The Journal of NCOSE, Volume I, Number I, July-September 1994

MODELING AND INDIRECT EXPERIMENTATION IN SYSTEM DESIGN EVALUATION

Wolter J. Fabrycky, Ph.D., P.E.
Lawrence Professor of Industrial and Systems Engineering
Virginia Polytechnic Institute and State University
Blacksburg, Virginia 24061-0118

ABSTRACT

The commitment to technology, system configuration, performance, and life-cycle cost is particularly acute during the early stages of system design. A large gap exists between this commitment and the system-specific knowledge available during conceptual and preliminary design. Powerful approaches utilizing modeling and indirect experimentation may be used to help narrow this gap. This paper presents a paradigm based on the structure of normative models from the domains of operations research and systems analysis. The paradigm involves the identification and incorporation of design-dependent parameters to link design characteristics with operational outcomes. Optimization and trade-off decisions are facilitated during the systems engineering process with the aid of a Design Evaluation Function and a Design Evaluation Display, both of which are described in this paper.

1. CONCEPTS AND THEORY

System design evaluation is an essential activity within the systems engineering process. But, it must not be pursued in isolation. It should be coordinated with system design and analysis as shown in Figure 1 [9]. Evaluation should be invoked continuously as the system life cycle unfolds; it is the assurance of continuous design improvement.

1.1. System Life-Cycle Concepts

Fundamental to the practice of Systems Engineering is an understanding of the system life cycle. The life cycle of a product, system, or structure begins with the identification of a need and extends through conceptual and preliminary design, detail design and development, production and/or construction, distribution and utilization, support, and then phaseout and disposal.

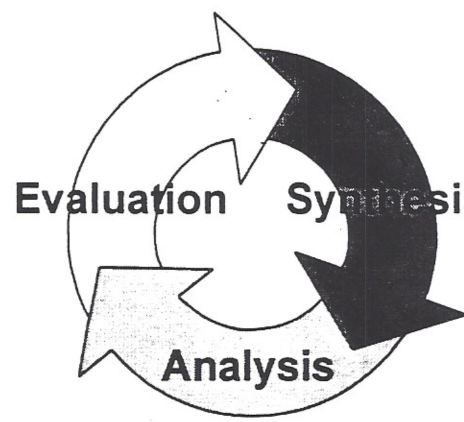

Figure 1 System Design, Analysis, and Evaluation

System Life-Cycle Engineering

All products, systems, and structures which have utility (the capacity to satisfy human wants) are physically manifested. It follows that utilities are created by altering physical factors. The purpose of Systems Engineering is to determine how physical factors may be altered to create the most utility for the least cost, in terms of design and development cost, production cost, and service cost.

The need for a new product comes into focus first, initiating the product life cycle. Conceptual and preliminary product design follows need determination, with simultaneous consideration for manufacturing system design -- activities best pursued before detail product design as a parallel life cycle. Product support system design, too often omitted as a design imperative, is the third life cycle. It should be synchronized with product design and manufacturing system design as illustrated in Figure 2[3,7].

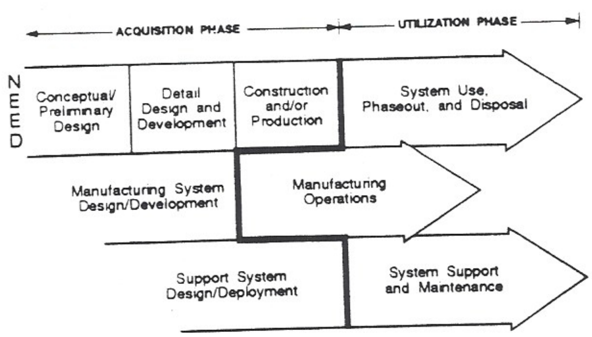

Figure 2 Product, Process, and Support Life Cycles

System life-cycle engineering is suggested as an integration approach for bringing competitive products into being in such a way as to minimize their deficiencies and life-cycle cost [6]. This integration involves design and development efforts to [3]:

1) Transform an operational need into a description of system performance parameters and preferred system configuration through the use of an iterative process of functional analysis, synthesis, optimization, definition, design, test, and evaluation;

2) Incorporate related technical parameters and assure compatibility of all physical, functional, and program interfaces in a manner that optimizes the total system definition and design; and

3) Integrate performance, producibility, reliability, maintainability, manability, supportability, and other "specialties" into the overall engineering effort.

Commitment and Knowledge

Great benefit can be derived from accelerating the accumulation of system specific-knowledge earlier in the life cycle. Fully two-thirds of the commitment to final system characteristics and life-cycle cost is made by the time conceptual and preliminary design is completed. This is shown conceptually in Figure 3 [7].

