CHAPTER

3b

CHAPMAN HALL/CRC

Risk Analysis in Engineering and Economics

SYSTEM DEFINITION AND STRUCTURE

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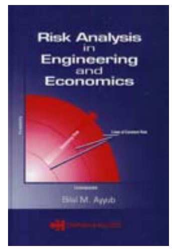

Risk Analysis for Engineering

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System Definition Models

- Bayesian Networks (cont'd)
  - Network Creation
    - Steps needed to create a Bayesian network:
      1. Create a set of variables representing the distinct key elements of the situation being modeled. Every variable in the real world situation is represented by a Bayesian variable. Each such variable describes a set of states that represent all possible distinct situations for the variable.
      2. For each such variable, define the set of outcomes or states that each can have. This set is referred to as mutually exclusive and collectively exhaustive outcomes. The set of outcomes must cover all possibilities for the variable, and that no important distinctions are shared between states. The causal

System Definition Models

relationships among the variables can be constructed by answering questions such as: (1) what other variables (if any) directly influence this variable; and (2) what other variables (if any) are directly influenced by this variable? In a standard Bayesian network, each variable is represented by an ellipse or squares or any other shape, called a node. A node is, therefore, a Bayesian variable.

3. Establish the causal dependency relationships among the variables. This step involves creating arcs leading from the parent variable to the child variable. Each causal influence relationship is described by an arc connecting the influencing variable to the influenced variable. The influence arc has a terminating arrowhead pointing to the influenced variable. An arc connects a parent (influencing) node to a child (influenced) node

System Definition Models

A directed acyclic graph (DAG) is desirable, in which only one semipath, i.e., sequence of connected nodes ignoring direction of the arcs, exists between any two nodes.

4. Assess the prior probabilities by supplying the model with numeric probabilities for each variable in light of the number of parents the variable was given in Step 3. Use conditional probabilities to represent dependencies as provided in Figure 12 for demonstration purposes. The figures also show the effect of arc reversal on the conditional probability representation. The first case show that X_2 and X_3 depend on X_1. The joint probability of the variables X_2, X_3, and X_1 can be computed using conditional probabilities based on these dependency as follows:

$$P(X_1, X_2, X_3) = P(X_3 \mid X_1) P(X_2 \mid X_1) P(X_1) \qquad (1)$$

System Definition Models

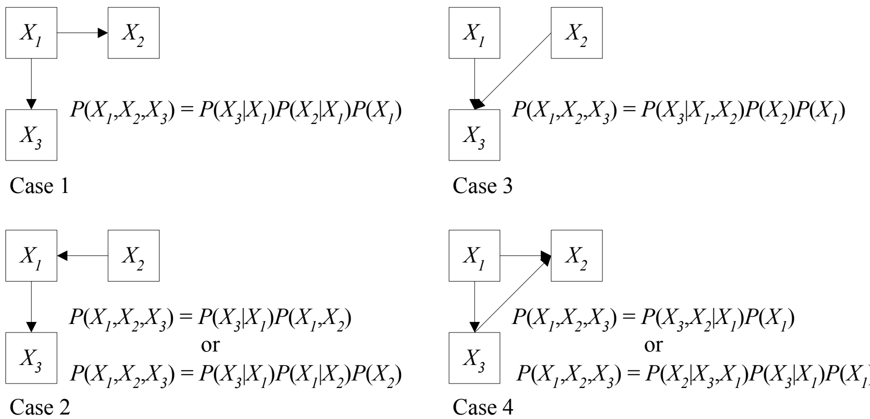


Figure 12. Conditional Probabilities for Representing Directed Arcs

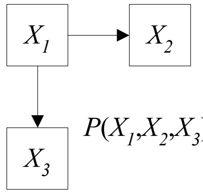
System Definition Models

The result for Case 1 is shown in Figure 12. Case two displays different dependencies of X_3 on X_1 and X_2 leading to the following expression for the joint probabilities as shown in Figure 12:

$$P(X_1, X_2, X_3) = P(X_3 \mid X_1, X_2)P(X_2)P(X_1) \qquad (2)$$

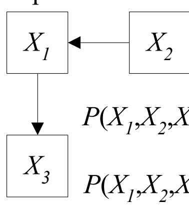
The models for Cases 3 and 4 are shown in Figure 12 and were constructed using the same approach. The reversal of arc changes the dependencies and conditional probability structure as illustrated in Figure 13. Bayesian tables and probability trees can be used to represent the dependencies among the variables. A Bayesian table is a tabulated representation of the dependencies, whereas a probability tree is a graphical representation of multi-level dependencies using directed arrows similar to Figure 12. The examples of the end of this section illustrate the use of Bayesian tables and probability trees for this purpose.

System Definition Models



$$P(X_1,X_2,X_3) = P(X_3|X_1)P(X_2|X_1)P(X_1)$$

Arc reversal leads to an equivalent representation as follows:



$$P(X_1,X_2,X_3) = P(X_3|X_1)P(X_1,X_2)$$

or

$$P(X_1,X_2,X_3) = P(X_3|X_1)P(X_1|X_2)P(X_2)$$

Figure 13. Arc Reversal and Effects on Conditional Probabilities

System Definition Models

5. Bayesian methods can be used to update the probabilities based on information gained as demonstrated in subsequent examples. By fusing and propagating values of new evidence and beliefs through Bayesian networks, each proposition eventually is assigned a certainty measure consistent with the axioms of probability theory. The impact of each new piece of evidence is viewed as a perturbation that propagates through the network via message-passing between neighboring variables.

System Definition Models

- Example 5: Bayesian Tables for Two Dependent Variables *A* and *B*
  - In this example, variable *B* affects *A*. The computations of the probability of *B* for two cases of given *A* occurrence, and given $\overline{A}$ occurrence can be represented using a Bayesian table, respectively as follows:

Variable A	Probability of	
A	$P(A\|B) = 0.95$	$P(A\|\overline{B}) = 0.01$
$\overline{A}$	$P(\overline{A}\|B) = 0.05$	$P(\overline{A}\|\overline{B}) = 0.99$

System Definition Models

- Example 5 (cont'd): Bayesian Tables for Two Dependent Variables *A* and *B*
  - For the case of given the occurrence of *A*,

Prior probability of Variable B		Conditional probabilities of variables A & B		Joint Probabilities of variables A & B		Posterior Probability of variable B after variable A has occurred	
$P(B) =$	0.0001	$P(A\|B) =$	0.95	$P(B)\,P(A\|B)$	0.000095	$P(B\|A) = P(B)\,P(A\|B)/P(A) =$	0.009412
$P(\overline{B}) =$	0.9999	$P(A\|\overline{B}) =$	0.01	$P(\overline{B})\,P(A\|\overline{B})$	0.009999	$P(\overline{B}\|A) = P(\overline{B})\,P(A\|\overline{B})/P(A) =$	0.990588
Total	1.0000			$P(A) =$	0.010094	$P(B\|A)+P(\overline{B}\|A) =$	1.000000

System Definition Models

- Example 5 (cont'd): Bayesian Tables for Two Dependent Variables *A* and *B*
  - For the case of given the occurrence of $\overline{A}$,

Prior probability of Variable B		Conditional probabilities of variables A & B		Joint Probabilities of variables A & B		Posterior Probability of variable B after variable A has occurred	
$P(B) =$	0.0001	$P(\overline{A}\|B) =$	0.05	$P(B)\ P(\overline{A}\|B)$	0.000005	$P(B\|\overline{A}) = P(B) \text{ x } P(\overline{A}\|B)/P(\overline{A})$	0.000005
$P(\overline{B}) =$	0.9999	$P(\overline{A}\|\overline{B}) =$	0.99	$P(\overline{B})\ P(\overline{A}\|\overline{B})$	0.989901	$P(\overline{B}\|\overline{A}) = P(\overline{B})\ P(\overline{A}\|\overline{B})/P(\overline{A})$	0.999995
Total	1.0000			$P(\overline{A}) =$	0.989906	Total $P(B\|\overline{A})+P(\overline{B}\|\overline{A}) =$	1.000000

It can be noted that Total $P(A)+P(\overline{A}) = 1$

System Definition Models

- Example 6: Probability Trees for Two Dependent Variables *A* and *B*
  - Probability trees can be used to express the relationships of dependency among random variables.
  - The Bayesian problem of Example 5 can be used to illustrate the use of probability trees.
  - The probability tree for the two cases of Example 5 is shown in Figure 14.

