CourseCode:20CS0531 **R20**

SIDDARTHA INSTITUTE OF SCIENCE AND TECHNOLOGY::PUTTUR
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QUESTION BANK(DESCRIPTIVE)

Subject with Code: **Soft Computing(20CS0531)** Course & Branch :**B.Tech-CSE**

Regulation:**R20** Year & Sem :**III-B.Tech & I–Sem**

UNIT–I
INTRODUCTION TO SOFT COMPUTING

1.	**a**	Illustrate the basic components of Artificial Intelligence and its applications.	[L3][CO1]	**[8M]**

The following are the components of Artificial Intelligence

a. Learning

Similar to humans, computer programs also learn in different manners. Talking of AI,learning by this platform is further segregated into a varied number of forms. One of the essential **components of ai,**learning for AI includes thetrial-and-error method.

The learning component of AI includes memorizing individual items like different solutions to problems, vocabulary, foreign languages, etc., also known as rote learning.

b. Reasoning

The art of reasoning was something that was only limited to humans until five decades ago. The ability to differentiate makes Reasoning one of the essential **components of artificial intelligence.** To reason is to allow the platform to draw inferences that fit with the provided situation.

c. Problem-solving

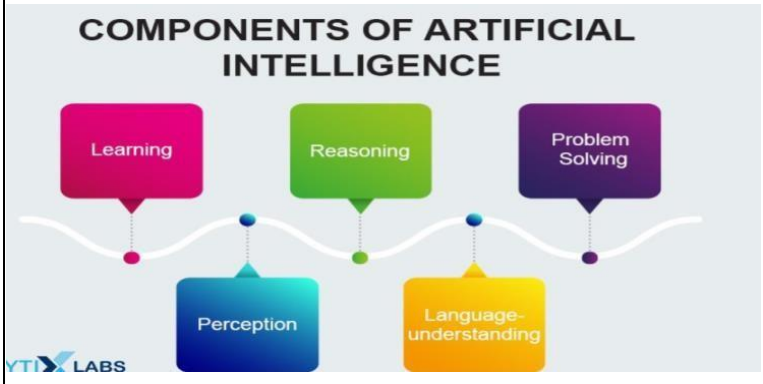
In its general form, the AI's problem-solving ability comprises data, where the solution needs to find x. he different methods of 'Problem-solving' count for essential **artificial intelligence components** that divide the queries into special and general purposes.

d. Perception

In using the'perception'component of Artificial Intelligence, the elements can any given environment by using different sense-organs, either artificial or real.

e. Language-understanding

In simpler terms, language can be defined as a set of different system signs that justify their means using convention. Occurring as one of the widely used **artificial intelligence components**, language understanding uses distinctive types of language over different forms of natural meaning, exemplified overstatements.

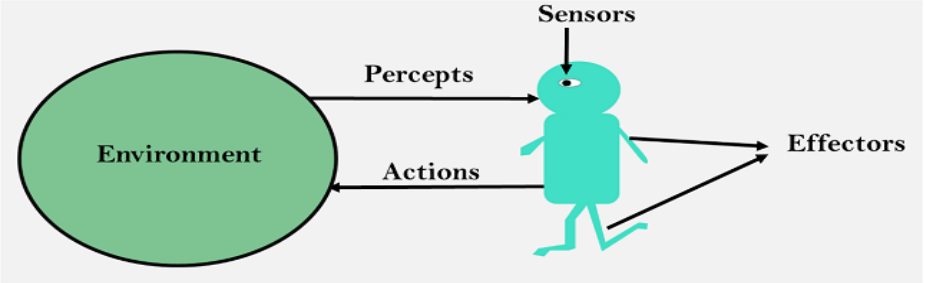


Intelligent agents work through three main components: sensors, actuators, and effectors. Getting an overview of these components can improve our understanding of how intelligent agents work.

Agent:This agent hassome level of autonomy that allows it to perform specific, predictable, and repetitive tasks for users or applications.

- **Sensors:** These are devices that detect any changes in the environment. This information is sent to other devices. In artificial intelligence, the environment of the system is observed by intelligent agents through sensors.
- **Actuators:** These are components through which energy is converted into motion. They perform the role of controlling and moving a system. Examples include rails, motors, and gears.
- **Effectors:** The environment is affected by effectors. Examples include legs, fingers, wheels, display screen, and arms.

The following diagram show these components are positioned in the AIsystem.



Applications of AI

AI has been dominant in various fields such as−

- **Gaming** − AI plays crucial role in strategic games such as chess,poker,tic-tac-toe, etc.,
- **Natural Language Processing** − It is possible to interact with the computer that understands natural language spoken by humans.
- **Expert Systems** −There are some applications which integrate machine, software, and special information to impart reasoning and advising
- **Vision Systems** –These systems understand, interpret, and comprehend visual input on the computer.
- **Speech Recognition** − It can handle different accents, slang words,noise in the background, change in human's noise due to cold,etc.
- **Handwriting Recognition** − The handwriting recognition software reads the text written on paper by a pen or on screen by astylus.
- **Intelligent Robots**−Robots are able to perform the tasks given by A human.

	b	Compare soft computing and hard computing	[L5][CO1]	**[4M]**

Difference between Soft Computing and Hard Computing:

S.NO	SoftComputing	HardComputing
1.	Soft Computing is liberal of in exactness, uncertainty, partial truth and approximation.	Hard computing needs a exactly state analytic model.
2.	Soft Computing relies on formal logic and probabilistic reasoning.	Hard computing relies on binary logic and crisp system.
3.	Soft computing has the features of	Hard computing has the features of

				Approximation and dispositionality.	Exactitude (precision) and categoricity.		
			4.	Soft computing is stochastic innature.	Hard computing is deterministic in nature.		
			5.	Soft computing works on ambiguous and noisy data.	Hard computing works on exact data.		
			6.	Soft computing can perform parallel computations.	Hard computing performs sequential computations.		
			7.	Soft computing produces approximate results.	Hard computing produces precise results.		
			8.	Soft computing will emerge its own programs.	Hard computing requires programs to be written.		
			9.	Soft computing incorporates randomness .	Hard computing is settled.		
			10.	Soft computing will use multivalued logic.	Hard computing uses two-valued logic.		

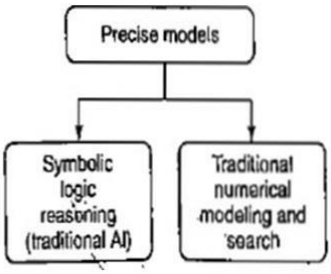


Figure 1.1: Hard Computing

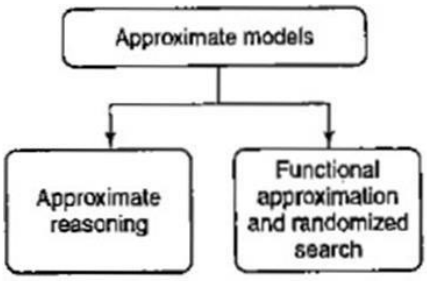
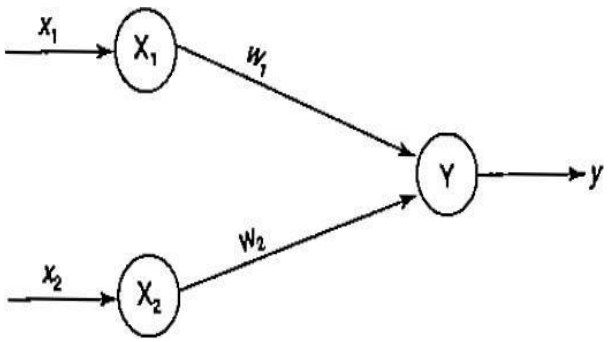


Figure 1.2: Soft Computing

2.	**a**	Explain the working principle of Artificial Neuron.	[L2][CO1]	**[8M]**

ArtificialNeuron

An artificial neural network (ANN) is an efficient information processing system which resembles the characteristics of biological neural network. ANNs contain large numberof highly inter connected processing elements called nodes or neurons or units. Each neuron is connected with other by connection link and each connection link is associated with weights which contain information about the input signal This information is used by neuron net to solve a particular problem.ANN shave ability to learn, recall and



generalize training pattern or data similar to that of human brain. The ANN processing elements called neurons or artificial neurons.

Each neuron has an internal state of its own, called activation or activity level of neuron which is the function of the inputs the neuron receives. The activation signal of aneuronis transmitted to other neurons. A neuron can send only one signal at a time which can be transmitted to several neurons.

Consider the figure1.5, here X_1 and X_2 are input neurons,Y is the output neuron W_1 and

W_2 are the weights net input is calculated as

$y_{in}=x_1w_1+x_2w_2$

where x_1 and x_2 are the activation of the input neurons X_1 and X_2, i.e., is the output of theinputsignals. The output y of the output neuron Y can be obtained by applying activationsoverthe netinput.

$y=f(y_{in})$

Output=Function (netinputcalculated)

The function to be applied over the net input is called activation function. The net inputcalculationissimilartothecalculationofoutputofapurelinearstraightlineequationy=mx

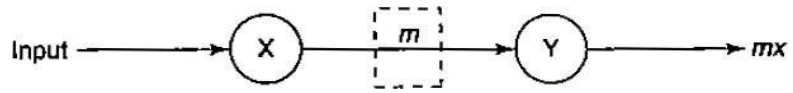


Figure1.6:Neuralnetofpurelinearequation

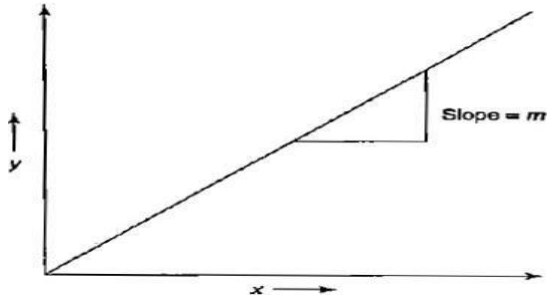


Figure 1.7:Graphfor *y =mx*

Theweightinvolve in theANN isequivalentto theslopeofthestraightline.

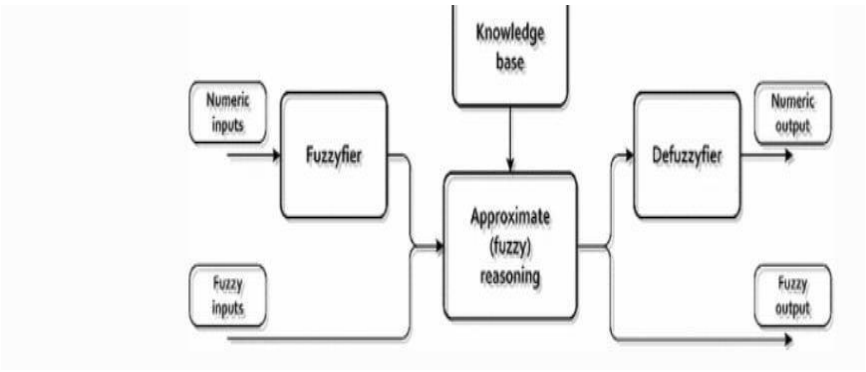
	b	DifferentiateBiologicalNeuronandArtificialNeuron.	[L4][CO1]	**[4M]**

Term	**Brain**	**Computer**
Speed	Executiontimeis few milliseconds	Executiontimeisfewnano seconds
Processing	Perform massive parallelloperationssimultaneously	Performseveralparallel operationssimultaneously. It isfaster thebiologicalneuron
Size andcomplexity	Number of Neuron is $10^{11}$and number ofinterconnectionsis10^{15}.Socomplexityofbrainishigherthan computer	It depends on the chosenapplication and networkdesigner.
Storage capacity	• Information is stored ininterconnections or insynapsestrength. • Newinformationisstored withoutdestroying oldone. • SometimesfailstorecollectInformation Draw biological neurondigram	• Stored in continuousmemorylocation. • Overloading maydestroyolderlocations. • Canbeeasilyretrieved Drawthediagramofartificialneuron

3.		Summarizethefollowingterms: i)FuzzySystems ii)GeneticAlgorithm	[L5][CO1]	[12M]

i) FuzzySystems:

Fuzzysystemsarestructuresbasedonfuzzytechniquesorientedtowardsinformation processing,wheretheusageofclassicalsetstheoryandbinarylogicisimpossibleor difficult.Intheliterature,termssuchasfuzzysystem,fuzzymodel,systembasedon fuzzyrules,fuzzycontroller,orfuzzyassociativememoryareusedinterchangeably dependingontheapplicationtype.Theirmaincharacteristicinvolvessymbolic knowledge representation in aformoffuzzy conditional(if-then)rules.



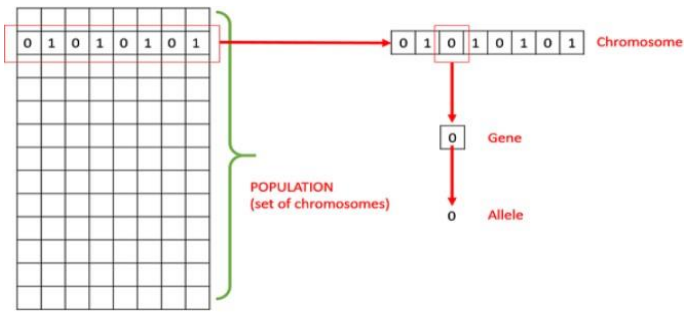
Thetypicalstructureofafuzzysystem

Thetypicalstructureofafuzzysystemconsistsoffourfunctionalblocks:thefuzzifier, thefuzzyinferenceengine,theknowledgebase,andthedefuzzifier.Bothlinguistic values(definedbyfuzzysets)andcrisp(numerical)datacanbeusedasinputsforafuzzy system.Ifcrispdataareapplied,thentheinferenceprocessisprecededbyfuzzification, whichassignstheappropriatefuzzysettothenonfuzzyinput.Thevaluesofinput variablesaremappedintolinguisticvaluesoftheoutputvariablebymeansofthe appropriatemethodofapproximatereasoning(inferenceengine)usingexpertknowledge, whichisrepresentedasacollectionoffuzzyconditionalrules(knowledgebase).In additionto thelinguisticvalues, thenumericaldata mayberequired asthefuzzy system output.Insuchcasesdefuzzificationmethodsareused,whichassigntherepresentativecrispdat a to theresultantoutputfuzzy set.

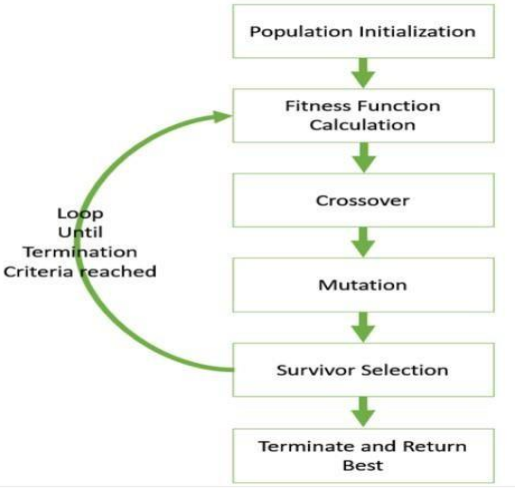
ii) **Geneticalgorithm**:Genetic Algorithm(GA)isa search-basedoptimization technique based on the principles of **Genetics and NaturalSelection**. GAs are a subset of a much larger branch of computation knownas**Evolutionary Computation**.

Basic Terminology

- **Population**−Itisasubsetofallthepossible(encoded)solutionstothegivenproblem.Thepopulatio n for a GA is analogous to the population for human beings except that instead ofhuman beings,wehave Candidate Solutionsrepresenting human beings.
- **Chromosomes**−Achromosomeisonesuchsolutiontothegivenproblem.
- **Gene**−Ageneisoneelementpositionofachromosome.
- **Allele**−Itisthevalueagenetakesforaparticularchromosome.



- **Genotype**−Genotypeisthepopulationinthecomputationspace.Inthecomputationspace,thsolutions arerepresentedinawaywhichcanbeeasilyunderstoodandmanipulatedusinga computingsystem.
- **Phenotype** − Phenotype is the population in the actual real world solution space in whichsolutionsare represented in awaytheyarerepresentedin realworld situations.

- **DecodingandEncoding**−Forsimpleproblems,the**phenotypeandgenotype**spacesarethesame.
- 

Basicstructure ofGA

Westartwithaninitialpopulation(whichmaybegeneratedatrandomorseededbyotherheuristics),selectparentsfromthis populationformating.Applycrossoverandmutationoperatorsontheparentstogeneratenewoff-springs.Andfinallytheseoff-springsreplacetheexistingindividualsinthepopulationandtheprocessrepeats.Inthiswaygenetic algorithms actuallytrytomimicthe humanevolutiontosomeextent.

4. **a** DistinguishbetweenSupervisedLearningandUnsupervisedLearning. [L4][CO1] **[6M]**

MajordifferencesbetweenSupervisedandUnsupervisedLearning

SupervisedLearning	UnsupervisedLearning
Supervised Learning can be used for 2 differenttypesofproblemsi.e.regressionandclassification	Unsupervised Learning can be used for2 different types of problems i.e.clusteringand association.
Input Data is provided to the model along with theoutput in the Supervised Learning.	Only input data is provided inUnsupervised Learning.
Outputis predicted bythe Supervised Learning.	Hidden patterns in the data can befound using the unsupervised learningmodel.
Labeled data is used to train supervised learningalgorithms.	Unlabeled data is used to trainunsupervisedlearningalgorithms.
Accurate results are produced using a supervisedlearningmodel.	The accuracy of results produced arelessinunsupervisedlearningmodels.
Training the model to predict output when a newdata is provided is the objective of SupervisedLearning.	Findingusefulinsights,hiddenpatternsfrom the unknown dataset is theobjective of the unsupervised learning.
Supervised Learning includes various algorithmssuch as Bayesian Logic, Decision Tree, LogisticRegression, Linear Regression, Multi-classClassification,SupportVectorMachineetc.	Unsupervised Learning includesvarious algorithms like KNN, AprioriAlgorithm, andClustering.
To assess whether right output is being predicted,direct feedback is accepted by the SupervisedLearning Model.	No feedback will be taken by theunsupervised learning model.
In Supervised Learning, for right prediction ofoutput, the model has to be trained for each data,hence Supervised Learning does not have closeresemblance toArtificial Intelligence.	Unsupervised Learning has moreresemblance to Artificial Intelligence,as it keeps learning new things withmoreexperience.
Number of classes are known in SupervisedLearning.	Number of classes are not known inUnsupervised Learning

	In scenarios where one is aware of output andinputdata,supervisedlearningcanbeused.	In the scenarios where one is not awareof output data, butis only aware of the		

			input data then Unsupervised Learningcould beused.		
		Computational Complexity is very complex inSupervised Learning compared to UnsupervisedLearning	There is less computational complexityin Unsupervised Learning whencomparedto Supervised Learning.		
		SupervisedLearningwilluseoff-lineanalysis	Unsupervised Learning uses Real timeanalysisof data.		
		Some of the applications of Supervised Learningare Spam detection, handwriting detection, patternrecognition,speech recognition etc.	Some of the applications ofUnsupervised Learning are detectingfraudulent transactions, datapreprocessingetc.		
	b	DescribethedifferentactivationfunctionsinNeuralNetworks.		[L2][CO1]	[6M]

ActivationFunctions:

Tomakeworkmoreefficientandforexactoutput,someforceoractivationisgiven.Likethat, activation function is applied over the net input to calculate the output of an ANN.Information processing of processing element has two major parts: input and output.
Anintegrationfunction(f)isassociatedwithinputofprocessingelement.Severalactivationfunctionsarethere.

1. Identity function: It is a linear function which is defined as

$$f(x) = x \text{ for all } x$$

The output is same as the input.

2. Binary step function: This function can be defined as

$$f(x) = \begin{cases} 1 \text{ if } x \geq \theta \\ 0 \text{ if } x < \theta \end{cases}$$

Where, θ represents thresh hold value. It is used in single layer nets to convert the net input to an output that is binary (0 or 1).

3. Bipolar step function: This function can be defined as

$$f(x) = \begin{cases} 1 \text{ if } x \geq \theta \\ -1 \text{ if } x < \theta \end{cases}$$

Where, θ represents threshold value. It is used in single layer nets to convert the net input to an output that is bipolar (+1 or -1).

4. Sigmoid function: It is used in Back propagation nets.

Two types:

a) **Binary sigmoid function**: It is also termed as logistic sigmoid function or unipolar sigmoid function. It is defined as

$$f(x) = \frac{1}{1 + e^{-\lambda x}}$$

where, λ represents steepness parameter. The derivative of this function is

$$f'(x) = \lambda f(x)[1 - f(x)]$$

Therangeofsigmoid function is0 to 1.

Bipolarsigmoidfunction:This functionisdefinedas

$$f(x) = \frac{2}{1 + e^{-\lambda x}} - 1 = \frac{1 - e^{-\lambda x}}{1 + e^{-\lambda x}}$$

Where λrepresentssteepnessparameterand thesigmoid rangeisbetween-1and +1.The

derivativeofthisfunctioncanbe

$$f'(x) = \frac{\lambda}{2}[1 + f(x)][1 - f(x)]$$

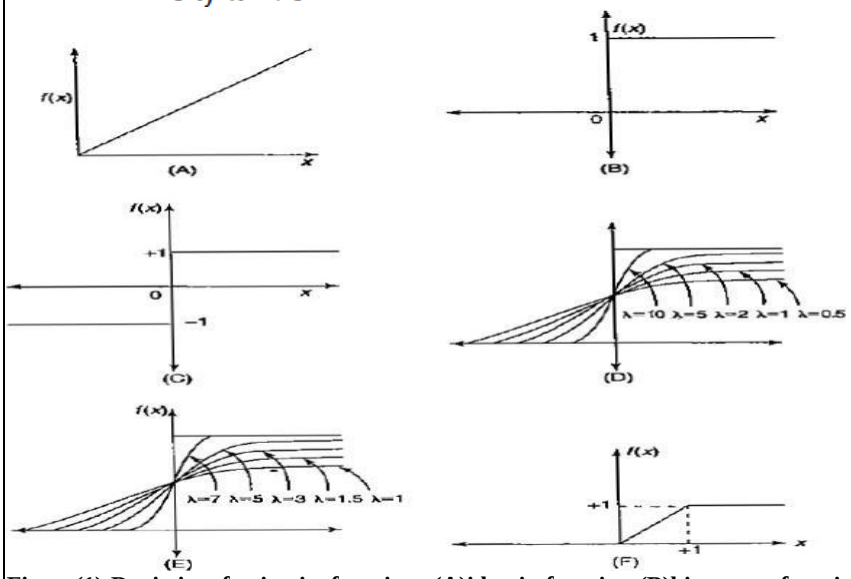
Itisclosely relatedtohyperbolictangentfunction,which iswrittenas

$$h(x) = = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

$$h(x) = = \frac{1 - e^{-2x}}{1 + e^{-2x}}$$

Thederivativeofthehyperbolictangentfunctionis
$h'(x)=[1+h(x)][1-h(x)]$
Rampfunction:Therampfunctionisdefinedas

$$f(x) = \{ \begin{matrix} 1 \; if x > 1 \\ x \; if \; 0 \leq x \leq 1 \\ 0 \; if \; x < 0 \end{matrix}$$



Figure(1):Depictionofactivationfunctions:(A)identityfunction;(B)binarystepfunction; (C)bipolarstepfunction;(D)binarysigmoidalfunction;(E)bipolarsigmoidalfunction;(F)rampfun ction

5.	InfertheclassificationsofArtificialNeuralNetworks.	[L2][CO1]	**[12M]**

Classifications ofANNs(Connections)

The arrangement of neurons to form layers and the connection pattern formed within andbetweenlayersiscalledthenetworkarchitecture.Thereexistfivebasictypesofconnectionarc hitecture.Theyare

1. Singlelayerfeedforwardnetwork
2. Multilayerfeed-forwardnetwork
3. Singlenodewithitsownfeedback
4. Single-layerrecurrentnetwork
5. Multilayerrecurrentnetwork

Feedforwardnetwork:If no neuronin the output layer is an input toa node in thesameayer/proceeding layer.

Feedbacknetwork:Ifoutputsaredirectedbackasinputtotheprocessingelementsintheamelayer/p roceeding layer.

Lateralfeedback:Ifthe outputis directedbacktotheinputofthesamelayer.**Recurrentnetworks**:Arenetworkswith feedbacknetworkswithclosedloop.**1.Singlelayerfeedforwardnetwo rk**

Layer is formed by taking processing elements and combining it with other processinglements.Inputandoutputarelinkedwith eachotherInputsareconnectedtotheprocessing

	nodes withvariousweights,resultinginseries ofoutputs onepernode.	

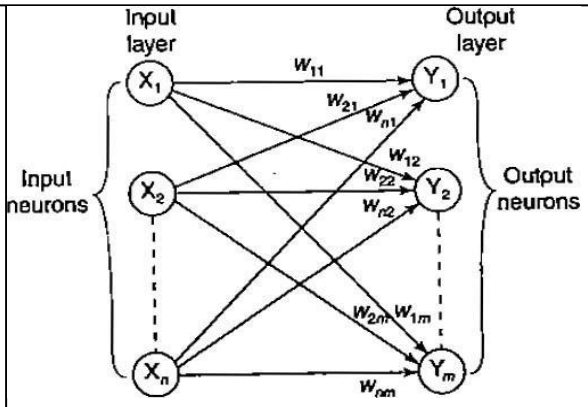


Figure 1.8:Single-layerfeed-forwardnetwork

Whenalayerofprocessingnodesisformedtheinputscanbeconnectedtothesenodeswithvarious weights, resulting in a serious of outputs, one per node. This is called singlelayereedforwardnetwork.

2.Multilayerfeed-forwardnetwork:

This network is formed by the interconnection of several layers. Input layer receives inputnd buffers input signal. Output layer generated output. Layer between input and output isalledhiddenlayer.Hiddenlayerisinternaltothenetwork.ThereareZerotoseveralhiddenayers in a network. More the hidden layer more is the complexity of network, but efficientoutputisproduced.

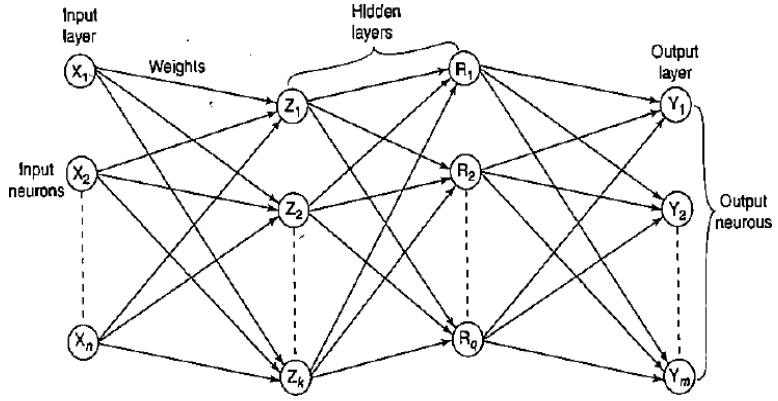


Figure1.9:Multilayer feed-forwardnetwork

3.Singlenodewithitsownfeedback:

Itisasimplerecurrentneuralnetworkhaving asingleneuronwithfeedbacktoitself.

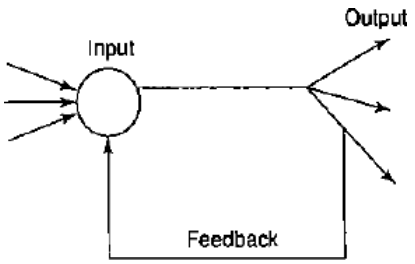


Figure1.10:Single node withownfeedback

4.Singlelayerrecurrentnetwork:

Asinglelayernetworkwithfeedbackfromoutputcanbedirectedtoprocessingelementitselfort o otherprocessingelement/both.

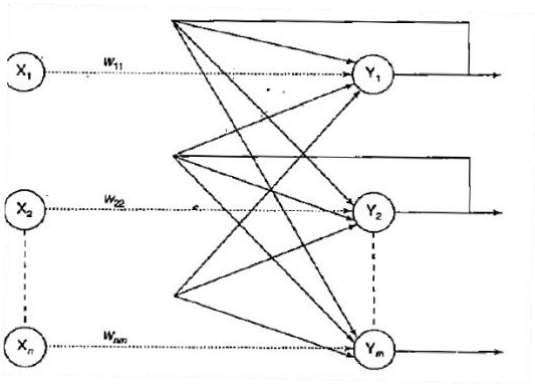


Figure1.11:Single-layerrecurrentnetwork

5.Multilayerrecurrentnetwork:

Processing element output can be directed back to the nodesin the preceding layer,formingamultilayerrecurrentnetwork.

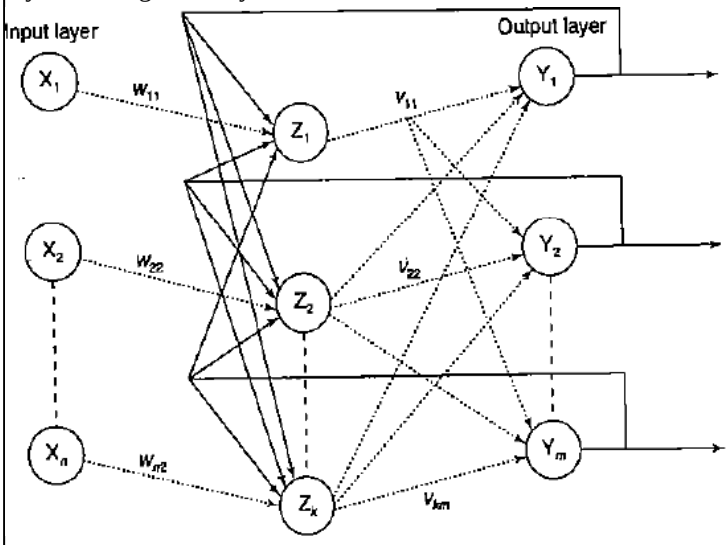


Figure1.12:Multilayer recurrentnetwork

Maxnet–competitiveinterconnectionshavingfixedweights.

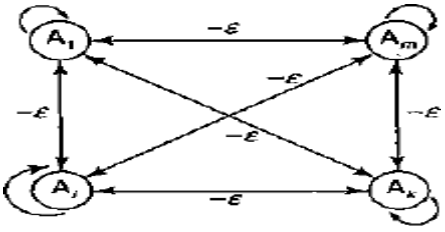


Figure1.13:Competitivenets

On-center-off-surround/lateral inhibition structure – each processingneuron receivestwo different classes of inputs- "excitatory" input from nearby processingelements &"inhibitory"elementsfrommoredistantlylocatedprocessingelements.Thistype ofinterconnectionisshown below

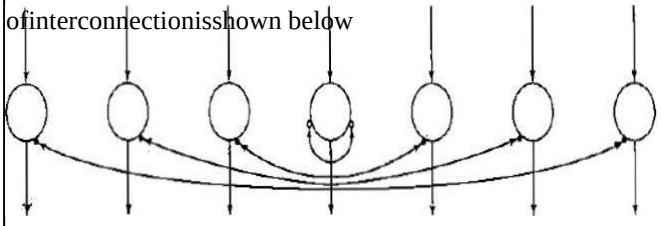


Figure1.14:Lateralinhibitionstructure

6.	**a**	AnalyzeSwarmIntelligentSystems.	[L4][CO1]	**[6M]**
		SwarmIntelligentSystems: **Swarm Intelligence (S.I.)** was introduced by **Gerardo Beni and Jing Wang in theyear1989**.S.I.simplymeansusingtheknowledgeofcollectiveobjects(people,insects,etc.)togetherandthenreachingtheoptimizedsolutionforagivenproblem.***"Swarm"meansagroupofobjects(people,insects,etc.)***. Let'stakeanexample***toprovethatthecollectiveknowledgeofobjectsisbetterthananyindividualobject*** Let's say we have a jar containing 500 marbles in that. The question is without touchingthe jar a person needs to predict how many marbles are in that jar. Suppose we take onlyone response from a person and it predicts that according to him the jar contains 400marbles. So by this result, we can conclude that this estimation of that person is not verybad since the ***difference(error) is of 100*** only, but thismight not be the best solution,we can optimize this even more. So now what we will do is instead of taking responsefrom only one person we will be taking response from 10 people let's say. Let 'P' denoteapersonthereforetheresponsesareasfollows: P1 P2 P3 P4 P5 P6 P7 P8 P9 P10 400 450 550 600 480 390 520 490 510 450 Soaftercollectingtheresponsesfrom10differentindividualswecantaketheaverageoftheirresponses. ***Average:*** *(400+450+550+600+480+390+520+490+510+450)/10* *Average=4840/10* ***=484(marblesinthejar)*** Now from this, we can say that from the collective predictions from 10 differentpersons we have reached a more optimal answerthat is 484 marbles in the jar.Weareveryclosetotheactualresultof 500marblesinthejar,hereinthiscasethe ***difference (error) reduces to only 16 marbles as compared to the previous errorwhich was 100***. So that is the main idea behind swarm intelligence, that is to use thecollectiveknowledgeofobjects.SomeoftheexamplesofswarmIntelligenc • **AntsColonyOptimization** • **SwarmofBees** • **ArtificialSwarmIntelligence(ASI)(humanswarm)** **ApplicationsofSwarmIntelligence** • Usedinmilitaryservices. • NASAisgeneratingtheideatouseswarmintelligenceforplanetarymapping. • UsedinDataMining. • M. Anthony Lewis and George A. Bekey presented the idea that with thehelp of swarm intelligence we can control nano bots in our body to killcancertumors. • Usedinbusinesstoreachbetterfinancialdecisionsetc.		
	b	DescribetheroleofEvolutionaryProgramminginSoftComputing.	[L2][CO1]	**[6M]**
		Evolutionary programming (EP) is an approach to simulated evolution thatiteratively generatesincreasinglyappropriatesolutionsinthelightofastationaryor non-stationary environment and desired fitness function. Standard EP makesuseofthe same fourcomponentsthatare standardtoallevolutionaryalgorithms		

		(EAs):		

- **initialization,**
- **variation**
- **evaluation**
- **selection**.