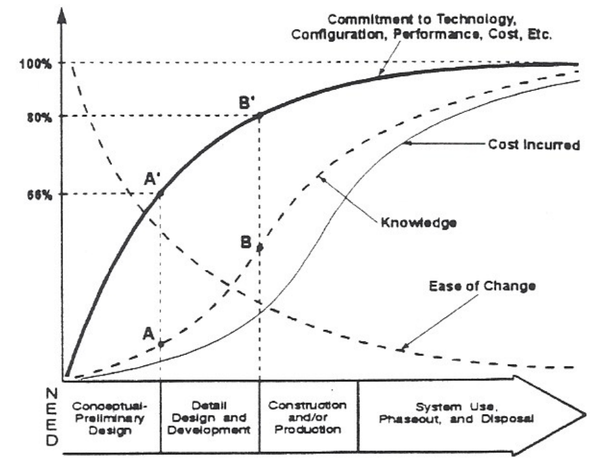

Figure 3 Commitment and System-Specific Knowledge

Traditional engineering design has focused mainly on the acquisition phase of the product life-cycle, however, experience indicates that a properly coordinated and functioning product or system, which is competitive in the marketplace, cannot be achieved through optimization efforts applied largely after it comes into being. Accordingly, it is essential that design optimization include operational considerations during the early stages of system development [4]. The objective is to narrow the "gap" between available knowledge and commitment (A-A' and B-B'), as shown in Figure 3.

1.2. Modeling and Indirect Experimentation

Modeling and the process of indirect experimentation provide an effective means for obtaining factual information about a system being designed or a system already in being. In component design it is feasible to build several prototypes, test them, and then modify the design based on the test results. This is often not possible in system design because of the length of the system life cycle and the cost involved. A major part of the systems engineering process requires decisions based on a model of the system, rather than decisions derived from the system itself.

Direct and Indirect Experimentation

In direct experimentation, the object, state, or event is subject to manipulation, and the results are observed. Direct experimentation may be applied to the rearrangement of equipment in a factory. Such a procedure is time-consuming, disruptive, and costly. Hence, simulation or indirect experimentation is employed, with models used to represent the equipment.

Direct experimentation in aircraft design would involve constructing a full-scale prototype to be flight-tested under real conditions. Although this is an essential step in the evolution of a new design, it would be very costly as the first step. The usual procedure is to evaluate several proposed configurations by building a model of each and then testing in a wind tunnel. This is the process of indirect experimentation, or simulation. It is extensively used in situations where direct experimentation is not economically feasible. It is essential when direct experimentation is not possible [8].

Evaluation Through Indirect Experimentation

In most design and operational situations, the objective sought is the optimization of cost-effectiveness. Rarely can this be done by direct experimentation with a system under development or a system in being [6]. The primary use of indirect experimentation in Systems Engineering is to explore the effects of alternative system characteristics on system performance, without actually producing and testing each candidate system.

Most simulation models used will be mathematical. The type will depend upon the questions to be answered. In some instances, simple algorithms will suffice. In others, mathematical or probabilistic representations will be needed. In many cases, simulation with the aid of an analog or digital computer will be required.

In most Systems Engineering undertakings, a number of different models should be formulated. These models form a hierarchy ranging from considerable aggregation to extreme detail. At the start of a systems project, knowledge about the system is quite sketchy and general. As the design progresses, this knowledge becomes more detailed. Consequently, the models used for indirect experimentation should be detailed. There is no available theory by which the best model for a given system evaluation can be selected. The choice of an appropriate model is determined as much by the background of the systems engineer as the system itself [3].

1.3. Evaluation Factors and Process

Good design for a primary function of a product often produces undesirable side effects in the form of operational problems. This is due to exclusive consideration of primary functions, rather than to the more challenging problem of designing in the face of other important design factors. Enough specialized knowledge exists to solve this problem. The impediment to its solution is the integrated use of what is known in a systematic manner.

Design evaluation in terms of life-cycle cost and system effectiveness should be pursued continuously as the life-cycle development process progresses. It is an activity best assigned to individuals with the appropriate analytical background. Proper evaluation includes numerous factors, some of which are illustrated in Figure 4 [3,7].

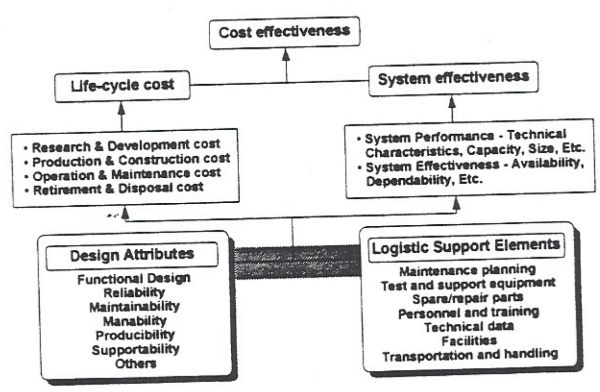

Figure 4 Factors to be Evaluated in Systems Design

The communication and coordination needed to bring the product, the process, and the service system along in a coordinated manner (as shown in Figure 2) is not easy to achieve. Progress will likely be facilitated by new technologies that make possible the more timely acquisition and utilization of design information. CAD/CAM is only one of these technologies. Others need to be developed which can integrate relevant activities of the enterprise over the spectrum of life cycles illustrated in Figure 2. The most promising of these is Computer-Aided Concurrent Engineering (CACE), illustrated schematically in Figure 5.