System Definition Models

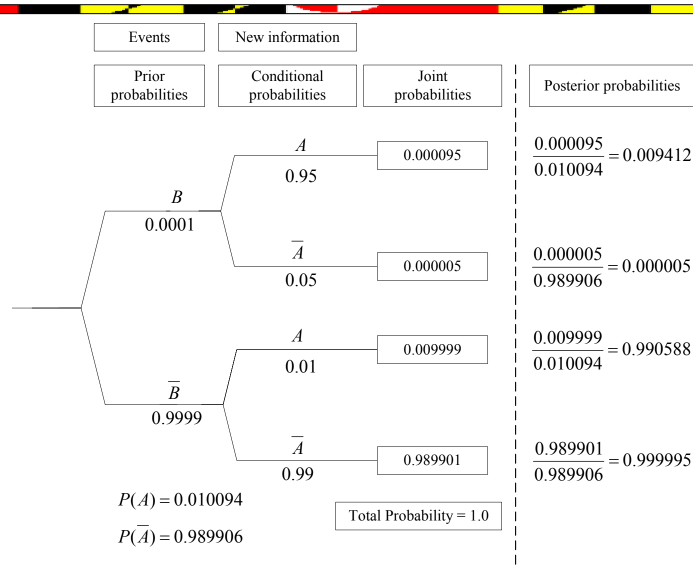


Figure 14. Probability-Tree Representation of a Bayesian Model

System Definition Models

- Example 7: Bayesian Network for Diagnostic Analysis
  - A Bayesian network can be used to represent a knowledge structure that models the relationships among possible medical difficulties, their causes and effects, patient information, and diagnostic tests results.
  - Figure 15 provides simplified schematics of these dependencies.

System Definition Models

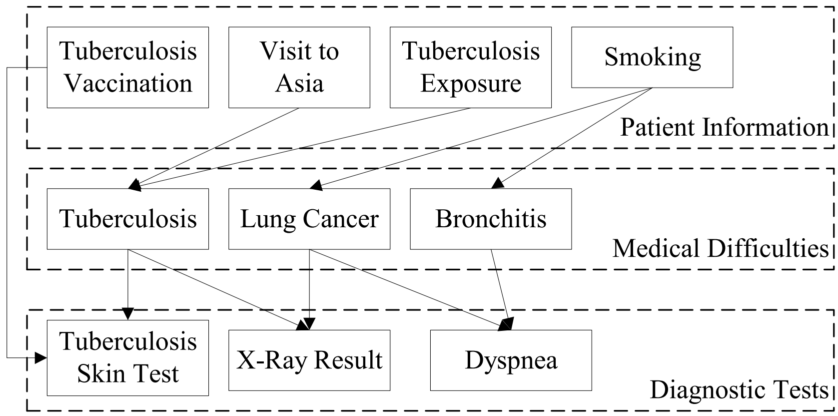


Figure 15. A Bayesian Network For Diagnostic Analysis of Medical Tests

System Definition Models

- Example 7 (cont'd): Bayesian Network for Diagnostic Analysis
  - The problem can be simplified by eliminating the tuberculosis vaccination and exposure boxes, and tuberculosis skin test box.
  - The probabilities of having dyspnea are given by the following values:

		Probability of Dyspnea	
Tuberculosis or Cancer	Bronchitis	Present	Absent
True	Present	0.9	0.1
True	Absent	0.7	0.3
False	Present	0.8	0.2
False	Absent	0.1	0.9

System Definition Models

- Example 7 (cont'd): Bayesian Network for Diagnostic Analysis
  - The true and false states in the first column are constructed from the following logic table:

Tuberculosis	Lung Cancer	Tuberculosis or Cancer
Present	Present	True
Present	Absent	True
Absent	Present	True
Absent	Absent	False

  - The unconditional or marginal probability distribution functions are frequently called the belief function of the nodes as shown in Figure 16a

System Definition Models

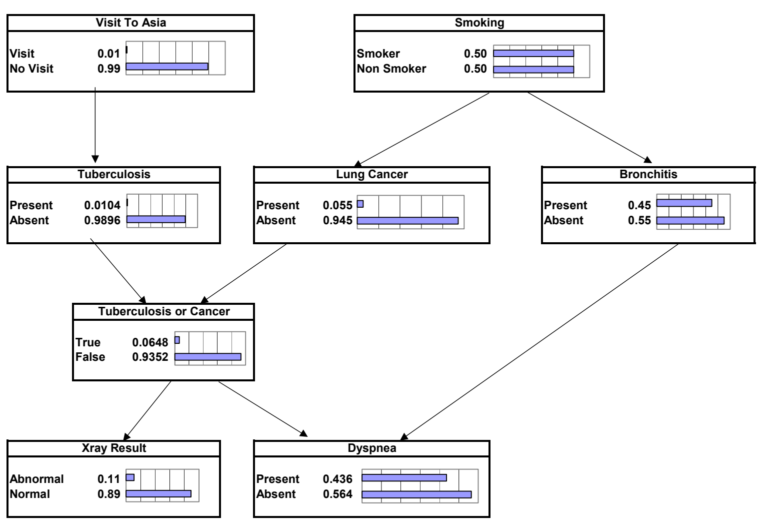


Figure 16a. Propagation of Probabilities in Percentages in a Bayesian Network

System Definition Models

- Example 7 (cont'd): Bayesian Network for Diagnostic Analysis
  - A simple computational example is used herein to illustrate the use of Bayesian methods to update probabilities for a case of two variables *A* and *B* with a directed arrow from *B* to *A*. indicating that *B* affect *A*. A priori probability of *B* is 0.0001. The conditional probability of *A* given *B*, denoted as P(*A*|*B*) is given by the adjacent table based on previous experiences.

	Conditional Probability of Events Related to the Variable *A* Given the Following:	
Variable *A*	B	$\overline{B}$
A	0.95	0.01
$\overline{A}$	0.05	0.99

System Definition Models

- Example 7 (cont'd): Bayesian Network for Diagnostic Analysis
  - The P(*B*|*A*) is of interest and can be computed as

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A)} \qquad (3)$$

  - The term P(A) in Eq. 3 can be computed based on the complement of *B* as follows:

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A \mid B)P(B) + P(A \mid \overline{B})P(\overline{B})} \qquad (4)$$

System Definition Models

- <u>Example 7 (cont'd):</u> Bayesian Network for Diagnostic Analysis
  - Substituting the probabilities from the table above, the following conditional probability can be computed:

$$P(B \mid A) = \frac{(0.95)(0.0001)}{(0.95)(0.0001) + (0.01)(1 - 0.0001)} = 0.009411 \quad (5)$$

  - A propagation algorithm can be used to update the beliefs attached to each relevant node in the network.
  - Interviewing a patient produces the information for the box of visiting Asia to certainty (100%) as shown in Figure 16b.