This approach to population-based search has its roots in the early work ofLawrenceJ. Fogel,

Evolutionary programming is **one of the four major evolutionary algorithmparadigms**.Itissimilartogeneticprogramming,butthestructureoftheprogramtobeoptimizedisfixed,whileitsnumericalparametersareallowedtoevolve.

- There is no fixed structure for representation.
- There is only mutation operation, and cross-over is not used in this method.
- Each child is determined by its parent in a way of mutation.
- So, we can conclude that there are three steps:
  - Initialize population and calculate fitness values for initial population
  - Mutate the parents and generate new population
  - Calculate fitness values of new generation and continue from the second step.

Someofthe ApplicationsofEP

- usedtooptimize the controlgainsforthe kinematiccontrolsystem
- roboticcontrolusedEPcoupledwithfuzzylogicforthecontrolofwheeledrobots
- areaofmobilenetworkstrategicplanning,appliedEPtodiscoveroptimalcellsizedetermination.

7.	**a**	ExplainMcCullochandPittsNeuronModel.	[L2][CO1]	**[6M]**

McCullochandPittsNeuron:

Itisdiscoveredin1943andusuallycalledasM-Pneuron.M-Pneuronsareconnectedbydirected weighted paths. Activation of M-P neurons is binary (i.e) at any time step theneuron may fire or may not fire. Weights associated with communication links may beexcitatory (wgts are positive)/inhibitory (wgts are negative). Threshold plays major rolehere.Thereisafixedthresholdforeachneuronandifthenetinputtotheneuronisgreaterthanthethresholdthentheneuronfires.Theyarewidelyusedinlogicfunctions.AsimpleM-Pneuronisshowninthe figure.Itisexcitatorywithweightw(w>0)/inhibitorywithweight–p (p<0). IntheFig.

inputs from x_1 to x_n possess excitatory weighted connection and X_{n+1} to x_{n+m} hasinhibitoryweighted interconnections.

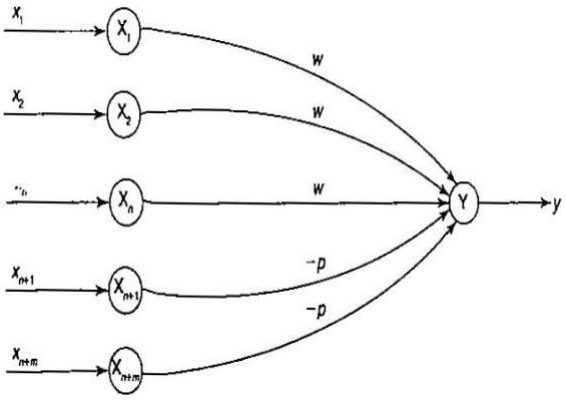


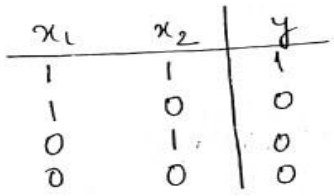
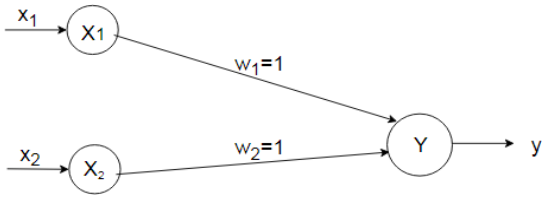
Figure1.19:McCulloch-Pins neuronmodel

Sincethefiringofneuronis basedonthreshold,activationfunctionis definedas

$$f(x)=\begin{cases}1 if\ y_{in}\geq\theta\\ 0 if\ y_{in}<\theta\end{cases}$$

Forinhibitiontobeabsolute,thethresholdwiththeactivationfunctionshouldsatisfythefollowingcondition: $\theta > nw - p$

Outputwillfire ifitreceives"k"ormoreexcitatoryinputsbutnoinhibitoryinputs

		where $kw \geq \theta > (k-1)w$ TheM-Pneuronhasnoparticulartrainingalgorithm.Ananalysisisperformedtodeterminetheweightsandthethreshold.Itisusedasabuildingblockwhereanyfunction orphenomenonismodeledbased on alogicfunction**.**		
	b	DemonstratehowANDfunctionisimplementedinM-PNeuronModel.	[L3][CO1]	**[6M]**
		Solution:TruthtableforANDis  InMcCulloch-PittsNeurononlyanalysisisperformed.hence,assumeweights bew1=w2=1 Thenetworkarchitecture is  Withthese assumedweights the netinputis calculatedforfourinputs,(i) (1,1)−**yin**=x1w1+x2w2=1×1+1×1=2 (ii) (1,0)−yin=x1w1+x2w2=1×1+0×1=1(iii) (0,1)−yin=x1w1+x2w2=1×0+1×1=1(iv)(0,0)−yin=x1w1+x2w2=0×1+0×1=0 For,ANDfunctionthe outputishighifboththeinputsare high.Forthisfunction,the netinputiscalculated as2. Hence,basedon thisinputthethresholdvalue isset,i.e., iftheoutputvalue isgreaterthanorequalto2 then theneuron fires, elseitdoesnotfire. So,thethresholdvalueis setto2(θ=2).This canbe obtainedby,θ≥nw−p Here,n=2,w=1(excitory)and p=0 (inhibitory) ∴θ≥2×1−0 ⇒θ≥2 Theoutputofneuron Y can bewritten as, $y = f(y_{in}) = \begin{cases} 1, & if \quad y_{in} \geq 2 \\ 0, & if \quad y_{in} < 2 \end{cases}$		
8.		DescribeHebbNetworkinArtificialNeuralNetworks.	[L2][CO1]	**[12M]**
		Hebbnetwork Donald Hebb stated in 1949 that "In brain, the learning is performed by thechange in the synaptic gap". When an axon of cell A is near enough to excitecell B, and repeatedly or permanently takes place in firing it, some growthprocess or metabolic change takes place in one or both the cells such that A'sefficiency,asoneofthecellsfiringB,isincreased.AccordingtoHebbrule,theweight vector is found to increase proportionately to the product oftheinputand the learning signal. InHebb learning, twointerconnectedneurons are'on'simultaneously.TheweightupdateinHebb ruleisgivenby		

		$w_i(new)=w_i(old)+x_iy$		

Hebbsnetworkissuitedmoreforbipolardata.Ifbinarydataisused,theweightupdationformulacannotdistinguishtwoconditionsnamely:

1. Atrainingpairinwhichaninputunitis “on”and thetargetvalueis “off”.
2. Atrainingpairinwhichboththe inputunitandthe targetvalueis“off”.

Trainingalgorithm

Thetrainingalgorithmisusedforthecalculationandadjustment ofweights.Theflowchartforthetrainingalgorithm ofHebbnetwork isgiven below

Step0:Firstinitializetheweights.Basicallyinthisnetworktheymaybesettozero,i.e. *w;*=0,fori=1to *n*where *"n"*may be thetotalnumberofinputneurons.

Step1:Steps2-4 havetobeperformedforeachinputtrainingvectorand targetoutputpair, s:t.

Step2: Inputunitsactivationsareset.Generally,theactivationfunctionofinputlayerisidentity function:$x_i = s_i$ *fori=1ton*

Step3:Outputunits activationsareset:$y=t$.

Step4:Weightadjustmentsandbiasadjustmentsare performed:

$$w_i(new) = w_i(old)+x_iy$$

$$b(new)=b(old)+y$$

In step 4, the weight updation formula can be written in vector form as

$$w(new) = w(old)+y$$

Hence, Change in weight is expressed as $\Delta w = xy$

Asaresult,

$$w(new)=w(old)+\Delta w$$

Hebbruleisusedforpatternassociation,patterncategorization,patternclassification andoverarangeofotherareas.

FlowchartofTrainingalgorithm

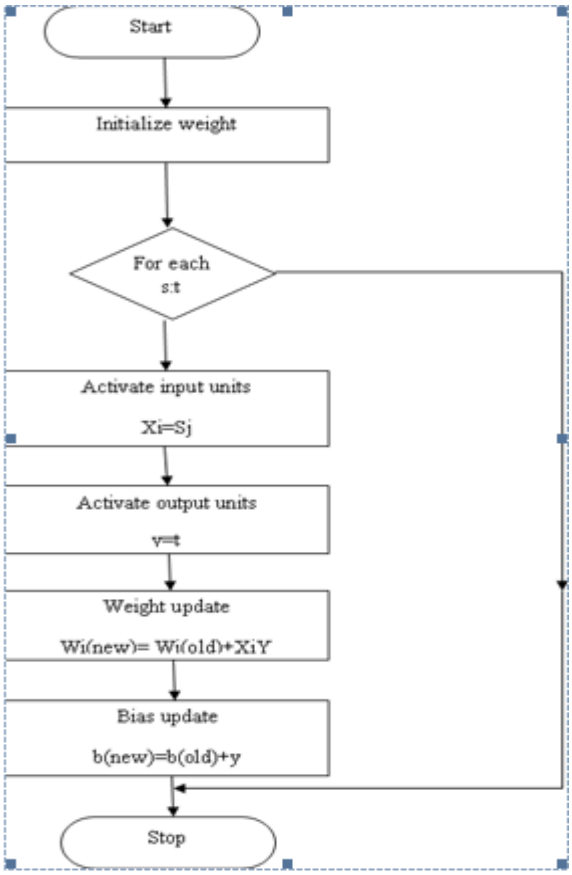


Figure 1.20: Flowchart of Hebb training algorithm

9.		IllustratethePerceptronNetworkwithneatdiagram.	[L3][CO1	**[12M]**

Perceptronnetworks

Perceptron networks come under single-layer feed-forward networks and are alsocalled simple perceptrons. Various types of perceptrons were designed by Rosenblatt(1962)and Minsky-Papert(1969, 1988).

Thekeypointstobenotedinaperceptronnetworkare:

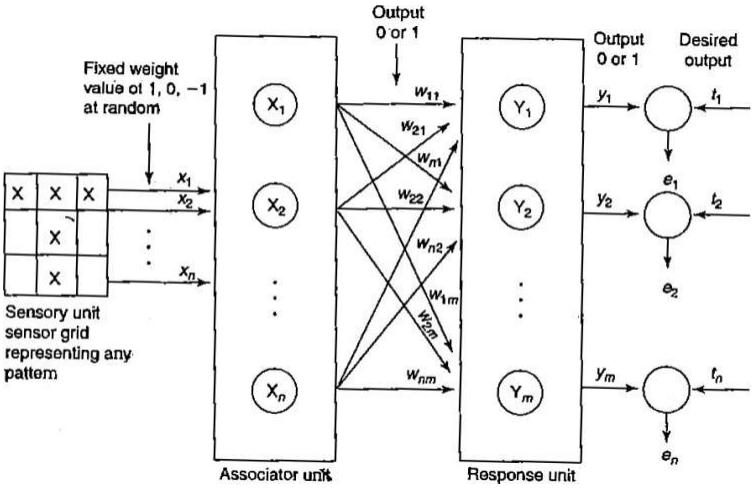
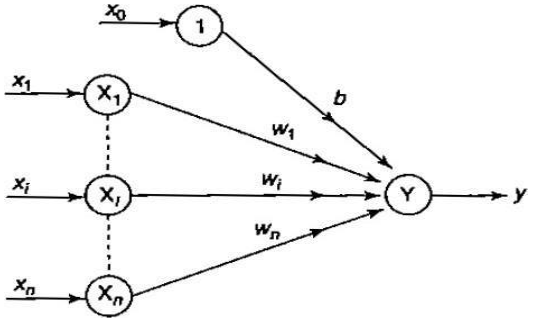
1. Theperceptronnetworkconsistsofthreeunits,namely,sensoryunit(input unit),associatorunit(hidden unit),andresponseunit(outputunit).
2. The sensory units are connected to associator units with fixed weightshavingvalues1,0or-l,which areassignedat random.
3. Thebinary activationfunction isusedin sensoryunitandassociatorunit.
4. The response unit has an activation of l, 0 or -1. The binary step withfixedthresholdθisusedasactivationforassociator.Theoutputsignalst hataresentfromtheassociatorunittotheresponseunitareonlybinary.
5. Theoutputoftheperceptronnetwork is given by

$$y=f(y_{in})$$

where$f(y_{in})$isactivationfunctionandisdefined as

$$f(y_{in})=\begin{cases}1 & if\ y_{in}>\theta\\ 0 & if\ -\theta\le y_{in}\le\theta\\ -1 & if\ y_{in}<-\theta\end{cases}$$

6. Theperceptronlearningruleisusedintheweightupdationbetweentheassoc iator unit and the response unit. For each training input, the netwillcalculatetheresponseanditwilldeterminewhetherornotanerrorhas occurred.
7. Theerrorcalculationisbasedonthecomparisonofthevaluesof targetswiththoseoftheca1culated outputs.

		8. Theweightsontheconnectionsfromtheunitsthatsendthenonzerosignalwil lget adjusted suitably. **9.** Theweightswillbeadjustedonthebasisofthelearningruleanerrorhasoccur red foraparticulartraining patterns.i.e.., $w_i(new)=w_i(old)+\alpha t x_i$ $b(new)=b(old)+\alpha t$ Ifnoerroroccurs,thereisnoweightupdationandhencethetrainingprocessmaybestopped.In theaboveequations,thetargetvalue$"t"$is+1or-landαisthelearningrate  **Figure2.1:Originalperceptronnetwork** ***Architecture***  **Figure2.2:Singleclassificationperceptronnetwork** Hereonlytheweightsbetweentheassociatorunitandtheoutputunitcanbeadjusted,andt heweightsbetween thesensory andassociatorunitsare fixed. **Drawthe flowchart.**		
10.		ExplainbrieflyAdalineand MadalineNetworks.	[L2][CO1]	**[12M]**
		ADALINE Adaline is a single unit neuron, which receives input from several units and also fromone unit called bias. The basic Adaline model consists of trainable weights. Inputs areeitherofthe two values(+1 or-1)and the weightshavesigns(positiveornegative).Initially, random weights are assigned. The net input calculated is applied to a quantizertransferfunction(possiblyactivationfunction)thatrestorestheoutputto+1or-1. ***TrainingAlgorithm*** Step0**:Weightsandbiasaresettosomerandomvaluesbutnotzero.Setthelea rningrateparameter*α*.** Step1**:PerformSteps2-6whenstoppingconditionisfalse.** Step2**:PerformSteps 3-5for eachbipolartrainingpair *s:t.*** Step3**:Setactivations for inputunits*i*=1to*n*.**		

		$x_i=s_i$		

Step4**:Calculatethenetinputtotheoutputunit.**

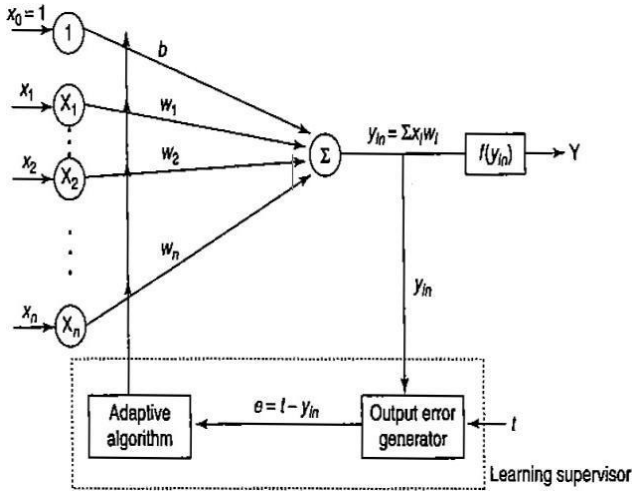
$$y_{in}=b+\sum_{i=1}^{n} x_i w_i$$

Step5**:Updatetheweights andbias for i=1ton**

$$w_i(new)=w_i(old)+\alpha(t-y_{in})x_i$$

$$b(new)=b(old)+\alpha(t-y_{in})$$

Step6**:**Ifthehighestweightchangethatoccurredduringtrainingissmallerthana specifiedtolerancethenstopthetrainingprocess,elsecontinue.Thisistherestfo rstopping conditionofanetwork.



TestingAlgorithm

Step0**:Initializetheweights.(Theweights areobtainedfromthetrainingalgorithm.)**

Step1**:PerformSteps 2-4for eachbipolar inputvectorx.**

Step2**:Settheactivations oftheinputunits tox.**

Step3**:Calculatethenetinputtotheoutputunit:**

$$y_{in}=b+\sum_{i=1}^{n} x_i w_i$$

Step4**:Applytheactivationfunctionoverthenetinputcalculated:**

$$y=\begin{cases} 1 \text{ if } y_{in} \geq 0 \\ -1 \text{ if } y_{in} < 0 \end{cases}$$

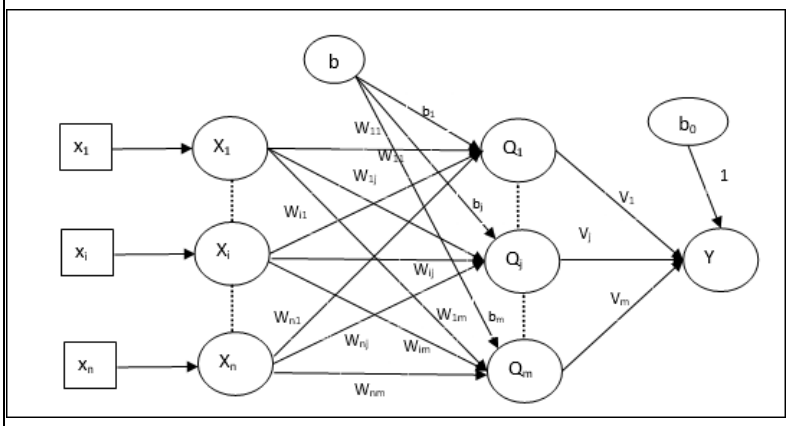
MultipleAdaptiveLinearNeuron(Madaline)

Madaline which stands for Multiple Adaptive Linear Neuron, is a network which consistsofmanyAdalinesinparallel.Itwillhaveasingleoutputunit.Someimportantpointsabout Madaline areasfollows−

- Itisjustlikeamultilayerperceptron,whereAdalinewillactasahiddenunitbetween theinputand the Madalinelayer.
- TheweightsandthebiasbetweentheinputandAdalinelayers,asinweseeintheAdaline architecture, areadjustable.
- TheAdaline andMadaline layers have fixedweightsandbiasof1.
- Trainingcanbe done withthe helpofDelta rule.

Architecture

The architecture of Madaline consists of **"n"** neurons of the input layer, **"m"** neurons oftheAdalinelayer,and1neuronoftheMadalinelayer.TheAdalinelayercanbeconsideredas the hidden layer as it is between the input layer and the output layer, i.e. the Madalinelayer.



TrainingAlgorithm

By now we know that only the weights and bias between the input and the Adaline layerare to be adjusted, and the weights and bias between the Adaline and the Madaline layerare fixed.

Step1− Initializethe followingtostartthe training−

- Weights
- Bias
- Learningrateα

foreasycalculationandsimplicity,weightsandbiasmustbesetequalto0andthelearningrate mustbesetequalto1.

Step2−Continue step3-8whenthestoppingconditionisnottrue.

Step3−Continuestep4-7foreverybipolartrainingpairs:t.Step4

−Activateeach inputunitas follows−

$$x_i = s_i \ (i = 1 \ to \ n)$$

Step 5 − Obtain the net input at each hidden layer, i.e. the Adaline layer with the following relation −

$$Q_{inj} = b_j + \sum_{i}^{n} x_i \, w_{ij} \quad j = 1 \ to \ m$$

Here **'b'** is bias and **'n'** is the total number of input neurons.

Step 6 − Apply the following activation function to obtain the final output at the Adaline and the Madaline layer −

$$f(x) = \begin{cases} 1 & if \ x \geqslant 0 \\ -1 & if \ x < 0 \end{cases}$$

Output at the hidden (Adaline) unit

$$Q_j = f(Q_{inj})$$

Finaloutputofthenetwork

$$y = f(y_{in})$$

i.e. $y_{inj} = b_0 + \sum_{j=1}^{m} Q_j v_j$

Step 7 – Calculate the error and adjust the weights as follows –

Case 1 – if **y ≠ t** and **t = 1** then,

$$w_{ij}(new) = w_{ij}(old) + \alpha(1 - Q_{inj})x_i$$

$$b_j(new) = b_j(old) + \alpha(1 - Q_{inj})$$

In this case, the weights would be updated on Q_j where the net input is close to 0 because **t = 1**.

Case 2 – if **y ≠ t** and **t = -1** then,

$$w_{ik}(new) = w_{ik}(old) + \alpha(-1 - Q_{ink})x_i$$

$$b_k(new) = b_k(old) + \alpha(-1 - Q_{ink})$$

In this case, the weights would be updated on Q_k where the net input is positive because **t = -1**.

Here **'y'** is the actual output and **'t'** is the desired/target output.

Case 3 – if **y = t** then

There would be no change in weights.

Step 8 – Test for the stopping condition, which will happen when there is no change in weight or the highest weight change occurred during training is smaller than the specified tolerance.

ThearchitectureofMadalineconsistsof"n"neuronsoftheinputlayer,"m"neuronsoftheAdalinel
ayer,and1neuronoftheMadalinelayer.TheAdalinelayercanbeconsideredasthehiddenlayerasi
tisbetweentheinputlayerandtheoutputlayer,i.e.theMadalinelayer.

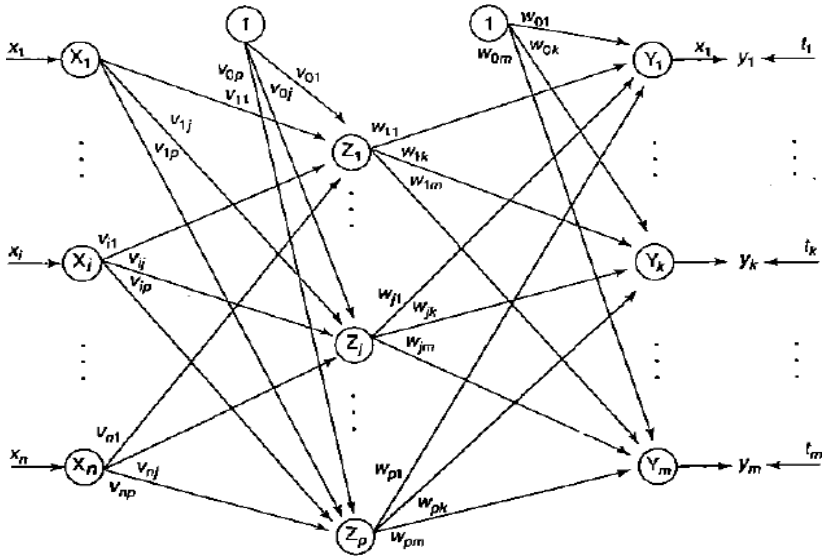
UNIT–II
ARTIFICIALNEURALNETWORKS

1		AnalyzetheBackpropagationofNeuralNetworkwithneatdiagram.	[L4][CO2]	**[12M]**

BackpropagationNetwork

The back propagation learning algorithm is one of the most important developmentsinneuralnetworks(BrysonandHo,1969;Werbos,1974;Lecun,1985;Parker,1985;umelhart, 1986). This learning algorithm is applied to multilayer feed-forwardnetworks consisting of processing elements with continuous differentiable activationfunctions. The networks associated with back-propagation learning algorithm are alsocalled back-propagation networks. (BPNs).

For a given set of training input-output pair, this algorithm provides a procedure forchanging the weights in a BPN to classify the given input patterns correctly. Thebasicconceptforthisweightupdatealgorithmissimplythegradientdescentmethod.



Thisisamethodswereerrorispropagatedbacktothehiddenunit.Backpropagationnetworkisatraining algorithm.

A back-propagation neural network is a multilayer, feed-forward neural networkconsistingofaninputlayer,ahiddenlayerandanoutputlayer.Theneuronspresentin the hidden and output layers have biases, which are the connections from theunits whose activation is always 1. The bias terms also acts as weights. During theback propagation phaseoflearning, signals are sent in the reverse direction. Theinputs sent to the BPN and the output obtainedfromthenetcouldbeeitherbinary(0,1)orbipolar (-1,+1).Theactivationfunction could be any functionwhich increases monotonically and is also differentiable**.** The commonly usedactivationfunctionsarebinary,sigmoidalandbipolarsigmoidalactivationfunctions.ThesefunctionsareusedintheBPNbecauseofthefollowingcharacteristics:(i)Continuity(ii)Differentiabilityiii)Nondecreasing monotonic.

TrainingAlgorithm

		Step0:Initializeweightsandlearningrate(takesomesmallrandomvalues).		

Step1:PerformSteps2-

9whenstoppingconditionisfalse.Step2:PerformSteps3-

8foreach trainingpair.

Feedforward Phase1

Step3:Eachinputunitreceivesinputsignal$x_i$and sendsittothehidden unit(i=l to n).

Step 4: Each hidden unit z_j (j = 1 to p) sums its weighted input signals tocalculatenetinput:

$$z_{inj}=v_{0j}+\sum_{i=1}^{n} x_i v_{ij}$$

Calculateoutputofthehiddenunitbyapplyingitsactivationfunctionsoverz_{inj}

(binaryorbipolarsigmoidalactivationfunction):

$$z_j= f(z_{inj})$$

andsend theoutputsignal fromthehiddenunittotheinputofoutputlayerunits.

Step5:Foreachoutputunity_k(k = 1tom),calculatethenetinput:

$$y_{ink}=w_{0k}+\sum_{j=1}^{p} z_j w_{jk}$$

andapplytheactivationfunction tocomputeoutputsignal

$$y_k=f(y_{ink})$$

Back-propagationoferror(PhaseII)

Step6:Each outputunity_k($k=1$ to m)receivesatargetpatterncorresponding to the inputtraining pattern and computes the error correctionterm:

$$\delta_k=(t_k-y_k)f'(y_{ink})$$

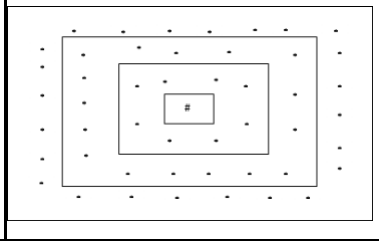
The derivative $f'(y_{ink})$ can becalculatedasinactivationfunctionsection.On the basisofthe calculated error correction term, update thechangeinweightsand bias:

$$\Delta w_{jk}=\alpha\delta_k z_j;\Delta w_{0k}=\alpha\delta_k$$

Also, send$\delta_k$tothehiddenlayerbackwards.

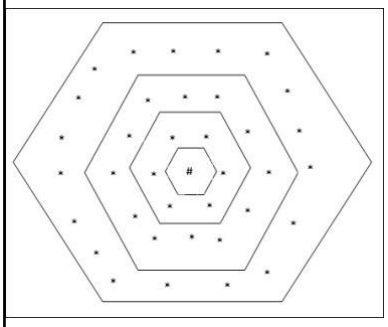
Step7:Eachhiddenunit(z_j=1top)sumsitsdeltainputsfromtheoutputunits:

$$\delta_{inj}=\sum_{m} \delta_k w_{jk}$$

		k=1 Thetermδ_{inj}getsmultipliedwiththe derivativeof$f(z_{inj})$tocalculatetheerrorterm: $\delta_j=\delta_{inj}f'(z_{inj})$ The derivative $f'(z_{inj})$ can be calculated as activation function sectiondependingonwhetherbinaryorbipolarsigmoidalfunctionisused.Onth ebasis ofthecalculatedδ_j,updatethe changeinweightsand bias: $\Delta v_{ij}=\alpha\delta_j x_i;\Delta v_{0j}=\alpha\delta_j$ **Weightandbiasupdation(PhaseIIl):** Step8:Eachoutputunit(y_k,k=1tom)updatesthebiasandweights: $w_{jk}(new)=w_{jk}(old)+\Delta w_{jk}$ $w_{0k}(new)=w_{0k}(old)+\Delta w_{0k}$ Eachhiddenunit(z_j,j=1top) updatesitsbiasandweights: $v_{ij}(new)=v_{ij}(old)+\Delta v_{ij}$ $v_{0j}(new)=v_{0j}(old)+\Delta v_{0j}$ Step 9: Check for the stopping condition. The stopping condition may becertainnumberofepochsreachedorwhentheactualoutputequalsthe targetoutput.		
2		DiscussSelf –OrganizingMapalgorithmanditsfeatures.	[L2][CO2]	**[12M]**
		KohonenSelf-OrganizingFeatureMaps It is one of the Dimensionality Reduction Technique. Suppose we have some pattern ofarbitrarydimensions,however,weneedtheminonedimensionortwodimensions.Thenthe process of feature mapping would be very useful to convert the wide pattern spaceinto a typical feature space.to convert the arbitrary dimensions into 1-D or 2-D, it mustalso have the ability to preserve the neighbor topology like grid topology, rectangulargridtopology. **RectangularGridTopology** Thistopologyhas24nodesinthedistance-2grid,16nodesinthedistance-1grid,and 8 nodes in the distance-0 grid, which means the difference between eachrectangular grid is8 nodes.Thewinning unitis indicatedby #. 		

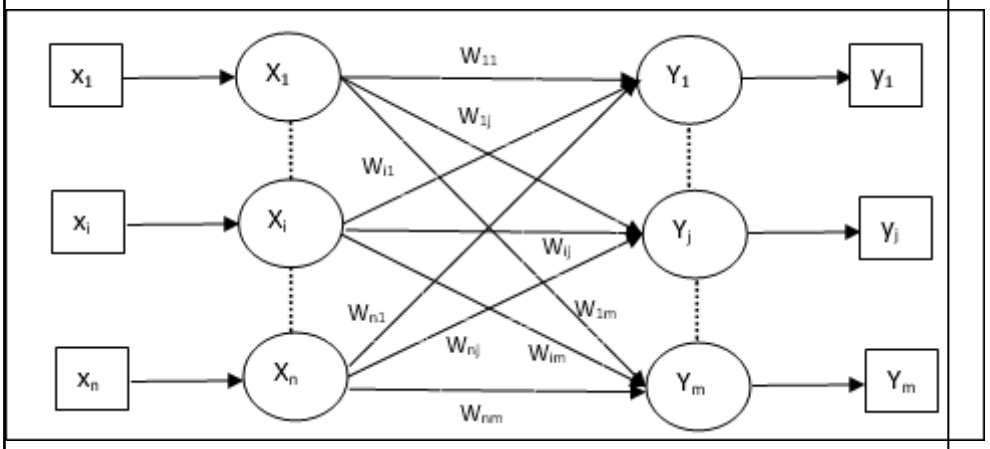
HexagonalGridTopology

Thistopologyhas18nodesinthedistance-2grid,12nodesinthedistance-1grid,and 6 nodes in the distance-0 grid, which means the difference between eachrectangular grid is6 nodes. Thewinning unitisindicatedby #.



Architecture

ThearchitectureofKSOMissimilartothatofthecompetitivenetwork.Withthehelpof neighborhoodschemes,discussedearlier,thetrainingcantakeplaceovertheextended region ofthenetwork.



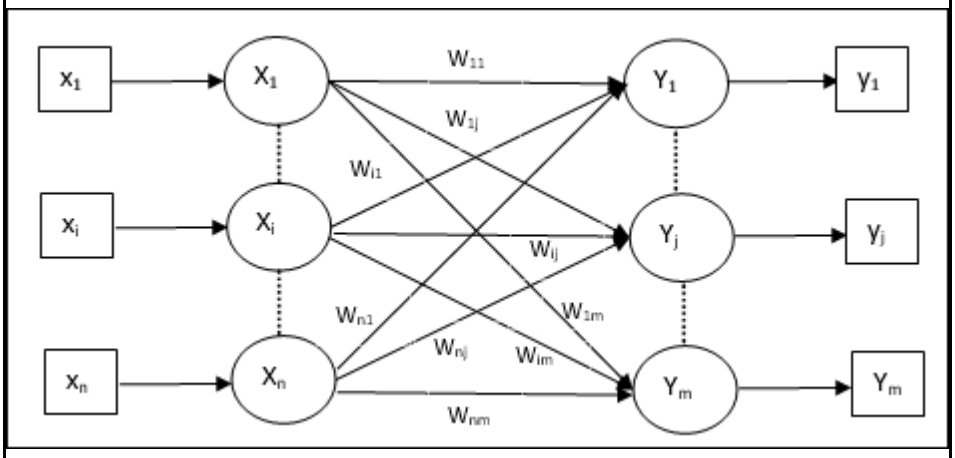
Algorithmfortraining

Step1−Initializetheweights,thelearningrate**α**andtheneighborhoodtopologicalsche me.