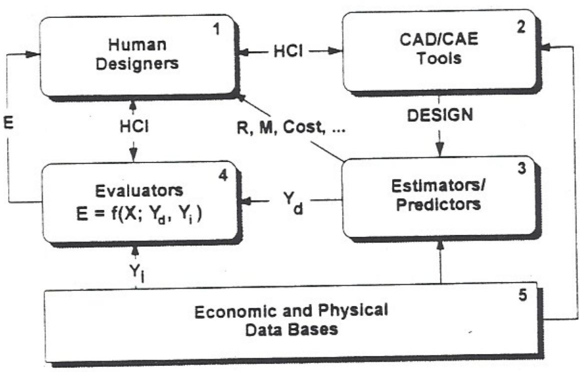

Figure 5 A Schematic for CACE

Opportunities for better design evaluation exist in Block 3 (estimation and prediction), Block 4 (design evaluation), and Block 5 (economic and physical data base development). Networking considerations for CACE workstations within the organi-zation can aid the systems engineering process and system design evaluation. With the advent of information system networking, and the increased availability of Computer-Aided X (where X = design, cost estimating, process planning, etc.), "facts" become more accessible, and hence, of diminishing relative value. The ability to apply facts (knowledge) in a creative and more rapid manner becomes more important during the systems engineering process.

1.4. Design Evaluation Mathemat

Design evaluation in terms of life-cycle cost and system effectiveness can be facilitated by adopting the design-dependent parameter approach. This approach is a mathematical way to link design actions with operational outcomes. It is based on models and indirect experimentation, and implemented in accordance with the process in Figure 5.

The Design Evaluation Function

The Design Evaluation Function (DEF) must be linked to all phases of the system life cycle of Figure 2. It is illustrated in Figure 6. This function, with its design-dependent parameters and design-independent para-meters, facilitates design optimization. It provides the basis for a clarification of the true difference between alternatives (a design-based choice) and optimization (a search-based choice) [3, 6].

To Optimally Achieve

ACQUISITION/UTILIZATION

Mathematically Link

DESIGN/OPERATIONS

Utilizing The

DESIGN EVALUATION FUNCTION (DEF)

$$E = f(X, Y_d, Y_i)$$

$$g(X, Y_d) \lesseqgtr C$$

Figure 6. The Design Evaluation Function

The origin and evolution of the Design Evaluation Function is illustrated in Figure 7. This function traces its origin to the first book published on Operations Research in 1957[5]. The decision-maker seeks optimum values for policy variables in the face of uncontrollable system parameters. In this form, the function is useful for optimizing operations; alternatives, as such, are not explicitly treated. Applicability of the basic idea to wide range of operations research and management science models was explored in 1984 [8].

References	Funcational Form	Application
Churchman, Ackoff, & Arnoff (1957)	$E = f(x_i, y_j)$ E = system effectiveness x_i = variables under control y_j = variables not suubject to control	Operations
Banks & Fabrycky (1987)	$E = f(X, Y_d, Y_i);\ g(X, Y_d) \lesseqgtr C$ E = system effectiveness X = procurement level and procurement quantity Y_d = source dependent parameters Y_i = source independent parameters	Procurement Operations
Blanchard & Fabrycky, 1990 & Fabrycky & Blanchard, 1991	$E = f(X, Y_d, Y_i);\ g(X, Y_d) \lesseqgtr C$ E = evaluation measure X = design variables Y_d = design dependent parameters Y_i = design independent parameters	Design Optimization

Figure 7. Origin and Evolution of the DEF

Inventory theory was extended in 1987 beyond when to procure (order point) and how much to procure (order quantity), and into the domain of procurement source determination [2]. This was accomplished by partitioning system parameters into source-dependent and source-independent subsets as indicated in Figure 7. Order point and order quantity are policy variables; this is an application to inventory operations.

Then, in 1990 and 1991, application of the evaluation function to design evaluation was presented by the explicit identification of design-dependent parameters. When partitioned from design-independent parameters, the function may be used for evaluating mutually exclusive alternatives. The evaluation proceeds by optimizing on design variables for each instance of the design-dependent parameter set.

Design Variables and Parameters

Design-dependent parameters are design characteristics inherent in the product or system. They are subject to manipulation by the designer during the process of seeking an optimal design. These parameters, when imbedded in models, are the key to indirect experimentation during the system design process. Their relationship to design-independent parameters and design variables is inherent in the DEF.

The design-dependent parameter approach is a mathematical way to link design actions with operational outcomes. It utilizes the Design Evaluation Function in Figures 6 and 7. From the following definitions of terms in the function, its application in system design evaluation should be evident:

E = a life-cycle complete evaluation measure (usually equivalent to life-cycle cost);

X = design variables (e.g., number of deployed units, armor thickness, retirement age, repair channels, rated thrust, pier spacing, etc.);

Y_d = design-dependent parameters (e.g., weight, reliability, design life, capacity, producibility, maintainability, etc.);

Y_i = design-independent parameters (e.g., cost of money, labor rates, material cost per unit, shortage cost penalty, etc.);

C = a set of constraints and/or design requirements.

