {1, 2, 3, 4, . . . }, {2, 3, 5, 7, 11, 13, 17, . . . } are all discrete sets.	Remember	CO 1
6	Define event.	Out of the total results obtained from a certain experiment, the set of those results which are in	Remember	CO 1

		favor of a definite result is called the event and it is denoted as E.		
7	Define equally likely events.	When there is no reason to expect the happening of one event in preference to the other, then the events are known equally likely events.	Remember	CO 1
8	Define exhaustive events.	All the possible outcomes of the experiments are known as exhaustive events.	Remember	CO 1
9	Define Probability of Occurrence of an Event	A measure of the likeliness that an event will happen. (or) The probability of occurrence of an event is defined as: P(occurrence of an event) is the ratio of Number of trials in which event occurred to the Total number of trials	Remember	CO 1
10	Define Mutually Exclusive Events.	If there be no element common between two or more events, i.e., between two or more subsets of the sample space, then these events are called mutually exclusive events.	Remember	CO 1
11	Define Conditional Probability	The probability of an event X is given then another event Y occurred is called conditional probability of X given Y. It is denoted by $P(X\|Y)$. $P(X\|Y) = P(X \cap Y)/P(y)$ Similarly, when the probability of Y given X is $P(Y\|X) = P(X \cap Y)/P(X)$	Remember	CO 1
12	Define Odds	Odds in probability of a particular event, means the ratio between the numbers of favorable outcomes to the number of unfavorable outcomes.	Remember	CO 1
13	Define axioms of probability.	1) The probability of any event is always a non-negative real number, i.e., either 0 or a positive real number. It cannot be negative or infinite; $P(A) \geq 0$ 2) When S is the sample space of an experiment; i.e., the set of all possible outcomes, $P(S) = 1$. 3) If A and B are mutually exclusive events then; $P(A \cup B) = P(A) + P(B)$.	Remember	CO 1
14	Define joint probability.	Joint probability is a statistical measure that calculates the likelihood of two events occurring together and at the same point in time. Joint probability is the probability of event Y occurring at the same time that event X occurs. $P(X \cap Y)=P(X)P(Y)$	Remember	CO 1
15	Define total probability.	Total Probability of an experiment means the likelihood of its occurrence. This likelihood is contributed towards by the various smaller events that the event may be composed of.	Remember	CO 1
16	Define Bayes' theorem.	theorem about conditional probabilities: the probability that an event A occurs given that another event B has already occurred is equal to the probability that the event B occurs given that A has already occurred multiplied by the probability of occurrence of event A and divided by the probability of occurrence of event B. $P(A\|B)=P(A \cap B) / P(B)$ $=P(A) \cdot P(B\|A) / P(B)$	Remember	CO 1
17	Define independent events.	Independent Events is the events which occur freely of each other. The events are independent of each other. In other words, the occurrence of one event does not affect the occurrence of the other. The probability of occurring of the two events are independent of each other;	Remember	CO 1

		P(A ∩ B) = P(A) P(B)		
18	Define a random variable.	A random variable is a function X: S ->R that assigns a real number X(S) to every element s ε S , where S is the sample space corresponding to a random experiment E.	Remember	CO 2
19	Define discrete random variable	If X is a random variable which can take a finite number or countably infinite number of values, X is called a discrete RV. (or) A random variable is called a discrete random variable if its probability density function fx (x) is a sum of delta function only, or correspondingly if its cumulative distribution function Fx(x) is a staircase function.	Remember	CO 2
20	Define continuous random variable	If X is a random variable which can take all values (i.e., infinite number of values) in an interval, then X is called a continuous RV. (or) A random variable is called a continuous random variable if its cumulative distribution function has no finite discontinuities or equivalently its probability density function fx(x) has no delta functions.	Remember	CO 2
21	Define one dimensional random variable	If a random variable X takes on single value corresponding to each outcome of the experiment, then the random variable is called one-dimensional random variables. It is also called as scalar valued RVs.	Remember	CO 2
22	Define mixed random variable	These are random variables that are neither discrete nor continuous, but are a mixture of both. In particular, a mixed random variable has a continuous part and a discrete part.	Remember	CO 2
23	Define Cumulative distribution function(CDF)	The distribution function of Random Variable, X is the function Fx(x)=P[X<=x]for any x between -∞ and ∞.	Remember	CO 2
24	Define discrete Probability Distribution	It is a mathematical function (denoted as p(x)) that satisfies the following properties: 1) The probability of any event x can take a specific value p(x) , mathematically denoted as,[P(X=x)]=p(x)=Px . 2) p(x) is non-negative for all real . 3)The sum of p(x) over all possible values of x is 1.	Remember	CO 2