Step 2−Continue step3-9,whenthe stoppingconditionisnottrue.

Step3 −Continuestep4-6for everyinputvector**x**.

Step 4 −CalculateSquare of EuclideanDistancefor**j =1tom**

		$$D(j) = \sum_{i=1}^{n}\sum_{j=1}^{m}(x_i - w_{ij})^2$$ **Step 5 –** Obtain the winning unit **J** where ***D(j)*** is minimum. **Step 6 –** Calculate the new weight of the winning unit by the following relation – $$w_{ij}(new) = w_{ij}(old) + \alpha[x_i - w_{ij}(old)]$$ **Step 7 –** Update the learning rate **α** by the following relation – $$\alpha(t+1) = 0.5\alpha t$$ **Step 8 –** Reduce the radius of topological scheme. **Step 9 –** Check for the stopping condition for the network.		
3		IllustrateLearningVectorQuantizationwithneatsketch.	[L3][CO2]	**[12M]**
		Learning Vector Quantization (LVQ), different from Vector quantization(VQ) and Kohonen Self-Organizing Maps (KSOM), basically is a competitivenetworkwhich uses supervised learning ***Architecture*** Following figure shows the architecture of LVQ which is quite similar to thearchitectureofKSOM. As wecan see, thereare **"n"** numberofinput unitsand**"m"**numberofoutputunits.Thelayersarefullyinterconnectedwithhavingweightson them. 		

Parameters Used

Following are the parameters used in LVQ training process as well as in the flowchart

- **x** = training vector ($x_1,...,x_i,...,x_n$)
- **T** = class for training vector **x**
- $\mathbf{w_j}$ = weight vector for $\mathbf{j^{th}}$ output unit
- $\mathbf{C_j}$ = class associated with the $\mathbf{j^{th}}$ output unit

Training Algorithm

Step 1 − Initialize reference vectors, which can be done as follows −

- **Step 1(a)** − From the given set of training vectors, take the first "**m**" (number of clusters) training vectors and use them as weight vectors. The remaining vectors can be used for training.
- **Step 1(b)** − Assign the initial weight and classification randomly.
- **Step 1(c)** − Apply K-means clustering method.

Step 2 − Initialize reference vector α

Step 3 − Continue with steps 4-9, if the condition for stopping this algorithm is not met.

Step 4 − Follow steps 5-6 for every training input vector **x**.

Step 5 − Calculate Square of Euclidean Distance for **j = 1 to m** and **i = 1 to n**

Step 6 − Obtain the winning unit **J** where **D(j)** is minimum.

Step 7 − Calculate the new weight of the winning unit by the following relation −

if $\mathbf{T = C_j}$ then $w_j(new) = w_j(old) + \alpha[x - w_j(old)]$

if $\mathbf{T \neq C_j}$ then $w_j(new) = w_j(old) - \alpha[x - w_j(old)]$

Step 8 − Reduce the learning rate α .

Step 9 − Test for the stopping condition. It may be as follows −

- Maximum number of epochs reached.
- Learning rate reduced to a negligible value.

Variants

ThreeothervariantsnamelyLVQ2,LVQ2.1andLVQ3havebeendevelopedbyKoho nen. Complexity in all these three variants, due to the concept that thewinner aswellastherunner-upunitwilllearn,is morethanin LVQ.

LVQ2

Asdiscussed,theconceptofothervariantsofLVQabove,theconditionofLVQ2isform edbywindow.Thiswindowwillbe basedonthefollowingparameters−

- **x** – the current input vector
- $\mathbf{y_c}$ – the reference vector closest to **x**
- $\mathbf{y_r}$ – the other reference vector, which is next closest to **x**
- $\mathbf{d_c}$ – the distance from **x** to $\mathbf{y_c}$
- $\mathbf{d_r}$ – the distance from **x** to $\mathbf{y_r}$

The input vector **x** falls in the window, if

$$\frac{d_c}{d_r} > 1 - \theta \; and \; \frac{d_r}{d_c} > 1 + \theta$$

Here, θ is the number of training samples.

Updating can be done with the following formula –

$$y_c(t+1) = y_c(t) + \alpha(t)[x(t) - y_c(t)]$$ **(belongs to different class)**

$$y_r(t+1) = y_r(t) + \alpha(t)[x(t) - y_r(t)]$$ **(belongs to same class)**

Here α is the learning rate.

LVQ3

In LVQ3, we will take the two closest vectors namely $\mathbf{y_{c1}}$ and $\mathbf{y_{c2}}$ and the condition for window is as follows –

$$Min\left[\frac{d_{c1}}{d_{c2}}, \frac{d_{c2}}{d_{c1}}\right] > (1-\theta)(1+\theta)$$

Here $\theta \approx 0.2$

Updating can be done with the following formula –

$$y_{c1}(t+1) = y_{c1}(t) + \beta(t)[x(t) - y_{c1}(t)]$$ **(belongs to different class)**

$$y_{c2}(t+1) = y_{c2}(t) + \beta(t)[x(t) - y_{c2}(t)]$$ **(belongs to same class)**

Here β is the multiple of the learning rate α and $\beta = m\alpha(t)$ for every **0.1 < m < 0.5**

4	**a**	ExplainHammingneuralnetworkwithneatdiagram.	[L2][CO2]	**[12M]**
		HammingNetwork Inmostoftheneuralnetworksusingunsupervisedlearning,itisessentialto computethedistanceandperformcomparisons.ThiskindofnetworkisHammingnet work,whereforeverygiveninputvectors,itwouldbeclustered		

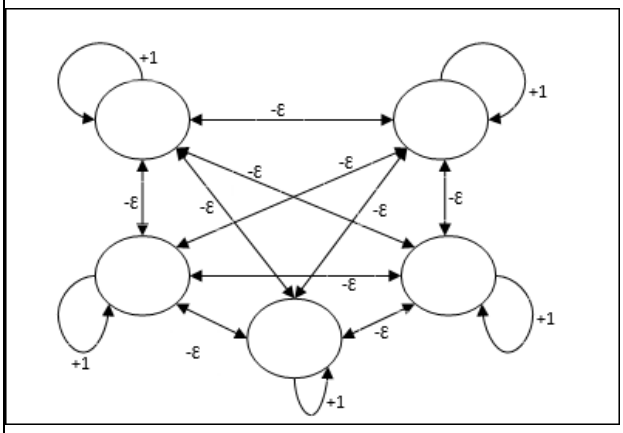
intodifferentgroups.FollowingaresomeimportantfeaturesofHammingNetworks −

- LippmannstartedworkingonHammingnetworksin1987.
- Itisa singlelayer network.
- Theinputscanbeeither binary{0,1}of bipolar {-1,1}.
- Theweightsofthenetare calculatedbythe exemplarvectors.
- Itisafixedweightnetworkwhichmeanstheweightswouldremainthesameeven during training.

MaxNet

This is also a fixed weight network, which serves as a subnet for selecting thenode having the highest input. All the nodes are fully interconnected and thereexistssymmetricalweights inalltheseweightedinterconnections.

Architecture



It uses the mechanism which is an iterative process and each node receivesinhibitory inputs from all other nodes through connections. The single nodewhose value is maximum would be active or winner and the activations of allother nodeswouldbe inactive.MaxNetusesidentityactivationfunctionwith

$$f(x) = \begin{cases} x & if\, x > 0 \\ 0 & if\, x \leq 0 \end{cases}$$

The task of this net is accomplished by the self-excitation weight of +1 and mutual inhibition magnitude, which is set like [$0 < \varepsilon < \frac{1}{m}$] where **"m"** is the total number of the nodes.

5		Describearchitecturalfunctionsanditscharacteristicsof HopfieldNeuralNetwork with neatsketch.	[L2][CO2]	**[12M]**
		HopfieldNetworks HopfieldneuralnetworkwasinventedbyDr.JohnJ.Hopfieldin1982.Itconsistsofasinglelayerwhichcontainsoneormorefullyconnectedrecurrentneurons.		

The Hopfield network is commonly used for auto-association and optimizationtasks.

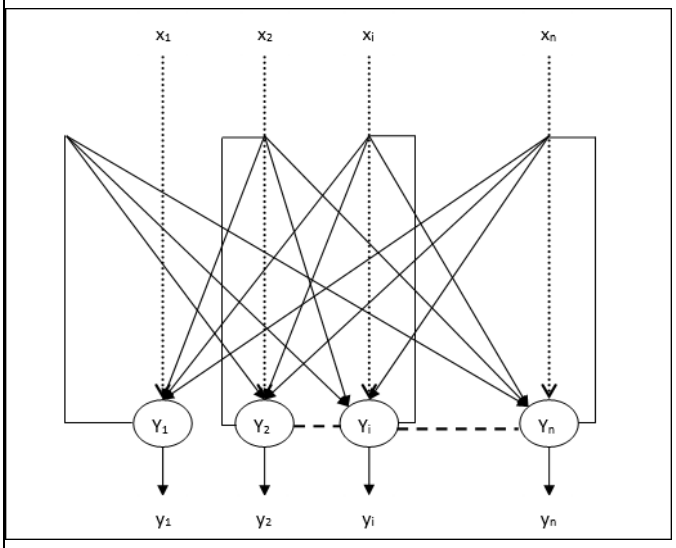
DiscreteHopfieldNetwork

A Hopfield network which operates in a discrete line fashion or in other words,itcanbesaidtheinputandoutputpatternsarediscretevector,whichcanbeeitherbinary (0,1) or bipolar (+1, -1) in nature. The network has symmetrical weightswithno self-connections i.e.,$w_{ij} = w_{ji}$and$w_{ii} = 0$.

Architecture

Followingaresomeimportantpointstokeepinmindaboutdiscrete Hopfieldnetwork –

- Thismodelconsistsofneuronswithoneinvertingandonenon-invertingoutput.
- Theoutputofeachneuronshouldbetheinputofotherneuronsbutnottheinputofself.
- Weight/connectionstrengthisrepresentedbyw_{ij}.
- Connections can be excitatory as well as inhibitory. It would be excitatory,iftheoutputof theneuronissameastheinput,otherwiseinhibitory.
- Weightsshouldbe symmetrical,i.e. $w_{ij}=w_{ji}$



The output from Y_1going to Y_2, $Y_i$and$Y_n$have theweights w_{12}, $w_{1i}$and w_{1n}respectively. Similarly, other arcs have the weights onthem.

TrainingAlgorithm

During training of discrete Hopfield network, weights will be updated. As weknow that we can have the binary input vectors as well as bipolar input vectors.Hence,inboththecases,weightupdatescanbedonewiththe followingrelation

Case 1 – Binary input patterns

For a set of binary patterns **s(p), p = 1 to P**

Here, **$s(p) = s_1(p), s_2(p), \ldots, s_i(p), \ldots, s_n(p)$**

Weight Matrix is given by

$$w_{ij} = \sum_{p=1}^{P} [2s_i(p) - 1][2s_j(p) - 1] \quad for\, i \neq j$$

Case 2 – Bipolar input patterns

For a set of binary patterns **s(p), p = 1 to P**

Here, **$s(p) = s_1(p), s_2(p), \ldots, s_i(p), \ldots, s_n(p)$**

Weight Matrix is given by

$$w_{ij} = \sum_{p=1}^{P} [s_i(p)][s_j(p)] \quad for\, i \neq j$$

TestingAlgorithm

Step1−Initializetheweights,whichareobtainedfromtrainingalgorithmbyusingHebbian principle.

Step 2−Performsteps3-9,ifthe activationsofthe networkisnotconsolidated.

Step 3 − For eachinputvector**X**,performsteps4-8.

Step4−Makeinitialactivationofthenetworkequaltotheexternalinputvector**X**asfollows−

$$y_i = x_i \quad for\, i = 1\, to\, n$$

Step 5 – For each unit Y_i, perform steps 6-9.

Step 6 – Calculate the net input of the network as follows –

$$y_{ini} = x_i + \sum_j y_j w_{ji}$$

Step 7 – Apply the activation as follows over the net input to calculate the output –

$$y_i = \begin{cases} 1 & if\, y_{ini} > \theta_i \\ y_i & if\, y_{ini} = \theta_i \\ 0 & if\, y_{ini} < \theta_i \end{cases}$$

Here θ_i is the threshold.

Step 8 – Broadcast this output y_i to all other units.

Step 9 – Test the network for conjunction.

Energy Function Evaluation

An energy function is defined as a function that is bonded and non-increasing function of the state of the system.

Energy function E_f, also called **Lyapunov function** determines the stability of discrete Hopfield network, and is characterized as follows –

$$E_f = -\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i y_j w_{ij} - \sum_{i=1}^{n} x_i y_i + \sum_{i=1}^{n} \theta_i y_i$$

Condition – In a stable network, whenever the state of node changes, the above energy function will decrease.

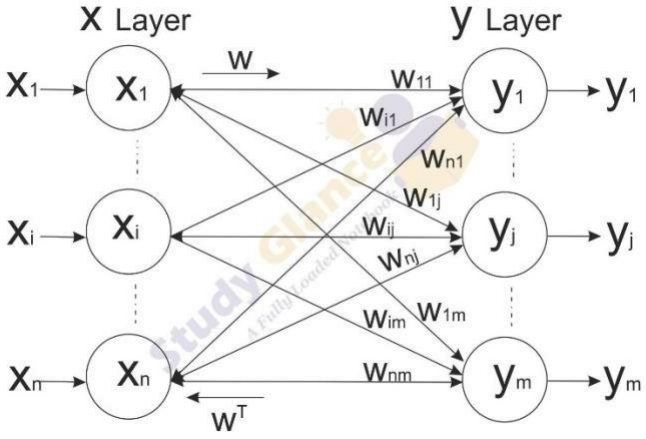
Suppose when node **i** has changed state from $y_i^{(k)}$ to $y_i^{(k+1)}$ then the Energy change ΔE_f is given by the following relation

6	**a**	DiscussBidirectionalAssociateMemoryanditsapplications.	[L2][CO2]	**[8M]**

BidirectionalAssociativeMemory(BAM)

Bidirectional associative memory (BAM), first proposed by Bart Kosko in theyear 1988. The BAM network performs forward and backward associativesearchesforstoredstimulusresponses.TheBAMisarecurrentheteroassociative pattern-marching nerwork that encodes binary or bipolar patternsusingHebbian learning rule

Architecture



The architecture of BAM network consists of two layers of neurons which areconnected by directed weighted pare interconnections. The network dynamicsinvolve two layers of interaction. The BAM network iterates by sending thesignalsbackandforthbetweenthetwolayersuntilalltheneuronsreachequilibrium. The weights associated with the network are bidirectional. Thus,BAMcan respond to theinputs in eitherlayer.

Figure shows a BAM network consisting of n units in X layer and m units in Ylayer.Thelayerscanbeconnectedinbothdirections(bidirectional)withtheresultthe weightmatrixsentfromtheXlayertotheYlayerisWandtheweightmatrixforsignalssentfromtheYlayertotheXlayerisW^T.Thus,theWeightmatrixis calculatedinbothdirections.

DeterminationofWeights

Lettheinputvectorsbedenotedbys(p)andtargetvectorsbyt(p).p=1,...,P.
Thentheweightmatrixtostoreasetof inputandtargetvectors,where

s(p) = (s_1(p), .. , s_i(p), ... , s_n(p))
t(p) = (t_1(p),.. ,t_j(p), ... ,t_m(p))

can be determined by Hebb rule training a1gorithm. In case of input vectors being binary, the weight matrix W = $\{w_{ij}\}$ is given by

$$w_{ij} = \sum_{p=1}^{P} [2s_i(p) - 1][2t_j(p) - 1]$$

When the input vectors are bipolar, the weight matrix W = $\{w_{ij}\}$ can be defined as

$$w_{ij} = \sum_{p=1}^{P} [s_i(p)][t_j(p)]$$

The activation function is based on whether the input target vector pairs used are binary or bipolar

The activation function for the Y-layer

1. With binary input vectors is

$$y_j = \begin{cases} 1 & if\ y_{inj} > 0 \\ y_j & if\ y_{inj} = 0 \\ 0 & if\ y_{inj} < 0 \end{cases}$$

2. With bipolar input vectors is

$$y_j = \begin{cases} 1 & if\ y_{inj} > \theta_i \\ y_j & if\ y_{inj} = \theta_j \\ -1 & if\ y_{inj} < \theta_j \end{cases}$$

The activation function for the X-layer

1. With binary input vectors is

$$x_i = \begin{cases} 1 & if\ x_{ini} > 0 \\ x_i & if\ x_{ini} = 0 \\ 0 & if\ x_{ini} < 0 \end{cases}$$

2. With bipolar input vectors is

$$x_i = \begin{cases} 1 & if\ x_{ini} > \theta_i \\ x_i & if\ x_{ini} = \theta_i \\ -1 & if\ x_{ini} < \theta_i \end{cases}$$

	b	AnalyzetheCharacteristics, limitationsand applicationsofAssociativememory	[L4][CO2]	**[4M]**

Associativememory isalsoknownascontentaddressablememory(CAM)orassociative storage or associative array. It is a special type of memory that is optimizedforperformingsearchesthroughdata,asopposedtoprovidingasimpledirectaccesst othedatabasedontheaddress.

Associativememoryofconventionalsemiconductormemory(usually RAM)withadded comparison circuity that enables a search operation to complete in a single clockcycle. It is a hardware search engine, a special type of computer memory used in certainvery highsearchingapplications.

ApplicationsofAssociativememory:-

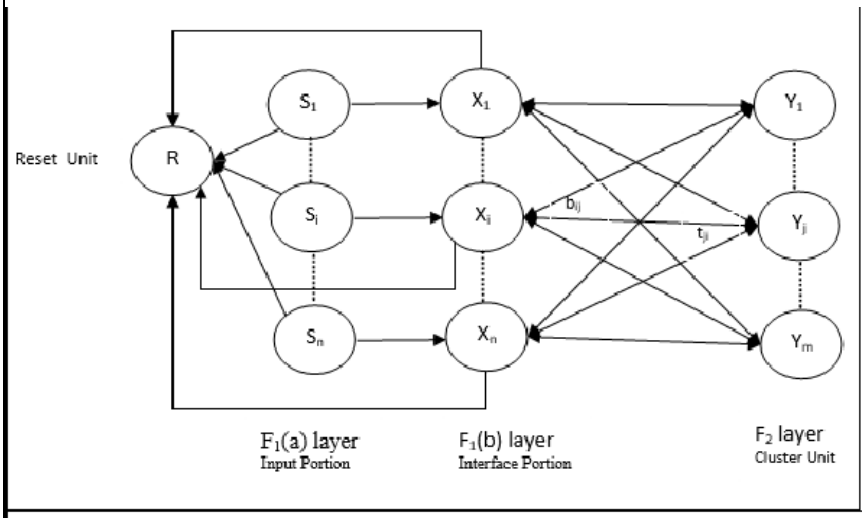
. Itcanbeonlyusedinmemoryallocationformat.

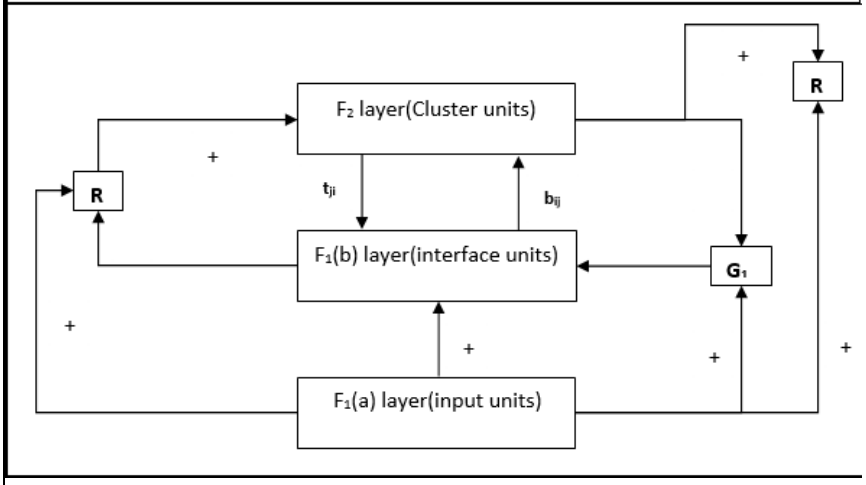
. Itiswidelyusedinthedatabasemanagementsystems,etc.

AdvantagesofAssociativememory:-

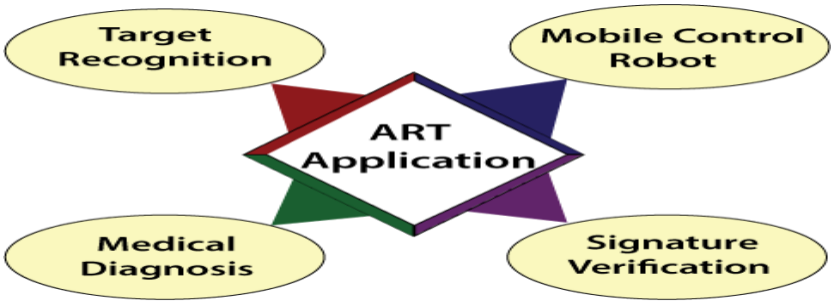
		. Itisusedwheresearchtimeneedstobelessorshort. . Itissuitableforparallelsearches. . Itisoftenusedtospeedupdatabases. . Itisusedinpagetablesusedbythevirtualmemoryandusedinneuralnetworks. **LimitationsorDisadvantagesofAssociativememory:-** . ItismoreexpensivethanRAM. Eachcellmusthavestoragecapabilityandlogicalcircuitsformatchingitscontentwith externalargument.		
7	**a**	GeneralizetheAdaptiveResonanceTheoryNeuralNetwork	[L6][CO2]	**[8M]**
		AdaptiveResonanceTheory This network was developed by Stephen Grossberg and Gail Carpenter in 1987.It is based on competition and uses unsupervised learning model. AdaptiveResonanceTheory(ART)networks,asthenamesuggests,isalwaysopentonewlearning (adaptive) without losing the old patterns (resonance). Basically, ARTnetwork is a vector classifier which accepts an input vector and classifies it intooneofthecategoriesdependinguponwhichofthestoredpatternitresemblesthemost. **ArchitectureofART1** Itconsistsofthefollowingtwounits− **ComputationalUnit**−Itismade upofthe following− • **Inputunit(F_1layer)**−Itfurtherhasthefollowingtwoportions− **F_1(a)layer(Inputportion)**−InART1,therewouldbenoprocessinginthis portionratherthanhavingtheinputvectorsonly.Itisconnected to F_1(b)layer (interfaceportion). **F_1(b) layer (Interface portion)** − This portion combines the signalfromtheinputportionwiththatof F_2 layer. F_1(b) layerisconnectedto F_2 layer through bottom up weights $\mathbf{b_{ij}}$ and F_2 layer is connected to F_1(b) layerthrough top downweights $\mathbf{t_{ji}}$. • **Cluster Unit (F_2 layer)** − This is a competitive layer. The unit having thelargest net input is selected to learn the input pattern. The activation of allother clusterunitaresetto 0. • **ResetMechanism** −Theworkofthismechanismisbaseduponthesimilarity between the top-down weight and the input vector. Now, if thedegreeofthissimilarityislessthanthevigilanceparameter,thentheclusterisnotallowed to learnthepatternand arestwould happen. **SupplementUnit** −Actuallytheissuewith Resetmechanismisthatthelayer $\mathbf{F_2}$must have to be inhibited under certain conditions and must also beavailablewhensomelearninghappens.Thatiswhytwosupplementalunits namely,$\mathbf{G_1}$and$\mathbf{G_2}$isaddedalongwithresetunit,**R**.Theyarecalled**gain**		

control units. These units receive and send signals to the other units present inthe network. '+' indicates an excitatory signal, while '–' indicates an inhibitorysignal.





	b	Identifysome applicationsofARTModel	[L2][CO2]	**[4M]**



Targetrecognition:

Fuzzy ARTMAP neural network can be used for automatic classification of targetsdepend on their radar range profiles. Tests on synthetic data show the fuzzy ARTMAPcan result in substantial savings in memory requirements when related to k nearestneighbor(kNN)classifiers.Theutilizationofmultiwavelengthprofilesmainlyimprov esthe performanceofboth kindsofclassifiers.

Medicaldiagnosis:

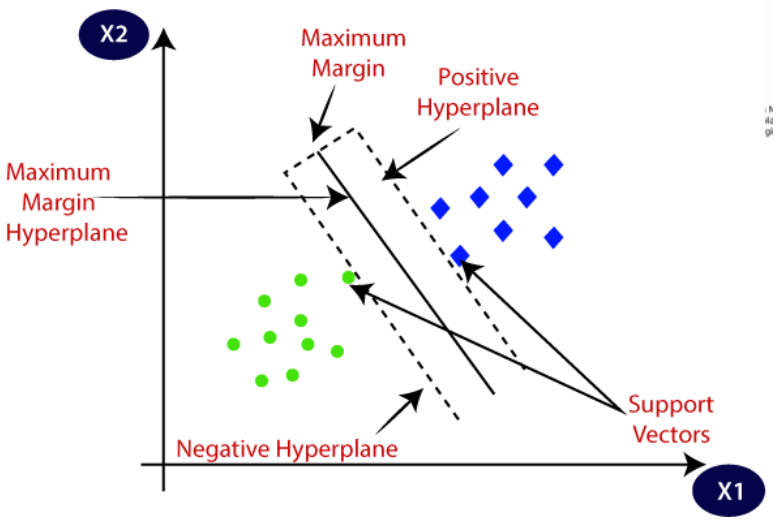
Medicaldatabasespresenthugenumbersofchallengesfoundingeneralinformation management settings where speed, use, efficiency, and accuracy are the prime concerns.Adirectobjectiveofimprovedcomputer-assistedmedicineistohelptodeliverintensive

		care in situations that may be less than ideal. Working with these issues has stimulatedseveralARTarchitecturedevelopments, including ARTMAP-IC. **Signatureverification:** Automaticsignatureverificationisawellknownandactiveareaofresearchwithvariousapplications such as bank check confirmation, ATM access, etc. the training of thenetworkisfinishedusingART1thatusesglobalfeatures asinputvectorandtheverification and recognition phase uses a two-step process. In the initial step, the inputvector is coordinated with the stored reference vector, which was used as a training set,andin thesecondstep, clusterformation takesplace. **Mobilecontrolrobot:**Nowadays,weperceiveawiderangeofroboticdevices.Itisstillafieldof researchintheirprogrampart,calledartificialintelligence.Thehumanbrainisan interesting subject as a model for such an intelligent system. Inspired by the structureof the human brain, an artificial neural emerges. Similar to the brain, the artificial neuralnetwork contains numerous simple computational units, neurons that are interconnectedmutuallytoallowthetransferofthesignalfromthe neuronstoneurons.Artificialneuralnetworksareusedtosolvedifferentissueswithgoodoutcomescomparedtoother decisionalgorithms.		
8		IllustratetheSupportVectorMachinewithneatdiagram.	[L3][CO2]	**[12M]**

CourseCode:19CS0544

SVM:

SupportVectorMachineorSVMisoneofthemostpopularSupervisedLearningalgorithms, which is used for Classification as well as Regression problems.However, primarily, it is used for Classification problems in Machine Learning.Itisinherently binary classifier.



The goalof theSVMalgorithmistocreate thebestline or decisionboundarythat can segregate n-dimensional space into classes so that we can easily putthe new data point in the correct category in the future. This best decisionboundary is calledahyperplane

TypesofSVM

SVMcanbeof twotypes:

- **LinearSVM:**LinearSVMisusedforlinearlyseparabledata,whichmeansifadataset canbeclassifiedintotwoclassesbyusingasingle

straight line, then such data is termed as linearly separable data, andclassifier is usedcalledas LinearSVMclassifier.

- **Non-linear SVM:** Non-Linear SVM is used for non-linearly separateddata, which means if a dataset cannot be classified by using a straightline, then such data is termed as non-linear data and classifier used iscalledasNon-linearSVMclassifier.

ApplicationsofSVM

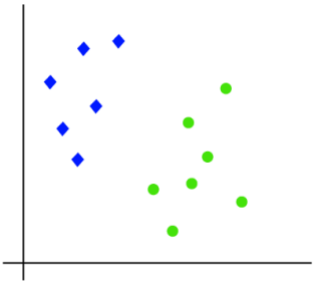
- **Facedetection**
- **imageclassification**
- **MedicalDiagnosis**
- **textcategorization,**etc.

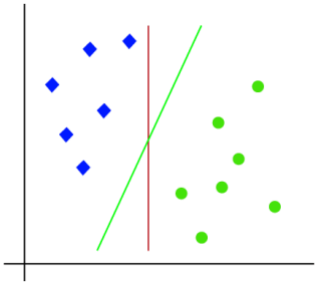
SupportVectors:

Thedatapointsor vectorsthataretheclosestto thehyperplaneandwhichaffectthe position of the hyperplane are termed as Support Vector. Since these vectorssupportthehyperplane, hencecalledaSupportvector.

LinearSVM:

The working of the SVM algorithm can be understood by using an example.Supposewehaveadatasetthathastwotags(greenandblue),andthedatasetha stwo features x1 and x2. We want a classifier that can classify the pair(x1, x2) ofcoordinatesineithergreenorblue.Considerthebelow image:

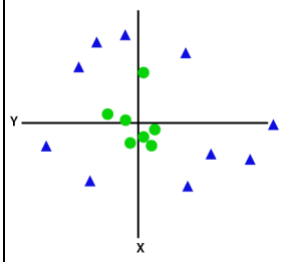




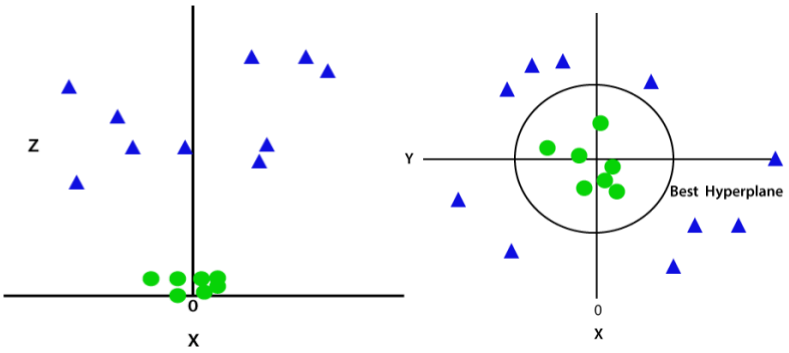
So as it is 2-d space so by just using a straight line, we can easily separatethese two classes. But there can be multiple lines that can separate theseclasses.

Non-LinearSVM:

If data is linearly arranged, then we can separate it by using astraight line, but for non-linear data, we cannot drawa singlestraightline.Consider thebelowimage:



Sotoseparate these datapoints,weneedtoaddone more dimension. For linear data, we have used two dimensions x and y, so fornon-linear data,wewilladd athirddimensionz.Itcanbecalculatedas:

		$z=x^2+y^2$ Byaddingthe thirddimension,the sample spacewillbecome asbelowimage:  		
9		Summarizethefollowingterms: i) HebbianLearningrule ii) perceptron,DeltaLearningRules	[L2][CO2]	**[12M]**
		HebbianLearningRule: This rule, one of the oldest and simplest, was introduced by Donald Hebb in hisbook TheOrganizationofBehavior in1949.Itisakindoffeed-forward,unsupervisedlearning. **Basic Concept**−Thisruleisbasedonaproposalgivenby Hebb,whowrote− "When an axon of cell A is near enough to excite a cell B and repeatedly orpersistentlytakespartinfiringit,somegrowthprocessormetabolicchangetakesplace in one or both cells such that A's efficiency, as one of the cells firing B, isincreased." From the above postulate, we can conclude that the connections between twoneurons might be strengthened if the neurons fire at the same time and mightweakenifthey fireatdifferenttimes. **MathematicalFormulation**−AccordingtoHebbianlearningrule,followingisthefo rmulatoincreasetheweightof connectionateverytimestep. $$\Delta w_{ji}(t) = \alpha x_i(t).y_j(t)$$ Here, $\Delta w_{ji}(t)$ = increment by which the weight of connection increases at time step **t** α = the positive and constant learning rate $x_i(t)$ = the input value from pre-synaptic neuron at time step **t** $y_i(t)$ = the output of pre-synaptic neuron at same time step **t**		

PerceptronLearningRule

This rule is an error correcting the supervised learning algorithm of single layerfeedforwardnetworkswithlinearactivationfunction,introducedbyRosenblatt.

Basic Concept − As being supervised in nature, to calculate the error, therewould be a comparison between the desired/target output and the actual output.If there is any difference found, then a change must be made to the weights ofconnection.