1.5. The Design Evaluation Display

System design evaluation must recognize and incorporate multiple criteria if it is to be viable as part of the systems engineering process. Multiple criteria considerations arise when both economic and non-economic elements are present in the evaluation. In these common situations, design evaluation is facilitated by the use of a Design Evaluation Display (DED), exhibiting both cost and effectiveness measures, as shown in Figure 8.

Effectiveness is a measure of mission fulfillment for a product or system, in terms of a stated need. Mission fulfillment may be expressed by one or more figures of merit, depending on the type of product or system and the objectives to be achieved. Some common effectiveness measures were shown on the right side of Figure 4.

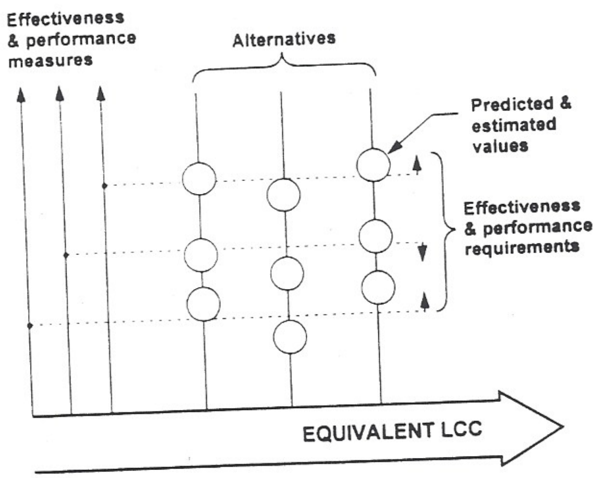

Figure 8. Design Evaluation Display

Life-cycle cost, shown on the left side of Figure 4, and one or more effectiveness measures may be displayed simultaneously as an aid in decision-making. A Decision Evaluation Display is one way of doing this. Note that effectiveness requirements, or thresholds, are shown on the display. These are useful to the decision-maker in subjectively assessing the degree to which each alternative satisfies effectiveness criteria. Life-cycle cost, shown on the horizontal axis, is an objective measure. The goal is to select the alternative with the lowest life-cycle cost that satisfies the effectiveness measures to an acceptable degree.

A formal trade-off between life-cycle cost and effectiveness measures would require the application of preference functions and utility theory. This is sometimes done, but in practice a simple weighting scheme is often used. In many applications it may be sufficient to have the decision-maker or team decide by visually inspecting the DED. In any event, the information displayed is best derived with the aid of models and simulation through indirect experimentation. In this manner operational problems can be identified and rectified before they become too costly, or impossible to address.

2. SYSTEM EVALUATION EXAMPLES

Three hypothetical but realistic examples will be presented in this section to illustrate how modeling and indirect experimentation for system design evaluation applies in different situations. These examples are: superstructure configuration design for a bridge, material selection for a buss bar, and repairable equipment population system design. Multiple criteria will be illustrated with the last example.

2.1. Superstructure Configuration Design

Consider the problem of specifying a configuration for the superstructure of a bridge [7]. Two alternative superstructure configurations are shown in Figure 9. Others are possible. Regardless of the final configuration specified, the weight of the superstructure per foot will be a function of the span between piers, S. Let:

L = bridge length (ft)
W = superstructure weight (lb per ft)
C_s = erected superstructure cost ($ per lb)
C_p = installed cost of piers ($ per pier)

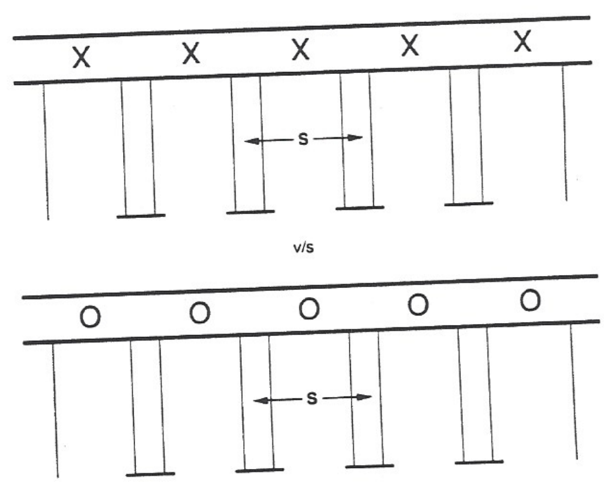

Figure 9. Bridge Design Configurations

The Design Evaluation Function (DEF) in Figure 6 establishes S as the design variable, X, W as the design-dependent parameters, Y_d, and C_s and C_p as design-independent parameters, Y_i. Design optimization requires a superstructure configuration design which will result in the lowest possible total first cost for the bridge.