25	Define Continuous Probability Distribution	It is a mathematical function (denoted as Fx(x)) that satisfies the following properties: 1) For all x, Fx(x)>=0 2) It is monotonically increasing continuous function 3) It is 1 at x=∞ and 0 at x=-∞, i.e. Fx(∞)=1 and Fx(-∞)=0 .	Remember	CO 2
26	Define Probability Density Function (PDF)	The probability density function fx (x) for a random X is a total characterization and is defined as the derivative of the cumulative distribution function fx(x)=d/dx(Fx(x))	Remember	CO 2
27	Define Bernoulli distribution function.	This describes a probabilistic experiment where a trial has two possible outcomes, a success or a failure. The parameter p is the probability for a success in a single trial, the probability for a failure thus being 1 − p (often denoted by q).	Remember	CO 2

		Both p and q is limited to the interval from zero to one. The distribution has the simple form $p(r;p) = \begin{cases} 1-p=q & \text{if} \quad r=0 \quad \text{(failure)} \\ p & \text{if} \quad r=1 \quad \text{(success)} \end{cases}$		
28	Define Binomial Distribution function	The Binomial distribution is given by $$p(r;N,p) = \binom{N}{r} p^r (1-p)^{N-r}$$ where the variable r with 0 <= r <=N and the parameter N (N > 0) are integers and the parameter p (0 <= p <=1) is a real quantity. The distribution describes the probability of exactly r successes in N trials if the probability of a success in a single trial is p (we sometimes also use q = 1 − p, the probability for a failure, for convenience).	Remember	CO 2
29	Define Poisson Random Variable	A discrete random variable X is called a Poisson random variable with the parameter λ if $\lambda > 0$ and $$p_X(k) = \frac{e^{-\lambda}\lambda^k}{k!}, \qquad k = 0,1,2,....$$	Remember	CO 2
30	Define Uniform Random Variable	A continuous random variable X is called uniformly distributed over the interval [a, b], $-\infty < a < b < \infty$, if its probability density function is given by $$f_X(x) = \begin{cases} \frac{1}{b-a}, & a \le x \le b \\ 0 \ , & \text{otherwise} \end{cases}$$	Remember	CO 2
31	Define gaussian random variable	A continuous random variable X is called a normal or a Gaussian random variable with parameters μ_X and σ_X^2 if its probability density function is given by, $$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma_X} e^{-\frac{1}{2}\left(\frac{x-\mu_X}{\sigma_X}\right)^2},$$ $-\infty < x < \infty$	Remember	CO 2
32	Define exponential random variable	A continuous random variable X is called exponentially distributed with the parameter $\lambda > 0$ if the probability density function is of the form $$f_X(x) = \begin{cases} \lambda e^{-\lambda x}, & x \ge 0 \\ 0 \ , & otherwise \end{cases}$$	Remember	CO 2
33	Define Rayleigh random variable.	A Rayleigh random variable *X* is characterized by the PDF $$f_X(x) = \begin{cases} \frac{x}{\sigma^2} e^{-x^2/2\sigma^2}, & x \ge 0 \\ 0 \ , & x < 0 \end{cases}$$ where σ is the parameter of the random variable.	Remember	CO 2
34	Define conditional distribution function	Consider the event $\{X \le x\}$ and any event *B* involving the random variable *X*. The conditional distribution function of *X* given *B* is defined	Remember	CO 2

		$F_X(x/B) = P[\{X \le x\}/B]$ $= \frac{P[\{X \le x\} \cap B]}{P(B)}$ $P(B) \ne 0$ as		
35	Define interval conditioning.	The distribution function of one random variable X conditioned by a second random variable Y With interval {ya ≤y ≤yb}	Understand	CO 2
36	Define point conditioning.	The distribution function of one random variable X conditioned by a second random variable Y With interval {y-Δy≤y≤ y+Δy }	Remember	CO 2
MODULE-II				
1	Define the marginal density of Y .	The marginal density of Y is f(y))=$\int_{-\infty}^{\infty} f_{X,Y}(x,y)dx$	Remember	CO 4
2	Define the pdf of y=2x-3.A random variable X has the density function f(x)=x/12 , 1<x<5 0, otherwise.	The pdf of y=2x-3 is 1/48(Y+3) by the transformation of a random variable.	Remember	CO 4
3	Define K $f_{xy}(x,y)$=KXY; 0<x<y<1 =0; elsewhere .	K=8 for a valid joint density function by finding area under the curve is one.	Remember	CO 4
4	Define the application of charateristic function.	Characteristic function is used to find moments about origin of a random variable	Remember	CO 3
5	Define the area under join density function.	The area under join density function $\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f_{xy}(x,y)dxdy$ is unity.	Remember	CO 4
6	Define Characteristic Function	Consider a random variable X with probability density function $f_X(x)$. The characteristic function of X denoted by is defined as $\Phi_{X}(\omega)=E(e^{j\omega x})$	Remember	CO 3
7	Define n^{th} moment from characteristic function.	Differentiation of characteristic function by n times with respect to ω and setting ω=0 gives n^{th} moment	Remember	CO 3
8	Define Moment Generating Function	Consider a random variable X with probability density function $f_X(x)$ The characteristic function of X denoted by $M_X(V)$ is defined as $M_X(V) =E(e^{Vx})$	Remember	CO 3