MathematicalFormulation−Toexplainitsmathematicalformulation,supposewe have 'n' number of finite input vectors, x(n), along with its desired/targetoutputvectort(n), wheren = 1 toN.

Now the output 'y' can be calculated, as explained earlier on the basis of the netinput, and activation function being applied over that net input can be expressedasfollows –

$$y = f(y_{in}) = \begin{cases} 1, & y_{in} > \theta \\ 0, & y_{in} \leqslant \theta \end{cases}$$

Where **θ** is threshold.

The updating of weight can be done in the following two cases −

Case I − when **t ≠ y**, then

$$w(new) = w(old) + tx$$

Case II − when **t = y**, then

No change in weight

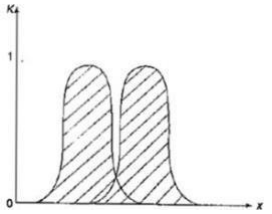
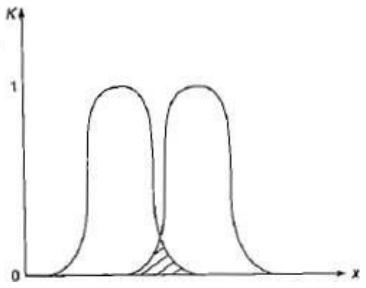
DeltaLearningRule(Widrow-HoffRule)

It is introduced by Bernard Widrow and Marcian Hoff, also called Least MeanSquare (LMS) method, to minimize the error over all training patterns. It is kindofsupervisedlearningalgorithmwithhavingcontinuousactivationfunction.

Basic Concept − The base of this rule is gradient-descent approach, whichcontinues forever. Delta rule updates the synaptic weights so as to minimize thenetinputto theoutputunitand thetargetvalue.

		MathematicalFormulation−Toupdatethesynapticweights,deltaruleis $\Delta w_i = \alpha . x_i . e_j$ Here Δw_i = weight change for i[th] pattern; α = the positive and constant learning rate; x_i = the input value from pre-synaptic neuron; $e_j = (t - y_{in})$, the difference between the desired/target output and the actual output y_{in} The above delta rule is for a single output unit only. The updating of weight can be done in the following two cases − **Case-I** − when **t ≠ y**, then $w(new) = w(old) + \Delta w$ **Case-II** − when **t = y**, then No change in weight		
10		Describethestructureofbackpropagationneuralnetworkand derivethelearning rulefor theback propagation algorithm.	[L2][CO2]	**[12M]**
		Itis sameasquestion1answer		

UNIT –III
FUZZY SYSTEMS

1		Explain thevarioustypesofoperationsonFuzzySetswithexamples.	[L2][CO3]	**[12M]**
		Operationsonfuzzysets **1.** Union: The union offuzzysets$A$and B, denoted by$A \cup B$isdefined as $\mu_{A \cup B}(x) = max[\mu_A(x), \mu_B(x)] = \mu_A(x) \vee \mu_B(x) for all x \in U$ where ∨indicatesmaxoperator.TheVenndiagramforunionoperationoffuzzysets$A$and Bisshown below figure.  Figure:Unionoffuzzysets$A$and$B$ **2.** *Intersection:TheIntersectionoffuzzysets$A$and$B$,denotedby$A \cap B$,is definedas* $\mu_{A \cap B}(x) = min[\mu_A(x), \mu_B(x)] = \mu_A(x) \wedge \mu_B(x) for all x \in U$ where ∧indicatesminoperator.TheVenndiagramforintersectionoperationoffuzzy sets$A$and$B$isshown belowfigure. Figure :Intersectionoffuzzy sets$A$and$B$  *Complement:* *When$\mu_A(x) \in [0,1]$,thecomplementof$A$,denotedas $\bar{A}$is definedby,* $\mu_{\bar{A}}(x) = 1 - \mu_A(x) for all x \in U$ The Venn diagram for complement operation of fuzzy set Aisshownbelow figure.		

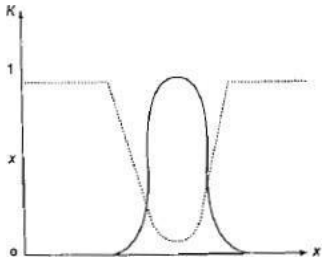


Figure :Complementoffuzzy set$A$

MoreoperationsonFuzzysetsAlgebraicsum

Thealgebraicsum$(A+B)$offuzzysets,fuzzysets$A and B$isdefinedas

$$\mu_{A+B}(x) = \mu_A(x) + \mu_B(x) - \mu_A(x).\,\mu_B(x)$$

Algebraicproduct

Thealgebraicproduct$(A.B)$offuzzysets,fuzzysets$A and B$isdefinedas

$$\mu_{A.B}(x) = \mu_A(x).\,\mu_B(x)$$

Boundedsum

The bounded sum $(A \oplus B)$ of fuzzy sets, fuzzy sets A and B is defined as

$$\mu_{A\oplus B}(x) = \min\{1, \mu_A(x) + \mu_B(x)\}$$

Boundeddifference

The bounded difference $(A \odot B)$ of fuzzy sets, fuzzy sets A and B is defined as

$$\mu_{A\odot B}(x) = \max\{0, \mu_A(x) - \mu_B(x)\}$$

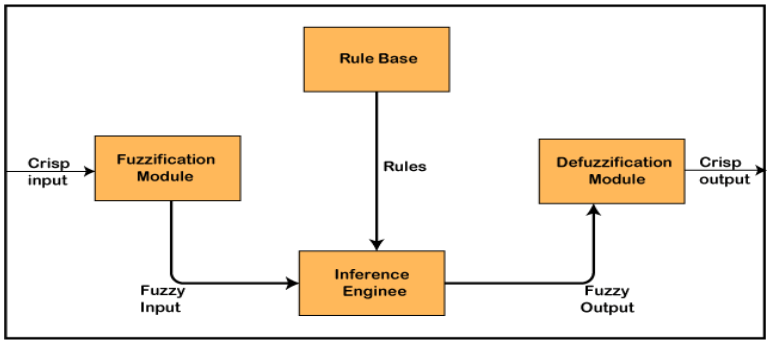
2	**a**	Explainwithneatblockdiagramthevariouscomponentsof aFuzzyLogic System.	[L2][CO3]	**[8M]**

ArchitectureofaFuzzyLogicSystem

In the architecture of the **Fuzzy Logic** system, each component plays an importantrole. The architecture consists of the different four components which are givenbelow.

1. Rule Base
2. Fuzzification
3. InferenceEngine
4. Defuzzification

Followingdiagramshows the architectureorprocessofa FuzzyLogic system:



1. RuleBase

RuleBaseisacomponentusedforstoringthesetofrulesandtheIf-Thenconditionsgivenbytheexpertsare usedforcontrollingthe decision-makingsystems.Thereareso many updates that come in the Fuzzy theory recently, which offers effectivemethodsfordesigningandtuningoffuzzycontrollers.Theseupdatesordevelopmentsdecreasesthenumberoffuzzy setofrules.

2. Fuzzification

Fuzzification is a module or component for transforming the system inputs, i.e., itconvertsthecrispnumberintofuzzysteps.Thecrispnumbersarethoseinputswhichare measured by the sensors and then fuzzification passed them into the controlsystemsforfurtherprocessing.Thiscomponentdividestheinputsignalsintofollowingfivestatesin any Fuzzy Logicsystem:

- LargePositive(LP)
- MediumPositive (MP)
- Small(S)
- Medium Negative(MN)
- Largenegative(LN)

3. InferenceEngine

This component is a main component in any Fuzzy Logic system (FLS), because allthe information is processed in the Inference Engine. It allows users to find thematching degree between the current fuzzy input and the rules. After the matchingdegree,thissystemdetermineswhichruleistobeaddedaccordingtothegiveninputfield. When all rules are fired, then they are combined for developing the controlactions.

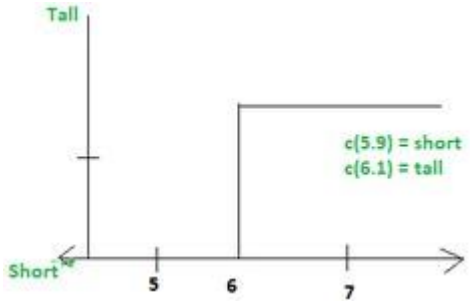
4. Defuzzification

Defuzzification isamoduleorcomponent,whichtakesthefuzzysetinputsgenerated by the **Inference Engine**, and then transforms them into a crisp value.Itisthelaststepintheprocessofafuzzylogicsystem.Thecrispvalueisatypeof value which is acceptable by the user. Various techniques are present to do this, butthe userhasto selectthebestoneforreducing theerrors.

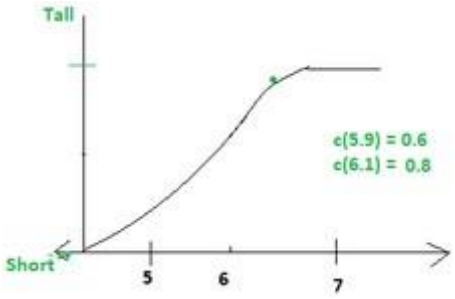
b Differentiate thefuzzysetsandclassicalsets [L4][CO3] **[4M]**

S.No	CrispSet	Fuzzy Set
1	Crisp set defines thevalueiseither0or1.	Fuzzy set defines the value between0and 1 including both 0 and 1.
2	Itisalsocalledaclassicalset.	It specifies the degree to whichsomethingis true.
3	Itshowsfull membership	Itshowspartialmembership.

		4	Eg1. She is 18 yearsold. Eg2.Rahulis1.6mtall	Eg1. She is about 18 years old.Eg2.Rahulisabout1.6mtall.	
		5	Crisp set applicationusedfordigitaldesign.	Fuzzysetusedinthefuzzycontroller.	
		6	It is bi-valued functionlogic.	Itisinfinite valuedfunctionlogic	
		7	Full membershipmeans totallytrue/false,yes/no,0/1.	Partial membership means true tofalse, yes to no,0 to 1.	



CrispSet



FuzzySet

3	**a**	DiscussthevariousoperationsonClassicalSetswithsimple examples.	[L2][CO3]	**[6M]**
		OperationsonClassicalsets **Union:** The union between two sets gives all those elements in the universe that belongto either set A or set B or both sets A and B. The union operation can be termedasalogicalORoperation.Theunionoftwo sets AandB isgiven as $A \cup B = \{x \mid x \in A or x \in b\}$ TheunionofsetsAandBis illustratedbytheVenndiagram shownbelow		

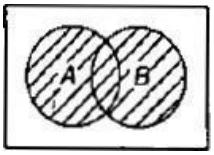


Figure 3.3:Unionoftwosets

Intersection

The intersection between two sets represents all those elements in the universethat simultaneously belong to both the sets. The intersection operation can betermedasalogicalAND operation.TheintersectionofsetsA and Bisgivenby

$$A \cap B = \{x | x \in A and x \in b\}$$

Theintersection ofsets*A*and*B*isillustratedbytheVenndiagram shownbelow

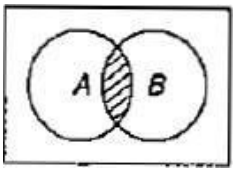


Figure 3.4:Intersectionoftwo sets

Complement

The complementofsetAisdefinedasthe collection ofallelementsinuniverse X that do not reside in set A, i.e., the entities that do not belong to A.Itisdenoted by A and isdefinedas

$$\bar{A} = \{x | x \notin A, x \in X\}$$

whereX istheuniversal set and A isagiven setformed fromuniverseX. Thecomplementoperation ofsetA isshow below

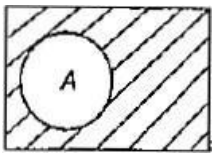


Figure 3.5:ComplementofsetA

Difference(Subtraction)

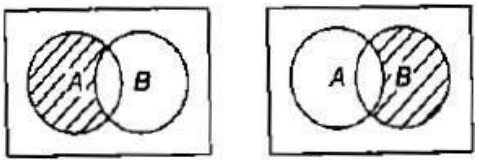
The difference of set A with respect to ser B is the collection of all elements inthe universe that belong to A but do not belong to B, i.e., the difference setconsists of all elements that belong to A bur do not belong to B. It is denoted byA lBorA-Band isgiven by

$$A|Bor(A-B) = \{x | x \in A and x \notin B\} = A-(A \cap B)$$Theviceversaofit

also canbe performed

$$B|Aor(B-A) = B-(B \cap A) = \{x | x \in B and x \notin A\}$$

Theaboveoperationsareshownbelow



(A) (B)

Figure3.6:(A)DifferenceA|Bor (A-B);(B)DifferenceB|Aor (B-A)

	b	Listoutthevariousoperationsonclassicalrelations.	[L1][CO3]	**[6M]**

Classicalrelations

Aclassical binaryrelationrepresentsthepresenceor absenceof aconnectionorinteractionbetween theelementsoftwo sets.

CartesianProductofRelation*:*
An ordered r-tuple is an ordered sequence of r-elements expressed in theform (a_1, a_2, a_3, ... , a_r). An unordered tuple is a collection of r-elementswithoutany restrictions in order.
For crisp sets A_1, A_2, ... , A_r, the set of all r-tuples (a_1,a2, a3, ... , ar), where a1∈A1, a2 ∈ A2 ... , ar ∈ Ar is called me Cartesian product of A1,A2.. ,Ar and isdenoted by A_1 x A_2 x ... x A_r.

CardinalityofClassicalRelation
ConsidernelementsoftheuniverseXbeingrelatedtomelementsofuniverse Y. When the cardinality of X= $n_X$and the cardinality of Y =n_Y, then thecardinalityofrelation Rbetweenthetwouniverseis

$$n_{X\times Y}=n_X\times n_Y$$

ThecardinalityofthepowersetP(X×Y)describing therelation is given by

$$n_{P(X\times Y)}=2^{(n_X n_Y)}$$

Operationsonclassicalrelations

LetRandSbetwoseparaterelationsontheCartesianuniverse X×Y.The null relation and the complete relation are defined by the relationmatrices $Ø_R$and E_R. An example of a 3 X 3 form of the $Ø_R$ and $E_R$matricesisgiven below:

$$Ø_R = \begin{bmatrix}0&0&0\\0&0&0\\0&0&0\end{bmatrix} \quad \text{and} \quad E_R = \begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}$$

1. **Union**

$$R \cup S \rightarrow \chi_{R\cup S}(x,y): \chi_{R\cup S}(x,y) = \max[\chi_R(x,y), \chi_S(x,y)]$$

2. **Intersection**

$$R \cap S \rightarrow \chi_{R\cap S}(x,y): \chi_{R\cap S}(x,y) = \min[\chi_R(x,y), \chi_S(x,y)]$$

3. **Complement**

$$\bar{R} \rightarrow \chi_{\bar{R}}(x,y) : \chi_{\bar{R}}(x,y) = 1 - \chi_R(x,y)$$

4. **Containment**

$$R \subset S \rightarrow \chi_R(x,y): \chi_R(x,y) \leq \chi_S(x,y)$$

5. **Identity**

$$\emptyset \rightarrow Ø_R \quad \text{and} \quad X \rightarrow E_R$$

CompositionofClassicalRelations

LetRbe arelationthatmapselementsfromuniverse Xtouniverse ane a relationthatmapselementsfrom universeY touniverseZ

$$R\subseteq X\times Y \text{ and } S\subseteq Y\times Z$$

Thecomposition operationsareoftwotypes:

Max-mincomposition

Themax-mincompositionis definedbythefunctiontheoreticexpressionas

$$T=R\circ S$$

$\chi_T(x,z)=\bigvee_{y\in Y}[\chi_R(x,y)A\chi_S(y,z)]$

Max-productcomposition

Themax-productcomposition isdefinedbythefunctiontheoreticexpressionas

$$T=R\circ S$$

$$\chi_T(x,z)=\bigvee_{y\in Y}[\chi_R(x,y).\chi_S(y,z)]$$

4	**a**	Describethevariousfuzzyrelationswithsuitableexamples.	[L2][CO3]	**[8M]**

Fuzzyrelations

Afuzzyrelationisafuzzy setdefinedontheCartesianproductofclassicalsets $\{X_I,X_2,...X_n\}$wheretuples(x_1,x_2,x_n)mayhavevaryingdegreesofmembership$\mu_R(x_1,x_2, .. , x_n)$within therelation.

$$R(X_1,X_2,\ldots,X_n)=\int_{X_1,X_2,\ldots,X_n}\mu_R(x_1,x_2,\ldots,x_n)|(x_1,x_2,\ldots, x_n),x_i\in X_i$$

Afuzzyrelationbetweentwosets XandYiscalledbinaryfuzzyrelationandisdenotedby R(X,Y).

Let

$$\underset{\sim}{X} = \{x_1, x_2, \ldots, x_n\} \qquad and \qquad \underset{\sim}{Y} = \{y_1, y_2, \ldots, y_n\}$$

Fuzzy relation $\underset{\sim}{R}(\underset{\sim}{X},\underset{\sim}{Y})$ can be expressed by an n × m matrix as follows:

$$\underset{\sim}{R}(\underset{\sim}{X},\underset{\sim}{Y}) = \begin{matrix} \mu_R(x_1, y_1) & \mu_R(x_1, y_2) & \cdots & \mu_R(x_1, y_m) \\ \mu_R(x_2, y_1) & \mu_R(x_2, y_2) & \cdots & \mu_R(x_2, y_m) \\ \vdots & \vdots & \cdots & \vdots \\ \mu_R(x_n, y_1) & \mu_R(x_n, y_2) & & \mu_R(x_n, y_m) \end{matrix}$$

Operationsonfuzzyrelations

1. **Union**

$$\mu_{R\cup S}(x, y) = \max[\mu_R(x, y), \mu_S(x, y)]$$

2. **Intersection**

$$\mu_{R\cap S}(x, y) = \min[\mu_R(x, y), \mu_S(x, y)]$$

3. **Complement**

$$\mu_{\bar{R}}(x, y) = 1 - \mu_R(x, y)$$

4. **Containment**

$$\underset{\sim}{R} \subset \underset{\sim}{S} \rightarrow \mu_R(x, y) \leq \mu_S(x, y)$$

5. **Inverse**

The inverse of a fuzzy relation R on X × Y is denoted by R^{-1}. It is a relation on Y × X defined by $R^{-1}(y, x) = R(x, y)$ for all pairs$(y, x) \in Y \times X$.

6. **Projection**

For a fuzzy relation R(X,Y), let $[R \downarrow Y]$ denote the projection of R onto Y. Then $[R \downarrow Y]$ is a fuzzy relation in Y whose membership function is defined by

Therearetwotypesoffuzzycompositiontechniques1.M

ax- Min Composition

2.Min-MaxComposition

FuzzyMAX-Min composition

		The max-min composition of R(X,Y) and S(Y,Z), denoted by $R(X,Y) \circ S(Y,Z)$ is defined by T(X,Z) as $\mu_T(x,z) = \mu_{R \circ S}(x,z) = \max_{y \in Y} \{\min [\mu_R(x,y), \mu_S(y,z)]\}$ $= \vee_{y \in Y} [\mu_R(x,y) \wedge \mu_S(y,z)] \quad \forall x \in X, \ z \in Z$ The min-max composition of R(X,Y) and S(Y,Z), denoted by $R(X,Y) \circ S(Y,Z)$ is defined by T(X,Z) as $\mu_T(x,z) = \mu_{R \circ S}(x,z) = \min_{y \in Y} \{\max [\mu_R(x,y), \mu_S(y,z)]\}$ $= \wedge_{y \in Y} [\mu_R(x,y) \vee \mu_S(y,z)] \quad \forall x \in X, \ z \in Z$ **Fuzzymax-productcomposition** *Themax-productcompositionofR(X,Y)andS(Y,Z),denotedbyR(X,Y)°S(Y, Z)isdefinedbyT(X,Z)as* The max-product composition of R(X,Y) and S(Y,Z), denoted by $R(X,Y) \circ S(Y,Z)$ is defined by T(X,Z) as $\mu_T(x,z) = \mu_{R \circ S}(x,z) = \min_{y \in Y} [\mu_R(x,y) . \mu_S(y,z)]$ $= \vee_{y \in Y} [\mu_R(x,y) . \mu_S(y,z)]$ The properties of fuzzy composition can be given as follows: $R \circ S \neq S \circ R$ $(R \circ S)^{-1} = S^{-1} \circ R^{-1}$ $(R \circ S) \circ M = R \circ (S \circ M)$		
	b	Differentiateclassicalrelationsand Fuzzyrelations	[L4][CO3]	**[4M]**
		Refer3.(a)and4.(b)answers **ClassicalrelationsVsFuzzyrelations** **Thedifferencebetweentheclassicalandfuzzyrelations canbe expressedintermsof** 1. **Cardinality** 2. **Operations** 3. **Properties**		

Classical Relations	Fuzzy Relations
Cardinality:	
Consider n elements of universe X being related to the m elements of universe Y. When the cardinality of X= ^{n}X & the cardinality of Y = ^{n}Y, then the cardinality of relation R between the two universe is $^{n}X*Y = {}^{n}X * {}^{n}Y$ The cardinality of the power set P(X *Y) describing the relation is given by $^{n}P(X*Y) = 2^{(^{n}X^{n}Y)}$	The cardinality of fuzzy sets on any universe is infinity; hence the cardinality of a fuzzy relation between two or more universe is also infinity.

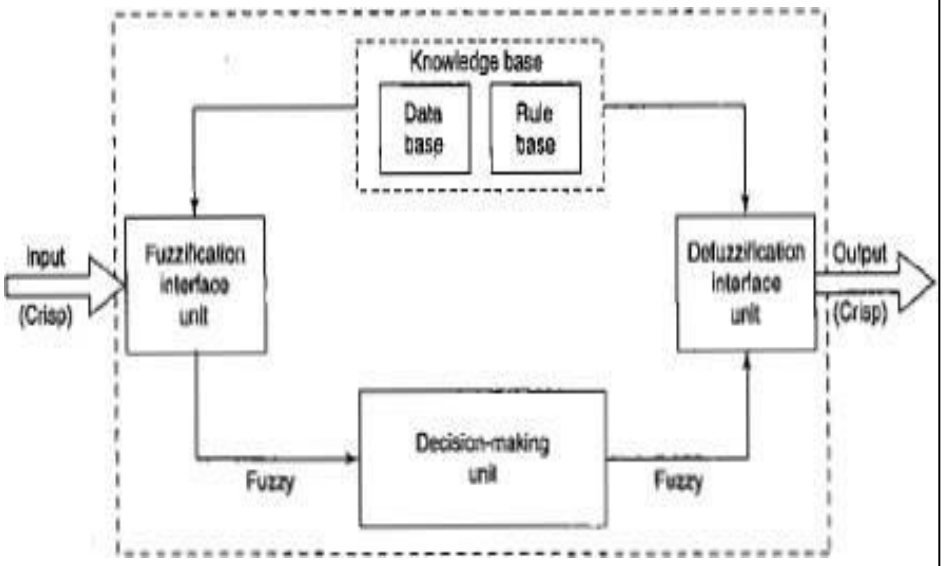
Operations	Classical Relations	Fuzzy Relations
Union	$R \cup S \rightarrow \chi R \cup S(x,y) = \max[\chi R(x,y), \chi S(x,y)]$	$\mu_{R \cup S}(x,y) = \max[\mu_R(x,y), \mu_S(x,y)]$
Intersection	$R \cap S \rightarrow \chi R \cap S(x,y) = \min[\chi_R(x,y), \chi_S(x,y)]$	$\mu_{R \cap S}(x,y) = \min[\mu_R(x,y), \mu_S(x,y)]$
Complement	$R \rightarrow \chi_R(x,y)$: $\chi_R(x,y) = 1 - \chi_R(x,y)$	$\mu_R(x,y) = 1 - \mu_R(x,y)$
Containment	$R \subset S \rightarrow \chi_R(x,y) \leq \chi_S(x,y)$	$R \subset S \Rightarrow \mu_R(x,y) \leq \mu_S(x,y)$
Identity	$\phi \rightarrow \phi R$ & $X \rightarrow E_R$	
Inverse		The inverse of fuzzy relation R on X*Y is denoted by R^{-1}. It is relation on Y*X defined by $R^{-1}(y,x) = R(x,y)$ for all pairs $(y,x) \in Y * X$
Projection		For fuzzy relation R(X,Y), let $[R \downarrow Y]$ denote the projection of R onto Y. $\overline{\mu_{[R\downarrow Y]}}(x,y) = \max_{y} \mu_R(x,y)$

Classical Relations	Fuzzy Relations
Properties	
• Commutativity • Associativity • Distributivity • Involution • Idempotency • DeMorgan's Law • Excluded middle law	• Commutativity • Associativity • Distributivity • Involution • Idempotency • DeMorgan's Law

5	Explainthe FrameworkofFuzzyInferenceSystemswithneatsketch.	[L2][CO3]	**[12M]**
	FuzzyInferenceSystems		

Fuzzyrulebasedsystems,fuzzymodels,andfuzzyexpertsystemsaregenerallyknownassystems.Thekeyunitofafuzzylogicsystemis FIS.Theprimaryworkofthissystemisdecisionmaking.FISuses"IF...THEN"rulesalongwithconnectors"OR"or"AND"for making necessary decision rules. The input to FlS may be fuzzy or crisp, but theoutputfrom FISisalwaysafuzzy set.

Constructionand WorkingPrincipleofFIS



1. ARulebasethatcontainsnumerousfuzzyIF-THENrules.
2. Adatabasethatdefinesthemembershipfunctionsoffuzzysetsusedinfuzzyrules.
3. Decision-makingunitthatperformsoperationonthe rules.
4. Fuzzificationinterfaceunitthatconvertsthecrispquantitiesintofuzzyquantities.
5. Defuzzification interface that converts the fuzzy quantities into crisp quantities.Initially,inthefuzzificationunit,thecrispinputisconvenedintoafuzzyinput.Various fuzzificationmethodsareemployed forthis.Afterthisprocess, rulebase isformed.Database and rule base are collectively called the knowledge base. Finally, defuzzificationprocessiscarriedouttoproducecrispoutput.Mainly,thefuzzyrulesareformedinthe rulebase andsuitabledecisionsaremadeinthe decision-making unit

Methodsof FIS:

Therearetwoimportanttypes ofFIS.Theyare

1. MamdaniFIS(1975);
2. SugenoFIS(1985);

Mamdanitypes

Ebsahim Mamdani proposed this system in the year 1975 to control a steamengine and boiler combination by synthesizing a set of fuzzy rules obtainedfrom people working on thesystem. In this case, the output membershipfunctions are expected to be fuzzy sets. After aggregation process, eachoutputvariable isafuzzyset,hencedefuzzification isimportantattheoutputstage.Thestepsinclude:

Step1:Determineasetoffuzzy rules.

Step2:Maketheinputsfuzzyusinginputmembershipfunctions.

Step 3: Combine the inputs according to the fuzzy rules for establishing arule strength. Step 4: Determine the consequent of the rule by combiningtherulestrengthandtheoutputmembershipfunction.

Step5:Combinealltheconsequentstogetanoutputdistribution.

Step6:Finally,adefuzzifiedoutputdistributionisobtained.

Thefuzzyrulesareformedusing"IF-THEN"statementsand"AND/OR"connectives.Theconsequenceoftherulecan beobtained in two steps:

- Bycomputingtherulestrengthcompletelyusingthefuzzifiedinputsfr omthefuzzycombination.
- Byclippingtheoutputmembership functionattherulestrength

The outputs of all the fuzzy rules are combined to obtain one fuzzy output distribution.FromFIS, it is desired to get only one crisp output. This crisp output may be obtainedfromdefuzzificationprocess.Thecommontechniquesofdefuzzificationusedarece nterofmassand mean ofmaximum.

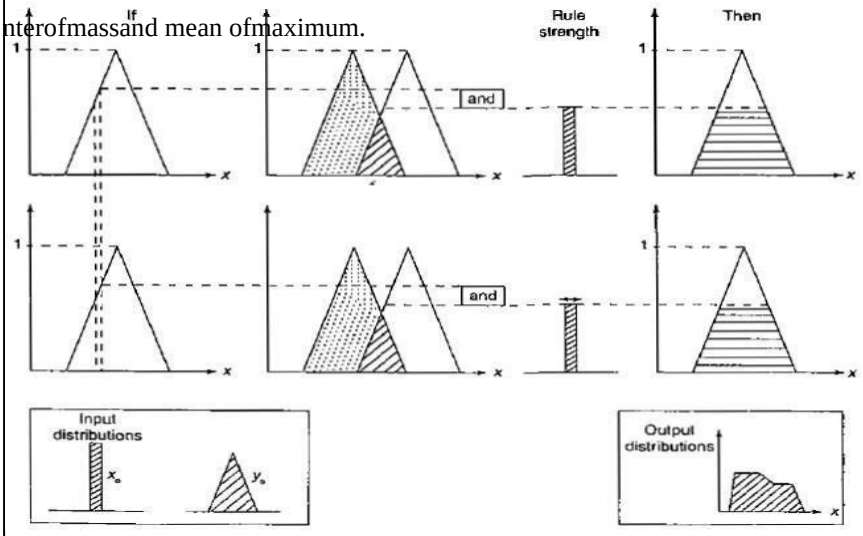


Figure :Atwo-input,two-ruleMamdaniFISwithafuzzyinput

Sugenotypes Takagi-SugenoFuzzyModel(TS Method)

SugenofuzzymethodwasproposedbyTakagi,SugenoandKangintheyeaR2085.Theformatofth efuzzy ruleofa Sugeno fuzzymodelisgiven by

IFx is Aandy is BTHEN z=f(x,y)

whereABarefuzzysetsintheantecedentsand z=f(x,y)isacrispfunction.Themainstepsofthefuzzy inferenceprocessnamely,

1. Fuzzifyingtheinputs.
2. Applyingthefuzzyoperator.

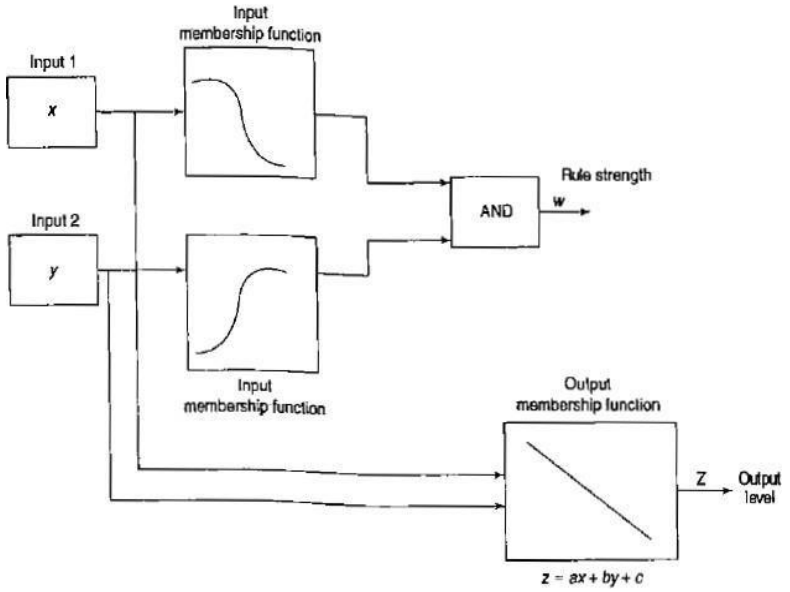
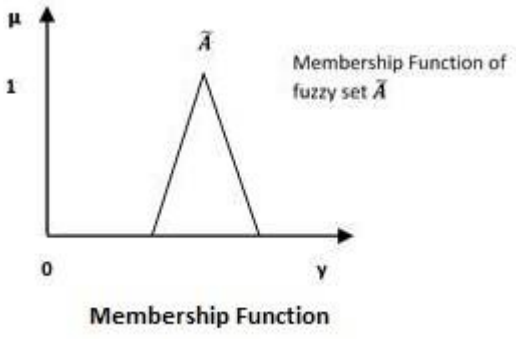


Fig.SugenoModel

6	**a**	Demonstrate themembershipfunctionsinfuzzylogic.	[L3][CO4]	**[6M]**

Fuzzylogicisnotlogicthatisfuzzybutlogicthatisusedtodescribefuzziness.Thisfuzzines s is best characterized by its membership function. In other words, we cansaythatmembershipfunction representsthedegree oftruthin fuzzylogic.



Membership Function

Fuzzy membership functions

Membership function defines the fuzziness in a fuzzy set irrespective of the elements in the set, which are discrete or continuous. A fuzzy set $\underset{\sim}{A}$ in the universe of discourse X can be defined as a set of ordered pairs:

$$\underset{\sim}{A} = \{(x, \mu_{\underset{\sim}{A}}(x)) \mid x \in X\}$$

where $\mu_{\underset{\sim}{A}}(.)$ is called membership function of $\underset{\sim}{A}$. The membership function $\mu_{\underset{\sim}{A}}(.)$ maps X to the membership space M, ie., $\mu_{\underset{\sim}{A}}: X \rightarrow M$. The membership value ranges in the interval [0, 1] ie., the range of the membership function is a subset of the non-negative real numbers whose supremum is finite.