System Definition Models

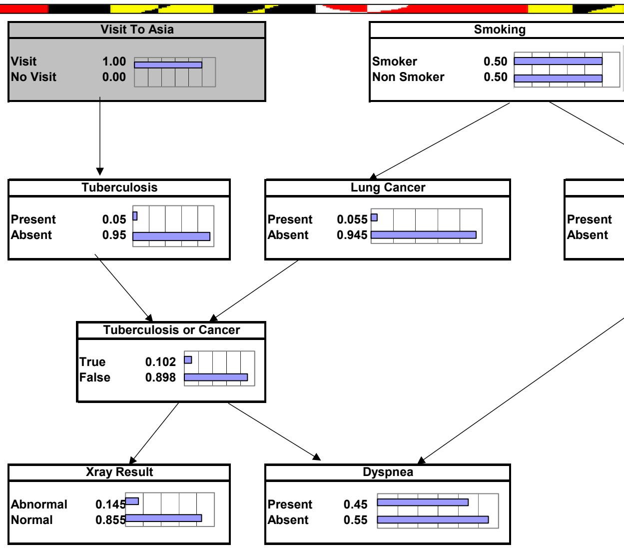


Figure 16b. Updating Probabilities Based on Visit to Asia

System Definition Models

- <u>Example 7 (cont'd):</u> Bayesian Network for Diagnostic Analysis
  - Such a finding propagates through the network, and the belief functions of several nodes are updated.
  - Further updates can be made based on knowing the patients to be a smoker, and based on test results of X-ray and dyspnea as shown in Figures 16c, 16d, and 16e, respectively.

System Definition Models

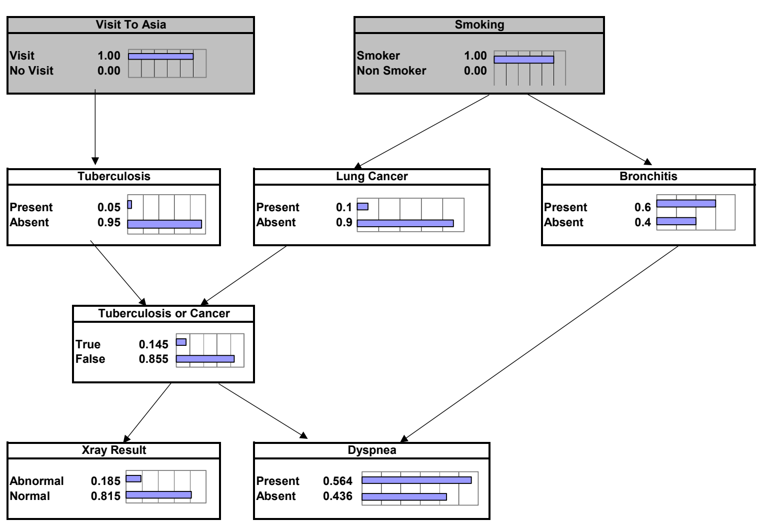


Figure 16c. Updating Probabilities Based on Visit to Asia and Smoking

System Definition Models

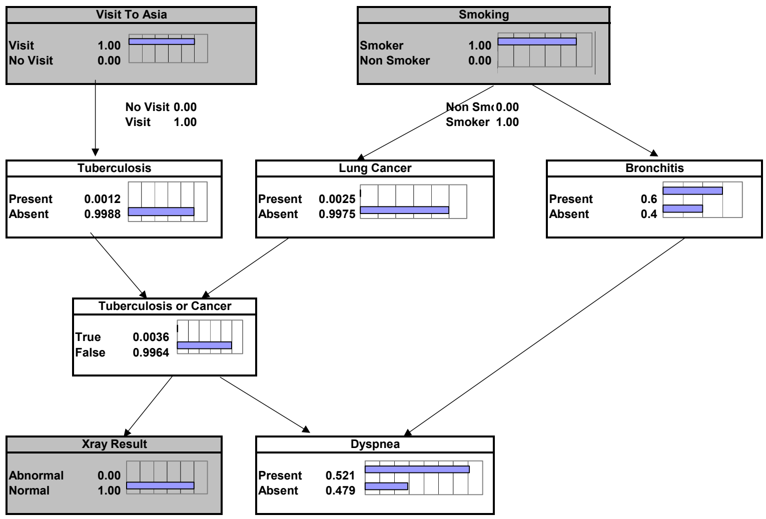


Figure 16d. Updating Probabilities Based on Visit to Asia, Smoking, and X-Ray Results

System Definition Models

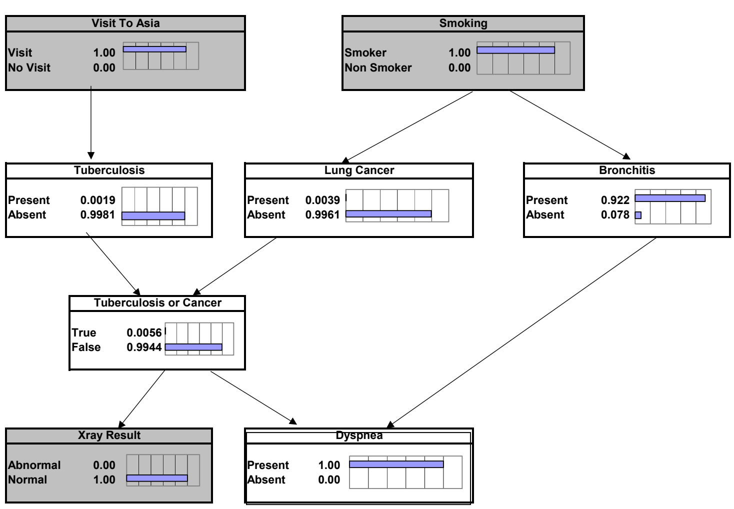


Figure 16e. Updating Probabilities Based on Visit to Asia, Smoking, X-Ray Results, and Dyspnea Results

System Definition Models

- Example 7 (cont'd): Bayesian Network for Diagnostic Analysis
  - The Bayesian table can be used to model a portion of the Bayesian network of this example.
  - The visit to Asia block can be denoted as variable *V* and that the tuberculosis block as variable *T*.
  - Using the conditional probabilities $P(T|V) = 0.05$ and $P(T|\overline{V}) = 0.01$, the Bayesian table can then be constructed for the first directed arrow of Figure 16a from *V* to *T* as follows:

System Definition Models

- Example 7 (cont'd): Bayesian Network for Diagnostic Analysis
  - For the case of given the occurrence of *V*, i.e., occurrence of a visit,

Prior probability of Variable *V*		Conditional probabilities of variables *T* & *V*		Joint Probabilities of variables *T* & *V*		Posterior Probability of variable *V* after variable *T* has occurred	
$P(V) =$	0.0100	$P(T\|V) =$	0.05	$P(V)\ P(T\|V)$	0.0005	$P(V\|T) = P(V)\ P(T\|V)/P(T) =$	0.04808
$P(\overline{V}) =$	0.9900	$P(T\|\overline{V}) =$	0.01	$P(\overline{V})\ P(T\|\overline{V})$	0.0099	$P(\overline{V}\|T) = P(\overline{V})\ P(T\|\overline{V})/P(T) =$	0.95192
Total	1.0000			$P(T) =$	0.0104	$P(V\|T)+P(\overline{V}\|T) =$	1.00000

  - The probability tree for these two cases is shown in Figure 17.