9	Define n^{th} moment from moment generating function.	Differentiation of moment generating function by n times with respect to V and setting V=0 gives n^{th} moment	Remember	CO 3
10	Define Transformation of random variable.	We have a set of random variables, X1, X2, X3,...Xn, with a known joint probability and/or density function. We may want to know the distribution of some function of these random variables Y = φ(X1, X2, X3,...Xn) is known as transformation of random variables.	Remember	CO 3
11	Define monotonic increasing transformation of random variable.	A Transformation T is called monotonically increasing if $T(x_1)<T(x_2)$ for any $x_1<x_2$	Remember	CO 3
12	Define monotonic decreasing transformation of random variable.	A Transformation T is called monotonically increasing if $T(x_1)>T(x_2)$ for any $x_1<x_2$	Remember	CO 3
13	Define joint distribution.	For two random variables X and Y, the $\{X \le x, Y \le y\} = \{X \le x\} \cap \{Y \le y\}$ event is called joint distribution.	Remember	CO 4
14	Define the properties of joint distribution.	It is a mathematical function (denoted as Fx(x)) that satisfies the following properties: 1) For all x, $F_{XY}(x,y)$>=0	Remember	CO 4

		2) It is monotonically increasing continuous function 3) It is 1 at x=∞ and 0 at x=-∞, i.e. $F_{XY}(\infty,\infty)=1$ and $F_{XY}(-\infty,-\infty)=0$		
15	Define marginal density function.	The marginal density functions $f_X(x)$ and $f_Y(y)$ of two joint RVs X and Y are given by the derivatives of the corresponding marginal distribution functions	Remember	CO 4
16	Define conditional distribution.	conditional distribution function is one random variables on the condition of a particular value of the other random variable $F_{Y/X}(y/x)=P(Y\le y/X\le x)$	Remember	CO 4
17	Define conditional density function.	$f_{Y/X}(y/x)$ is called the *conditional probability density function* of Y given X. $f_{Y/X}(y/x)=\frac{f_{XY}(X,Y)}{f_X(x)}$	Remember	CO 4
18	Define joint density function.	The probability density function $f_{xy}(x,y)$ for a random X is a total characterization and is defined as the derivative of the cumulative distribution function $f_{xy}(x,y)=\frac{\partial^2}{\partial x\partial y}(F_{xy}(x,y))$	Remember	CO 4
19	Define properties of joint density.	$f_{XY}(x,y)$ is always a non-negative quantity. That is, $f_{XY}(x,y)\ge 0$. The area under joint density function is unity. $\int_{-\infty}^{\infty}\int_{-\infty}^{-\infty} f_{XY}(xy)\,dxdy = 1$	Remember	CO 4
20	Define statistical independence of random variable.	Then X and Y are independent if $\{X\le x\}$ and $\{Y\le y\}$ are independent events. Thus, $F_{XY}(x,y)=F_X(x)F_Y(y)$.	Remember	CO 4
21	Define distribution and density function of sum of random variables.	Probability density function of $Z = X + Y$ is convolution between $f_X(x)$ and $f_Y(y)$. $f_Z(z)=f_X(x)*f_Y(y)$	Remember	CO 5
22	Define central limit theorem.	Consider n independent random variables X1,X2,…. .The mean and variance of each of the random variables are assumed to be known. Suppose $E[X_i]=\mu_{xi}$ and $var(X_i)=\sigma^2_{Xi}$. Form a random variable Yn=X1+X2+……+Xn *The mean and variance of Y_n are given by* $\mu_{Yn}=\mu_{x1}+\mu_{x2}+\dots\dots+\mu_{xn}$ $\sigma^2_{yn}=\sigma^2_{x1}+\sigma^2_{x2}\dots\dots+\sigma^2_{xn}$	Remember	CO 5
23	Define the expected value of discrete random variable.	Let X be a discrete random variable with probability function $P_X(x)$. Then the expected value of X, E(X), is defined to be $E(X) = \sum xP_X(x)$. It is also called the mean or statistical average of the random variable X	Remember	CO 3
24	Define expected value of continues random variable	Let X be a continuous random variable with probability density function $f_X(x)$ $E[X]=\int_{-\alpha}^{\alpha} x\, fX(x)dx$	Remember	CO 3
25	Define expected value of a function of a random variable.	Let X be a discrete random variable with probability mass function $p_X(x)$ and g(X) be a real valued function of X. Then the expected value of g(X) is given by $E[g(X)] = \int_{-\alpha}^{\alpha} g(x)\, fX(x)dx$	Remember	CO 3
26	Define moments about origin.	If $g(x)=x^n$ n=0,1,2… Then n^{th} moment about the origin is defined as $m_n=E[g(x)]=\int_{-\alpha}^{\alpha} x^n f_X(x)dx$	Remember	CO 3
27	Define central moment.	Moments about the mean value of X are called central momets. If $g(x)=(x-\bar{X})^n$ n=0,1,2…	Remember	CO 3

		Then n^{th} moment about the origin is defined as $\mu_n = E[g(x)] = \int_{-\alpha}^{\alpha} (x - \bar{X}^n) f_X(x) dx$		
28	Define variance	The second central moment μ_2 is called variance. $\sigma_X^2 = E(X - \mu_X)^2 = \int_{-\infty}^{\infty} (x - \mu_X)^2 f_X(x) dx$	Remember	CO 3
29	Define skewness	The third central moment measures lack of symmetry of the pdf of a random variable is called the *coefficient of skewness* $\frac{E(X - \mu_X)^3}{\sigma_X^3}$	Remember	CO 3
30	Define Standard Deviation	Standard Deviation is the square root of the Variance. $\sigma_X = \sqrt{E(X - \mu_X)^2}$	Remember	CO 3
31	Define Chebyshev's Inequality	Chebyshev's inequality is a probabilistic inequality. It provides an upper bound to the probability that the absolute deviation of a random variable from its mean will exceed a given threshold.	Remember	CO 3
