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COMPARISON OF SIMULATION ENVIRONMENTS THROUGH ANALYTIC HIERARCHY PROCESS

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ABSTRACT

This paper describes the application of analytic hierarchy process to evaluate a new methodology for simulation against conventional approaches. The study utilizes structured pair-wise comparison of analytic hierarchy process to reach a scale of preference between the two simulation modeling approaches. Both tangible and intangible aspects of modeling and simulation are combined to create a comprehensive platform for comparing simulation environments.

1 INTRODUCTION

This paper describes the application of the Analytic Hierarchy Process (AHP) to evaluate various aspects of the framework and the object-oriented methodology developed by Karacal and Mize (1996a, 1996b) against conventional simulation approaches. In simple terms, AHP is a multi-objective, multi-criteria decision methodology that utilizes structured pair wise comparisons among similar aspects of alternatives to reach a scale of preference. It is especially powerful when the problem has many aspects that are hard to quantify. In literature, most of the studies focused on comparing simulation environments or languages are based on tangible and measureable criteria such as execution speed, graphics capability, model size and complexity (Wallace, 1987). Although there were some approaches that tried to evaluate simulation systems through qualitative considerations, they were based on a set of disjoint, usually conflicting criteria. Several aspects of a simulation study such as ease of modeling and model effectiveness are difficult to measure. A comparision of environments based on a single or few number of aspects may lead to a narrow perspectived conclusions. The objective of this work is to unify tangible and intangible aspects of a simulation study through AHP to form a common platform for comparing traditional simulation approaches and the developed methodology.

2 ANALYTIC HIERARCHY PROCESS

The AHP process consists of a systematic approach based on breaking the decision problem into a hierarchy of interrelated elements. Applications of the methodology includes several diverse areas from economics to health care planning and energy policy (Wallace, 1987). A more comprehensive application of AHP for simulation environment evaluation purposes can also be seen from Beaumariage's (1990) study which compares object-oriented simulation environments against traditional environments such as SLAM and SIMAN.

Zahedi (1986) summarizes the AHP procedure in terms of four steps:

1) *Break the decision problem into a hierarchy of interrelated problems*: top level being the macro decision objective such as selecting the best alternative. The lower levels contain attributes which contribute to the quality of this decision. The next lower levels represents the increased details of these attributes. The bottom of the hierarchy contain decision alternatives or selection of choices. Figure 1 illustrates the standard format for AHP decision model.

2) *Provide the matrix data for pairwise comparision of the decision elements* : to express judgements in pairwise comparisions, the following scale of absolute values must be provided: 1, equal (weight); 3, moderate; 5, strong; 7, very strong; 9, extreme; 2, 4, 6,

8, for compromise; reciprocals are used for the inverse comparisions. The elements in the next hierarchical level are arranged in the form of a matrix and pairwise judgemental values are assigned in satisfying the decision element of the present level for which the comparision matrix is built. Similarly, elements in the next level down are subjected to pairwise comparisions for a particular decision element in previous level and values are assigned.

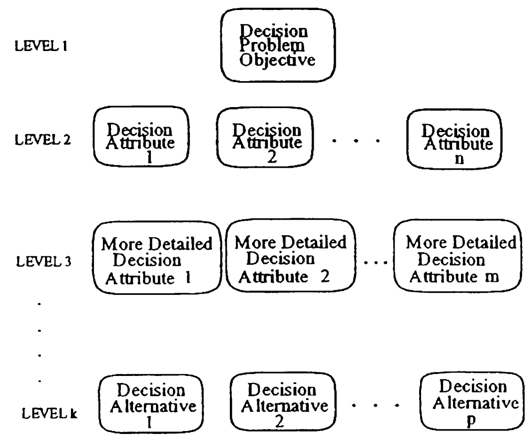

Figure 1: Standard Format of an AHP Decision Model

3) *Solve the pairwise comparision matrices for the eigen values and eigen vectors in order to estimate the relative weights of the decision elements*: The pairwise comparision values produce a ratio scale (a class of numbers whose ratios remain the same when each of them multiplied by a constant) of weights of the relative importance. AHP assumes that the evaluator does not know the actual weights, represented with vector W. Therefore the observed pairwise relative weights matrix, A, contains inconsistencies. The matrix A has rank 1.