Total first cost for the bridge is the sum of the superstructure cost and the pier cost, as

$$TFC = SC + PC.$$

The superstructure cost may be expressed as

$$SC = (W)(L)(C_S)$$

where $W = AS + B$, with W given in terms of the parameters of the weight estimating relationship A and B. These may be derived by curve-fitting to empirical data as shown hypothetically in Figure 10.

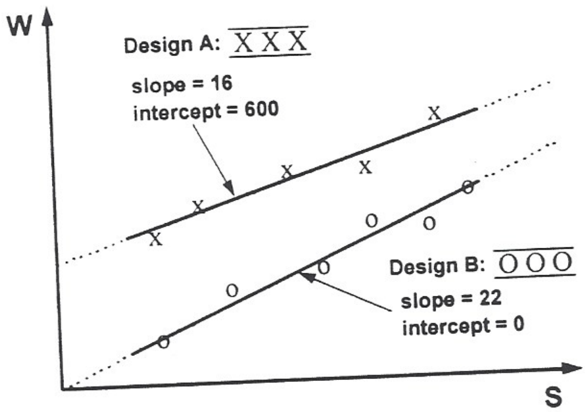

Figure 10. Weight Estimating Relationships

If each abutment is included as a pier, the pier cost may be expressed as

$$PC = (L/S + 1)(C_P)$$

Total first cost is then

$$TFC = (AS + B)(L)(C_S) + (L/S + 1)(C_P),$$

The optimum span between piers, S*, is found by differentiating TFC with respect to S

$$S^* = \sqrt{C_P / AC_S}$$

Substituting S* into the TFC equation gives the minimum total first cots, designated TFC*, as

$$TFC^* = 2\sqrt{AC_PL^2C_S} + BLC_S + C_P.$$

Consider an example with design-independent parameters as follows:

$L = 1{,}000$ feet; $C_S = \$0.65$; $C_P = \$220{,}000$. For Design A, the weight of the superstructure is found to be $W = 16S + 600$, from Figure 10. And, for Design B the weight of the superstructure is found to be $W = 22S + 0$, also from Figure 10.

TFC* can be found from the parameters A and B for each superstructure design configuration, considering design independent parameter values. It is \$2,294,280 for Design A with S* = 87.7 feet. For Design B, it is \$2,219,158 with S* = 74.8 feet. Figure 11 shows TFC as a function of the span between piers.

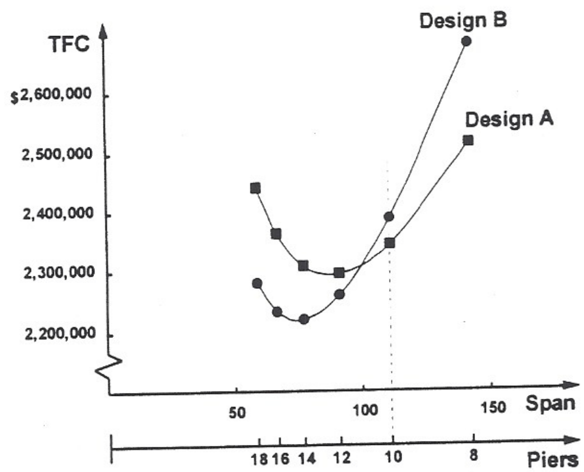

Figure 11. Bridge TFC as a Function of S.

Design B should be chosen for the unconstrained case. However, if the span between piers must be at least 100 feet so that barge traffic may pass, then Design A would be chosen. Note the design decision reversal due to the presence of a constraint.

2.2. Material Selection For a Buss Bar

Another classic example of indirect experimentation for system design evaluation is the design of an electrical conductor [7]. The design variable of interest is the cross-sectional area, with increasing and decreasing cost components. As the area increases, so does the installed cost of the conductor. However, the power-loss cost is inversely proportional to the area. The sum of these costs will be a minimum at the optimum cross-sectional area.

If alternative designs (material types) are under consideration, then the Design Evaluation Function (DEF) applies. Design-dependent parameters arise from the material choice and are key to the selection from among design alternatives. Let:

A	=	conductor cross-sectional area (in^2)
L	=	length of the conductor (feet)
I	=	transmission load (amperes)
H	=	hours conductor is utilized per year
i	=	interest rate (%)
n	=	conductor useful life (years)
C_e	=	cost of electricity ($ per KWatt)
C_i	=	fixed installation cost ($)
C_m	=	unit cost of the conductor ($ per lb)
R_m	=	resistance of the conductor (ohms)
D_m	=	density of conductor material (lb per ft^3)
W_m	=	weight of conductor material (lb)
F_m	=	salvage value of the conductor ($ per lb)

In the notation above, the subscript m designates the material selected for a given design alternative.

The annual equivalent life-cycle cost is composed of the cost due to power loss and the capital investment cost, expressed as

AELCC = Power loss cost+Investment cost.