System Definition Models

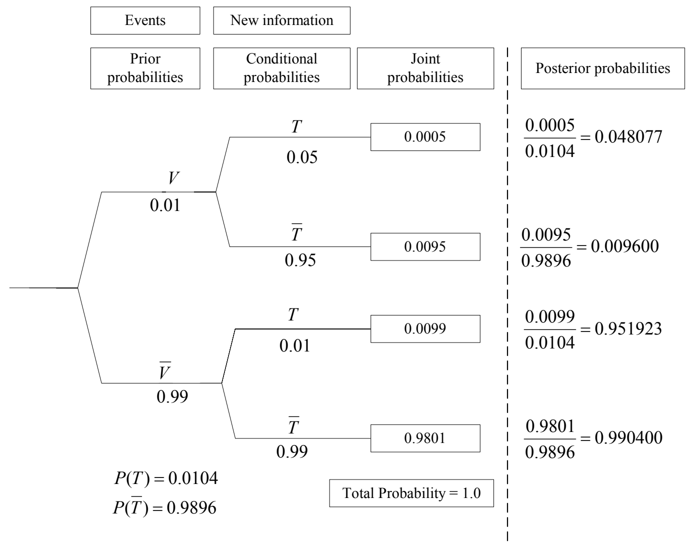


Figure 17. Probability-Tree Representation of a Diagnostic Analysis Problem

System Definition Models

- Example 7 (cont'd): Bayesian Network for Diagnostic Analysis
  - Similar treatments can be developed for all the relationships, i.e., directed arrows, of Figure 16a using the following summary of conditional probabilities based on these arrows:

Note: These conditional probabilities can be used to construct the rest of Figure 16a. Figures 16b to 16e can be constructed using similar process involving trial and error to obtain set consequent results in some cases

System Definition Models

- <u>Example 7 (cont'd):</u> Bayesian Network for Diagnostic Analysis

Event Affected	Causal event(s) or condition(s)	Conditional Probability
Tuberculosis (*T*)	Visit to Asia (*V*)	0.05
Tuberculosis (*T*)	Did not Visit to Asia ($\overline{V}$)	0.01
Lung cancer (*L*)	Smoker (*S*)	0.10
Lung cancer (*L*)	Nonsmoker ($\overline{S}$)	0.01
Bronchitis (*B*)	Smoker (*S*)	0.60
Bronchitis (*B*)	Nonsmoker ($\overline{S}$)	0.30
Positive X-ray (*X*)	Tuberculosis or Cancer (*TC*)	0.04906
Positive X-ray (*X*)	No Tuberculosis Nor Cancer ($\overline{TC}$)	0.98911
Dyspnea (*D*)	*B* and *TC*	0.90
Dyspnea (*D*)	*B* and $\overline{TC}$	0.70
Dyspnea (*D*)	$\overline{B}$ and *TC*	0.80
Dyspnea (*D*)	$\overline{B}$ and $\overline{TC}$	0.10

System Definition Models

- <u>Example 8:</u> Bayesian Tables for Identifying Defective Electric Components
  - A batch of 1000 electric components were produced in a week at a factory, and was found after excessive and time-consuming tests, that 30% of them are defective and 70% are non-defective. Unfortunately, all components are mixed together in a large container.
  - Selecting at random a component from the container has a non-defective prior probability of 0.7.

System Definition Models

- Example 8 (cont'd): Bayesian Tables for Identifying Defective Electric Components
  - The objective of the company herein is to screen all the components to identify the defective components.
  - A quick test on each component can be used for this screening.
  - This test has a detection probability of a non-defective component of 0.8, and a detection probability of a defective component of 0.9.

System Definition Models

- Example 8 (cont'd): Bayesian Tables for Identifying Defective Electric Components
  - The prior probabilities need to be updated using the probabilities associated with this quick test.
  - The Bayesian tables can be constructed based on the following definition of variables:

Component is non-defective = B

Component is defective = $\overline{B}$

Component passing the quick test = A

Component not passing the quick test = $\overline{A}$

System Definition Models

- Example 8 (cont'd): Bayesian Tables for Identifying Defective Electric Components
  - The Bayesian tables can then be constructed for two cases as follows:
    - For the case of given the occurrence of A,

Prior probability of Variable B		Conditional probabilities of variables A & B		Joint Probabilities of variables A & B		Posterior Probability of variable B after variable A has occurred	
$P(B)=$	0.0700	$P(A\|B)=$	0.80	$P(B)\,P(A\|B)$	0.560000	$P(B\|A)=P(B)\,P(A\|B)/P(A)=$	0.949153
$P(\bar{B})=$	0.3000	$P(A\|\bar{B})=$	0.10	$P(\bar{B})\,P(A\|\bar{B})$	0.030000	$P(\bar{B}\|A)=P(\bar{B})\,P(A\|\bar{B})/P(A)=$	0.050847
Total	1.0000			$P(A)=$	0.590000	$P(B\|A)+P(\bar{B}\|A)=$	1.000000

System Definition Models

- Example 8 (cont'd): Bayesian Tables for Identifying Defective Electric Components
    - For the case of given the occurrence of $\bar{A}$,

Prior probability of Variable B		Conditional probabilities of variables A & B		Joint Probabilities of variables A & B		Posterior Probability of variable B after variable A has occurred	
$P(B)=$	0.7000	$P(\bar{A}\|B)=$	0.200	$P(B)\,P(\bar{A}\|B)$	0.140000	$P(B\|\bar{A})=P(B)\times P(\bar{A}\|B)/P(\bar{A})$	0.341463
$P(\bar{B})=$	0.3000	$P(\bar{A}\|\bar{B})=$	1.900	$P(\bar{B})\,P(\bar{A}\|\bar{B})$	0.270000	$P(\bar{B}\|\bar{A})=P(\bar{B})\,P(\bar{A}\|\bar{B})/P(\bar{A})$	0.658537
Total	1.0000			$P(\bar{A})=$	0.410000	Total $P(B\|\bar{A})+P(\bar{B}\|\bar{A})=$	1.000000

It can be noted that Total $P(A)+P(\bar{A}) = 1$

System Definition Models

- Example 8 (cont'd): Bayesian Tables for Identifying Defective Electric Components
  - Figure 18 shows the probability tree for this decision situation.
  - It also shows the conditional probabilities obtained from the information of the test.
  - The probability that a component is non-defective and fails the test can be computed as the joint probability by applying the multiplication rule as follows:

P (non-defective and failing the test) = 0.7 (0.2) = 0.14

System Definition Models

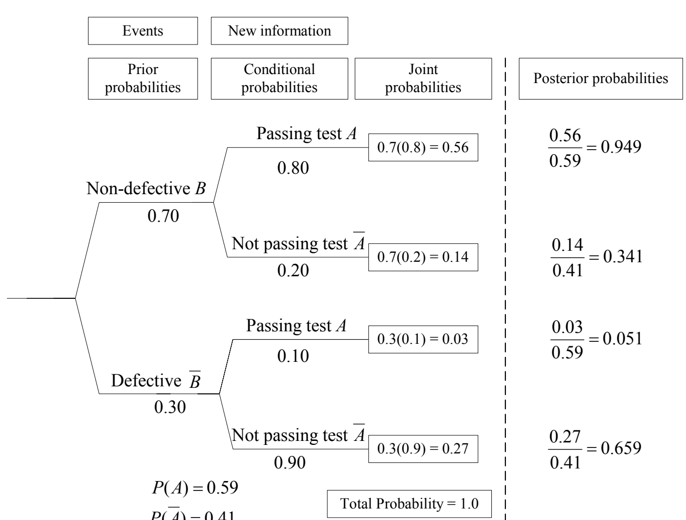


Figure 18. Probability-Tree Representation of a Defective Electric Components Problem

System Definition Models

- Example 8 (cont'd): Bayesian Tables for Identifying Defective Electric Components
  - The probability that a component is defective and fails the test is

    P (defective and failing the test) = 0.3 (0.9) = 0.27

  - Therefore, a component can fail the test in two cases of being non-defective and being defective. The probability of failing the test can then be computed by adding the two joint probabilities as follows

    P (failing the test) = 0.14 + 0.37 = 0.41

System Definition Models

- Example 8 (cont'd): Bayesian Tables for Identifying Defective Electric Components
  - Hence, the probability of the component passing the test can be computed as the probability of the complementary event as follows:

    P (passing the test) = 0.56 + 0.03 = 0.59

  - The posterior probability can be determined by dividing the appropriate joint probability by respective probability values.

System Definition Models

- Example 8 (cont'd): Bayesian Tables for Identifying Defective Electric Components
  - For example to determine the posterior probability that the component is non-defective, the joint probability that comes from the tree branch of a non-defective component of 0.14 can be used as follows:

  Posterior P (component non-defective) = 0.14/0.41 = 0.341

  - All other posterior probabilities on the tree are calculated similarly. The posterior probabilities of non-defective component defective component must add up to one, i.e., 0.341+0.659=1

System Definition Models

- Process Modeling Methods
  - The definition of a system can be viewed as a process that emphasizes an attribute of the system.
  - Example Processes:
    - Engineering systems as products to meet user demand.
    - Engineering systems with lifecycles.
    - Engineering systems defined by a technical maturity process.

System Definition Models

- Process Modeling Methods (cont'd)
  - System Engineering Process
    - The system engineering process focuses on the interaction between human and the environment.
    - The steps involved in a system engineering process can be viewed to constitute a spiral hierarchy.
    - A system engineering process has the following steps as shown in Figure 19:
      1. Recognition of need or opportunity.
      2. Identification and qualification of the goal, objectives, and performance and functional requirements.

System Definition Models

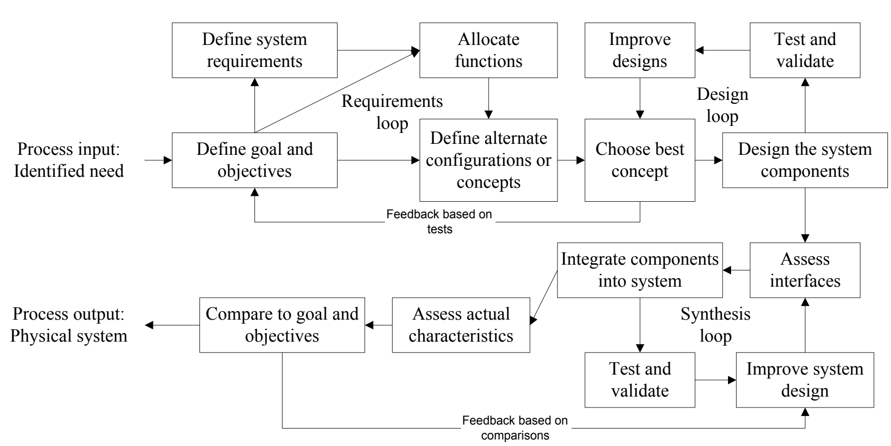


Figure 19. System Engineering Process

System Definition Models

- Process Modeling Methods (cont'd)
  - System Engineering Process
    3. Creation of alternative design concepts.
    4. Testing and validation.
    5. Performance of tradeoff studies and selection of a design.
    6. Development of a detailed design.
    7. Implementing the selected design decisions.
    8. Performance of missions.

System Definition Models

- Process Modeling Methods (cont'd)
  - Lifecycle of Engineering Systems
    - Engineering products can be treated as systems that have a lifecycles.
    - A generic lifecycle of a system begins with initial identification of a need and extends through
      - Planning
      - Research
      - Design
      - Production or Construction
      - Evaluation
      - Consumer use
      - Field support
      - Product phase (out or disposal)

System Definition Models

- Process Modeling Methods (cont'd)
  - Lifecycle of Engineering Systems

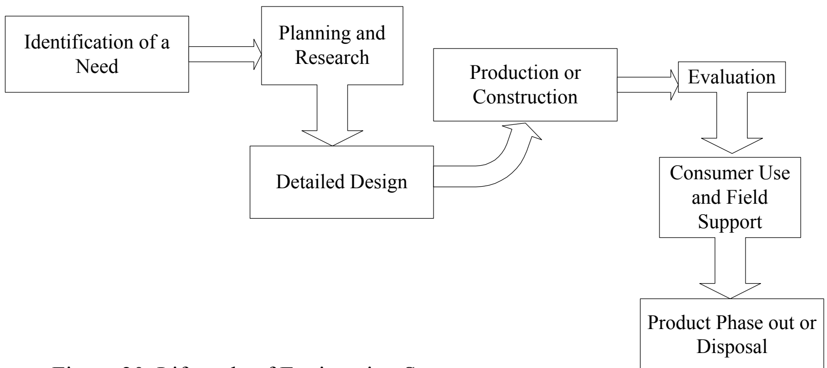


Figure 20. Lifecycle of Engineering Systems

System Definition Models

Table 1

System Lifecycles Phases	Consumer-to-Consumer Cycle Phases	Activities
Identification of Need	Consumer	"Wants or desires" for systems because of obvious deficiencies/problems or made evident through basic research results.
System Planning Function	Producer	Marketing analysis; feasibility study; advanced system planning through system selection, specifications and plans, acquisition plan research/design/ production, evaluation plan, system use and logistic support plan; planning review; proposal.
System Research Function		Basic research; applied research based on needs; research methods; results of research; evolution from basic research to system design and development.
System Design Function		Design requirements; conceptual design; preliminary system design; detailed design; design support; engineering model/prototype development; transition from design to production.
Production and/or Construction Function		Production and/or construction requirements; industrial engineering and operations analysis such as plant engineering, manufacturing engineering, methods engineering, and production control; quality control; production operations.
System Evaluation Function	Consumer	Evaluation requirements; categories of test and evaluation; test preparation phase including planning and resource requirements; formal test and evaluation; data collection, analysis, reporting, and corrective action; re-testing.
System Use and Logistic Support Function		System distribution and operational use; elements of logistics and lifecycle maintenance support; system evaluation. Modifications, product phase-out; material disposal, reclamation, and recycling.