Features ofMembershipFunctions

The three main basic features involved in characterizing membership functionare thefollowing.

1. Core

The core of a membership function for some fuzzy set A is defined as that region of universe that is characterized by complete membership in the set A. The core has elements x of the universe such that

$$\mu_A(x) = 1$$

The core of a fuzzy set may be an empty set.

2. Support

The support of a membership function for a fuzzy set A is defined as that region of universe that is characterized by a non zero membership in the set A.

$$\mu_A(x) > 0$$

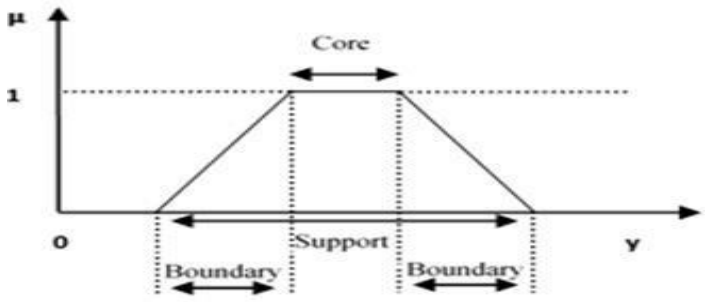
A fuzzy set whose support is a single element in X with $\mu_A(x) = 1$ is referred to as a fuzzy singleton.

3. Boundary

The support of a membership functions as the region of universe containing elements that have a non zero but not complete membership. The boundary comprises those elements of x of the universe such that

$$0 < \mu_A(x) < 1$$

The boundary elements are those which possess partial membership in the fuzzy set A.



Features of Membership Function

NormalandSubnormalfuzzy sets

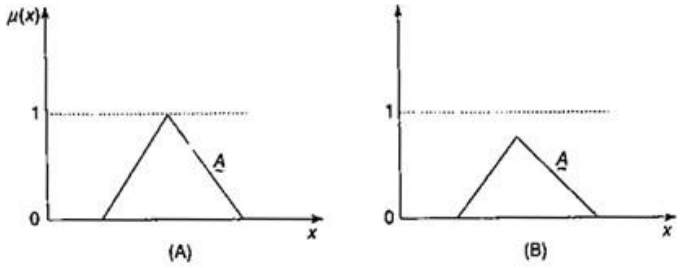


Figure 4.2: (A) Normal fuzzy set and (B) subnormal fuzzy set

ConvexandNonconvexfuzzysets

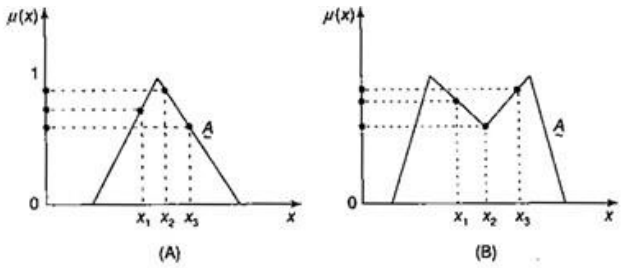


Figure 4.3: (A) Convex normal fuzzy set and (B) Nonconvex normal fuzzy set

Crossoverpointof fuzzyset

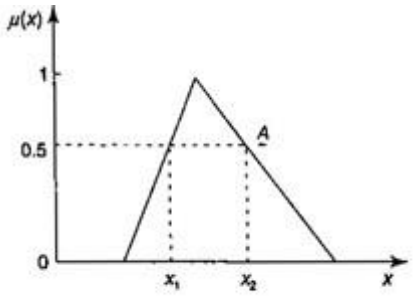


Figure 4.4: Crossover point of a fuzzy set

	b	Analyze Fuzzificationandexplainmembershipvalueassignment in fuzzylogic.	[L4][CO4]	**[6M]**

Fuzzification

It is defined as the process of transforming a crisp set to a fuzzy set or a fuzzy set tofuzzierset.Basically,thisoperationtranslatesaccuratecrispinputvaluesintolinguistic variables.

Followingarethetwoimportantmethods offuzzification−

SupportFuzzification(s-fuzzification)Method

Inthismethod,thefuzzifiedsetcanbeexpressedwiththehelpofthefollowingrelation−

$$A\tilde{}=\mu 1Q(x1)+\mu 2Q(x2)+...+\mu nQ(xn)$$

Herethefuzzyset Q(xi)Q(xi)iscalledaskerneloffuzzification.Thismethodis implementedbykeepingμiconstantand xibeing transformed to a fuzzysetQ(xi)Q(xi).

GradeFuzzification (g-fuzzification)Method

Itisquitesimilartotheabovemethodbutthemaindifferenceisthatitkeptxiconstantandμiis expressed asafuzzyset.

MembershipvalueassignmentsI ntuition

Intuitionmethodisbaseduponthecommonintelligenceofhuman.ltisthecapacity ofthehumantodevelopmembershipfunctionsonthebasisoftheirownintelligenceand understanding capacity.

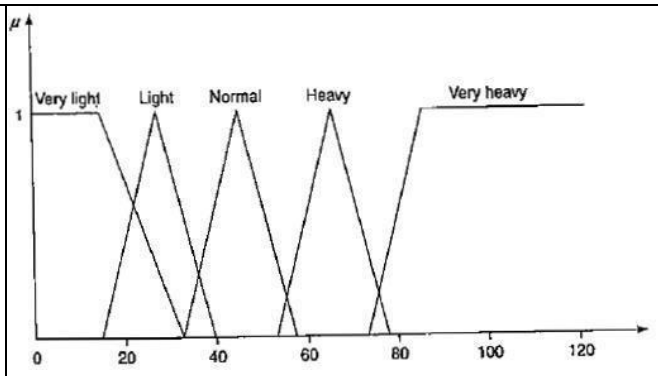


Figure:Membershipfunctionforthefuzzyvariable"weight"

Inference

Theinferencemethodusesknowledgetoperformdeductivereasoning.Ded uction achieves conclusion by means inference. There are variousmethodsforperforming deductivereasoning.
Themembershipfunctionsmaybedefinedbyvariousshapes:triangular,trapezoidal, bell-shaped, Gaussian and so on. The inference method here isdiscussedviatriangularshape.

Consideratriangle,whereX,YandZareanglessuchthatX≥Y≥Z≥ 0,andletUbetheuniverseoftrianglesi.e.,

There are various types of triangles available.

$\underset{\sim}{I}$ = isosceles triangle (approximate)

$\underset{\sim}{E}$= equilateral triangle (approximate)

$\underset{\sim}{R}$ = right-angle triangle (approximate)

$\underset{\sim}{IR}$ = isosceles and right-angle triangle (approximate)

$\underset{\sim}{T}$= other triangles

Rankordering:

Theformationofgovernmentisbasedonthepollingconcept;toidentifyabeststudent, ranking may be performed; to buy a car, one can ask for severalopinionsandso on**.**

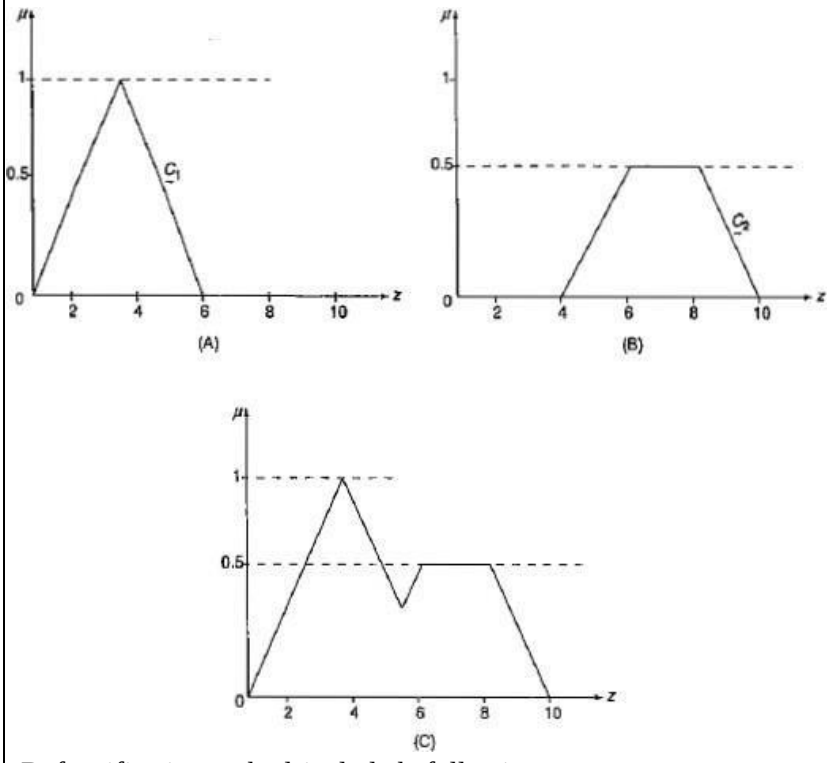
Lambda–cutsforfuzzysets:

Considerafuzzyset$A$.Theset$A\lambda(0<\lambda<1)$,calledthelambda(λ)-cut(oralpha[α]-cut)set, is acrispsetofthefuzzysetandisdefinedasfollows:

$$A_\lambda = \{(x, \mu_{\underset{\sim}{A}}(x) \geq \lambda)\} \ \lambda \in [0,1]$$

The set $A\lambda$is called weak lambda-cut set if it consists of all the elementsof a fuzzy set whose membership function have values greater than orequal to the specified value. The set $A\lambda$is called strong lambda cut if itconsist of all elements of a fuzzy set whose membership functions havevalues strictly greater than a specified value. A strong λ– cut set is givenby

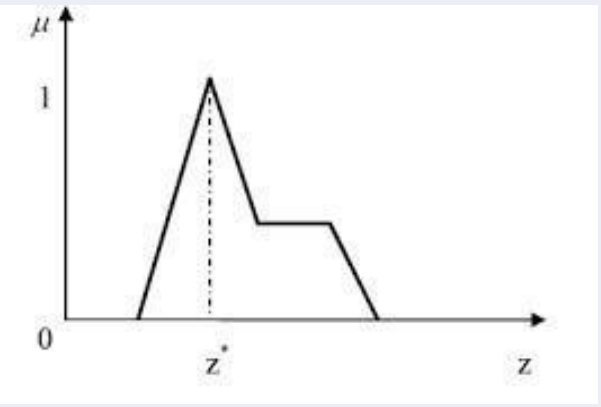
$$A_\lambda = \{(x, \mu_{\underset{\sim}{A}}(x) > \lambda)\} \ \lambda \in [0,1]$$

		The properties of λ cut are as follows 1. $(A \cup B)_{\lambda} = A_{\lambda} \cup B_{\lambda}$ 2. $(A \cap B)_{\lambda} = A_{\lambda} \cap B_{\lambda}$ 3. $(A)_{\lambda} \neq (\overline{A})_{\lambda}$ *except when* $\lambda = 0.5$ 4. For any $\lambda \leq \beta$, where $0 \leq \beta \leq 1$, it is true that $A_{\beta} \subseteq A_{\lambda}$, *where* $A_0 = X$		
7		Analyzethedifferenttypesofdefuzzificationmethodswithrelevantmathematicalexpression and diagram.	[L4][CO4]	**[12M]**
		Defuzzificationmethods Defuzzification is the process of conversion of a fuzzy quantity into a precisequantity. The output of a fuzzy set process may be union of two or more fuzzymembershipfunctionsdefinedontheuniverseofdiscourseoftheoutputvariable .  Defuzzificationmethodsincludethefollowing: 1. Maxmembershipprinciple 2. Centroidmethod 3. Weightedaveragemethod 4. Mean-maxmembership 5. Centerofsums 6. Centeroflargestarea 7. Firstofmaxima, lastofmaxima		

DefuzzificationMethods:

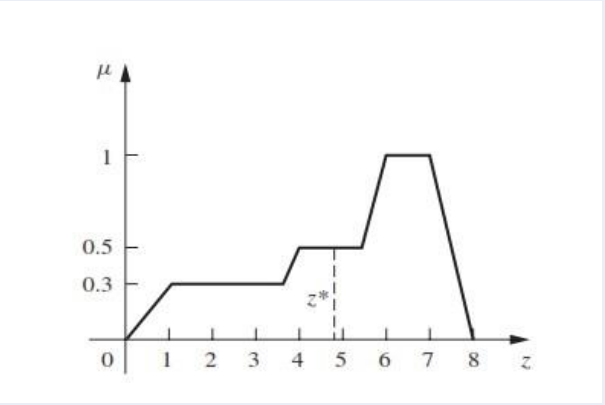
1. Max-MembershipPrinciple

This method is also known as height method and is limited to peak outputfunctions.Thismethodisgiven bythealgebraic expression:
μ(z*)>=**μ**(z)forallz∈Z.



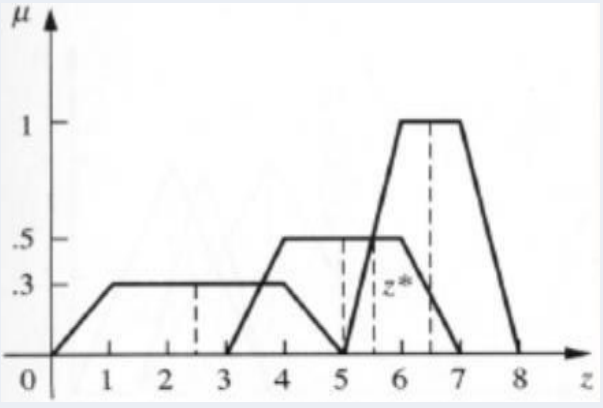
2. CentroidMethod

This methodisalsoknownasthe centre ofmass,centre ofareaorcentre ofgravity.It is the most commonly used defuzzification method. The defuzzified output z* isgiven by:
z*=∫μ(z).zdz/ ∫μ(z)dz



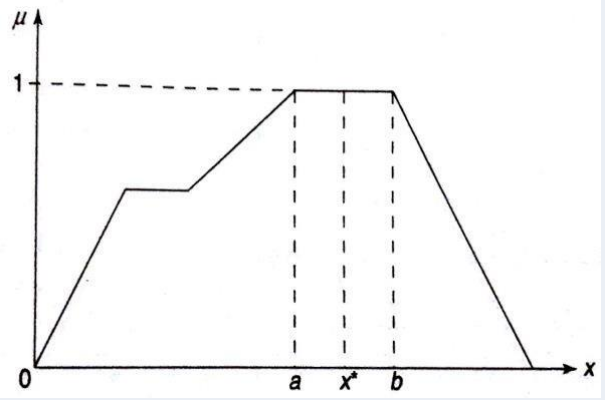
3. WeightedAverage Method

This method is valid for symmetrical output membership functions only. Eachmembership function is weighted by its maximum membership value. The output inthe caseisgiven by
z* = ∑μ(z').z' / ∑μ(z') ; where z' is the maximum value of the membershipfunction.



4. Mean-MaxMembership

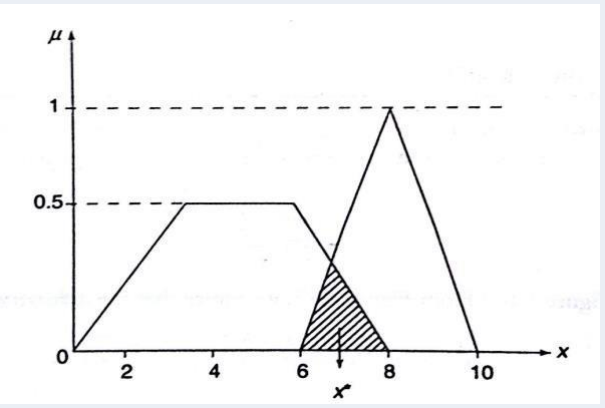
This methodisalsoknownasthe middle ofthe maxima.Thisiscloselyrelatedtothe max-membership method, except that the locations of the maximummembership can benonunique.Theoutputhere isgiven by:
z*=∑z'/n;where z' is the maximumvalue ofthe membership function.



5. CentreofSums

This method employs the algebraic sum of the individual fuzzy subsets instead oftheir union. The calculations here are very fast, but the main drawback is that theintersectingareasareaddedtwice.Thedefuzzifiedvaluez* isgiven by

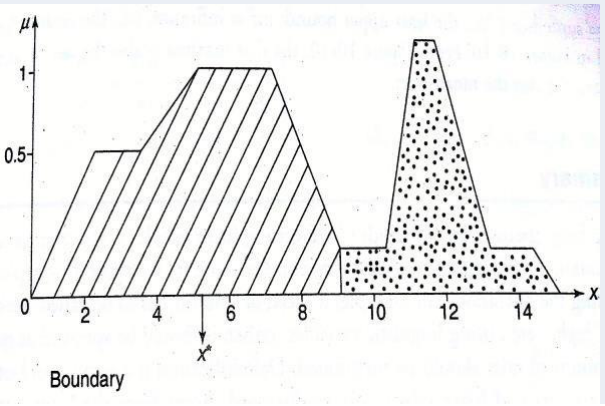
z*=∫z*∑μ(z).zdz/∫∑μ(z)dz



6. Centre ofLargestArea

This method can be adopted when the output of at least two convex fuzzy subsetswhich are not overlapping. The output, in this case, is biased towards a side of onemembership function. When output fuzzy st has at least two convex regions, thenthe centre ofgravityofthe convex fuzzysubregionhavingthe largestare isused toobtainthedefuzzified valuez*. The valueisgiven by

z*=∫μc(z).zdz /∫∑μc(z)dz



8		Summarizethefollowingterms: i) FuzzyArithmeticii)FuzzyMeasures	[L5][CO4]	**[12M]**
		FuzzyArithmetic: Theimprecisedatafromthemeasuringinstrumentsaregenerallyexpressedinthe formofintervals,andsuitablemathematicaloperationsareperformedovertheseintervalsf orobtainareliabledataofthemeasurements(whicharealsointheform		

of intervals). This type of computation is ca!led*interval arithmetic* o*intervalanalysis.*Fuzzy arithmetic isa majorconceptin possibility theory.

Fuzzy arithmetic is also a tool for dealing with fuzzy quantifiers in approximatereasoningFuzzy numbers are an extension of the concept of intervals. Intervals areconsidered at only one unique level. Fuzzy numbers consider them at several levelsvaryingfrom0to 1.

IntervalAnalysisofUncertainValues

Table 11-1 Set operations on intervals

Conditions	Union, ∪	Intersection, ∩
$a_1 > b_2$	$[b_1, b_2] \cup [a_1, a_2]$	ϕ
$b_1 > a_2$	$[a_1, a_2] \cup [b_1, b_2]$	ϕ
$a_1 > b_1, a_2 < b_2$	$[b_1, b_2]$	$[a_1, a_2]$
$b_1 > a_1, b_2 < a_2$	$[a_1, a_2]$	$[b_1, b_2]$
$a_1 < b_1 < a_2 < b_2$	$[a_1, b_2]$	$[b_1, a_2]$
$b_1 < a_1 < b_2 < a_2$	$[b_1, a_2]$	$[a_1, b_2]$

Themathematicaloperationsperformedoninrcrvalsareas follows:

1. **Addition (+):** Let $\underline{A} = [a_1, a_2]$ and $\underline{B} = [b_1, b_2]$ be the two intervals defined. If $x \in [a_1, a_2]$ and $y \in [b_1, b_2]$, then

$$(x + y) \in [a_1 + b_1, a_2 + b_2]$$

This can be written as

$$\underline{A} + \underline{B} = [a_1, a_2] + [b_1, b_2] = [a_1 + b_1, a_2 + b_2]$$

2. **Subtraction (−):** The subtraction for the two intervals of confidence is given by

$$\underline{A} - \underline{B} = [a_1, a_2] - [b_1, b_2] = [a_1 - b_2, a_2 - b_1]$$

That is, we subtract the larger value out of b_1 and b_2 from a_1 and the smaller value out of b_1 and b_2 from a_2.

3. **Multiplication (·):** Let the two intervals of confidence be $\underline{A} = [a_1, a_2]$ and $\underline{B} = [b_1, b_2]$ defined on non-negative real line. The multiplication of these two intervals is given by

$$\underline{A} \cdot \underline{B} = [a_1, a_2] \cdot [b_1, b_2] = [a_1 \cdot b_1, a_2 \cdot b_2]$$

If we multiply an interval with a non-negative real number α, then we get

$$\alpha \cdot \underline{A} = [\alpha, \alpha] \cdot [a_1, a_2] = [\alpha \cdot a_1, \alpha \cdot a_2]$$
$$\alpha \cdot \underline{B} = [\alpha, \alpha] \cdot [b_1, b_2] = [\alpha \cdot b_1, \alpha \cdot b_2]$$

4. **Division (÷):** The division of two intervals of confidence defined on a non-negative real line is given by

$$\underline{A} \div \underline{B} = [a_1, a_2] \div [b_1, b_2] = \left[\frac{a_1}{b_2}, \frac{a_2}{b_1}\right]$$

If $b_1 = 0$ then the upper bound increases to $+\infty$. If $b_1 = b_2 = 0$, then interval of confidence is extended to $+\infty$.

5. **Image ($\overline{A}$):** If $x \in [a_1, a_2]$ then its image $-x \in [-a_2, -a_1]$. Also if $\underline{A} = [a_1, a_2]$ then its image $\overline{A} = [-a_2, -a_1]$. Note that

$$\underline{A} + \overline{\underline{A}} = [a_1, a_2] + [-a_2, -a_1] = [a_1 - a_2, a_2 - a_1] \neq 0$$

That is, with image concept, the subtraction becomes addition of an image.

6. **Inverse (A^{-1}):** If $x \in [a_1, a_2]$ is a subset of a positive real line, then its inverse is given by

$$\left(\frac{1}{x}\right) \in \left[\frac{1}{a_2}, \frac{1}{a_1}\right]$$

Similarly, the inverse of $\underline{A}$ is given by

$$\underline{A}^{-1} = [a_1, a_2]^{-1} = \left[\frac{1}{a_2}, \frac{1}{a_1}\right]$$

That is, with inverse concept, division becomes multiplication of an inverse. For division by a non-negative number $\alpha > 0$, i.e. $(1/\alpha) \cdot \underline{A}$, we obtain

$$\underline{A} \div \alpha = \underline{A} \cdot \left[\frac{1}{\alpha}, \frac{1}{\alpha}\right] = \left[\frac{a_1}{\alpha}, \frac{a_2}{\alpha}\right]$$

7. **Max and min operations:** Let two intervals of confidence be $\underline{A} = [a_1, a_2]$ and $\underline{B} = [b_1, b_2]$. Their max and min operations are defined by

$$\text{Max: } \underline{A} \vee \underline{B} = [a_1, a_2] \vee [b_1, b_2] = [a_1 \vee b_1, a_2 \vee b_2]$$
$$\text{Min: } \underline{A} \wedge \underline{B} = [a_1, a_2] \wedge [b_1, b_2] = [a_1 \wedge b_1, a_2 \wedge b_2]$$

		FuzzyMeasures: Afuzzymeasureexplainstheimprecisionorambiguityassignmentofanelementatorwoor morecrispsets.Forrepresentinguncenaintycondition,knownas .ambiguity,we assigna value in the unitinterval[0,1). 1. BeliefandPlausibilityMeasures 2. Probabilitymeasures 3. Posibility,necessitymeasures A fuzzy measure is defined by a function $g : P(X) \rightarrow [0, 1]$ whichassignsto eachcrisp subsetofauniverseofdiscourse*X*anumberin theunitimerval[0,1], where *P(X)*is powersetof*X*. Afuzzymeasureisalsodescribed asfollows: *g:B*->[0, 1] where*B*C *P(X)*isafamily ofcrisp subsetsof*X*Here*B*isaBorelfield ora*a*field.Also **BeliefMeasure:** Thebeliefmeasureisafuzzymeasurethatsatisfiesthreeaxiomsgl,g2andg3andanadditionalaxiomof subaddiriviry.Abelief measureis afunction bel->[0,1] satisfyingaxiomsgl, g2andg3 offuzzymeasuresandsubadditivityaxiom.Itisdefinedasfollows: $\text{bel}(A_1 \cup A_2 \cup \cdots \cup A_n) \geq \sum_i \text{bel}(A_i) - \sum_{i<j} \text{bel}(A_i \cap A_j) + \cdots + (-1)^{n-1} \text{bel}(A_1 \cap A_2 \cap \cdots \cap A_n)$ Possibilitymeasures: The possibility measure $\prod$ and necessity measure N are functions $\prod : B \rightarrow [0, 1]$ $N : B \rightarrow [0, 1]$ such that both $\prod$ and N satisfy the axioms g1, g2 and g3 of fuzzy measures and the following additional axiom (g7): $\prod(A \cup B) = \max(\prod(A), \prod(B)) \quad \forall A, B \in B$ $N(A \cap B) = \min(N(A), N(B)) \quad \forall A, B \in B$ As necessity and possibility measures are special subclasses of belief and plausibility measures, respectively, they are related to each other by $\prod(A) = 1 - N(\bar{A})$ $N(A) = 1 - \prod(\bar{A}) \quad \forall A \in \sigma$ field ProbabilityMeasures A probability measure is a function $P : B \rightarrow [0, 1]$ satisfying the three axioms g1, g2 and g3 of fuzzy measures and the additivity axiom (axiom g6) as follows: $P(A \cup B) = P(A) + P(B)$ whenever $A \cap B = \phi, A, B \in B$ $P : X \rightarrow [0, 1]$ such that $P(x) = m(\{x\})$ This function $P(X)$ is called probability distribution function. Within probability measure, the total ignorance is expressed by the uniform probability distribution function $P(x) = m(\{x\}) = \frac{1}{\lvert X \rvert}$ for all $x \in X$		
9		ExplainaboutFuzzyrulebaseandapproximatereasoninginFuzzylogic .	[L2][CO4]	**[12M]**
		Fuzzy Logic RuleBase Itisaknownfactthatahumanbeingisalwayscomfortablemaking conversationsinnaturallanguage.Therepresentationofhumanknowledgecanbedonewit hthehelpoffollowing naturallanguageexpression − **IF**antecedent **THEN**consequent		

The expressionasstatedabove isreferred toasthe FuzzyIF-THENrule base.

CanonicalForm

Followingis the canonicalformofFuzzyLogic Rule Base−

Rule1−IfconditionC1,thenrestrictionR1

Rule2−IfconditionC1,thenrestrictionR2

.

.

.

Rulen−IfconditionC1,thenrestrictionRn

InterpretationsofFuzzyIF-THENRules

FuzzyIF-THENRulescanbeinterpretedinthe followingfourforms −

AssignmentStatements

Thesekindsofstatementsuse"="(equaltosign)forthepurposeofassignment.Theyare ofthefollowing form−

a =

helloclimate=sum

mer

ConditionalStatements

Thesekindsofstatementsusethe"IF-THEN"rulebaseformforthepurposeofcondition.They areofthefollowing form−

IF temperature is high THEN Climate is

hotIFfood isfresh THEN eat.

UnconditionalStatements

Theyare ofthefollowingform−

GOTO10

turnthe Fanoff

LinguisticVariable

We have studied that fuzzy logic uses linguistic variables which are the words orsentences

inanaturallanguage.Forexample,ifwesaytemperature,itisalinguisticvariable; the values of which are very hot or cold, slightly hot or cold, very warm,slightlywarm, etc.Thewordsvery, slightlyarethe linguistichedges.

Followingare the differentmodesof**approximatereasoning** −

CategoricalReasoning

In this mode of approximate reasoning, the antecedents, containing no fuzzyquantifiersandfuzzyprobabilities,are assumedtobe incanonicalform.

QualitativeReasoning

Inthismodeofapproximatereasoning,theantecedentsandconsequentshavefuzzylinguisticvariables;theinput-outputrelationshipofasystemisexpressed as a collection of fuzzy IF-THEN rules. This reasoning is mainlyusedin controlsystemanalysis.

SyllogisticReasoning

In this mode of approximation reasoning, antecedents with fuzzy quantifiersarerelated toinferencerules.Thisisexpressedas−

		x = S_1A′s are B′sy=S_2C′sareD′ s		

		---------- z = S_3E′s are F′sHereA,B,C,D,E,Farefuzzy predicates. • S_1andS_2aregivenfuzzyquantifiers. • S_3isthefuzzyquantifier whichhastobedecided. DispositionalReasoning In this mode of approximation reasoning, the antecedents are dispositionsthatmaycontainthefuzzyquantifier"usually".Thequantifier**Usuall y**linkstogetherthedispositionalandsyllogisticreasoning;henceitpaysanimporta ntrole. For example, the projection rule of inference in dispositional reasoning canbegiven asfollows− usually((L,M) is R) ⇒ usually (L is [R ↓ L])Here**[R↓L]**istheprojectionof fuzzy relation**R** on**L**		
10	**a**	CompareMamdaniFISandSugenoFIS.	[L5][CO4]	**[8M]**
		The main difference between Mamdani and Sugeno methods lies in the outputmembership functions. The Sugeno output membership functions are eitherlinearorconstant.Thedifference alsoliesintheconsequentsoftheirfuzzyrulesas a result their aggregation and defuzzification procedures differ suitably. AlargenumberoffuzzyrulesmustbeemployedinSugenomethodforapproximating periodic or highly oscillatory functions. The configuration ofSugeno fuzzy systems can be reduced and it becomes smaller than that ofMamdani fuzzy systems if nontriangular or nontrapezoidal fuzzy input sets areused.Sugenocontrollershavemoreadjustableparametersintheruleconsequenta nd the number of parameters grows exponentially with the increase of thenumber of input variables. There exist several mathematical results for Sugenofuzzy controllers than for Mamdani controllers. Formation of Mamdani FIS iseasierthanSugeno FIS. • ThemainadvantageofMamdanimethod are: 1. Ithaswidespreadacceptance. 2. Itis well-suitableforhumaninput. 3. Itisintuitive. • TheadvantagesofSugenomethod include: 1. Itis computationallyefficient. 2. Itiscompactandworkswellwithlineartechnique,optimiza tiontechniqueandadaptivetechnique. 3. Itisbestsuited foranalysis. 4. Ithasaguaranteedcontinuityofthe outputsurface.		
	b	DemonstratetheFuzzyDecisionMakingbriefly.	[L3][CO4]	**[4M]**
		Fuzzydecisionmaking: Itisanactivitywhichincludesthestepstobetakenforchoosingasuitablealternativ efromthosethatareneeded forrealizingacertaingoal.		

Stepsfor DecisionMaking

DeterminingtheSetofAlternatives−Inthisstep,thealternativesfromwhichthedecisionhas tobetaken mustbedetermined.

EvaluatingAlternative−Here,thealternativesmustbeevaluatedsothatthedecision canbetakenaboutoneof thealternatives.

ComparisonbetweenAlternatives−Inthisstep,acomparisonbetweenthe evaluatedalternatives is done.

TypesofDecision making:

Individual Decision Making:In this type of decision making, only a single personis responsible for taking decisions. The decision making model in this kind can becharacterizedas−

- Set of possible actions
- Set of goals $G_i\,(i \in X_n)$;
- Set of Constraints $C_j\,(j \in X_m)$

The goals and constraints stated above are expressed in terms of fuzzy sets.

Now consider a set A. Then, the goal and constraints for this set are given by −

$$G_i\,(a) \text{ = composition } [G_i\,(a)] = G_i^1\,(G_i\,(a)) \text{ with } G_i^1$$

$$C_j\,(a) \text{ = composition } [C_j\,(a)] = C_j^1\,(C_j\,(a)) \text{ with } C_j^1 \text{ for } a \in A$$

The fuzzy decision in the above case is given by −

$$F_D = min[i \in X_n^{in} fG_i\,(a), j \in X_m^{in} fC_j\,(a)]$$

Multi-personDecisionMaking

Decisionmakinginthiscaseincludesseveralpersonssothattheexpertknowledgefromvarious personsis utilizedtomakedecisions.