$$A \cdot W = n \cdot W$$

where n is the eigenvalue and W is the eigen vector of A.

$$\hat{A} \cdot \hat{W} = \lambda_{max} \cdot \hat{W}$$

where $\hat{A}$ is the observed pairwise comparisions matrix, λ_{max} is the largest eigenvalue of $\hat{A}$, and $\hat{W}$ is the estimation of W. λ_{max} may be considered the estimation of n . The closer the value of computed λ_{max} is to n, the more consistent are the observed values of $\hat{A}$. As a result, two measures called Consistency Index (CI) and Consistency Ratio (CR) are defined as follow:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad \text{and} \quad CR = \frac{CI}{ACI} * 100$$

where ACI is the average index of randomly generated weights for a matrix of similar size. A CR value of 0.10 or less is considered acceptable, otherwise to resolve the inconsistencies in pairwise comparisions, the values of matrix $\hat{A}$ must be reassesed. Saaty (1988) recommends four different methods to estimate the values of W one of which is normalizing each column by dividing the elements of each column by the sum of the column and adding the elements in each resulting row and dividing this sum by the number of elements in the row. This is the process of averaging over the normalized columns.

4) *Aggregate the relative weights of the decision elements to obtain a rating for decision alternatives* : The last step of the process is the aggregation of the relative weights through the hierarchy by weighting relative values and summing the totals for each decision alternative and normalizing the results to sum to 1.

3 COMPARISION OF SIMULATION ENVIRONMENTS THROUGH AHP

The preliminary AHP model developed by the authors was discussed, critiqued, and iterated by a five member AHP study group formed at Industrial Engineering department of Oklahoma State University. Once the levels, the major aspects, and the criteria were finalized in terms of a set of nodes, the definition of linkages between the nodes is acomplished through an iterative process. Next, the resulting preference matrices were formed and weighted by the group, again in an iterative manner. The following section gives a summary of the resulting levels, major aspects, criteria and assessed weight matrices. The numbers before each aspect/criteria designate the node number.

Level 1 : Definition of the problem

1.1 - Best simulation approach : The problem on hand is the selection of the best simulation modeling methodology and the resulting model. The methodology in this context is interpreted as the whole process of conceptualizing and representing the system in terms of a simulation model using the underlying structures. The objective of the study is to reach a measure of preference between traditional simulation methodology based on existing simulation and programming languages and the new approach based on developed formalism and object oriented environment. In the new approach, the modeling is done by visualizing the system under study in terms of independent modular software constructs that represent the physical, logical, communication aspects of each system entity. These basic building blocks are designed using the sets and state-space representation scheme of the developed formalism. The formalism and the software also provide for nonprogrammed decision making capabilities through the use of knowledge-bases and artificial intelligence techniques. More detailed information on the new approach can be obtained from references Karacal and Mize (1996a and 1996b).

Level 2 : Main Aspects

2.1 - Model effectiveness : This is the model's capability of being used as a realistic decision support tool. That is to say, how closely the model expresses the real system in terms of the aspects that can be represented and the performance measures that can be obtained . In addition, the model's ability to manage change, extension, reusability, and detail level are also considered as part of this aspect. This node links to node 1.1.

2.2 - Model developer's potency and modeling effort : This aspect of the decision problem addresses the capabilities that are associated with the model developer and the effort required to build a model. The model developer's activities heavily depends on the conceptualization of the model, and the tools and facilities provided by the modeling environment. The lower level criteria are evaluated either in terms of increasing the modeler's capability or decreasing the modeling effort required. This node also links to 1.1.

2.3 - Model execution performance : This is basically the time required to experiment with the model. This aspect is considered as one of the main factors due to rapid deterioration of model execution time performance as layers of knowledge-based systems are added to the model in the developed methodology. This node links to 1.1.