System Definition Models

- Example 9: Lifecycle of NASA Engineering Systems
  - The NASA model can generally be defined to include the following phases:
    - Pre-phase A. Advanced Studies
    - Phase A. Conceptual Design Studies
    - Phase B. Concept Definition
    - Phase C. Design and Development
    - Phase D. Fabrication, Integration, Test and Certification
    - Phase E. Pre-Operations
    - Phase F. Operations and Disposal

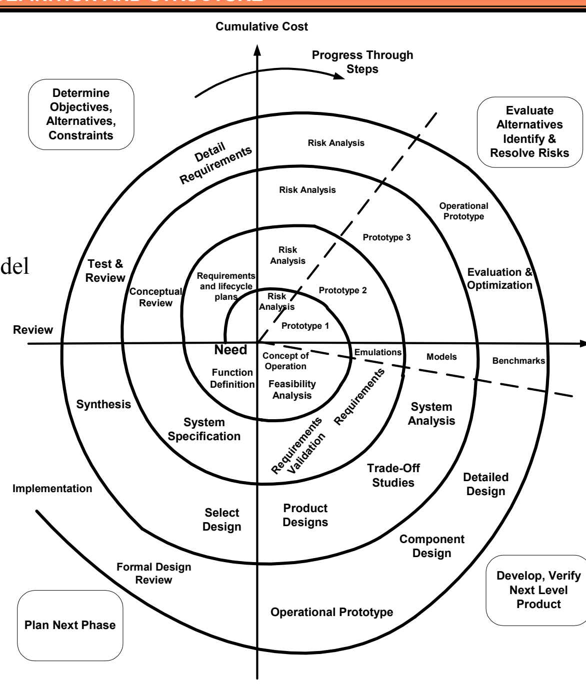
System Definition Models

- Process Modeling Methods (cont'd)
  - Technical Maturity Model
    - The technical maturity model is another view of the lifecycle of a project.
    - According to this model, the lifecycle considers a program as an interaction between society and engineering.
    - The model concentrates on the engineering aspects of the program and not on the technology development through research.
    - The program must come to fruition by meeting both the needs of the customer and also meeting the technical requirements.

System Definition Models

- Process Modeling Methods (cont'd)
  - Spiral Development Process
    - A product or a system can be developed using a spiral process as shown in Figure 21.
    - Spiral development is used for designing marine, aerospace, and other advanced systems.
    - Figure 21 shows similar phases to what was included in previously presented process modeling methods in this chapter with an added spiral organization and risk review and analysis at various levels of development.

Figure 21.
Spiral Development Model



System Definition Models

- Black-Box Method
  - Historically, engineers have built analytical models to represent natural and human-made systems using empirical tools of observing system attributes of interest (called system output variables) and trying to relate them to some other controllable or uncontrollable input variables.
  - For example, a structural engineer might observe the deflection of a bridge as an output of an input such as a load at middle of its span.

System Definition Models

- Black-Box Method (cont'd)
  - By varying the intensity of the load, the deflection changes.
  - Empirical test methods would vary the load incrementally and the corresponding deflections are measured, thereby producing a relationship such as

$$y = f(x) \qquad (6)$$

x = input variable
y = output variable
f = a function that relates input to output

System Definition Models

- Black-Box Method (cont'd)
  – In general, a system might have several input variables that can be represented as a vector ***X***, and several output variables that can be represented by a vector ***Y***.

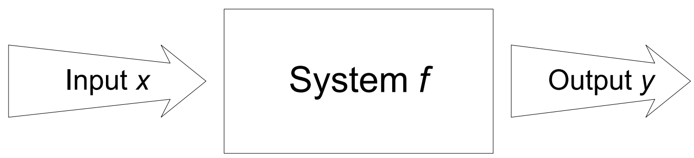


Figure 22. Black-Box System Model

System Definition Models

- Black-Box Method (cont'd)
  - Knowledge of the physics of the system helps.
  - The analyst needs to decide on the nature of the time relation between input and output by addressing questions such as
    – Is the output instantaneous as a result of the input?
    – If the output lags behind the input, what is the lag time? Are the lag times for the input and output related, e.g., exhibiting nonlinear behavior?
    – Does the function f depend on time, number of input applications, or magnitude of input?
    – Does the input produce an output, and linger within the system affecting future outputs?

System Definition Models

- <u>Example 10:</u> Probable Maximum Flood
  - Dams classified according to their
    - Size
    - Hazard
  - Dam Sizes
    - Small dams: 25 to 40 ft high
    - Intermediate dams: 40 to 100 ft high
    - Large dams are over 100 ft high
  - Low hazard dams are those for which failure of the dam would result in no loss of life and minimal economic loss.

System Definition Models

- <u>Example 10 (cont'd):</u> Probable Maximum Flood
  - A significant hazard is one that would cause a few losses of life and appreciable economic loss.

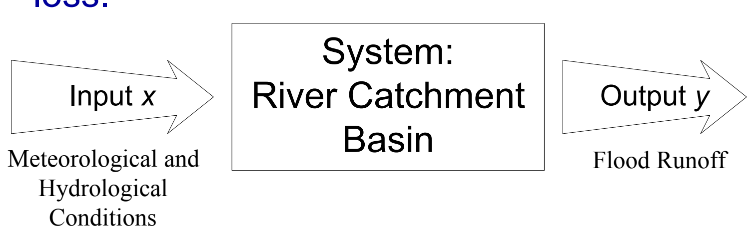


Figure 22. Lifecycle of Engineering Systems

System Definition Models

- Example 10 (cont'd): Probable Maximum Flood
  - A high hazard would result in the loss of more than a few lives and excessive economic loss.
  - Three methods used by USACE for determining extreme floods:
    - Frequency Analyses (small dams with significant hazard)
    - Standard Project Flood, SPF (some risk can be tolerated)
    - Probable Maximum Flood, PMF (high hazard and substantial reduction in risk)

System Definition Models

- State-based Method
  - A convenient modeling method of systems can be based on identifying state variables that would be monitored either continuously or at discrete times.
  - The values of these state variables over time provide a description of the needed model of a system.
  - The state variables should be selected such that each one provides unique information.
  - Redundant state variables are not desirable.

System Definition Models

- State-based Method (cont'd)
  - The challenge faced by system engineers is to identify the minimum number of state variables that would accurately represent the behavior of the system over time.
  - Components of the a system can have two possible states: *a functional state* or failed state.
  - In general, component models can have more than two states.
  - Such models provide the tools necessary to model repairable systems.

System Definition Models

- State-based Method (cont'd)
  - Example:
    - A method used to develop reliability models is the ***state-space method for system reliability evaluation.***
  - According to this method, a system is described by its state and by the possible transitions between these states.
  - The system states and the possible transitions are illustrated by a *state-space diagram* (Markov diagram). See Figure 24

System Definition Models

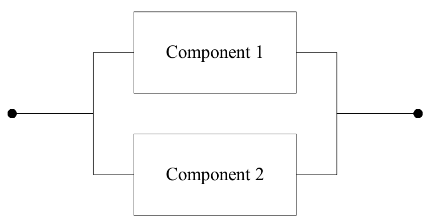


Figure 24a.
A Two-Component in Parallel System

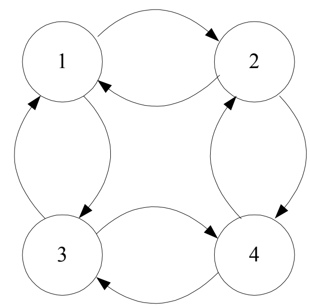


Figure 24b.
State Space Diagram for the Parallel System

System Definition Models

- State-based Method (cont'd)
  - The various states of the system can be defined as the combination of all possible states as summarized in the table

System State According to Figure 3-24b	State of Component 1 of Figure 3-24a	State of Component 2 of Figure 3-24a	Description of the State of the System
1	Functioning	Functioning	System survival based on both components functioning.
2	Failed	Functioning	System survival based on one component functioning and one component failed.
3	Functioning	Failed	System survival based on one component functioning and one component failed.
4	Failed	Failed	System failure based on both components failed.