32	Define Conditional Probability Density Function	The conditional density function $f_X(x/B)$ of the random variable *X* given the event *B* as $f_X(x/B) = \frac{d}{dx} F_X(x/B)$	Remember	CO 3
33	Define E [X-E[X])n]	The nth central moment is $\int_{-\infty}^{\infty} (x - E[X])^n f_X(x) dx$	Remember	CO 3
34	Define E [X.Y] .If the X and Y random variables are independent .	If the X and Y random variables are independent E [X.Y] = E [X].E [Y]	Remember	CO 3
35	Define the relation between joint density function and characteristic function.	The joint density function is inverse fourier transform of joint characteristic function	Remember	CO 3
		MODULE-III		
1	Define expected value of random variables.	Let X and Y be a continuous random variables with joint probability density function $f_{XY}(x,y)$ $E[X Y] = \int_{-\alpha}^{\alpha} \int_{-\alpha}^{\alpha} x\, y\, fXY(x, y) dxdy$	Remember	CO 6
2	Define joint moments about the origin.	Two continuous random variables X and Y, *the joint moment of order* m+n is defined as $E[X^m Y^n] = \int_{-\alpha}^{\alpha} \int_{-\alpha}^{\alpha} x^m y^n fXY(x, y) dxdy$	Remember	CO 6
3	Define central moments.	Joint central moment of order *m+n is defined as* $E[(X-\mu_X)^m (Y-\mu_y)^n] = \int_{-\alpha}^{\alpha} \int_{-\alpha}^{\alpha} (x - \mu x)^m (y - \mu y)^n fXY(x, y) dxdy$	Remember	CO 6
4	Define Joint Characteristic Functions	Consider random variable X and Y with joint probability density function The characteristic function of X and Y denoted by is defined as $\Phi_{XY}(\omega_1, \omega_2) = E(e^{j(\omega 1x + \omega 2x)})]$	Remember	CO 6
5	Define Jointly Gaussian Random Variables	The jointly Gaussian random variables X and Y with the joint pdf $f_{X,Y}(x,y) = \frac{e^{-\frac{1}{2(1-\rho_{X,Y}^2)}\left[\left(\frac{x-\mu_X}{\sigma_X}\right)^2 - 2\rho_{X,Y}\left(\frac{x-\mu_X}{\sigma_X}\right)\left(\frac{y-\mu_Y}{\sigma_Y}\right) + \left(\frac{y-\mu_Y}{\sigma_Y}\right)^2\right]}}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho_{X,Y}^2}}$	Remember	CO 6
6	Define properties of Gaussian random	The Normal or Gaussian pdf is a bell-shaped curve that is symmetric about. the mean μ and	Remember	CO 2

	variables.	that attains its maximum value of 1.		
7	Define covariance.	The covariance between two jointly distributed real-valued random variables X and Y with finite second moments is defined as the expected product of their deviations from their individual expected values	Remember	CO 6
8	Define Orhthogonality	Two random variables X and Y are called orthognal if E(XY) = 0,	Remember	CO 6
9	Define correlation coefficient.	The correlation coefficient is a statistical measure that calculates the strength of the relationship between the relative movements of two variables.	Remember	CO 6
10	Define variance of sum of random variables.	If X and Y random variables are independent $\sigma^2_{X+Y} = \sigma^2_X + \sigma^2_Y$	Remember	CO 6
11	Define E $[X^2+ Y^2]$. If the X and Y random variables are independent	If the X and Y random variables are independent then E $[X^2+ Y^2]$= E $[X^2]$+.E $[Y^2]$	Remember	CO 6
12	Define ,variance of the random variable Z=3X-Y.	X and Y are two statistically independent random variables. Then,variance of the random variable Z=3X-Y is 9.var(X)+var(Y)	Remember	CO 5
13	Define the second order joint moment about the origin .	Two continuous random variables X and Y, *the joint moment of order* 2 is defined as E[X Y]= $\int_{-\alpha}^{\alpha}\int_{-\alpha}^{\alpha} x^m y^n fXY(x,y)dxdy$	Remember	CO 6
14	Define the covariance of X+a,Y+b. If X and Y are two random variables, then Where 'a'and 'b' are constants is	If X and Y are two random variables, then the covariance of X+a, Y+b, where 'a'a nd 'b' are constants is Cov (X+a,Y+b) = Cov (X,Y) = CXY	Remember	CO 6
15	Define the mean square value of (Y-Z) . X, Y and Z are independent random variables with same mean variances	X, Y and Z are independent random variables with same mean variances the mean square value of (Y-Z) is $2\sigma^2_x$	Remember	CO 6
16	Define the correlation coefficient between (X+Y) and(Y+Z). If X Y Z are uncorrelated random variables with same variance.	If X Y Z are uncorrelated random variables with same variance. Find the correlation coefficient between (X+Y) and(Y+Z) is 0.5	Remember	CO 6
17	Define the joint characteristic function.	The joint characteristic function is fourier transform of joint density function.	Remember	CO 6
18	Define the Jacobian of the transformation x=v; y=0.5(u-v)	The Jacobian of the transformation x=v; y=0.5(u-v) is -0.5.	Remember	CO 7
19	Define K if X and Y are Gaussian random variables with variances σ^2_x and σ^2_y.Then the random variables V=X+kY and W=X-kY are statistically independent .	X and Y are Gaussian random variables with variances σ^2_x and σ^2_y.Then the random variables V=X+kY and W=X-kY are statistically independent for k equal to σx/ σy	Remember	CO 7
20	Define variance of Y. Two Gaussian RVs X1 and X2 have variances 4 and 9	The variance of y is 28,252 by using transformation of gaussian random variables.	Remember	CO 7

	respectively. Covariance is 3 then $Y_1=X_1-2X_2$ and $Y_2=3X_1+4X_2$.			