The power loss cost in dollars per year is

$$C_e I^2 R_m \frac{H}{1000A}.$$

The annual equivalent capital investment cost (capital recovery) is

$$C_i(\overset{A/P,i,n}{\quad}) + (C_m - F_m)(\overset{A/P,i,n}{\quad}) W_m + F_m W_m i$$

where

$$W_m = \frac{LAD_m}{144}.$$

Therefore, the AELCC is

$$C_i(\overset{A/P,i,n}{\quad}) + (C_m - F_m)(\overset{A/P,i,n}{\quad}) \frac{LAD_m}{144} +$$

$$F_m \frac{LAD_m}{144} i + C_e I^2 R_m \frac{H}{100A}.$$

To optimize AELCC, the minimum cost cross-sectional area, A*, must be found. Taking the derivative of AELCC with respect to A, setting the result equal to zero, and solving for A gives

$$A^* = \sqrt{\frac{C_e I^2 R_m \dfrac{H}{1000}}{(C_m - F_m)(\overset{A/P,i,n}{\quad}) \dfrac{LD_m}{144} F_m \dfrac{LD_m}{144} i}}.$$

Assume that a copper conductor is being considered to transmit 2,000 amperes continuously throughout the year for 10 years, over a distance of 120 feet. The resistivity of a copper conductor is 0.000982 ohms, and copper has a density of 555 pounds per cubic foot. The interest rate is 15%. Other parameters are:

C_i	=	$300
C_c	=	$1.30 per lb
F_c	=	$0.78 per lb
C_e	=	$0.052 per KWatt

The optimal cross-sectional area is found to be 4.19 in^2 at an AELCC* of $914.39. At this point, the copper design alternative is considered to be the current best (or baseline design).

Conductors can be fabricated from materials other than copper. Assume that aluminum is being considered as an alternative. The resistivity of an aluminum conductor is 0.001498 ohms, and aluminum has a density of 168 pounds per cubic foot. Other parameters are:

C_i	=	$300
C_a	=	$1.10 per lb
F_a	=	$0.66 per lb
C_e	=	$0.052 per KWatt

The optimal cross-sectional area is found to be 10.22 in^2. This occurs at an AELCC* of

\$593.98. At this point the designer is ready to make a decision. The annual equivalent cost curves for both the copper design alternative and the aluminum design alternative are presented graphically in Figure 12. The aluminum design, with an equivalent annual cost of \$593.98, provides the lower-cost alternative. It should be selected unless there are other factors of greater concern.

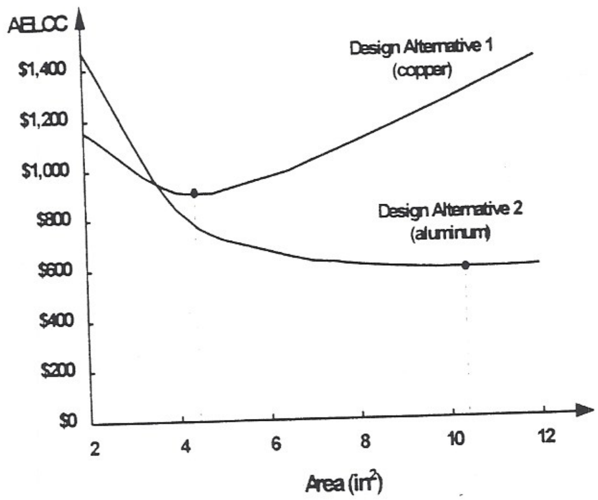

Figure 12. AELCC for Conductor Design Alternatives

2.3. Repairable Equipment Population System (REPS) Design

Consider the following situation: A finite population of repairable equipment is to be procured and maintained in operation to meet a demand. As equipment units fail or become unserviceable, they will be repaired and returned to service. As they age, the older units will be removed from the system and replaced with new units. The system design problem is to determine the population size, the replacement age of units, and the number of repair channels for each set of design-dependent parameters in the face of design-independent parameters, so that design requirements will be met at a minimum life-cycle cost [3, 7].

A general schematic of REPS is shown in Figure 13. Repairable equipment systems exist in many operational settings. Both the airlines and the military operate and maintain aircraft with these system characteristics. In ground transit, vehicles such as rental automobiles, taxis, and commercial trucks constitute repairable item systems. Production equipment types, such as autoclaves, drill presses, and weaving looms, are populations of equipment which also fit the repairable classification.

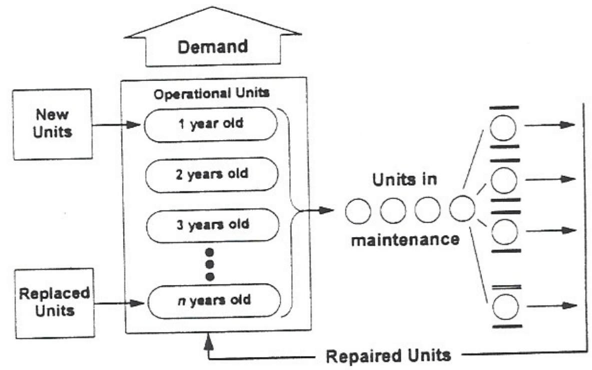

Figure 13. Repairable Equipment Population System

Table 1 summarizes the design-variables and system parameters for REPS. Note that the design dependent parameters of unit cost (C_u), reliability (MTBF), and maintainability (MTTR) are central to the system design problem.