System Definition Models

- Example 11: Markov Modeling of Repairable Systems
  - Repairable systems can be assumed for the purpose of demonstration to exit in either a normal, i.e., operating, state, or failed state as shown in Figure 25.
  - A system in a normal state makes transitions to either normal states that are governed by its reliability level, i.e., it continues to be normal; or to the failed states through failure.

System Definition Models

- Example 11 (cont'd): Markov Modeling of Repairable Systems

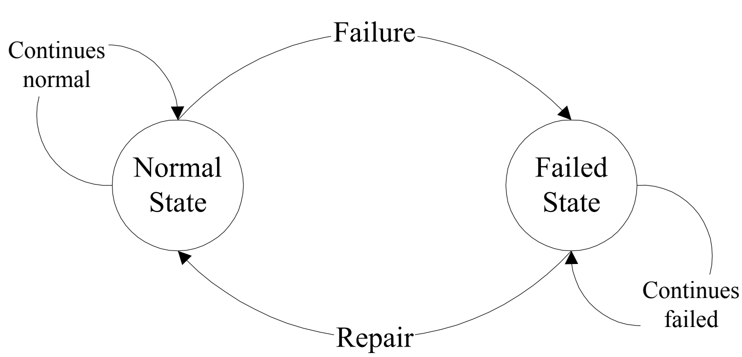


Figure 25. A Markov Transition Diagram for Repairable Systems

System Definition Models

- Example 11 (cont'd): Markov Modeling of Repairable Systems
  - Once it is in a failed state, the system makes transitions to either failed states that are governed by its repairable-ease level, i.e., it continues to be failed; or to the normal states through repair.
  - Four transition probabilities are needed for the following cases:
    - Normal-to-normal state transition
    - Normal-to-failed state transition
    - Failed-to-failed state transition
    - Failed-to-normal state transition

System Definition Models

- Example 11 (cont'd): Markov Modeling of Repairable Systems
  - The transition probabilities in this case can be constructed using reliability analysis as provided in Table 3 for illustration purposes.

Table 3. Daily Transition Probabilities

From State	To State	Probability	Comments
Normal State	Failed State	0.10	The probabilities originating from one node must add up to one, i.e., 0.10 + 0.90 = 1.0
Normal State	Normal State	0.90	
Failed State	Normal State	0.50	The probabilities originating from one node must add up to one, i.e., 0.10 + 0.90 = 1.0
Failed State	Failed State	0.50	

System Definition Models

- Component Integration Method
  - In structural engineering, a roof truss can viewed as a multiple-component system.
  - The truss in Figure 26 has 13 members.
  - Member forces can be determined using statics.
  - Other system attributes such as member deflection and stresses can be computed based on in the internal forces and material properties.

System Definition Models

- Component Integration Method (cont'd)

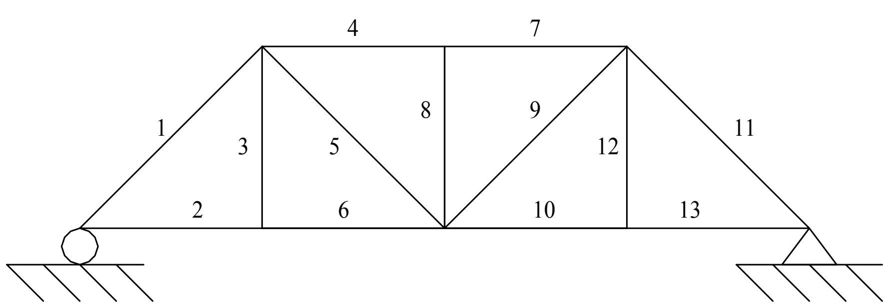


Figure 26. A Truss Structural System

System Definition Models

- Component Integration Method (cont'd)
  - The physical connectivity of the real components can be defined as the connectivity of the components in the structural analysis model.
  - However, if one is interested in the reliability and/or redundancy of the truss, a more appropriate model would be as shown in Figure 27, called a *reliability block diagram*.

System Definition Models

- Component Integration Method (cont'd)
  - Figure 27 shows the attributes of reliability or redundancy. According to this model, the failure of one component would result in the failure of the truss.

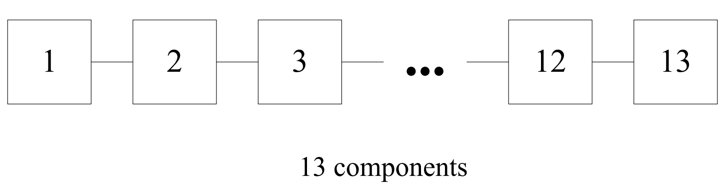


Figure 27. A System in Series for the Truss as a Reliability Block Diagram

Hierarchical Definitions of Systems

- Knowledge and Information Hierarchy
  - Source Systems
    - At the first level of knowledge, which is usually referred to as level (0), the system is known as a *source system*.
    - Source systems comprise three different components, namely *object systems, specific image systems and general image systems*.
    - The object system constitutes a model of the original object.
    - It is composed of an object, attributes and a backdrop.

Hierarchical Definitions of Systems

- Knowledge and Information Hierarchy
  - Source Systems (cont'd)
    - The object represents the specific problem under consideration.
    - The attributes are the important and critical properties or variables selected for measurement or observation as a model of the original object.
    - The backdrop is the domain or space within which the attributes are observed.

Hierarchical Definitions of Systems

- Knowledge and Information Hierarchy
  - Data Systems
    - The second level of a hierarchical system classification is the data system.
    - The data system includes a source system together with actual data introduced in the form of states of variables for each attribute.
    - The actual states of the variables at the different support instances yield the overall states of the attributes.
    - Special functions and techniques are used to infer information regarding an attribute, based on the states of the variables representing it.

Hierarchical Definitions of Systems

- Knowledge and Information Hierarchy
  - Generative Systems
    - At the generative knowledge level, support independent relations are defined to describe the constraints among the variables.
    - These relations could be utilized in generating states of the basic variables for a prescribed initial or boundary condition.
    - The set of basic variables includes those defined by the source system and possibly some additional variables that are defined in terms of the basic variables..

Hierarchical Definitions of Systems

- Knowledge and Information Hierarchy
  - Generative Systems (cont'd)
    - Two main approaches for expressing these constraints:
      1. The first approach consists of a support independent function that describes the behavior of the system. A function defined as such is known as a *behavior function*.
      2. The second approach consists of relating successive states of the different variables. A function defined as such is known as a *state-transition function*.
    - An example state-transition function was provided in Example 11 using Markov chains.

Hierarchical Definitions of Systems

- Knowledge and Information Hierarchy
  - Structure Systems
    - Structure systems are sets of other systems or subsystems.
    - The subsystems could be source, data or generative systems.
    - These subsystems may be coupled due to having common variables or due to interaction in some other form.