21	Define covariance matrix of two random variables.	The covariance of two random varibles $[Cx]=\begin{bmatrix}\sigma_{X1}{}^2 & \rho\sigma_{X1}\sigma_{X2}\\ \rho\sigma_{X1}\sigma_{X2} & \sigma_{X2}{}^2\end{bmatrix}$	Remember	CO 7
22	Define covariance.	Covariance is defined as $Cij = E[(X_i - \bar{X}_i)(X_j - \bar{X}_j)]$	Remember	CO 6
23	Define Jacobian.	Jacobian is defined by $J=\det\begin{bmatrix}\frac{\partial g_1^{-1}}{\partial y_1} & \cdots & \frac{\partial g_1^{-1}}{\partial y_n}\\ \vdots & \ddots & \vdots\\ \frac{\partial g_n^{-1}}{\partial y_1} & \cdots & \frac{\partial g_n^{-1}}{\partial y_n}\end{bmatrix}$	Remember	CO 7
24	Define expected value of discrete multiple random variables.	The excepectation of discrete random varibles is $E(X^mY^n)=\sum_x\sum_y x^m y^n f_{XY}(x,y)$	Remember	CO 6
25	Define Marginal characteristic function.	Marginal characteristic function is $Ø_{XY}(\omega 1, 0)$.	Remember	CO 6
		MODULE-IV		
1	Define random process.	A random process is also known as stochastic process. A random process X(t) is used to explain the mapping of an experiment which is random with a sample space S which contribute to sample functions X(t,λi).For every point in time t1,X(t1) is a random variable. 1) t represents time and it can be discrete or continuous. 2) The range of t can be finite, but generally it is infinite. It means the process contains infinite number of random variables.	Remember	CO 8
2	Define continuous random process	Voltage in a circuit, temperature at a given location over time, temperature at different positions in a room.	Remember	CO 8
3	Define discrete random process	Quantized voltage in a circuit over time.	Remember	CO 8
4	Define continuous random sequence	Sampled voltage in a circuit over time.	Remember	CO 8
5	Define discrete random sequence	Sampled and quantized voltage from a circuit over time.	Remember	CO 8
6	Define deterministic random process.	When the future values of any sample function are predicted depending on the knowledge of the past values, then the random process is known as deterministic random process.	Remember	CO 8
7	Define non-deterministic random process.	A random process is the combination of time functions, the value of which at any given time cannot be pre-determined. So it is known as non-deterministic process.	Remember	CO 8
8	Define stationary random process.	All joint density functions of the random process do not depend on the time origin. Here the mean values are fixed and it does not depend on the time with absolute values.	Remember	CO 8
9	Define non-stationary random process	The probability density function depends on the time origin. At least one or more of the mean values will depend on time	Understand	CO 8
10	Define Nth order stationarity.	A random process is called stationary to order N or Nth order stationary if fX (x1, ..., xN ;t1, ..., tN) = fX (x1, ..., xN ;t1 + Δ, ..., tN + Δ) for all possible x1, ..., xN , t1, ..., tN , and Δ.	Remember	CO 8
11	Define distribution Function of a random process	the cumulative distribution function (CDF) of random process X(t) at time t1 as Fx(x1;t1) = P [X(t1) ≤ x1]	Remember	CO 8
12	Define density Function of a random process	probability density functions (PDFs) from random variables to density functions for random processes. The first order density function for	Remember	CO 8

		random process X(t) is then fx(x1;t1) = ∂ /∂x1 Fx (x1;t1)		
13	Define Independent Processes	Two random process X(t) and Y(t) are called independent if all possible random variables generated by sampling from X(t) are independent of all possible random variables generated by sampling from Y(t).	Remember	CO 8
14	Define first order stationarity	A random process X(t) is called stationary to order one if its first order density function does not change with a shift in time, or in terms of our density notation: fX (x1;t1) = fX (x1;t1 + Δ), for all x1, t1 and Δ. If X(t) is stationary to order random variables X1 = X(t1) and X2 = X(t2) will have the same PDF for any selection of t1 and t2. This means that the expectation of any function of X(t) will be a constant over t. That is, E {g [X (t1)]} E {g [X (t2)]}for any function g (·), t1 and t2.	Remember	CO 8