Number of persons preferring x_i to x_j = $N(x_i, x_j)$

Total number of decision makers = n

Then, $SC(x_i, x_j) = \frac{N(x_i, x_j)}{n}$

Multi-objectiveDecisionMaking

Multi-objective decision making occurs when there are several objectives toberealized.There arefollowingtwoissuesinthistype ofdecisionmaking−

- Toacquireproperinformationrelatedtothesatisfactionoftheobjectives by variousalternatives.
- Toweightherelativeimportanceofeachobjective.Mathematically we

can define a universe of n alternatives as −A=[a1,a2,...,ai,...,an]Andthesetof "m" objectivesas O=[o1,o2,...,oi,...,on]

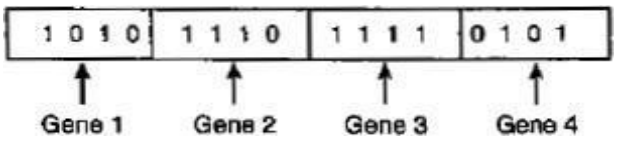
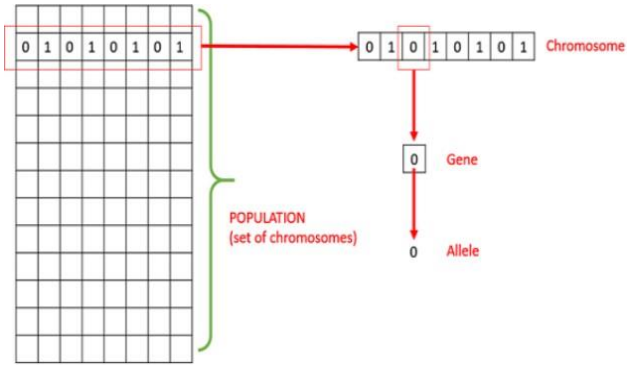
Multi-attributeDecisionMaking

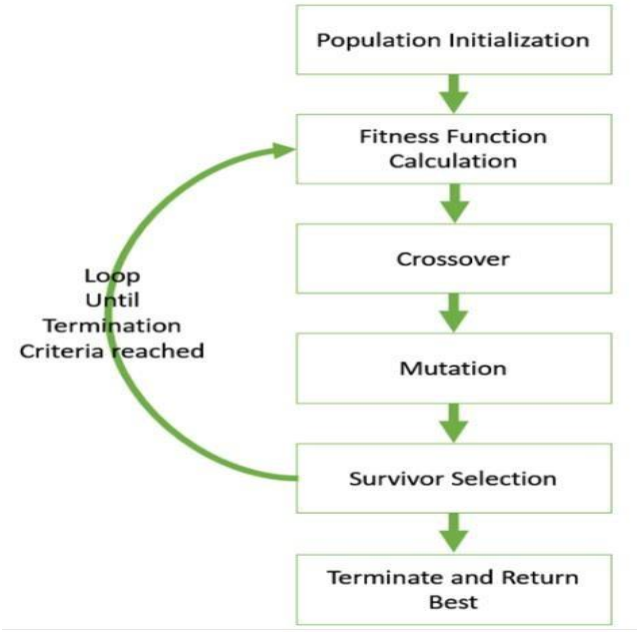
Multi-attributedecisionmakingtakesplacewhentheevaluationofalternatives can be carried out based on several attributes of the object. Theattributescanbe numericaldata,linguistic dataandqualitativedata.

Mathematically, the multi-attribute evaluation is carried out on the basis oflinear equation asfollows−

Y=A1X1+A2X2+...+AiXi+...+ArXr

UNIT–IV
GNETICALGORITHMS

1		Explain the basic terminologies in Genetic Algorithmand illustrate theworkingofGA?	[L3][CO5]	**[12M]**
		Basic Terminologies in Genetic AlgorithmIndividuals: Anindividualis asinglesolution. **Population**−Itisasubsetofallthepossible(encoded)solutionstothegivenproblem. **Chromosomes** − A chromosome is one such solution to the given problem.**Gene**−Agene isone elementpositionofa chromosome.Genesarethebasic"instructions"forbuildingaGA.Agene isa bitstring ofarbitrarylengths  **Figure: Representation of a** **geneAllele**−Itisthe value agene takes fora particularchromosome.  **Genotype** −Genotypeisthepopulationinthecomputationspace.Inthecomputation space, the solutions are represented in a way which can be easilyunderstood and manipulated using acomputing system. **Phenotype** − Phenotype is the population in the actual real world solution space inwhichsolutionsarerepresentedinawaytheyarerepresentedinrealworldsituations. **DecodingandEncoding** −Forsimpleproblems,the **phenotype andgenotype**spacesarethesame. **Fitness Function** − A fitness function simply defined is a function which takes thesolution as input and produces the suitability of the solution as the output. In somecases, the fitness function and the objective function may be the same, while inothersitmightbedifferentbased onthe problem. **GeneticOperators**−Thesealterthegeneticcompositionoftheoffspring.These include crossover,mutation,selection,etc.		



Basicstructure ofGA

Westartwithaninitialpopulation (whichmaybegeneratedatrandomorseededbyother heuristics), select parents from this population for mating. Apply crossoverandmutationoperatorsontheparentstogeneratenewoff-springs.Andfinallytheseoff-springsreplacetheexistingindividualsinthepopulationandtheprocessrepeats.In this way genetic algorithms actually try to mimic the human evolution to someextent.

WorkingPrincipleof GeneticAlgorithm (GeneralGeneticAlgorithm)

Step1:Createarandominitialstate

An initial population is created from a random selection of solutions(whichareanalogoustochromosomes).Thisisunlikethesituatio nforsymbolic AI systems, where the initial State in a problem is alreadygiven.

Step2:Evaluatefitness

Avalueforfitnessisassignedtoeachsolution(chromosome)depending on how close it actually is w solving the problem (thusarriving to the answer of the desired problem). (These "solutions" arenot to be confused with "answers" to the problem; think of them aspossiblecharacteristicsthatthesystemwouldemployinordertoreachthe answer.)

Step3:Reproduce(andchildrenmutate)

Those chromosomes with a higher fitness value are more likely toreproduceoffspring(whichcanmutateafterreproduction).Theoffspring is a product of the father and mother, whose compositionconsistsofacombinationofgenesfromthetwo(thisprocessisk nownas"crossing over").

Step4:Nextgeneration

Ifthenewgenerationcontains asolutionthatproducesanoutputthatis close enoughor equal to the desired then the problem has beensolved.Ifthisisnotthecase,thenthenewgenerationwillgothroughth e same process as their parents did. This willcontinue untilasolutionisreached.

2		DiscussaboutSimplegeneticalgorithmwithneatsketch	[L2][CO5]	**[12M]**
		SimpleGeneticAlgorithm(SGA)isoneofthethreetypesofstrategiesfollowedinGen eticalgorithm. SGAstartswiththecreationofaninitialpopulationofsizeN. Then,weevaluatethegoodness/fitness of eachof thesolutions/individuals.Afterthat,theconvergencecriterionischecked,ifitmeetsthen weconvergethealgorithmotherwisegoforthenextsteps–		

1. SelectNpindividualsfromthepreviouspopulation.
2. Createthematingpoolrandomly.
3. PerformCrossover.
4. PerformMutationinoffspringsolutions.
5. Performinversioninoffspringsolutions.
6. Replacetheoldsolutionsofthelastgenerationwiththenewlycreatedsolution sandgoto step(2).

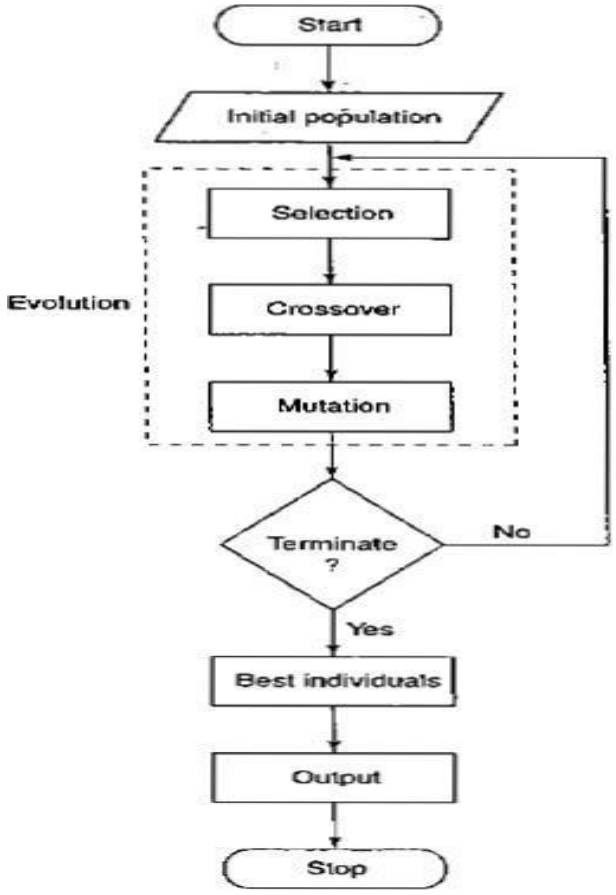


Figure:Flowchartforgeneticalgorithm

ImportantParameterswhilesolvingproblemsinSimpleGeneticAlgorithm:

1. InitialPopulationN

   Anindividualis asinglesolutionwhile a populationisa setofindividualsatan instantofsearching process.
2. MatingpoolsizeNp
3. Convergencethreshold.
4. Selection

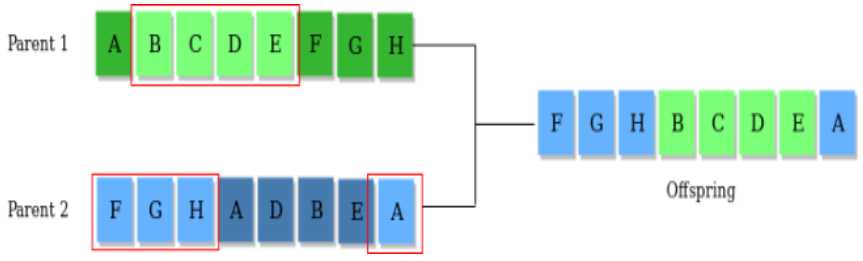
   Selection is the process of choosing two parents randomly from the populationfor crossing. The idea is to give preference to the individuals with good fitnessscoresandallowthemtopasstheirgenestosuccessivegenerations.
5. Crossover

Crossoveristheprocessoftakingtwoparentsolutionsandproducingfromthema child. After the selection (reproduction) process, the population is enrichedwith better individuals.Reproduction makes clones of good strings but does notcreatenewones.Crossoveroperatorisappliedtothematingpoolwiththehopethat it creates a better offspring. Crossover is a recombination operator thatproceedsin threesteps:

1. Thereproductionoperatorselectsatrandomapairoftwoindividualst ringsforthemating.
2. Acrosssiteis selectedarerandomalongthestringlength.
3. 3. Finally, the position values are swapped between the twostringsfollowing thecrosssite.

6. Mutation

   Mutationtoapplyrandomchangestoindividualparentsinordertoform children

		7. Inversion Astringfromthepopulationis selectedandthe bitsbetweentworandomsitesare inverted **Applications:** • LearningrobotbehaviorusingSimpleGeneticAlgorithm. • Inthefinanceindustry. • Neuralnetworks. • SoftcomputingApplicationslikeFuzzylogic,Neurocomputing. • Optimizationproblems.		
3		ExplaintheVariousOperatorsingeneticalgorithm?	[L2][CO5]	**[12M]**
		Once the initial generation is created, the algorithm evolves the generation usingfollowingoperators– **1) SelectionOperator:**Selectionistheprocessofchoosingtwoparentsfromthepopulationforcrossing. Theideaistogivepreferencetotheindividuals with good fitness scores and allow them to pass their genes tosuccessivegenerations **VariousSelectiontechniques** 1. RoulettewheelSelection 2. Randomselection 3. RankSelection 4. TournamentSelection 5. SteadyStateSelection 6. BoltzmannSelection GiveExplanationforeachmethod **2) CrossoverOperator:** Thisrepresentsmatingbetweenindividuals.Twoindividuals are selected using selection operator and crossover sites are chosenrandomly. Then the genes at these crossover sites are exchanged thus creating acompletelynewindividual(offspring). VarioustechniquesofCrossoverOperation 1. SinglePointCrossover 2. Two–PointCrossover 3. MultipointCrossover 4. UniformCrossover 5. Uniformcrossoverwithmask 6. LinearCrossover GiveExplanationforeachmethodForex ample–  **3) Mutation Operator:** The key idea is to insert random genes in offspring tomaintainthediversityinthepopulationtoavoidprematureconvergence.For		

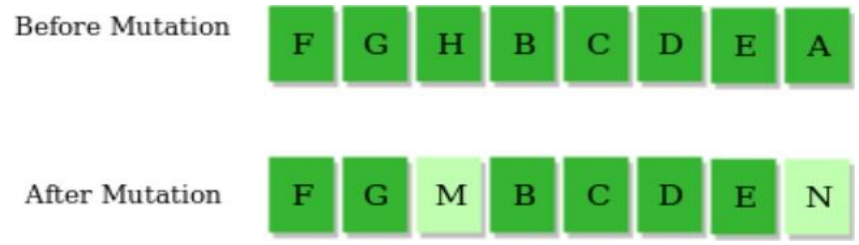
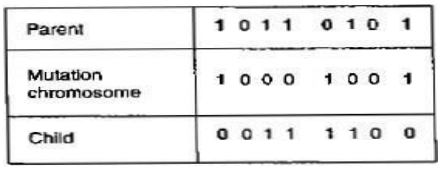
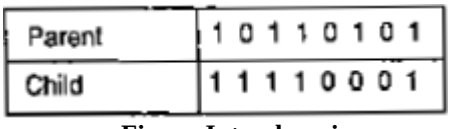
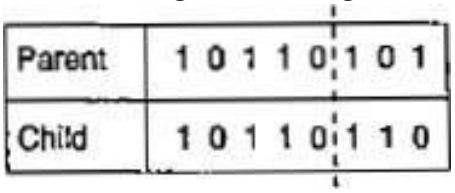
		example–  TypesofMutationoperations 1. Bitflipmutation 2. Swapping 3. Reversing 4. Scramble 5. RandomResetting 6. Inversion Givetheexplanationforeachmethod.Ref erQ.No.4		
4		Summarizethefollowingterms: i)Mutationoperationii)Selectionoperation.	[L5][CO5]	**[12M]**
		a) Mutation operationMutation Aftercrossover,thestringsaresubjectedtomutation.Mutationplaystheroleofrecovering thelostgeneticmaterialsaswellasforrandomlydistributinggenericinformation. It introduces new generic structures inthe population by randomlymodifyingsomeofitsbuilding blocks. **BITFlipping** Flipping of a bit involves changing 0 to 1 and 1 to 0 based on a mutationchromosome generated. A parent is considered and a mutation chromosome israndomly generated. For a 1 in mutation chromosome, the corresponding bit inparent chromosome is flipped (0 to 1 and 1 to 0) and child chromosome isproduced.  **Figure:MutationflippingI nterchangingorSwapping** Two random positions of the string are chosen and the bits corresponding tothose positionsareinterchanged.  **Figure:Interchanging** **Reversing** Arandompositionischosenandthebitsnexttothatpositionarereversedandchildchromosomeisproduced.		

Figure :Reversing



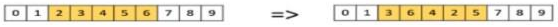
Random Resetting

- Random Resetting is an extension of the bit flip for the integer representation.
- In this, a random value from the set of permissible values is assigned to a randomly chosen gene.

Value ranges from [1, 8]

Scramble Mutation

- Scramble mutation is also popular with permutation representations.
- In this, from the entire chromosome, a subset of genes is chosen and their values are scrambled or shuffled randomly.



Inversion Mutation

Select a subset of genes like in scramble mutation, but instead of shuffling the subset, we merely invert the entire string in the subset.

b)

c)

d)<u>Selectionoperation</u>

Selectionistheprocessofchoosingtwoparentsrandomlyfromthepopulationforcrossing.Thepurposeofselectionistoemphasizefitterindividualsinthe-population in hopes that their offspring have higher fitness. According toDarwin'stheoryofevolutionthebestonessurvivetocreate newoffspring.

Twotypesofselection:

- **Proportionate-basedselection**

Proportionate-based selection picks out individuals based upon their fitnessvaluesrelativetothefitnessoftheotherindividualsinthepopulation.

- **Ordinal-basedselection**

Ordinal-based selection schemes select individuals not upon their raw fitness,but upon their rank within the population. This requires that the selectionpressure is independent of the fitness distribution of the population, and issolelybased **upontherelativeordering (ranking)ofthe population.**

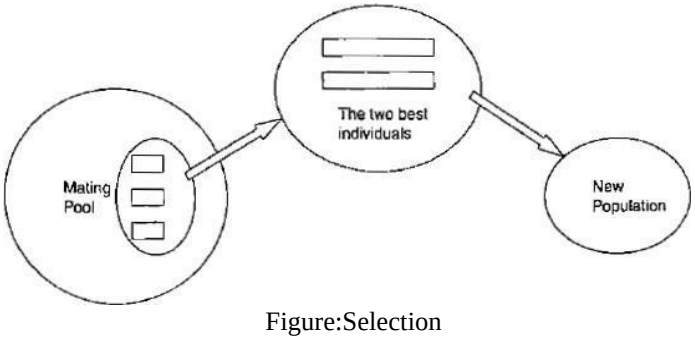


Figure:Selection

RouletteWheelSelection

TheRouletteprocesscanalsobeexplainedasfollows:

The expectedvalue ofan individualis individual's fitness divided by the actualfitness of the population. In a roulette wheel selection, the circular wheel is dividedas described before. A fixed point is chosen on the wheel circumference as shownand the wheel is rotated. The region of the wheel which comes in front of the fixedpointischosenasthe parent.Forthesecondparent,the sameprocessisrepeated.

Each individual is assigned a slice of the Roulette wheel, the size ofthe slice being proportional to theindividual's fitness. A target value is set,which is a random proportion of the sum of the fitness's in the population. Afitindividualwillcontributemore tothe targetvalue,butifitdoesnotexceedit, the next chromosome in line has a chance, and it may be weak. The wheelis spun N times, where N is the number of individuals in the population. Oneachspin,theindividualunderthewheel'smarkerisselectedtobe inthepoolofparentsforthenextgeneration.

Roulette-Wheel selection

- The most common fitness-proportionate selection technique is called Roulette Wheel Selection.
- Probability for an individual being selected is considered to be proportional to its fitness.

The probability that i-th individual will be pointed is

$$p_i = \frac{f_i}{\sum_{i=1}^{N} f_i}$$

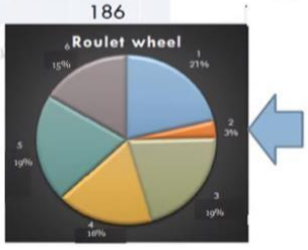
- f_i is the evaluation associated with the individual i in the population.
- N – Size of population
- These probabilities are represented on a wheel

Roulette-Wheel selection

Parents are selected according to their fitness values

The better chromosomes have more chances to be selected

Chromosome	Fitness	Probability	Chance (N*Pi)	Actual c
1	50	50/186= .2688	.2688*6= 1.61	2
2	6	6/186 = 0.0322	.0322*6=0.19	0
3	36	36/186 = 0.1935	0.1935*6 =1.16	1
4	30	30/186 =0.1612	0.1612*6 =0.97	1
5	36	36/186 = 0.1935	0.1935*6 =1.16	1
6	28	28/186 = 0.1505	0.1505*6= 0.90	1
	186		6	6



RandomSelection

This technique randomly selects a parent from the population. In terms ofdisruption of generic codes, random selection is a little more disruptive, onaverage,than Roulettewheelselection.

.**RankSelection**

Rank selection

- Individuals are arranged in an ascending order of their fitness values.
- The individual, which has the lowest value of fitness is assigned rank 1, and other individuals are ranked accordingly.
- The individual, which has the best value of fitness is assigned rank N
- Apply the Roulette-Wheel selection based on their assigned ranks.

The % area to be occupied by a particular individual i, is given by

$$\frac{r_i}{\sum_{i=1}^{N} r_i} \times 100$$

where r_i indicates the rank of $i-th$ individual.

Chrom #	Fitness
1	37
2	6
3	36
4	30
5	36
6	28

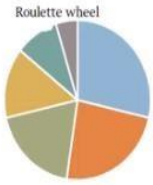
Sort according to fitness

Chrom #	Fitness
1	37
3	36
5	36
4	30
6	28
2	6

Assign raking

Chrom #	Rank
1	6
3	5
5	4
4	3
6	2
2	1

Chrom #	% of RW
1	6/21= 29
3	5/21= 24
5	4/21= 19
4	3/21=14
6	2/21=10
2	1/21=5



Chrom #	EC	AC
1	.29*6=1.714	2
3	1.429	1
5	1.143	1
4	0.857	1
6	0.571	1
2	0.286	0

TournamentSelection

In K-Way tournament selection, we select K individuals from the population atrandomandselectthebestoutofthesetobecomeaparent.Thesame processisrepeated forselecting thenextparent..

Tournament selection

- In tournament selection several tournaments are played among a few individuals.
- Select the tournament size n (say 2 or 3) at random.
- Pick n individuals from the population, at random and determine the best one in terms of their fitness values.
- The best individual is selected

Tournament selection

$N = 8, N_U = 2, N_p = 8$

Input :

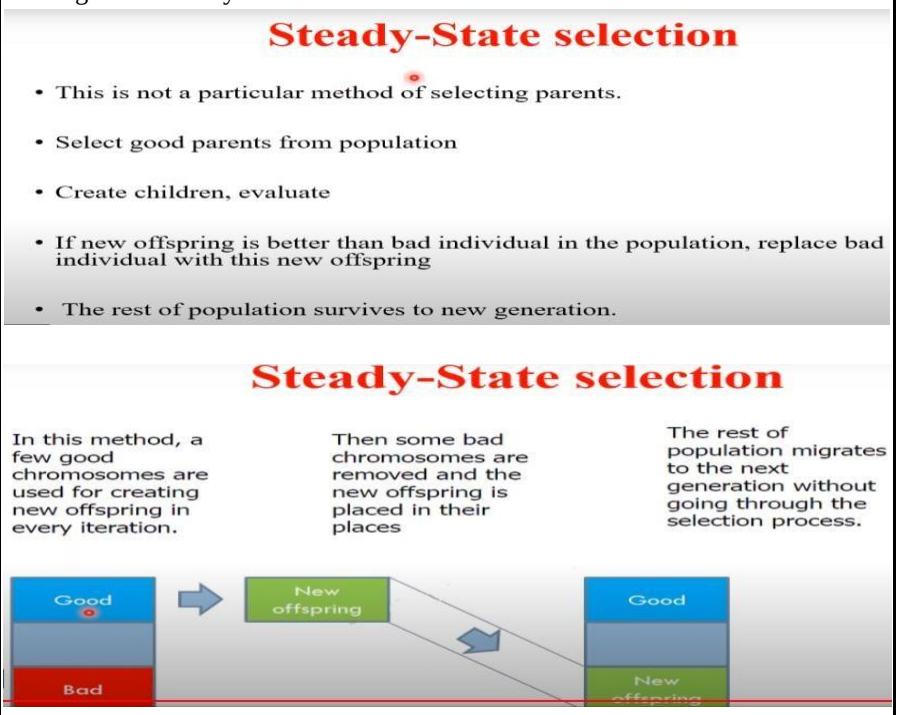
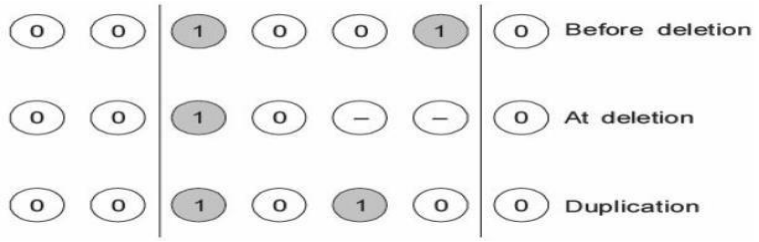
Individual	1	2	3	4	5	6	7	8
Fintess	1.0	2.1	3.1	4.0	4.6	1.9	1.8	4.5

Output :

Trial	Individuals	Selected
1	2, 4	4
2	3, 8	8
3	1, 3	3
4	4, 5	5
5	1, 6	6
6	1, 2	2
7	4, 2	4
8	8, 3	8

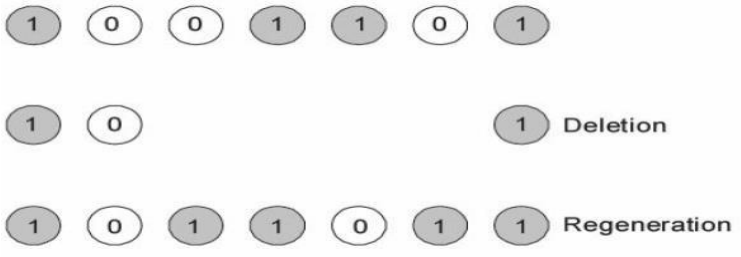
BoltzmannSelection

In Boltzmann selection, a continuously varying temperature controls the rate ofselectionaccordingtoapresetschedule.Thetemperaturescansourhigh,whichmea nsthattheselectionpressureislow.Thetemperatureisgraduallylowered,

		whichgraduallyincreasestheselectionpressure,therebyallowingtheGAto narrowinmorecloselytothebestpartofthesearchspacewhilemaintainingtheapprop riatedegreeofdiversity. 		
5	a	AnalyzeInversionandDeletionOperators inGA. **Inversion** Astringfromthepopulationisselectedandthebitsbetweentworandomsitesareinverted. **Linear+end-inversion** Linear+end-inversionperformslinearinversionwithaspecifiedprobability of 0.75. If linear inversion was not performed, the end inversion wouldbe performed with equal probability of 0.125 at either the left or right end of thestring. Under end inversion, the left or right end of the string was picked as oneinversion-point and a second inversion-point was picked uniformly at random fromthe pointno fartheraway than onehalfofthestring length. **Continuousinversion** In continuous inversion, inversion was applied with specified inversionprobabilityPrto each new individualwhen itiscreated. **Massinversion** No inversion takes place until a new population is created and thereafter,one-halfofthepopulationundergoesidenticalinversion(usingthesametwoinvertingpoints). **DeletionandDuplication** Any two or three bits at random in order are selected and the previous bits areduplicated 	[L4][CO5]	**[6M]**

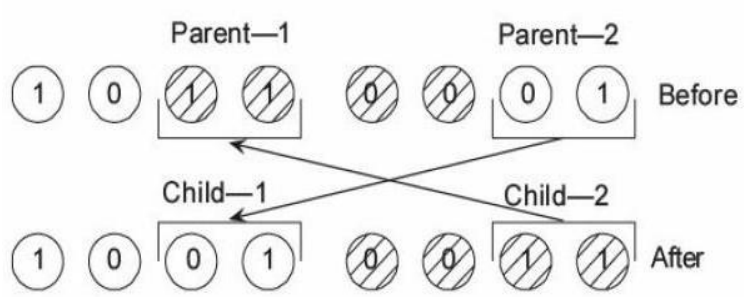
DeletionandRegeneration

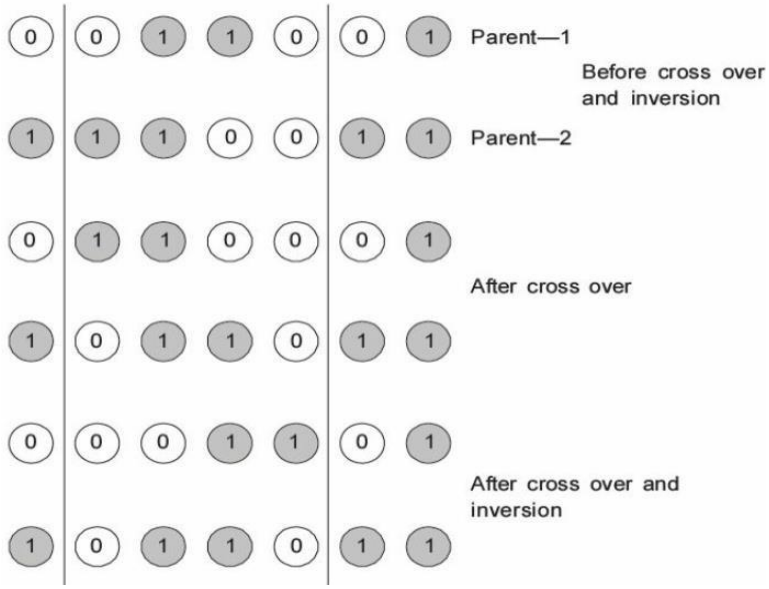
Genes betweentwocross-sites are deletedandregeneratedrandomly.



Segregation

The bitsoftheparentsare segregatedand thencrossed overtoproduceOffspring





	b	Describetheapplicationsofgeneticalgorithm.	[L1][CO5]	**[6M]**

TheVariousapplications of GeneticAlgorithmare:

Optimization −GeneticAlgorithmsaremostcommonlyusedinoptimizationproblems wherein we have to maximize or minimize a given objective functionvalueunderagivensetofconstraints.TheapproachtosolveOptimizationproblemshasbeen highlighted throughout thetutorial.

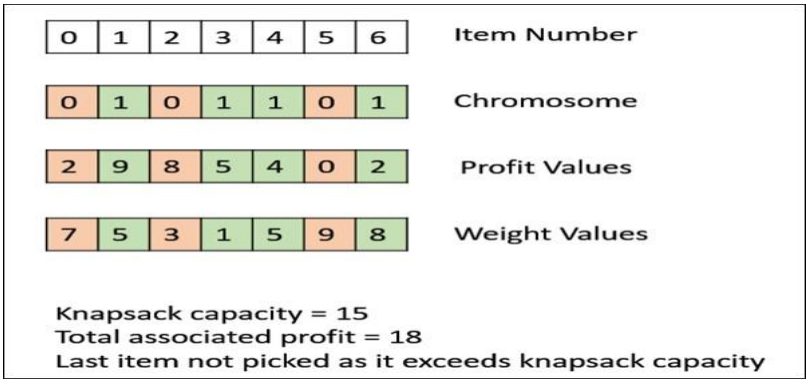
Economics − GAs are also used to characterize various economic models like thecobwebmodel,gametheoryequilibriumresolution, assetpricing,etc.

NeuralNetworks −GAsarealsousedtotrainneuralnetworks,particularlyrecurrentneuralnetworks.

Parallelization− GAs also have very good parallel capabilities, and prove to bevery effective means in solving certain problems, and also provide a good area forresearch.

Image Processing − GAs are used for various digital image processing (DIP) tasksaswelllikedensepixelmatching.

Vehicleroutingproblems−Withmultiplesofttimewindows,multipledepotsand a heterogeneousfleet.

		Scheduling applications − GAs are used to solve various scheduling problems aswell,particularlythetimetabling problem. **MachineLearning** −asalreadydiscussed,geneticsbasedmachinelearning(GBML)isanicheareain machine learning. **RobotTrajectoryGeneration** −GAshavebeenusedtoplanthepathwhicharobotarmtakesby moving fromonepointto another. **ParametricDesignofAircraft**−GAshavebeenusedtodesignaircraftsbyvaryingthe parametersand evolving bettersolutions. **DNA Analysis** − GAs have been used to determine the structure of DNA usingspectrometricdata aboutthesample. **MultimodalOptimization** −GAsareobviouslyverygoodapproachesformultimodaloptimizationinwhichwe havetofindmultiple optimumsolutions. **Traveling salesman problem and its applications** − GAs have been used to solvethe TSP, which is a well-known combinatorial problem using novel crossover andpacking strategies.		
6	**a**	HowFitnessfunction canbeevaluatedinGenetic Algorithm?	[L1][CO5]	**[4M]**
		Fitnessfunction The fitness function simply defined is a function which takes a **candidatesolution to the problem as input and produces as output** how "fit" ourhow"good"thesolutioniswithrespecttotheprobleminconsideration. Calculation of fitness value is done repeatedly in a GA and therefore itshould be sufficiently fast. A slow computation of the fitness value canadverselyaffectaGA and makeitexceptionally slow. Afitnessfunctionshouldpossessthefollowingcharacteristics− • The fitnessfunctionshouldbe sufficientlyfasttocompute. • It must quantitatively measure how fit a given solution is or how fitindividualscan beproduced fromthegivensolution. The following image shows the fitness calculation for a solution of the 0/1Knapsack.Itisasimplefitnessfunctionwhichjustsumstheprofitvaluesofthe items being picked (which have a 1), scanning the elements from left torighttilltheknapsack is full.  		
	b	Describe variousEncodingTechniquesofGeneticalgorithm.	[L2][CO5]	**[8M]**

		Encoding Encodingisaprocessofrepresentingindividualgenes.Theprocesscanbeperformedusingbits, numbers, trees,arrays,listsorany otherobject. **BinaryEncoding** Eachchromosomeencodesabinary(bit)string.Eachbitinthestringcanrepresentsomecharacteristicsofthesolution.Everybitstringthereforeisa		

solution but not necessarily the best solution. Another possibility is that thewholestringcanrepresenta number.Thewaybitstringscancode differsfromproblemtoproblem.

Binary encoding gives many possible chromosomes with a smaller number ofalleles. Binary coded strings with 1s and 0s are mostly used. The length of thestringdependsontheaccuracy.

Chromosome 1	1 1 0 1 0 0 0 1 1 0 1 0
Chromosome 2	0 1 1 1 1 1 1 1 1 1 0 0

Figure:Binaryencoding

OctalEncoding

This encodinguses stringmadeupofoctalnumbers(0-7).

Chromosome 1	03467216
Chromosome 2	15723314

Figure:Octalencoding

HexadecimalEncoding

This encodinguses stringmadeupofhexadecimalnumbers (0-9,A-F).

Chromosome 1	9CE7
Chromosome 2	3DBA

Figure:Hexadecimalencoding

PermutationEncoding(RealNumberCoding*)*

Everychromosomeisastringofnumbers,representedinasequence.Inpermutation encoding, every chromosome is a suing of integer/real values,which representsnumber in asequence.