Hierarchical Definitions of Systems

- Knowledge and Information Hierarchy
  - Metasystems
    - Metasystems are introduced for the purpose of describing changes within a given support set.
    - The metasystem consists of a set of systems defined at some lower knowledge level and some support-independent relation.
    - Referred to as a replacement procedure, this relation defines the changes in the lower level systems.
    - All the lower level systems should share the same source system.

Hierarchical Definitions of Systems

- Knowledge and Information Hierarchy
  - Metasystems (cont'd)
    - There are two different approaches whereby a metasystem could be viewed in relation to the structure system:
      - The first approach is introduced by defining the system as a structure metasystem.
      - The second approach consists of defining a metasystem of a structure system whose elements are behavior systems.

Hierarchical Definitions of Systems

- Example 12: System Definition of Structural
  - A structure, such as a building, can be defined using a hierarchy of information levels to assess the structural adequacy resulting from loads applied to the structure.
  - The system levels for this case are provided for demonstration purposes as follows:
    - **Goal:** The goal is to assess the structural adequacy of the building

Hierarchical Definitions of Systems

- Example 12 (cont'd): System Definition of Structural
    - **Source System objects:** Columns, beams, slabs, footings, dead load, live load, etc.
    - **Data System:** Dimensions, material properties, load intensities, etc.
    - **Generative System:** Prediction models of stress, such as, stiffness analysis, stress computation, ultimate strength assessment of components in flexure, shear, and buckling.

Hierarchical Definitions of Systems

- Example 12 (cont'd): System Definition of Structural
  - **Structure System:** Performance functions can be defined as strength of components minus respective load effects. The reliability of each component can be assessed based on these performance functions.
  - **Metasystem:** The overall structural adequacy assessment of system based on its components using system reliability concepts

System Complexity

- Our most troubling long-range problems, such as economic forecasting and trade balance, defense systems, and genetic modeling, center on systems of extraordinary complexity.
- The systems that host these problems - computer networks, economics, ecologies, and immune systems - appear to be as diverse as the problems.

System Complexity

- Understanding and modeling system complexity can be viewed as a pretext for solving complex scientific and technological problems, such as, finding cure for the acquired immune deficiency syndrome (AIDS) or solving long-term environmental issues or using genetic engineering safely in agricultural products.
- The study of complexity led to, for example, chaos and catastrophe theories.

System Complexity

- Even if complexity theories would not produce solutions to problems, they can still help us to understand complex systems and perhaps direct experimental studies.
- Theory and experiment go hand in glove, therefore providing opportunities to make major contributions.

System Complexity

"No data processing systems, whether artificial or living, can process more than 2×10^{47} bits per second per gram of its mass,"

$$k^n \leq 10^{93} \qquad (7)$$

Figure 28 shows a plot of this inequality for values of k = 2 to 10 colors

System Complexity

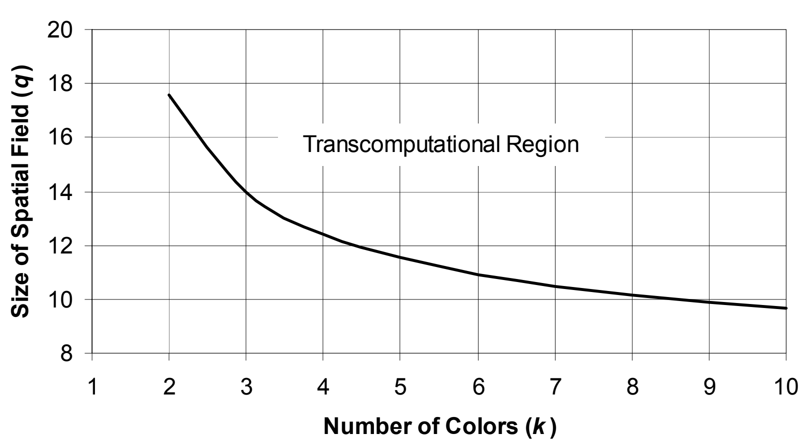


Figure 28. The Bremermann's Limit for Pattern Recognition

System Complexity

- For example using only two colors, a transcomputational state is reached at $q >$ 18 colors.
- These computations in pattern recognition can be directly related to human vision and the complexity associated with processing information by the retina of a human eye.

System Complexity

- According to Klir and Folger (1988), if we consider a retina of about one million cells with each cell having only two states of active and inactive in recognizing an object, modeling the retina in its entirety would require the processing of

$$2^{1,000,000} = 10^{300} \qquad (7)$$

bits of information, far beyond the Bremermann's limit.

System Complexity

- Miller (1978) described these relationships for living systems using the following hypothesis that was analytically modeled and experimentally validated:

"As the information input to a single channel of a living system – measured in bits per second – increases, the information output – measured similarly – increases almost identically at first but gradually falls behind as it approaches a certain output rate, the channel capacity, which cannot be exceeded. The output then levels off at that rate, and finally, as the information input rate continues to go up, the output decreases gradually towards zero as breakdown or the confusion state occurs under overload."

System Complexity

- The above hypothesis was used to construct families of curves to represent the effects of information input overload as shown schematically in Figure 29.
- Once the input overload is removed, most living systems recover instantly from the overload and the process is completely reversible; however, if the energy level of the input is much larger than the channel capacity, a living system might not fully recover from this input overload.

System Complexity

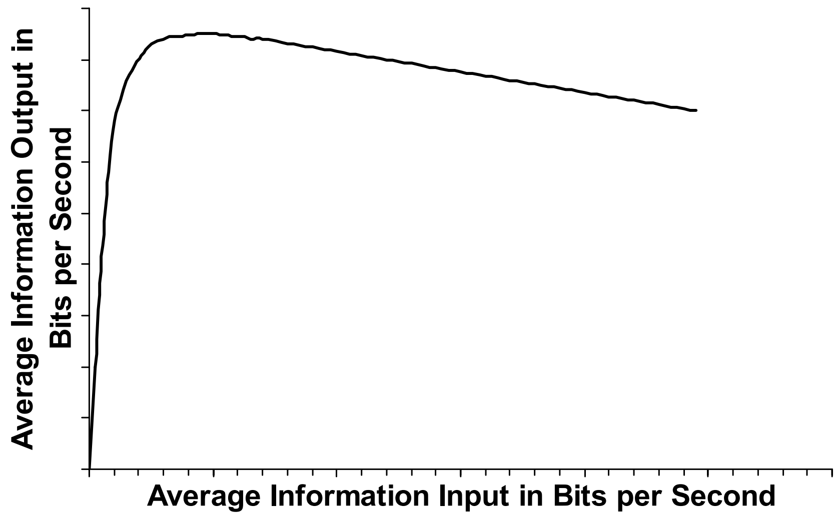


Figure 29. A Schematic Relationship of Input and Output Information Transmission Rates for Living Systems

System Complexity

- Living systems also adjust the way they process information in order to deal with an information input overload using one or more of the following processes by varying degrees depending on the level of a living system in terms of complexity:
  1. omission by failing to transmit information,
  2. error by transmitting information incorrectly,
  3. queuing by delaying transmission,

System Complexity

4. filtering by giving priority in processing,
5. abstracting by processing messages with less than complete details,
6. multiple channel processing by simultaneously transmitting messages over several parallel channels,
7. escape by acting to cut off information input, and
8. chuncking by transformation information in meaningful chunks.

Homework Assignment #3

Problems:
3.2
3.5
3.9
3.12
3.13