15	Define second order stationarity.	A random process X(t) is called second order stationary or stationary to order two if fX (x1, x2;t1, t2) = fX (x1, x2;t1 + Δ, t2 + Δ) for all possible selections of x1, x2, t1, t2 and Δ.	Remember	CO 8
16	Define Wide Sense Stationarity	A random process is called Wide Sense Stationary if E [X (t)] = X, a constant over all t, and Rxx (t1, t2) = Rxx (τ) where τ = t2 − t1	Remember	CO 8
17	Define time averages	Consider a random process X(t). Let x(t) be a sample function which exists for all time at a fixed value in the given sample space S. The average value of x(t) taken over all times is called the time average of x(t). It is also called mean value of x(t). It can be expressed as $\overline{x} = A[x(t)] = \lim_{T\to\infty} \frac{1}{2T}\int_{-T}^{T} x(t)dt$	Remember	CO 8
18	Define Ergodic Theorem and Ergodic Process	The Ergodic theorem states that for any random process X(t), all time averages of sample functions of x(t) are equal to the corresponding statistical or ensemble averages of X(t). i.e. $\bar{x} = \bar{X}$ or $\mathcal{R}_{xx}(\tau) = R_{XX}(\tau)$ Random processes that satisfy the Ergodic theorem are called Ergodic processes.	Remember	CO 8
19	Define mean ergodic processes	A process with a mean value X which is not dependent on t is called mean ergodic or ergodic in the mean if its statistical average, $\overline{X} = E[X]$equals the time average, $\overline{x} = A[x(t)]$ of any sample function x(t) with probability 1.	Remember	CO 8
20	Define time autocorrelation function	Consider a random process X(t). The time average of the product X(t) and X(t+τ) is called time average autocorrelation function of x(t) and is denoted as $\mathcal{R}_{xx}(\tau) = A[X(t)\, X(t+\tau)]$ (or) $\mathcal{R}_{xx}(\tau) = \lim_{T\to\infty} \frac{1}{2T}\int_{-T}^{T} x(t)x(t+\tau)dt.$	Remember	CO 9
21	Define time mean square function	If τ = 0, the time average of x2(t) is called time mean square value of x(t) defined as $A[X^2(t)] = \lim_{T\to\infty} \frac{1}{2T}\int_{-T}^{T} x^2(t)dt.$	Remember	CO 8
22	Define time cross correlation function	Let X(t) and Y(t) be two random processes with sample functions x(t) and y(t) respectively. The time average of the product of x(t) y(t+ τ) is	Remember	CO 9

		called time cross correlation function of x(t) and y(t). Denoted as $R_{xy}(\tau) = \lim_{T\to\infty} \frac{1}{2T}\int_{-T}^{T} x(t)y(t+\tau)dt.$		
23	Define Autocorrelation Ergodic Process	A stationary random process X(t) is said to be Autocorrelation Ergodic if and only if the time autocorrelation function of any sample function x(t) is equal to the statistical autocorrelation function of X(t). $A[x(t)\ x(t+\tau)] = E[X(t)\ X(t+\tau)]$ (or) $R_{xx}(\tau) = R_{XX}(\tau).$	Remember	CO 8
24	Define Cross Correlation Ergodic Process	Two stationary random processes X(t) and Y(t) are said to be cross correlation Ergodic if and only if its time cross correlation function of sample functions x(t) and y(t) is equal to the statistical cross correlation function of X(t) and Y(t). $A[x(t)\ y(t+\tau)] = E[X(t)\ Y(t+\tau)]$ (or) $R_{xy}(\tau) = R_{XY}(\tau).$	Remember	CO 8
25	Define Auto Covariance function	Consider two random processes X(t) and X(t+ τ) at two time intervals t and t+ τ. The auto covariance function can be expressed as $C_{XX}(t, t+\tau) = E[(X(t)\text{-}E[X(t)])\ ((X(t+\tau) - E[X(t+\tau)])]$ (or) $C_{XX}(t, t+\tau) = R_{XX}(t, t+\tau) - E[(X(t)\ E[X(t+\tau)]$	Remember	CO 9
26	Define Cross Covariance Function	If two random processes X(t) and Y(t) have random variables X(t) and Y(t+ τ), then the cross covariance function can be defined as $C_{XY}(t, t+\tau) = E[(X(t)\text{-}E[X(t)])\ ((Y(t+\tau) - E[Y(t+\tau)])]$ (or) $C_{XY}(t, t+\tau) = R_{XY}(t, t+\tau) - E[(X(t)\ E[Y(t+\tau)].$	Remember	CO 9