2.4 - Model's degree of correspondence to the real system : This aspect is very important for the model's acceptance as a valid tool for gaining insight about the real system. Depending on the desired level of detail in the system to be represented, this aspect evaluates how accurately the real system can be expressed in the model. Similar to the other nodes of this level, this node also links to 1.1 to allow the relations defined at lower levels to factor into the final result.

Level 3 : Criteria Considered

3.1 - Formal modeling structures / modeling methodology : This criterion covers the underlying structures of the simulation paradigm and the modeling methodology dictated by those structures. In a sense, it is the science base of the simulation that gives the ability to answer questions like, how does one develop a model and why? This node links to model developer's potency and modeling effort, which is node 2.2.

3.2 - Model flexibility : This is the model's ability to express different aspects of the system as well as ease of model alteration and extension. The capability of developing models with different levels of detail without major model overhauls is also part of the flexibility criteria. This links to nodes 2.1, 2.2, and 2.4.

3.3 - Output provisions : This criterion represents the versatility of the data and the information from a simulation run. This includes the data collection facilities on physical and logical aspects of the system being modeled. This criterion has a strong influence on model effectiveness and therefore is linked to node 2.1.

3.4 - Execution speed : The computer time required to run the simulation model represents the execution speed. This criterion interacts only with node 2.3, which is the model execution performance aspect of a simulation.

3.5 - Physical, information, and control components : This is the simulation environment's ability to represent physical, information, and control components of the system under study in a modular fashion. This criterion increases the validity of the model, thereby promoting the credibility of the whole simulation study. This criterion links with all the aspects defined at level 2, except model execution performance. Therefore, it links to nodes 2.1, 2.2, and 2.4.

3.6 - Primitive modeling constructs : These are the basic building blocks of the model. The modularity and the variety of the constructs along with their expressiveness bring significant advantages to the whole simulation process. The primitive modeling constructs affect model developer's potency and model's degree of correspondence to the real system, and hence is linked to nodes 2.2 and 2.4.

3.7 - Non-programmed decision facilities : This criterion represents the simulation's ability to employ a hierarchical set of non-programmed decision support modules within the model. This is where mimicking the behavior of intelligent system entities that drive the entire operation of the real system comes into play. This criterion is considered to have an impact on all aspects defined at level 2, including model execution performance, and is linked to nodes 2.1, 2.2, 2.3, and 2.4.

Level 4 : Alternative Simulation Approaches

4.1 - Conventional simulation approach : This is the traditional approach to simulation. The system is mainly conceptualized in terms of physical components with no explicit information or control modules attached. The logic that governs the model behavior is implicitly expressed through a set of generic (not system relevant) and abstract modeling constructs. Modeling in this approach is analogous to developing a computer program in a simulation language.

4.2 - Formalism and OOP based simulation framework: This approach includes the new modeling methodology and its underlying formalism. In this approach, the system (manufacturing system) is perceived in terms of a set of interacting physical, information, and control components. These highly uniform, modular and alterable components are the basic model building blocks. Simulation modeling in this approach is the process of tailoring these default intelligent/nonintelligent constructs and defining the linkages among them to accurately represent a particular system's behavior.

Figure 2 shows the AHP hierarchical diagram. Tables 1 through 12 show the original pairwise weights of the AHP matrices agreed on by the study group.