Indirect experimentation with REPS may proceed on the basis of a mathematical model. Let:

AELCC = annual equivalent life-cycle cost
PC = annual equivalent population cost
RC = annual equivalent repair cost
SC = annual shortage cost

The major cost components for the DEF are:

1) Population Annual Equivalent Cost:

$$PC=C_uN$$

$$\text{where } C_u = (P-F)(\;\overset{A/P,i,n}{}\;) + F(i)$$

2) Repair Facility Annual Equivalent Cost:

$$RC = C_r M$$

3) Annual Shortage Cost:

$$SC = C_s[E(S)]$$

where

$$E(S) = \sum_{j=1}^{D} jP_{(N-D+j)}$$

from finite queuing, with $P_{(N-D+j)}$ being the probability of shortage ranging from 0 to D units.

Table 1. Design Variables and System Parameters

Variables/Parameters	Design Var.	Design Dep.	Design Ind.
D = Demand for deployed units			X
N = Number of units deployed	X		
M = Number of maintenance channels	X		
n = Retirement age of deployed units	X		
C_u = Annual equivalent unit cost per unit		X	
C_r = Annual channel cost per channel			X
C_s = Shortage cost per unit short per period			X
MTBF = Mean time between unit failure		X	
MTTR = Mean time to repair a unit		X	

Consider two REPS design alternatives (candidate systems) for which the system parameters are given in Table 2. Design-dependent parameters are marked with an asterisk.

Table 3 gives a summary of the optimization results for effectiveness measures (cost and shortages) and system design variable values. From this it is evident that Candidate B is best on the basis of life-cycle cost. However, Candidate A is best on the probability of being one or more units short, as well as on the average MTBF value (see Table 2).

Table 2. System Parameters for REPS

Variables/Parameters	Candidate A	Candidate B
Demand	15	15
Shortage cost per day	\$200	\$200
Interest rate	10%	10%
Cost of equipment unit*	\$55,000	\$44,000
Salvage value*	\$7,000	\$6,000
Design life (years)*	6	6
Average MTBF (years)*	0.316	0.210
Average MTTR (years)*	0.054	0.043

Table 3. Optimized Outputs for REPS

Output Item	Candidate A	Candidate B
Population cost	\$228,986	\$202,804
Repair facility cost	\$179,804	\$179,804
Shortage penalty cost	\$ 32,329	\$ 51,794
Expected (AELCC)	\$441,119	\$434,402
Probability of one or more short	0.214	0.288
Mean units short	0.44	0.71
Means units down	3.15	4.36
Total number of units deployed	19	20
Repair channels	4	4
Retirement age	5	3

Design variable values are also shown in Table 3. These are to be used to implement optimal procurement and operating policy in the face of design requirements. For example, assume that the design requirements are:

1) Design to cost - the deployed population shall have a first cost not exceeding \$1,000,000.

2) Probability of shortages - the probability of being one or more

equipment units short of demand shall not exceed 0.25.

3) Reliability - the mean time between failure for equipment units shall not be less than 0.3 years.

Selection of the best alternative (candidate system) in the face of design requirements is facilitated by the Design Evaluation Display illustrated in Figure 14.

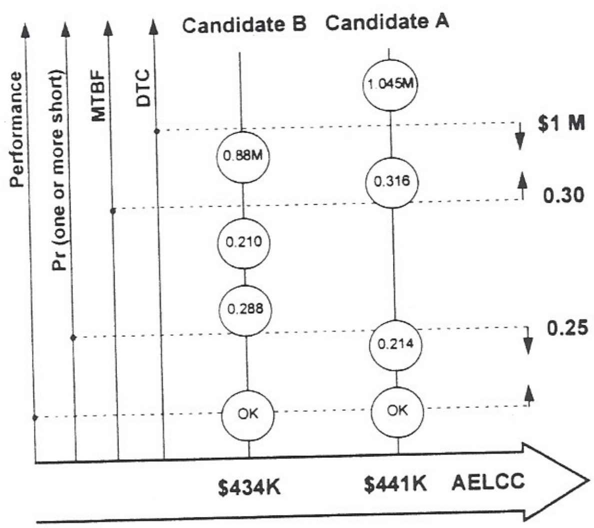

Figure 14. Design Evaluation Display

If Candidate A is selected, 19 units are to be deployed at a first cost of $1,045,000. This exceeds the design-to-cost requirement. However, both the probability of shortage and the reliability requirements are met. If Candidate B is selected, 20 units are to be deployed at a first cost of $880,000. This is within the design-to-cost requirement.

However, both the probability of shortage and the reliability requirements are violated. Annual equivalent life-cycle cost for this candidate is lower than for Candidate A by $6,717. If this candidate is selected, equipment units would be retired after three years, not five as for Candidate A.