Chromosome A	1 5 3 2 6 4 7 9 8
Chromosome B	8 5 6 7 2 3 1 4 9

Figure:Permutationencoding

ValueEncoding

Everychromosomeisastringofvaluesandthevaluescanbeanythingconnected to the problem. In value encoding, every chromosome is a string ofsome values. Values can beanything connected to problem, form numbers, realnumbersorcharacterstosomecomplicatedobjects.

Chromosome A	1.2324 5.3243 0.4556 2.3293 2.4545
Chromosome B	ABDJEIFJDHDIERJFDLDFLFEGT
Chromosome C	(back), (back), (right), (forward), (left)

Figure:Valueencoding

TreeEncoding

Thisencodingismainlyusedforevolvingprogramexpressionsforgenetic programming.Everychromosomeisatreeofsomeobjectssuchasfunctionsandcom mandsofaprogramming language

7		IllustratethedifferentbitwiseoperatorsinGA	[L3][CO5]	**[12M]**
		Usually,binary coding isused moreextensivelyin thecoding mechanismto generatealgorithmstructure.Inthepresentwork,geneticalgorithmprogramaswrittenin“C”languagewiththehelpofbuiltinoperatorsin“C”(thebit-wise		

operators),wecandirectlymanipulatetheindividualbitswithinawordofmemory.These operators can be carried out easily and efficiently.These can operate onintegers and characters but not on floats and doubles. Byron S. Gotfried (1990)categorizesbit-wiseoperatorsinto three, namely,

1. Theone'scomplementoperator,
2. The logicalbit-wiseoperator, and
3. The shiftoperator.

One'sComplementOperator

The one's complement operator (~) is an unary operator that causes the bits of itsoperand to be inverted (i.e. reversed), so that 1 becomes zero and zero becomes 1.Thisoperatoralwaysprecedesitsoperand.

LogicalBit-wise Operators

Thereare three logicalbit-wise operators,namely,

1. Bit-wise AND,
2. Bitwise Exclusive-OR, and
3. Bit-wise OR.

Bit-wiseAND(&)operator

Abit-wiseAND(&)expressionreturns1ifboththebitshave avalue1,otherwiseitreturnsavalue0.

Parent1a=1010 1010→ 10 10

Parent2b =11000011 → 12 3

Childa&b =1000 0010 → 82

Bit-wiseexclusive-OR (A)operator

Abit-wiseexclusive-OR(A)expressionreturnsa1ifoneofthebitshavea valueof1and theotherhasavalueof0 otherwiseitreturnsavalue0.

Parent1a=1010 1010→ 10 10

Parent2b =11000011 → 12 3

Childa&b =0110 1001 → 6 9

Bit-wiseOR(|)operator

Abit-wiseOR(|)expressionreturnsa1ifoneormorebitshaveavalueof1otherwise itreturnsavalue0.

Parent1a=1010 1010→ 10 10

Parent2b =1100 0011→ 12 3

Childa&b =1110 1011 → 13 11

ShiftOperators

Two bit-wise shift operators are, shift left (<<) and shift right (>>) operators. Eachoperator operates on a single variable but requires two operands. The first operandis anintegertypeoperand thatrepresentsthebitpattern tobeshifted andthesecondis an unsigned integerthatindicatesthenumberofdisplacements.

Shiftleftoperator (<<)

The shift left operator causes all the bits in the first operand to be shifted to the leftby the number of positions indicated by the second operand. The leftmost bits (i.e.theoverflowbits)intheoriginalbitpatternis lost.The Rightmostbitpositionsthatbecome vacantareto befilled with zeroes.

a = 1010 0110 → 10 6

		a << 2 = 1001 1000 → 9 8 **Shiftrightoperator(>>)** The shift right operator causes all the bits in the first operand to be shifted to theright by the number of positions indicated by the second operand. The right mostbits (i.e. the underflow bits) in the original bit pattern are lost. The left most bitpositionsthatbecomevacantarethen filled with zeroes. **a = 1010 0110 → 10 6** **a >> 2 = 0010 1001 → 2 9** **Masking** Masking is a process in which a given bit pattern is transformed into another bitpattern by means of logical bit-wise operation. The original bit pattern is one of theoperands in the bit-wise operation. The second operand called mask, is a speciallyselected bit pattern that brings about the desired transformation. There are severaldifferent kinds of masking operations. For example, a portion of a given bit patterncan be copied to a new word, while the remainder of the new word is filled with 0.Thus,partofthe originalbitpatternwillbe"maskedoff" fromthe finalresult. **BIT-WISEOPERATORSUSEDINGA** Logicalbit-wiseoperatorsareusedindifferentcombinations.Eachoperatoroperates on two individuals and generates one resultant so as to keep the number ofindividuals in the population constant. Two different operators are used in GAprocess. Populations are selected randomly for mating and on each pair bit-wise AND andbit-wiseORoperatorsareperformed.Similarly,ANDandexclusive-ORorORandexclusive-ORoperationscanbeperformedtoproducechildrenorpopulationforthe nextgeneration.		
8		Analyzethevarious crossoveroperationsperformedinGA	[L2][CO5]	**[12M]**
		Crossover(Recombination) Crossoveristheprocessoftakingtwoparentsolutionsandproducingfromthema child. After the selection (reproduction) process, the population is enrichedwith better individuals.Reproduction makes clones of good strings but does notcreatenewones.Crossoveroperatorisappliedtothematingpoolwiththehopethat it creates a better offspring. Crossover is a recombination operator thatproceedsin threesteps: 1. The reproduction operator selects at random a pair of two individualstringsforthemating. 2. Acrosssiteis selectedarerandomalongthestringlength. 3. Finally,thepositionvaluesareswappedbetweenthetwostringsfollowingth ecrosssite. **Single-PointCrossover** The two mating chromosomes are cut once at corresponding points and thesections after thecutsexchanged.Here, a crosssite orcrossoverpoint isselected randomly along the lengthof the mated strings and bits next to thecrosssitesareexchanged.Ifappropriatesiteischosen,betterchildrencanbe obtainedbycombining goodparents,elseitseverelyhampersstringquality.		

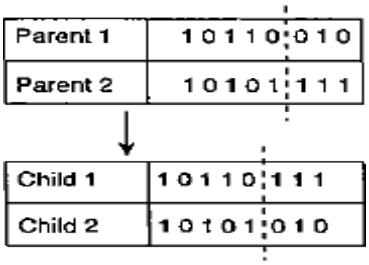


Figure:Single –pointcrossover

Two-PointCrossover

In two-point crossover, two crossover points are chosen and the contentsbetweenthesepointsare exchanged betweentwomatedparents.

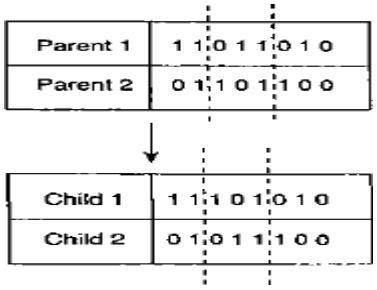


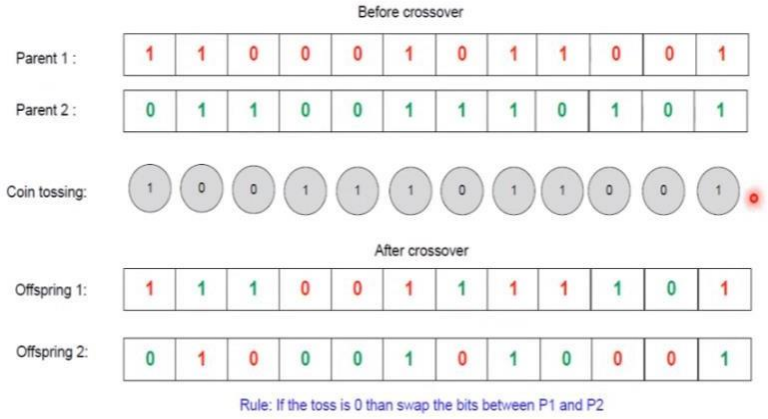
Figure:Two–pointcrossover

Originally, GAs were using one point crossover which cuts two chromosomesin one point and splices the two halves to create new ones. But with this one-pointcrossover,the head and the tail of one chromosome cannot be passedtogether to the offspring. If both the head and the tail of a chromosome containgoodgeneticinformation,noneoftheoffspringobtaineddirectlywithone-pointcrossoverwillsharethetwogoodfeatures.Usingatwo-pointcrossoveronecanavoid this drawback, and so it is generally considered better than one-pointcrossover.

UniformCrossover

Each gene in the offspring is created by copying the corresponding gene fromoneortheotherparentchosenaccordingtoarandomgeneratedbinarycrossover maskofthesamelengthasthechromosomes.Wherethereisa1inthecrossovermask,th egeneiscopiedfromthefirstparent,andwherethereisa0inthemaskthe geneis copied from thesecond parent. A new crossover mask is randomlygenerated for each pair of parents. In the below figure, while producing child 1,when there is a 1 in the mask, the gene is copied from parent 1 else it is copiedfrom parent 2. On producing child 2, when there isa 1 in the mask, the gene iscopiedfromparent2,andwhenthereisa0inthemask,thegeneiscopiedfromthepare nt1.

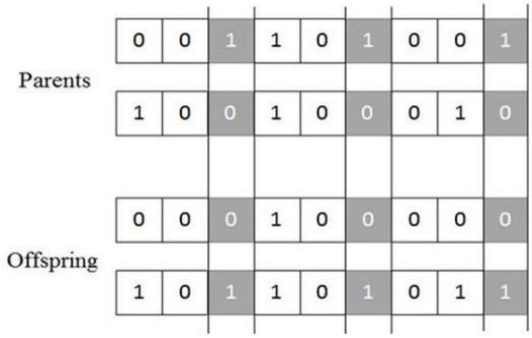
Uniform Crossover



Rule: If the toss is 0 than swap the bits between P1 and P2

MultipointCrossover(N-PointCrossover)

Therearetwowaysinthiscrossover.Oneisevennumberofcrosssiresandtheotheroddnumber of cross sites. In the case ofeven number of cross sites, the cross sitesare selected randomly around a circle and information is exchanged. In the case ofodd number of cross sites, a different cross point is always assumed at the stringbeginning**.**



Three-ParentCrossover

In this crossover technique, three parents are randomly chosen. Each bit of thefirst parent is compared with the bit of the second parent. If both are the same,the bit is taken for the offspring, otherwise the bit from the third parent is takenfortheoffspring.

Parent 1	1 1 0 1 0 0 0 1
Parent 2	0 1 1 0 1 0 0 1
Parent 3	0 1 1 0 1 1 0 0
Child	0 1 1 0 1 0 0 1

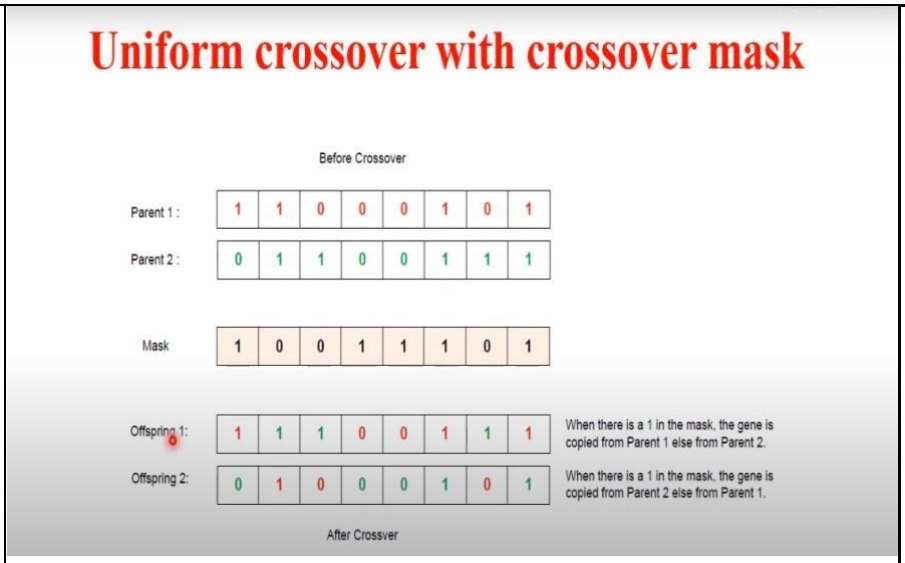
Figure :Three-parentcrossover

Uniform crossover with crossover mask

- Each gene is created in the offspring by copying the corresponding gene from one or the other parent chosen according to a random generated binary crossover mask of the same length as the chromosome.
- Where there is a 1 in the mask, the gene is copied from the first parent
- Where there is a 0 in the mask, the gene is copied from the second parent.

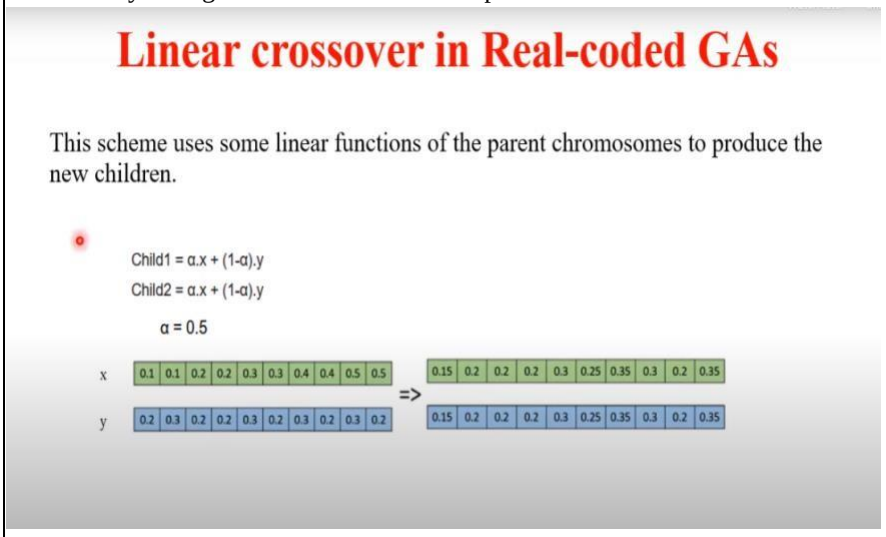
Uniform crossover with crossover mask

- Each gene is created in the offspring by copying the corresponding gene from one or the other parent chosen according to a random generated binary crossover mask of the same length as the chromosome.
- Where there is a 1 in the mask, the gene is copied from the first parent
- Where there is a 0 in the mask, the gene is copied from the second parent.



ShuffleCrossover

Shuffle crossover is related to uniform crossover. A single crossover position(as in crossover) is selected. But before the variables are exchanged, they arerandomly shuffled inboth parents. After recombination, the variables in theoffspring are unshuffled. This removes positional bias as the variables arerandomlyreassigned each rimecrossoverisperformed.



CrossoverProbability

Crossover probability is a parameter to describe how often crossover will beperformed.Ifthereisnocrossover,offspringareexactcopiesofparents.Ifthereis crossover, offspring are made from parts of both parents chromosome. Ifcrossover probability is 100%, then alloffspring are made by crossover. If it is0%, whole new- generation is made from exact copies of chromosomes fromoldpopulation.

9	**a**	Listoutthedifferentreproductionandinheritanceoperators usedin GA.	[L2][CO5]	**[6M]**
		REPRODUCTIONOPERATORS:alsocalledSelectiontechniques. **VariousSelectiontechniques** 1. RoulettewheelSelection 2. Randomselection 3. RankSelection 4. TournamentSelection 5. SteadyStateSelection 6. BoltzmannSelection		

		INHERITANCEOPERATORS Asalreadyseen,geneticalgorithmmakesuseoftheDarwiniansurvivalofthefittestprocedure. Genetic algorithms are search procedures based on mechanics of naturalgeneticsand naturalselection. Geneticalgorithmderives powerfromthegenetic operators listedhere.Low-leveloperators, namely 1. Inversion 2. Dominance 3. Deletion 4. Intrachromosomalduplication 5. Translocation 6. Segregation 7. Speciation 8. Migration 9. Sharing 10. Mating Asimplegeneticalgorithmlargelyuses threebasicoperators whichare 1. Reproduction 2. Crossover 3. Mutation		
	b	IdentifytheAdvantagesandDisadvantages ofGenetic Algorithm.	[L2][CO5]	**[6M]**
		Advantagesof GeneticAlgorithm • Itcanfindsolutionstoproblems thatare difficultorimpossibletosolveusing traditionalmethods. • Theparallelcapabilities ofgeneticalgorithms arebest. • Ithelpsinoptimizingvariousproblemssuchasdiscretefunctions,multi-objective problems, and continuousfunctions. • Itprovidesa solutionfora problemthatimprovesovertime. • Agenetic algorithmdoes notneedderivativeinformation. **LimitationsofGeneticAlgorithms** • Geneticalgorithmsarenotefficientalgorithmsforsolvingsimpleproblems. • Itdoesnotguarantee the qualityofthe finalsolutiontoaproblem. • Repetitivecalculationoffitnessvaluesmaygeneratesomecomputationalchallenges. • Itisdifficulttodebug and canbecomputationallyexpensive. • It is sensitive to the initial conditions and can sometimes converge to localoptima.		
10		BrieflyexplainConvergenceofGeneticAlgorithm.	[L2][CO5]	**[12M]**
		TheterminationconditionofaGeneticAlgorithmisimportantindeterminingwhena GA run will end. It has been observed that initially, the GA progresses very fastwith better solutions coming in every few iterations, but this tends to saturate in thelater stages where the improvements are very small. We usually want a terminationcondition such that our solution is close to the optimal, at the end of the run.In astandard genetic algorithm, binary strings of 1s and 0s represent the chromosomes.Each chromosome is assigned a fitness value expressing its quality reflecting thegiven objective function. Such a population is evolved by means of reproductionand recombination operators in order to breed the optimal solution's chromosome.The evolution keeps running until some termination condition is fulfilled. The bestchromosomeencounteredsofaristhenconsideredasthefoundsolution.		

- Usually,wekeeponeofthefollowingterminationconditions−
- Whenthere hasbeennoimprovementinthe populationforXiterations.
- When wereachan absolutenumberofgenerations.
- Whentheobjective functionvaluehasreacheda certainpre-definedvalue.
- For example, in a genetic algorithm we keep a counter which keeps trackofthegenerationsforwhichtherehasbeennoimprovementinthepopulation.
- Initially, we set this counter to zero. Each time we don't generate off-springswhicharebetterthantheindividualsinthepopulation,weincrementthecounter.
- However, if the fitness any of the off-springs is better, then we reset thecounter to zero. The algorithm terminates when the counter reaches apredeterminedvalue.
- Like other parameters of a GA, the termination condition is also highlyproblemspecificandtheGAdesignershouldtryoutvariousoptionstoseewhatsuitshisparticularproblemthebest.

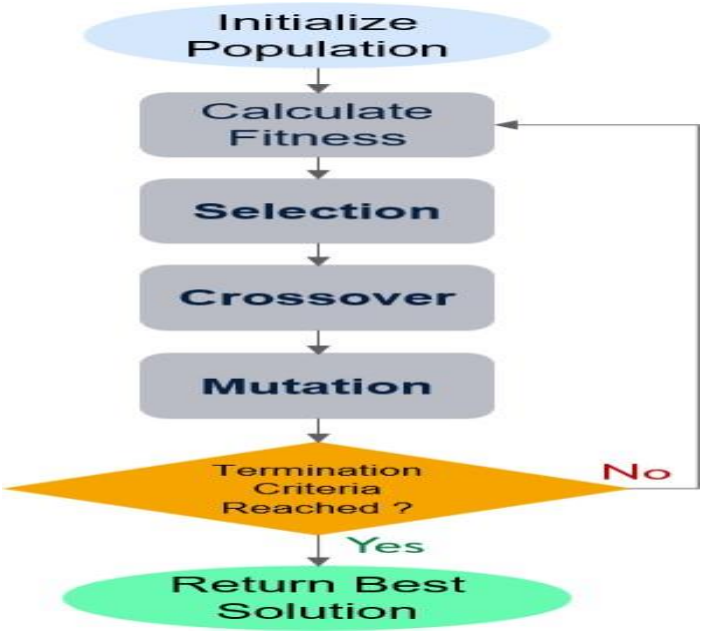
StoppingConditionforGenericAlgorithm Flow

1. Maximum generations: The GA stops when the specified number ogenerationshasevolved.
2. Elapsed time: The generic process will end when a specified time haelapsed.
   Note:Ifthemaximumnumberofgenerationhasbeenreachedbeforethespecified timehaselapsed, theprocesswillend.
3. No change in fitness: The genetic process will end if there is no changtothepopulation'sbestfitnessforaspecifiednumberofgenerations.
4. Stall generations: The algorithm stops if there is no improvement in theobjective functionfor a sequence of consecutive generations of length"Stallgenerations."
5. Stalltimelimit.Thealgorithmstopsifthereisnoimprovementintheobjective functionduringanintervaloftimeinsecondsequalto"Staltime limit."

TerminationorConvergenceCriteria

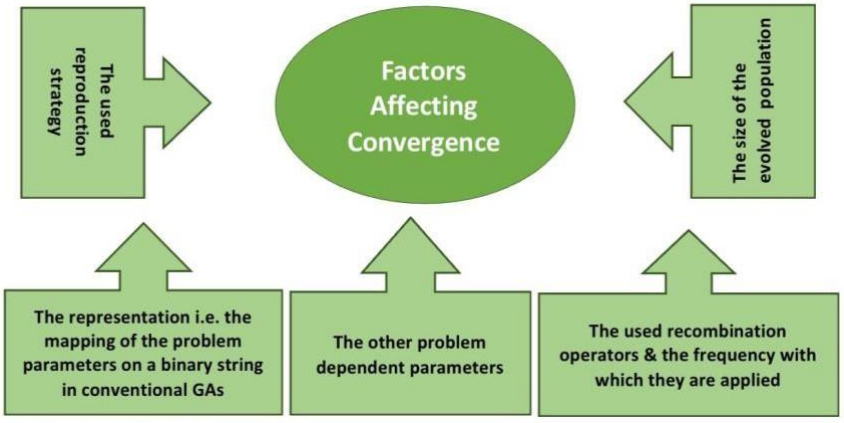
- Each iteration should be tested with some convergence test.
- Commonly known convergence test or termination conditions are :

1. A solution is found that satisfies the objective criteria.
2. Fixed number of generation is executed.
3. The highest ranking solution fitness is reaching or has reached a solution such that successive iterations no longer produce better result.
4. Allocated budget (such as computation time) has reached.
5. Combination of the above.



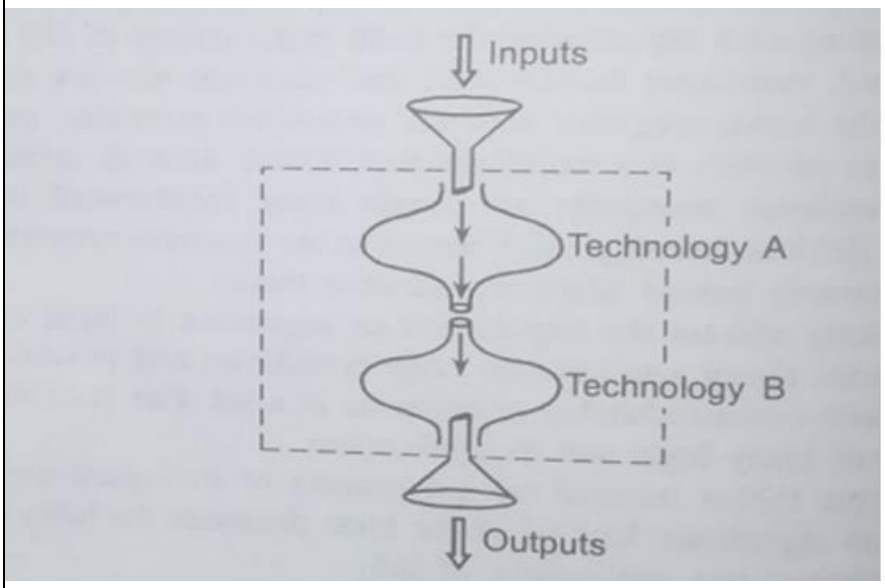
Explainthe above mentionedflowchartalso.

FactorsaffectingConvergence:



UNIT–V

HYBRIDSYSTEMS

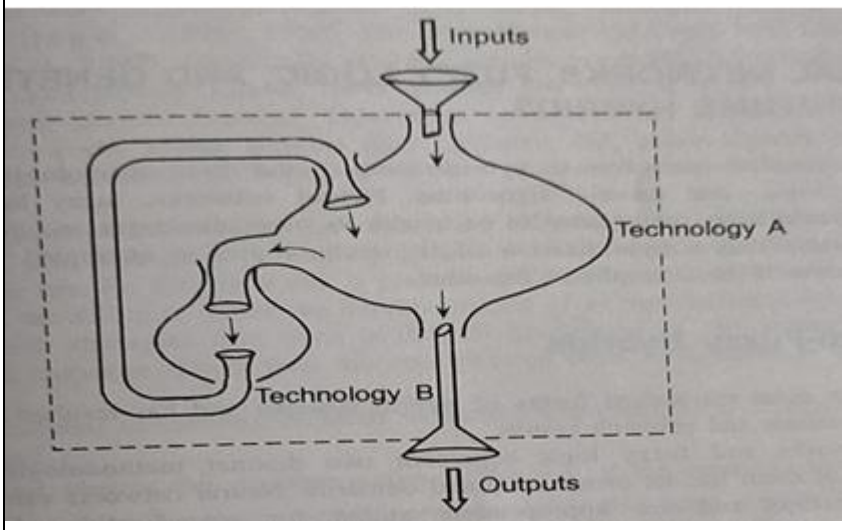
1		**Demonstratethedifferenttypesofhybrid systems.**	[L3][CO6]	**[12M]**
		Hybridsystems: Hybrid systems have been classified as (Refer Gray and Kilgour, 1997) A Hybridsystem is an intelligent system that is framed by combining at least two intelligenttechnologieslikeFuzzyLogic,Neuralnetworks,Geneticalgorithms,reinforcementlearning,etc.Thecombinationofdifferenttechniquesinonecomputationalmodel makesthesesystemspossessanextendedrangeofcapabilities i.e. Hybrid systems are those for which more than one technology isemployedtosolvetheproblemThesesystemsarecapableofreasoningandlearning in an uncertain and imprecise environment. These systems can providehuman-like expertise like domain knowledge, adaptation in noisy environments,etc.Thereare3differenttypesofHybridSystems **1. SequentialHybrids,** **2. AuxiliaryHybrids** **3. Embedded** **Hybrids.SequentialHybrid** **Systems** As the name indicates, sequential hybrid systems make use of technologies in apipeline-likefashion.Thus,onetechnology'soutputbecomesanother'sinputandsoon.Fig(1)illustratestheschemaforasequentialhybrid.  Fig(1)Sequentialhybridsystems Thisisoneoftheweakestformsofhybridizationsinceanintegratedcombinationofthetechnologiesisnot present. AnexampleisaGApreprocessorwhichobtainstheoptimalparametersfor		

		differentinstancesofaproblemandhandsoverthe'preprocessed'datasettoanNNforfurtherprocessing.		

AuxiliaryHybridSystems

In this, one technology calls the other as a "subroutine" to process or manipulateinformationneededbyit.Thesecondtechnologyprocessestheinformationprovidedbythefirstandhandsoverforfurtheruse.Figure2illustratesanauxiliary hybrid system. This type of hybridization though better than sequentialhybrids,isconsideredtobeofintermediarylevelonly.

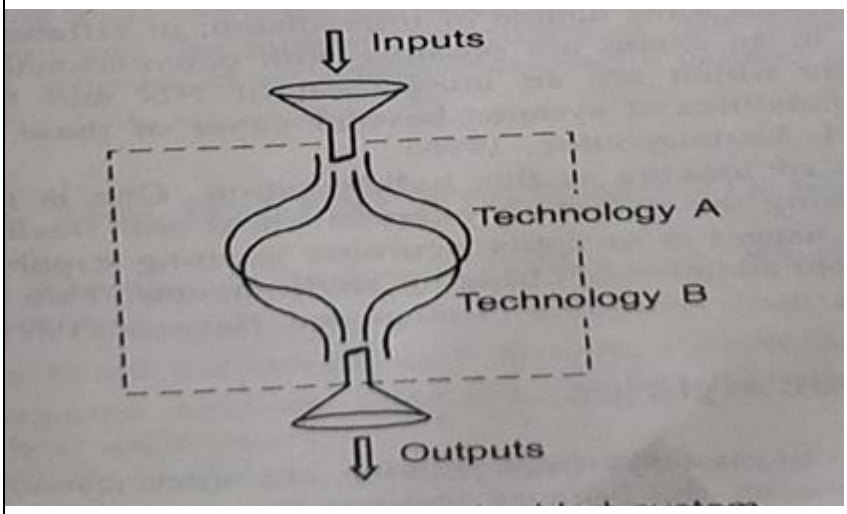
An example is a neuro-genetic system in which an NN employs a GA to optimizeitsstructuralparameters,i.e.parameterswhichdefinesitsarchitecture.



Fig(2)AuxillaryHybridSystems

EmbeddedHybridSystems

In Embedded hybrid systems, the technologies participating are integrated in sucha manner that they appear intertwined. The fusion is so complete that it wouldappear that no technology can be used without the others for solving the problem.Figure3illustratestheschemaforanembeddedhybridsystem.Here,thehybridizationisabsolute.



Fig(3)Embeded HybridSystems

ByCombiningtheSoftcomputingconstituents,TypesofHybridSystems:

- Neuro-FuzzyHybridsystems

		• NeuroGeneticHybridsystems • FuzzyGeneticHybridsystems **Neuro-FuzzyHybridsystems:** Neuro-fuzzy system canbe seenas a 3-layerfeedforward neural network. Thefirst layer represents input variables, the middle (hidden) layer represents fuzzyrules and the third layer represents output variables. Fuzzy sets are encoded asconnection weights within the layers of the network, which provides functionalityinprocessingandtrainingthemodel. **NeuroGeneticHybridsystems:** A Neuro Genetic hybrid system is a system that combines **Neuralnetworks**:which arecapableto learn varioustasksfrom examples, classify objectsandestablishrelationsbetweenthem,anda **Geneticalgorithm**:whichservesimportantsearchandoptimizationtechniques. **Fuzzy Genetic Hybrid systems:**AFuzzyGeneticHybridSystemisdevelopedtousefuzzylogic-basedtechniquesforimprovingandmodelingGeneticalgorithmsandvice-versa. Threeapproachesthatcanbeusedtodevelopsuchasystemare:Michiga n Approach PittsburghApproach IRLApproach		
2		Explainthe LRtype fuzzyNumbers	[L2][CO6]	**[12M]**
		LR-TypeFuzzyNumbers The LR-typefuzzy numbersarespecialtype ofrep resentationsforfuzzynumbers,proposedbyDuboisandPrade(1979).Theyintroduced functionscalled L (and R) which map R+ → [0, 1] and are decreasingshapefunctions if L(0)=1, L(x)<0, ∀x<1, L(1)=0 or [L(x) > 0 ∀x, and L(∞)= 0] **Definition** AfuzzynumberisofLR-type ifthere existreference functionsL(forleft),R (forright)andscalars, α >0, β>0) Here,m, calledthemeanvalueof,isa realnumberand αand βarecalledtheleftand rightspreads, respectively. Here,is the membership function of fuzzy number. An LR-typefuzzy number Mcanbeexpressed as(m, α, β)LR IfαandBare both zero,the LR-type function indicatesa crispvalue. $$\mu_{\tilde{M}}(x) = \begin{cases} L\left(\frac{m_1 - x}{\alpha}\right) & \text{for } x \le m_1,\ \alpha > 0 \\ R\left(\frac{x - m_2}{\beta}\right) & \text{for } x \ge m_2, \beta > 0 \\ 1 & \text{otherwise} \end{cases}$$		

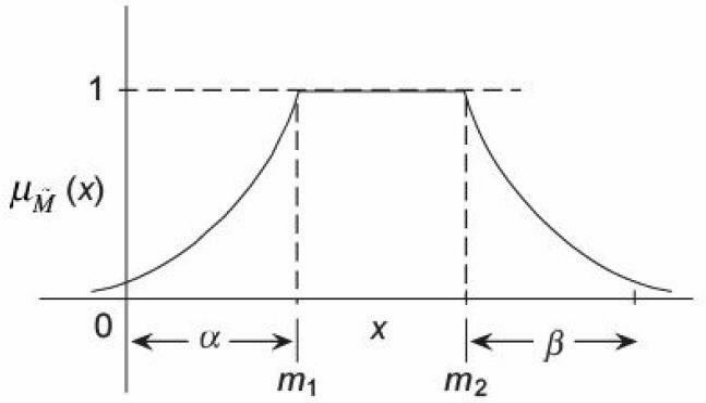


Fig.SymmetrictriangularLR-typefuzzynumber.