27	Define Gaussian Random Process	Consider a continuous random process X(t). Let N random variables X1=X(t1),X2=X(t2), . . . ,XN =X(tN) be defined at time intervals t1, t2, . . . tN respectively. If random variables are jointly Gaussian for any N=1,2,…. And at any time instants t1,t2,. . . tN. Then the random process X(t) is called Gaussian random process. The Gaussian density function is given as $f_X(x_1, x_2 \ldots\ldots x_N ; t_1, t_2, \ldots\ldots t_N) =$ $\frac{1}{(2\pi)^{N/2}\|[C_{XX}]\|^{1/2}} exp(-[X-\overline{X}]^T[C_{XX}]^{-1}[X-\overline{X}])/2$ where Cxx is a covariance matrix.	Remember	CO 9
28	Define Poisson’s random process	The Poisson process X(t) is a discrete random process which represents the number of times that some event has occurred as a function of time. If the number of occurrences of an event in any finite time interval is described by a Poisson distribution with the average rate of occurrence is λ, then the probability of exactly occurrences over a time interval (0,t) is $P[X(t)=K] = \frac{(\lambda t)^K e^{-\lambda t}}{k!}$, K=0,1,2, . . . And the probability density function is $f_X(x) = \sum_{k=0}^{\infty} \frac{(\lambda t)^K e^{-\lambda t}}{k!}\ \delta\ (x\text{-}k).$	Remember	CO 9

29	Define System Response	Let a random process X (t) be applied to a continuous linear time invariant system whose impulse response is h(t). Then the output response Y (t) is also a random process. It can be expressed by the convolution integral, Y (t) = h (t) *X (t) The output response is Y (t) = $\int_{-\infty}^{\infty} h(\tau)X(t-\tau)d\tau$.	Remember	CO 11
30	Define Mean Value of Output Response	Consider that the random process X (t) is wide sense stationary process. Mean value of output response=E[Y (t)], Then E[Y (t)] = E [h (t) * X (t)]	Remember	CO 11
31	Define Mean square value of output response	Mean square value of output response is E [Y2(t)] = E [(h (t) * X (t))2] = E [(h (t) * X (t)) (h (t) * X (t))]	Remember	CO 11
32	Define Autocorrelation Function of Output Response	The autocorrelation of Y (t) is $R_{YY}(\tau_1, \tau_2)$ = E [Y (t_1) Y (t_2) = E [(h (t1) * X (t1)) (h (t2) * X (t2))]	Remember	CO 11
33	Define Cross Correlation Function of Response	If the input X (t) is WSS random process, then the crosscorrelation function of input X (t) and output Y(t) is $R_{XY}(t, t+\tau)$ = E [X (t) Y (t + τ)] $R_{XY}(\tau)$ = E [X (t)$\int_{-\infty}^{\infty} h(\tau_1)$ X (t + τ - τ_1) dτ_1]	Remember	CO 11
		MODULE-V		
1	Define Power Spectral Density (PSD)	A Power Spectral Density (PSD) is the measure of signal's power content versus frequency. A PSD is typically used to characterize broadband random signals.	Remember	CO 10
2	Define Cross Spectral Density	For two jointly WSS random processes and we define the cross spectral density as the Fourier transform of the cross-correlation function	Remember	CO 10
3	Define Power Density Spectrum of Response	Consider that a random process X (t) is applied on an LTI system having a transfer function H(ω). The output response is Y (t). If the power spectrum of the input process is SXX (ω), then the power spectrum of the output response is given by $S_{YY}(\omega) = \lvert H(\omega) \rvert^2 S_{XX}(\omega)$.	Remember	CO 12
4	Define Spectrum Bandwidth	The spectral density is mostly concentrated at a certain frequency value. It decreases at other frequencies. The bandwidth of the spectrum is the range of frequencies having significant values. It is defined as “the measure of spread of spectral density” and is also called rms bandwidth or normalized bandwidth. $W_{rms}^2 = \frac{\int_{-\infty}^{\infty} \omega^2 S_{XX}(\omega)d\omega}{\int_{-\infty}^{\infty} S_{XX}(\omega)d\omega}$	Remember	CO 12
5	Define Low pass random processes	A random process is defined as a low pass random process X (t) if its power spectral density SXX (ω) has significant components within the frequency band	Remember	CO 12
6	Define Band pass random processes	A random process X (t) is called a band pass process if its power spectral density SXX (ω) has significant components within a band width W that does not include ω =0.	Remember	CO 12
7	Define Band Limited random processes	A random process is said to be band limited if its power spectrum components are zero outside the	Remember	CO 12

		frequency band of width W that does not include ω =0.		