2.4. Summary of Examples

Each design evaluation example in this section utilized the Design Evaluation Function as a means for indirect experimentation. The main points illustrated are discussed next.

Total first cost was optimized in the bridge configuration design example by trading-off the investment in superstructure and piers for each configuration. Maintenance and operating cost would have to be added to consider life-cycle costing over time. Design decision reversal was shown to occur for design in the face of a constraint.

In the buss bar design example, investment, as well as operating cost, was optimized over the life-cycle. The choice of a conductor material was made on the basis of a comparison of the optimum cross-sectional area for each buss bar alternative. Like the bridge design example, the buss bar design example used classical calculus as a means for optimization.

The prior examples were relatively simple, in that a single design variable and a single criterion were involved. In the repairable equipment population system example, three design variables and multiple criteria were considered. In addition, probabilistic factors were present in the model. Optimization for each candidate system was accomplished by enumeration, since the model did not permit the classical calculus approach.

3. SUMMARY AND CONCLUSIONS

In these times of intensifying global competition, commercial firms are searching for ways to gain a sustainable competitive advantage in the marketplace [1, 4]. Advertising alone is not sufficient. One promising strategy is to adopt a life-cycle development methodology for proposed new products, their required manufacturing activities, and product support systems.

System design evaluation may be formalized by the identification of design dependent parameters, the formulation of a Design Evaluation Function, and the use of a Design Evaluation Display. By incorporating life-cycle factors into this function, design alternatives can be compared so that improvements in system design can be recognized and implemented.

Product development -- embracing system optimization by modeling and indirect experimentation -- has an excellent chance of enhancing consumer satisfaction, corporate identity, and company profitability through the integration of important design considerations (performance, cost, and quality). But these desiderata may not be attainable, unless the importance of system design evaluation is recognized and implemented [4,6].

REFERENCES

[1] J.A. Adam, "Competing in a Global Economy," in *IEEE Spectrum*, Vol. 27, No. 4, April, 1990.

[2] J. Banks and W. J. Fabrycky, *Procurement and Inventory Systems Analysis*. Prentice Hall, Inc., 1987.

[3] B.S. Blanchard and W.J. Fabrycky, *Systems Engineering and Analysis*. 2nd Edition, Prentice Hall, Inc., 1990.

[4] CAM-I, "Product Optimization Prospectus." Consortium for Advanced Manufacturing, Inc., September, 1989.

[5] C.W. Churchman, R.L. Ackoff, and E.L. Arnoff, *Introduction to Operations Research*. John Wiley, Inc., 1957.

[6] W.J. Fabrycky, "Indirect Experimentation for System Optimization: A Paradigm Based on Design Dependent Parameters," in *Proceedings, Second International Symposium*. NCOSE, Seattle, Washington, 1992.

[7] W.J. Fabrycky and B.S. Blanchard, *Life-Cycle Cost and Economic Analysis*. Prentice Hall, Inc., 1991.

[8] W.J. Fabrycky, P.M. Ghare, and P.E. Torgersen, *Applied Operations Research and Management Science*. Prentice Hall, Inc., 1984.

[9] D. Verma and J. Knezevic, "Application of Fuzzy Logic in the Assurance Sciences," in *Proceedings, Annual Reliability and Maintainability Conference*. Anaheim, California, January 24-27, 1994.

AUTHOR BIOGRAPHY

Wolter J. Fabrycky received the Ph.D. in Engineering in 1962 from Oklahoma State University, the M.S. in Industrial Engineering in 1958 from the University of Arkansas, and the B.S. in Industrial Engineering in 1957 from Wichita State University. Dr. Fabrycky taught at Arkansas and Oklahoma State, and then joined Virginia Tech in 1965, where he served as Chairman of Systems Engineering, Associate Dean of Engineering, and then as Dean of Research for the University. He is now the John L. Lawrence Professor of Industrial and Systems Engineering.

Fabrycky received the Lohmann Medal from the College of Engineering at Oklahoma State in 1992 for Outstanding Contributions to Industrial and Systems Engineering Education, Research, and Publications. In 1990, he received the Hotlzman Distinguished Educator Award from the Institute of Industrial Engineers. Fabrycky was elected to the Arkansas Academy of Industrial Engineering in 1989

Dr. Fabrycky was elected to the rank of Fellow in the Institute of Industrial Engineers in 1978, and the rank of Fellow in the American Association for the Advancement of Science in 1980. He is listed in Who's Who in Engineering and Who's Who in America. Fabrycky is a Registered Professional Engineer in Arkansas and Virginia.

Fabrycky is co-author of six Prentice-Hall books. These are: Engineering Economy (1993), Life-Cycle Cost and Economic Analysis (1991), Systems Engineering and Analysis (1990), Procurement and Inventory Systems Analysis (1987), Applied Operations Research and Management Science (1984), and Economic Decision Analysis (1980). Dr. Fabrycky also co-edits the Prentice-Hall International Series in Industrial and Systems Engineering.