The basic operations

areAddition

$$(m,\alpha,\beta)_{LR} \oplus (n,\gamma,\delta)_{LR} = (m+n,\alpha+\gamma,\beta+\delta)_{LR}$$

$$(m,\alpha,\beta)_{LR} \oplus (n,\gamma,\delta)_{RL} = (m-n,\alpha+\delta,\beta+\gamma)_{LR}$$

Multiplication

$$(m,\alpha,\beta)_{LR} \otimes (n,\gamma,\delta)_{LR} = (mn, m\gamma+n\alpha, m\delta+n\beta)_{LR} \text{ for } m\geq 0,\ n\geq 0$$

$$(m,\alpha,\beta)_{RL} \otimes (n,\gamma,\delta)_{LR} = (mn, n\alpha-m\delta, n\beta-m\gamma)_{RL} \text{ for } n\geq 0,\ m<0$$

$$(m,\alpha,\beta)_{LR} \otimes (n,\gamma,\delta)_{LR} = (mn, -n\beta-m\delta, -n\alpha-m\gamma)_{RL} \text{ for } m<0,\ n<0$$

ScalarMultiplication

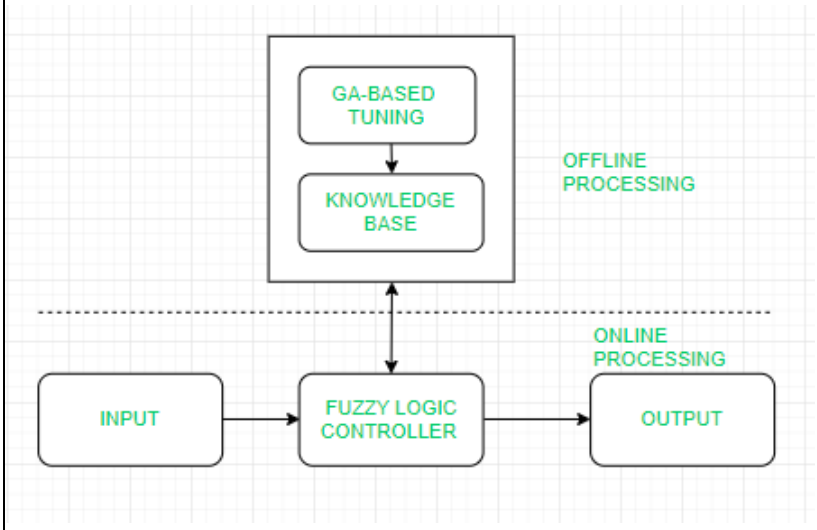
$$\lambda \bullet (m,\alpha,\beta)_{LR} = (\lambda m, \lambda\alpha, \lambda\beta)_{LR},\quad \forall\lambda\geq 0,\ \lambda\in R$$

$$\lambda \bullet (m,\alpha,\beta)_{LR} = (\lambda m, -\lambda\alpha, -\lambda\beta)_{RL},\quad \forall\lambda< 0,\ \lambda\in R$$

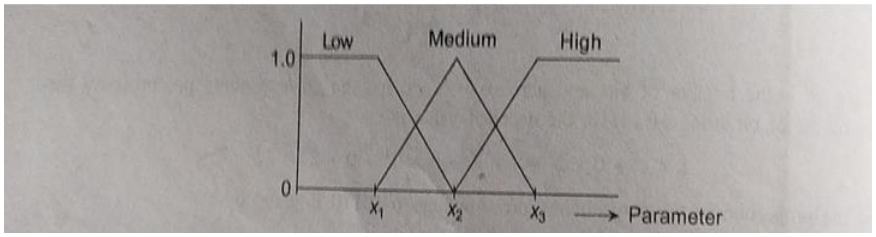
3		**Discussin detailaboutFuzzy-Genetichybrid system.**	[L4][CO6]	**[12M]**

FuzzyGeneticHybridsystems:

AFuzzyGeneticHybridSystemisdevelopedtousefuzzylogic-basedtechniquesforimprovingandmodelingGeneticalgorithmsandvice-versa.



Threeapproachesthatcanbeusedtodevelopsuchasystemare:

		• MichiganApproach • PittsburghApproach • IRLApproach **WorkingFlow:** • Startwithaninitialpopulationofsolutionsthatrepresentthefirstgeneration. • FeedeachchromosomefromthepopulationintotheFuzzylogiccontrollerandcomputeperformanceindex. • Create anew generation using evolution operatorstill someconditionismet **Advantages:** • GAsareusedtodevelopthebestsetofrulestobeusedbyafuzzyinferenceengine • GAsareusedtooptimizethechoiceofmembershipfunctions. • AFuzzyGAisadirectedrandomsearchoveralldiscretefuzzysubsets. • Itcanmimicthehumandecision-makingprocess. **Disadvantages:** • Interpretationofresultsisdifficult. • Difficulttobuildmembershipvaluesandrules. • Takeslotsoftimetoconverge. **Applications:** • MechanicalEngineering • ElectricalEngine • ArtificialIntelligence • Economics		
4		DesignaFuzzyLogicControllerusing GeneticAlgorithm.	[L6][CO6]	**[12M]**
		GAINFUZZYLOGICCONTROLLERDESIGN • Foroptimalcontrolproblems,fuzzylogictechniquesareprimarilyapplied since quick controlstrategy is needed and imprecise andqualitativedefinition of action plansareavailable. • While designing an optimal fuzzy controller, one has to look fortwoprimary activities ➢ Find optimal membership functions for control and actionvariable. ➢ Findanoptimalsetof rulesbetweencontrolandactionvariable. Intheabove twocases,GAshavebeensuitablyused.  Fig.Fuzzy membership functions and typical variables used to optimize theparametes The above Figure shows typical membership functions for a variable (control oraction)havingthreechoices**low,medium,andhigh.**Sincethemaximum		

membershipfunctionvalueofthesechoicesisalwaysone,theabscissamarkedby Xareusually chosen by the user.

These abscissa can be treated as variables in GA and an optimization problem canbe posed to find these variables for minimizing or maximizing a control strategysuchastimeofvariableoperation, productquality,and others.

Consider an example given by Deb (1999) to illustrate how GA can be uniquelyappliedto theaboveproblem.

Letusassumethatthere**aretwocontrolvariables**(**temperatureandhumidity**)andth erearethreeoperationsforcach,low,medium,andhigh.Thereisone**actionvariable** (**water jet flow rate**) which also takes three choices low, medium, andhigh.

Considering individual effect of each control variable separately, there are total of**4 * 4 - 1 = 15** combinations of control variables possible as shown in the belowTable.

Humidity	Temperature			
	Low	Medium	High	No action
Low	High	Medium	–	Medium
Medium	Low	–	Medium	Medium
High	Medium	High	–	–
No action	–	–	High	–

Fig.Actionvariablesforstringrepresentingfuzzyrule base

Thus, finding an optimal rule base is equivalent to finding the four operations(fourth operation-not known) or the action variable for each combination of thecontrolvariables.

AGAwith astringlengthof15andwithaternarycodingcanbeusedtorepresenttherulebaseforthisp roblem.Considering realvaluesto4forrepresentationas**1-Low, 2-Medium, 3-High, 4-No action**, thereby signifying the absence of thecorresponding combination of action variables in the rule base. Table shows therule baseandthiscan be represented by thefollowing string.

312424344243224

Although this rule base may not be the optimal one, GA can process apopulation of such rule bases and finally find the optimal rule base. Oncethe rows present in the rule base are determined from the string user,definedfixedmembershipfunctionscanbeusedtosimulatetheunderlying process. **The objective function can be evaluated and the usual singlepointcrossoverandamutationoperator(oneallelemutatingtooneof threeotheralleles)canbeusedwiththiscodingGAcanfind**theoptimalnumbe r ofrules to solvetheproblem.

Ifonewantstousebinarystringsinsteadofternarystringsandtwobitsareused to represent each of four operations, **a total of 30 bits** is necessary torepresentarulebase.Thiskindoftechniquehasbeenusedtodesignfuzzylogic controllerformobilerobotnavigationamongdynamicobstacles(Debetal., 1998).

Both optimum membership function determination and optimal rule basetasks can be achieved simultaneously by using a concatenation of-twocodings mentioned above. A part of the overall string will represent theabscissaofthecontrolvariablesandtherestofthestringwillrepresentthe rulespresentinthe rulebase.Fitnessiscalculatedasexplained above.

5		Illustratetheoperationalfeaturesandworkingprincipleoffuzzy ARTMAP	[L3][CO6]	**[12M]**

FUZZYARTMAP:ABRIEFINTRODUCTION

Fuzzy ARTMAP is an architecture which synthesizes fuzzy logic with adaptiveresonancetheory neuralnetworks.

Figure illustrates the architecture of fuzzy ARTMAP. The architecture comprisestwo ART modules, ART_a, and ART_b, that create stable recognition categories inresponse to arbitrary sequenceofinputpatterns.

During supervised learning, given a set of input patterns {a,b}, ART, receives astream(a)ofinputpatternsand ART, astreamof(BP).

These modules are linked by an associative learning network and an internalcontrollerthatensuresautonomoussystemoperation in realtime.

F^{ab} which is the inter-art module that links together ARTa, and ARTb, modulesand known as the map field gets triggered whenever one of the ART, or ART,categoriesisactive.

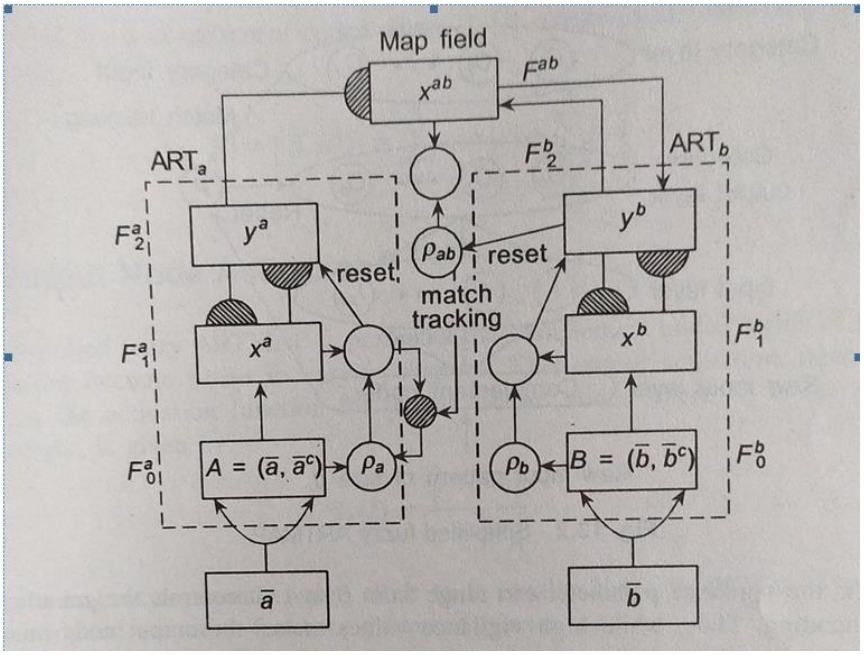


Figure.ArchitectureofFuzzyARTMAP

The complement coding processor in ARTa and ARTb, transforms the inputpatternsa andbintocomplementcodedinputpairsA={a,a)andB =((b,b)}respectively. FiandFireceiveA andBasinputs.

When a prediction made by ART, module is disconfirmed at ART, inhibition ofthe mapfieldactivationinducesthe matchtrackingprocess.Matchtracking raisesthe ART, vigilance Pa to just above Fi to Fa match ratio. This triggers an ART,search which results in the activation of either an ART, category that predicts bcorrectlyorto apreviouslyuncommitted ART,categorynode.

6		Witha neatArchitecture,explainFuzzyBackpropagationnetwork.	[L2][CO6]	**[12M]**

FUZZYBPARCHITECTURE

Fuzzy BP is a three layered feedforward architecture. The three layers are- **inputlayer, hidden layer, and output layer.** As in BPN, the functioning of fuzzy BPproceedsin two stages, namely

1. Learningor Training,and

2. Inference.

Consider a configuration of l - m - n (**I input neurons, m hidden neurons, andoutputneurons**)forthefuzzy BP model. Figure illustrates thearchitectureoffuzzy BP.

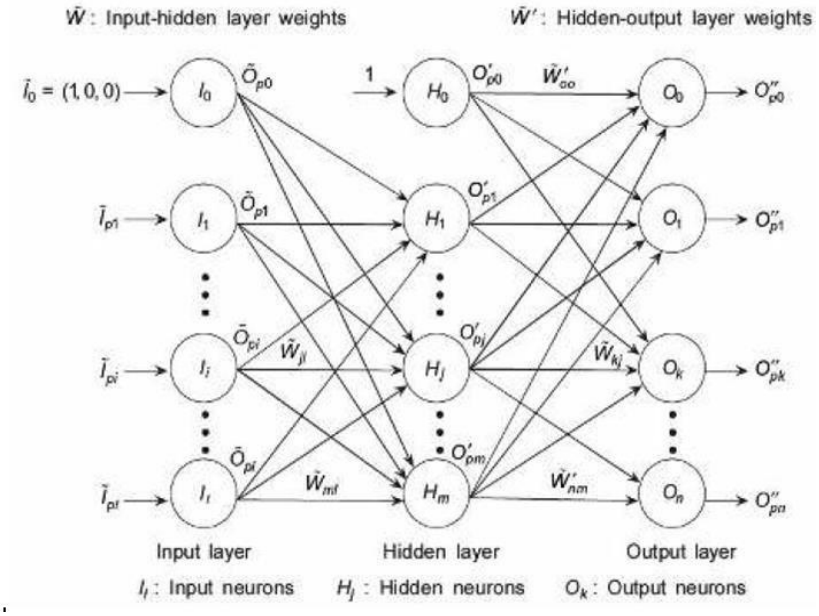


Fig.

Architecture ofFuzzyBP

Let $\tilde{I}_p = (\tilde{I}_{p1}, \tilde{I}_{p2}, \ldots, \tilde{I}_{pl})\ p = 1, 2, \ldots, N$ be the pth pattern among N input patterns that fuzzy BP needs to be trained, with $\tilde{I}_o = (1, 0, 0)$ as the bias.

Here, $\tilde{I}_{pi}$ indicates the ith input component of the input pattern p and is an LR-type triangular fuzzy number, i.e. $\tilde{I}_{pi} = (I_{pmi}, I_{p\alpha i}, I_{p\beta i})$. Let $\tilde{O}_{pi}$ be the output value of the ith input neuron, O'_{pj} and O''_{pk} are the jth and kth crisp defuzzification outputs of the hidden and output layer neurons respectively. $\tilde{W}_{ji}$ and $\tilde{W}_{kj}$ are the LR-type fuzzy connection weights between the ith input neuron and the jth hidden neuron, and the jth hidden neuron and kth output neuron respectively. In addition, CE and f are the sigmoidal and centroid functions as explained in Eqs. (12.9) and (12.10).

The computations carried out by each layer are:

$\tilde{W}_{kj}$

$$\tilde{O}_{pi} = \tilde{I}_{pi} = 1, 2, \ldots, l;\ \tilde{O}_{po} = (1, 0, 0)$$

$$O'_{pj} = f(NET_{pj}),\quad j = 1, 2, \ldots, m;\quad O'_{po} = 1$$

$$NET_{pj} = CE\left(\sum_{i=0}^{l} \tilde{W}_{ji}\tilde{O}_{pi}\right)$$

$$O''_{pk} = f(NET'_{pk}),\quad k = 0, 1, 2, \ldots, n-1$$

$$NET'_{pk} = CE\left(\sum_{j=0}^{m} \tilde{W}'_{kj}\, O'_{pj}\right)$$

7		Inferthe FuzzyLogicControllerwithneatarchitecture.	[L4][CO6]	**[12M]**
		FUZZYLOGICCONTROLLER SohandYang(1996).YangandSoh(2000)haveinvestigatedfuzzybasedstructural optimization using GA. Using the approach of Soh and Yang as seen afuzzy logic controller (FLC) a rule based system incorporating the flexibility ofhumandecision making isused forfuzzystructuraloptimization. Thefuzzyfunctionsareintendedtorepresentahumanexpert'sconceptionofthe linguisticterms,thusgivinganapproximationoftheconfidencewithwhichprecisenumericvalueisdescribed by alinguisticlabel.		

ComponentsofFuzzyLogicController(FLC)

AsshowninFig.,fuzzy logic controllerprocessisdividedintothree stages.

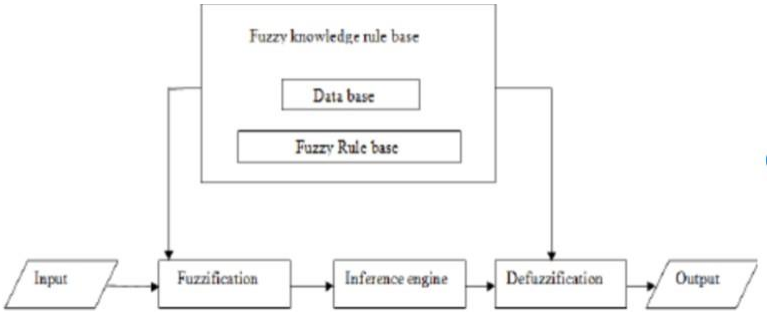


Fig:Frameworkforfuzzylogic controller

(a) **Fuzzificataion**-
Tocalculatefuzzyinput(i.e.toevaluatetheinputvariableswithrespecttocorrespondinglinguistic termsinthe conditionside).

(b) **Fuzzyinference**-Tocalculatefuzzyoutput(i.e.toevaluatetheactivationstrength ofevery rulebaseand combinetheiractionsides).

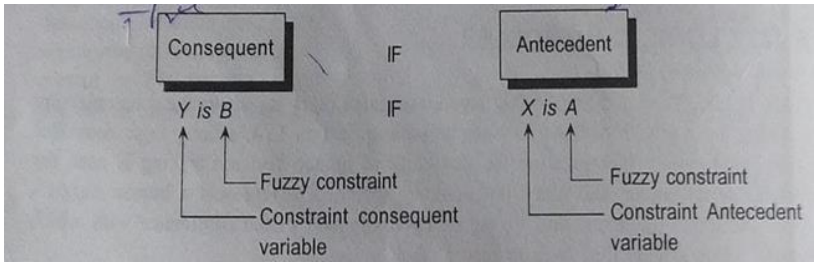
(c) **Defuzzificatio**n-
Tocalculatetheactualoutput(i.e.toconvertthefuzzyoutputintoprecisenumerical value).

FuzzyIF-THENRules

Fuzzy rules take the form IF (conditions) and THEN (actions), where conditionsand actions are linguistic variables, respectively. An example of Fuzzy IF-THENrule isgiven below.

- **Increaseinterestratesslightlyifunemploymentislowandinflationismoderate.**
- **Increaseinterestratessharplyifunemploymentislowandinflationis moderatebut rising sharply.**
- **Decreaseinterestratesslightlyifunemploymentislowbutincreasingandinflationrateislowandstable.**

TheprimaryformatofIF-THENrules isgivenin Fig.



FigformattofIFTHENrules

Example
Volume issmallifpressurehigh.
.

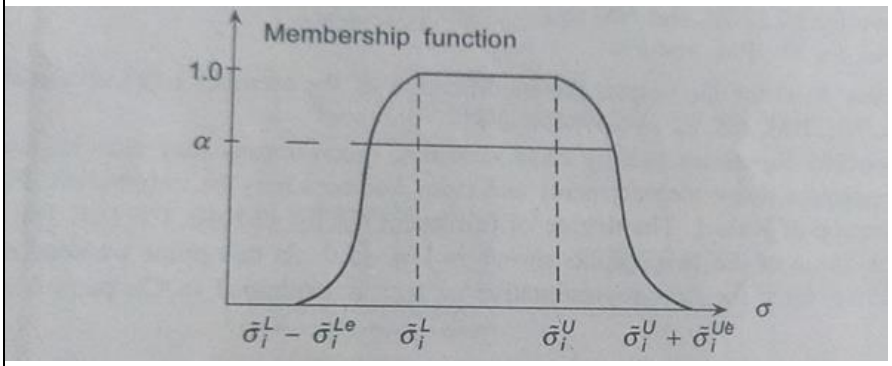
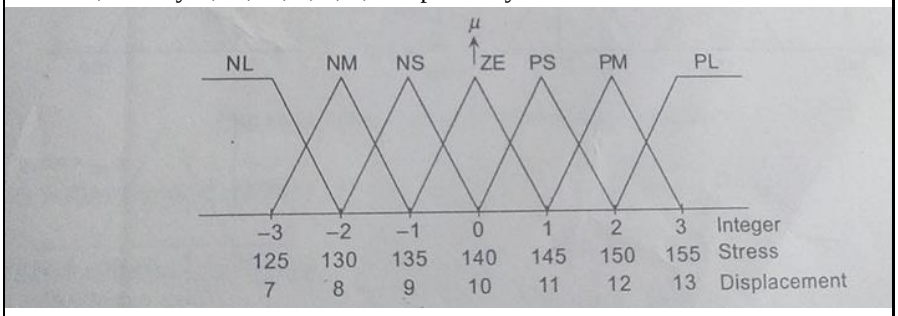
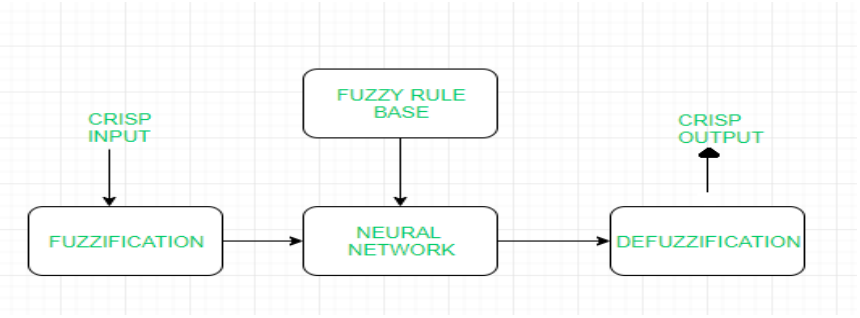
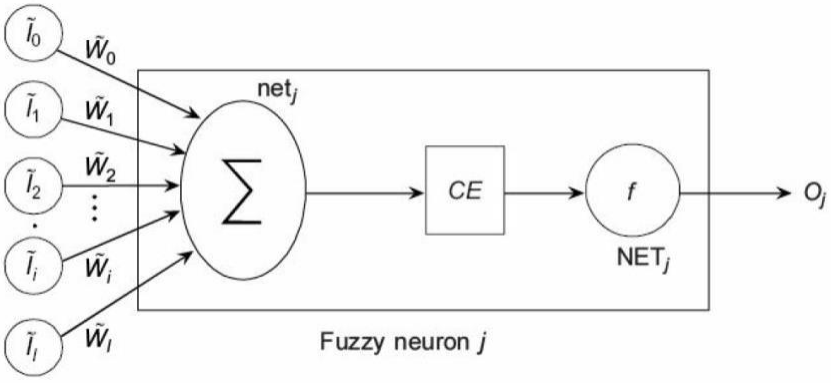


Fig.Fuzzyconstraintsforstress

Here, the symbol means fuzzy variable operator and a represents a series

oflinguisticvariablesthatmeans"veryverysmall","small","medium","large","verylarge",and"veryverylarge"andsoforth.AccordingtoZadeh(1987),the

		following seven fuzzy variables are usually in the study of structural optimizationas negative large (NL), negative medium (NM), negative small (NS), zero (ZE),positive small(PS),positivemedium(PM),andpositivelarge (PL). TheyaredefinedbythemembershipfunctionsasshowninFig.Fortheconvergence of implementation, seven fuzzy variables are assigned seven integerreference numbers, namely-3, -2, -1, 0, 1, 2, 3respectively.  Fig.Memebershipfunctionforfuzzyvariables		
8	a	ExplainGeneticAlgorithmbasedbackpropagationnetwork.	[L1][CO6]	**[5M]**
		GeneticAlgorithmbasedBackpropagationNetwork This is a Neuro-Genetic hybrid which makes use of GAs to determine the weightsofamultilayerfeedforwardnetwork with backpropagation learning. The GA based backpropagation though not guaranteed to obtain global optimumsolution,hasbeenfoundtoobtain"acceptablygood'solutions'acceptablyquickly.The hybrid system has been demonstrated on two problems, namely k-factordesignandelectricalload forecasting. **Fuzzy-BackpropagationNetwork** ThisisaNeuro-Fuzzyhybridsysteminwhichthe**hostisamultilayerfeedforward network** the network maps fuzzy input vectors to crisp outputsmakinguseofbackpropagation likelearning. The architecture has been applied to the problems of knowledge-based evaluationand earthquakedamageevaluation. **SimplifiedFuzzyARTMAP** Fuzzy ARTMAP (Carpenter et al., 1992) is a neuro-fuzzy hybrid in which **the hostisarecurrent networkwitha** kindof competitivelearningtermedadaptiveresonancetheorysimplifiedfuzzyARTMAP is avastsimplificationof fuzzyARTTMAP. **FuzzyAssociativeMemories** Fuzzy Associative Memory (FAM) is a neuro-fuzzy system with the hostarchitecture as a recurrent or a single layer network. FAMs map fuzzy sets andcan encode fuzzy rules. It is on account of this mapping capability that theybehave likeassociativememories. **FuzzyLogicControlledGeneticAlgorithms** Thisis aFuzzy-Genetic hybridsystemapplicableonfuzzyoptimizationproblems. The system obtains optimal solution to problems with fuzzyconstraints and fuzzy variables.		
	b	Illustrate neuro- fuzzyhybridsystemswithneatdiagram.	[L3][CO6]	**[7M]**
		Neuro-FuzzyHybridsystems: TheNeuro-fuzzysystemisbasedonfuzzysystemwhich istrainedon thebasisoftheworkingofneuralnetworktheory.Thelearningprocess operatesonly on thelocalinformationandcausesonlylocalchangesin the underlyingfuzzysystem.		

		A neuro-fuzzy system can be seen as a 3-layer feedforward neural network. Thefirst layer represents input variables, the middle (hidden) layer represents fuzzyrulesandthethirdlayerrepresentsoutputvariables. Fuzzy sets are encoded as connection weights within the layers of the network,whichprovidesfunctionalityinprocessingandtrainingthemodel.  **Workingflow**: • Intheinputlayer,eachneurontransmitsexternalcrispsignalsdirectlytothe nextlayer. • Each fuzzification neuron receives a crisp input and determines thedegreetowhichtheinputbelongstotheinputfuzzyset. • Thefuzzyrulelayerreceivesneuronsthatrepresentfuzzysets. • An output neuron combines all inputs using fuzzy operation UNION.Eachdefuzzificationneuronrepresentsthesingleoutputoftheneuro-fuzzysystem		
9		Summarizethefollowing i) FuzzyNeuron ii) Neuro-Genetic System	[L4][CO6] [L4][CO6]	**[4M]** **[8M]**
		i) FUZZYNEURON The fuzzy neuron is the basic element of the fuzzy BP model.Figureillustrates the architecture of the fuzzy neuron. Given the input vector (I)andweightvectorW, thefuzzy neuron computes the crispoutputgiven by  		

$$\tilde{I} = (\tilde{I}_0, \tilde{I}_1, \ldots, \tilde{I}_l)$$

$$\tilde{W} = (\tilde{W}_0, \tilde{W}_1, \ldots, \tilde{W}_l)$$

$$O = f(NET) = f\left(CE\left(\sum_{i=o}^{l} \tilde{W}_i \cdot \tilde{I}_i\right)\right)$$

$$\tilde{I}_0$$

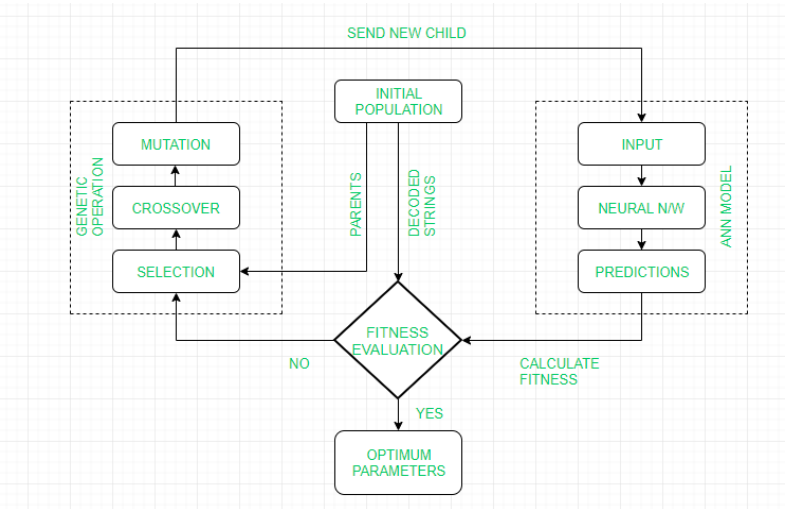
$$\tilde{net} = \sum_{i=0}^{l} \tilde{W}_i \cdot \tilde{I}_i$$

Fuzzy number $\tilde{I} = (\tilde{I}_0, \tilde{I}_1, \ldots, \tilde{I}_l)$ is the input vector and $\tilde{W} = (\tilde{W}_0, \tilde{W}_1, \ldots, \tilde{W}_l)$ is the fuzzy weight vector, where $\tilde{I}_0$ is the bias. The fuzzy weighted summation $\tilde{net} = \sum_j \tilde{W}_j \tilde{I}_j$ and the inference result $NET = CE(\tilde{net})$ are also shown in figure

i) Neuro-GeneticHybridSystem

A Neuro Genetic hybrid system is a system that combines **Neuralnetworks**:which arecapableto learn varioustasksfrom examples, classify objectsandestablishrelationsbetweenthem,anda

Geneticalgorithm:whichservesimportant search and optimization techniques. Genetic algorithms can be used toimprove the performance of Neural Networks and they can be used to decide theconnection weights of the inputs. These algorithms can also be used for topologyselection andtrainingnetworks.



WorkingFlow:

GA repeatedly modifies a population of individual solutions. GA uses threemain types of rules at each step to create the next generation from the currentpopulation:

- **Selection**toselecttheindividuals,calledparents,thatcontributetothe populationat thenextgeneration
- **Crossover**tocombinetwoparentstoformchildrenforthenextgenerat ion
- **Mutation**toapplyrandomchangestoindividualparentsinordertofor mchildren

- GAthensendsthenewchildgenerationtoANNmodelasanewinputparameter.

Finally,calculatingthefitnessbythedevelopedANNmodelisperformed.

10	**a**	**Explain variousSoftcomputingtools.**	[L2][CO6	**[6M]**

FuzzyLogic asaSoft ComputingTool

The realization of uncertainty, vagueness and ambiguity in the world has led to theconceptoffuzziness.

In the last three decades, significant progress has been made in the development offuzzysets, fuzzy logictheory, and theirusein engineering applications.

Thesuccessfulapplicationoffuzzysetsandfuzzylogiccanbeattributedtothe factthat fuzzy theory reflects the true situation in the real world, where human thinkingis dominated by approximate reasoning logic.

This is suited for applications where the ability to model real-world problems inprecise mathematicalformsisdifficult.

In a traditional optimization techniques, the constraints must strictly be satisfied.However, it is not reasonable to discard those designs that slightly violate one ormore constraintsduring theearlydesign stage.

Thesecomplexitiesanduncertaintiesencounteredintheoptimizationanddesignofreal structures provide the main motivation for the fuzzy integrated system. Hence,fuzzylogiccan beconsidered asasoft computing tool.

Genetic Algorithm asaSoftComputingTool

A system to be optimized is represented by a binary string which encodestheparameters ofthesystem.

A population of strings with initial random parameters is used. A numberof generations are simulated with operators representing the majorelements of evolution such as competition, fitness based selection,recombination,andmutation.Thewholeprocessis highlyrandom. However, the evolutionary process lead to filter individuals in thepopulationclosertosatisfyingtheobjectivefunctionoftheoptimizationpro blem.

Geneticalgorithmshave allthecharacteristicsofsoftcomputing.Themethodologyis highlyrobustand imprecisiontolerant.

If a unique optimum exists, the procedure approaches it through gradualimprovementof thefitnessandif theoptimumisnotunique,themethod willapproachone ofthe optimumsolutions.

b CompareNeuralProcessingandFuzzyProcessing [L5][CO6] **[6M]**

ComparisonofFuzzySystemswithNeuralNetworks*:*

Whenneuralnetworksareconcerned,ifoneproblemis expressedbysufficientnumberofobservedexamplesthenonlyitcanbeused.Theseo bservationsareused to train the black box. Though no prior knowledge about the problem isneeded extracting comprehensible rules from a neural network'sstructure isverydifficult.

A fuzzy system, on the other hand, does not need learning examples as priorknowledge,rather linguistic rules are required. Moreover, linguistic descriptionoftheinputandoutputvariablesshouldbegiven.Iftheknowledgeisinco mplete,wrong orcontradictory,then thefuzzy systemmustbetuned.This is a timeconsumingprocess.

Neuralprocessing	Fuzzyprocessing
Mathematicalmodelnotnecessary	Mathematicalmodelnotnecessary
Learningcan be donefromsearch	Aprioriknowledgeisneeded
There are several learningalgorithms	Learningisnotpossible
Black-box behavior	Simple interpretationand implementation

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