8	Define Narrow band random processes	A band limited random process is said to be a narrow band process if the band width W is very small compared to the band centre frequency, i.e. W<< ω0, where W=band width and ω0 is the frequency at which the power spectrum is maximum.	Remember	CO 12
9	Define Average cross power	The average cross power PXY of the WSS random processes X(t) and Y(t) is defined as the cross correlation function at τ =0. That is $P_{XY} = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} R_{XY}(t,t)dt$	Remember	CO 10
10	Define Wiener-Khinchin-Einstein theorem	The Wiener-Khinchin-Einstein theorem is also valid for discrete-time random processes. The power spectral density of the WSS process is the discrete-time Fourier transform of autocorrelation sequence. $S_X(\omega) = \sum_{m=-\infty}^{\infty} R_X[m]e^{-j\omega m} \quad -\pi \le w \le \pi$	Remember	CO 10
11	Define Energy-Spectral Density	Energy, or power, spectrum analysis is concerned with the distribution of the signal energy or power in the frequency domain. For a deterministic discrete-time signal, the energy-spectral density is defined as $\lvert X(f)\rvert^2 = \left\lvert \sum_{m=-\infty}^{\infty} x(m)e^{-j2\pi fm} \right\rvert^2$	Remember	CO 10
12	Define fourier transform	The Fourier Transform is a magical mathematical tool. The Fourier Transform decomposes any function into a sum of sinusoidal basis functions. Each of these basis functions is a complex exponential of a different frequency. The Fourier Transform therefore gives us a unique way of viewing any function - as the sum of simple sinusoids.	Remember	CO 10
13	Define inverse Fourier transform	A mathematical operation that transforms a function for a discrete or continuous spectrum into a function for the amplitude with the given spectrum; an inverse transform of the Fourier transform.	Remember	CO 10
14	Define energy signal	A signal x(t) is said to be an energy signal if its normalized energy is non-zero and finite. Hence for the energy signals, the total normalized energy (E) is non-zero and finite. i.e., $0<E<\infty$	Remember	CO 10
15	Define power signal	The signal having finite non-zero power are called as Power Signals $0<P<\infty$.	Remember	CO 10
16	Define average power of a random process	The average power of a random process is $E[\lvert x(t)\rvert^2] = R_{xx}(0) = \int_{-\infty}^{\infty} S_{xx}(f)\,df$ (or) $\lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} \lvert x(t)\rvert^2 \, dt$	Remember	CO 10
17	Define the even signal property of power spectral density.	Power spectral density is said to be even $S_{XX}(\omega)= S_{XX}(-\omega)$	Remember	CO 10
18	Define power spectral density if X(t) & Y(t)are uncorrelated and have constant mean values .	The power spectral density is $S_{XX}(\omega)=2\pi\mu_x\mu_y\delta(\omega)$ if X(t) & Y(t) are uncorrelated and have constant mean values.	Remember	CO 10
19	Define linear system.	System satisfies superposition and homogeneity then it is called linear system.	Remember	CO 11

20	Define the mean value of Response of a linear system.	The response of the system y(t)= x(t)*h(t)= $\int_{-\infty}^{\infty} h(\tau) . x(t-\tau) . d\tau$ Mean value of the Output Process Expected Value of the output is $E[y(t)] = E[\int_{-\infty}^{\infty} h(\tau) . x(t-\tau)] . d\tau$ $= \int_{-\infty}^{\infty} h(\tau) . E(x(t-\tau)) d\tau$	Remember	CO 12
21	Define autocorrelation Function of the Output Process.	autocorrelation Function $R_{YY}(\tau) = \int_{-\infty}^{\infty} h(\tau 1) . h(\tau 2) .Rxx(\tau - \tau 2 + \tau 1). d\tau 1 \; d\tau 2$	Remember	CO 12
22	Define the properties of power spectral density.	The area under power spectral is equal to the average power of that signal. The autocorrelation function and power spectral density form a fourier transform.	Remember	CO 11
23	Define cross correlation Function of the Output Process.	Cross correlation Function of the Output Process is convolution between auto correlation of input and system function .	Remember	CO 12
24	Define mean square value of the Output Process.	Mean square value of the Output is $E[y^2(t)] = Ryy(0)$ $\int_{-\infty}^{\infty} h(\tau 1) . h(\tau 2) .Rxx(-\tau 2 + \tau 1). d\tau 1 \; d\tau 2$	Remember	CO 12
25	Define the power at the output of the LTI system	The power at the output of the LTI system is the area enclosed by the output PSD	Remember	CO 12
26	Define relation between the PSDs of the input process and output process of an LTI Systems	The output power spectral density is the product of input power spectral density and square of the transfer function.	Remember	CO 12
27	Define parseval's theorem	Parseval's theorem defines the power of the signal in terms of its fourier series coefficients.	Remember	CO 10
28	Define average power.	The average power is defined as the power dissipated by a voltage x(t) applied across a 1 ohm resistor.	Remember	CO 10
29	Define energy spectral density.	Energy spectral density is defined as the distribution of energy of a signal in frequency domain.	Remember	CO 10
30	Define spectrum.	Any waveform can be represented by a summation of a (possibly infinite) number of sinusoids, each with a particular amplitude and phase. Such a representation is referred to as the signal's spectrum	Remember	CO 10
31	Define convolution	Convolution is a mathematical operation on two functions (f and g) to produce a third function that expresses how the shape of one is modified by the other.	Remember	CO 10
32	Define power spectral density of $A_c\cos(\omega ct)$	Two impulses at ω=ωc and ω=-ωc with an amplitude of π.	Remember	CO 12

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