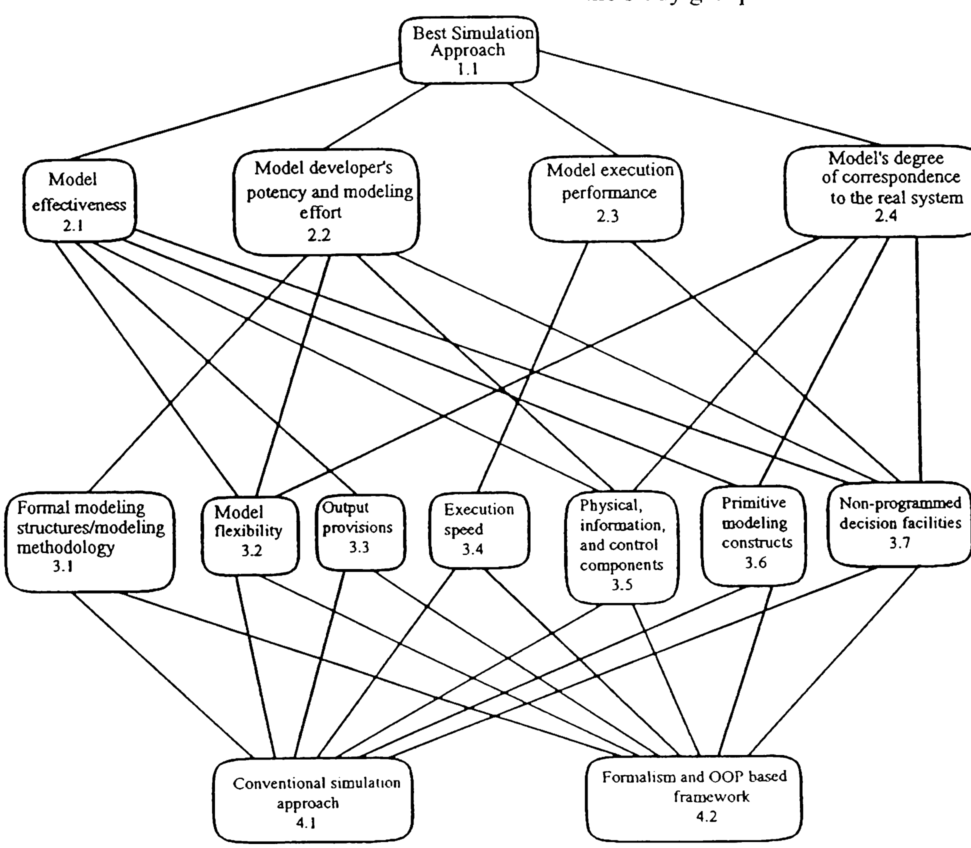

Figure 2 : AHP Hierarchical Diagram

Table 1: Node 1.1 Best Simulation Approach

Links from Lower Level:

1) Node 2.1 - Model effectiveness
2) Node 2.2 - Model developer's potency and modeling effort
3) Node 2.3 - Model execution performance
4) Node 2.4 - Model's degree of correspondence to the real system

Original weights

Row \ Col	1	2	3	4
1	1.000	5.000	8.000	3.000
2	0.200	1.000	6.000	0.250
3	0.125	0.167	1.000	0.167
4	0.333	4.000	6.000	1.000

Table 2 : Node 2.1 Model Effectiveness

Links from Lower Level:

1) Node 3.2 - Model flexibility
2) Node 3.3 - Output provisions
3) Node 3.5 - Physical, information, and control components
4) Node 3.7 - Non-programmed decision facilities

Original weights

Row \ Col	1	2	3	4
1	1.000	0.250	0.500	0.200
2	4.000	1.000	3.000	3.000
3	2.000	0.333	1.000	3.000
4	5.000	0.333	0.333	1.000

Table 3 : Node 2.2 Model Developer's Potency and Modeling Effort

Links from Lower Level:

1) Node 3.1 - Formal model structures and modeling methodology
2) Node 3.2 - Model flexibility
3) Node 3.5 - Physical, information, and control components
4) Node 3.6 - Primitive modeling constructs
5) Node 3.7 - Non-programmed decision facilities

Original weights

Row \ Col	1	2	3	4	5
1	1.000	0.333	0.333	0.333	3.000
2	3.000	1.000	4.000	2.000	3.000
3	3.000	0.250	1.000	0.333	4.000
4	3.000	0.500	3.000	1.000	4.000
5	0.333	0.333	0.250	0.250	1.000

Table 4 : Node 2.3 Model Execution Performance

Links from Lower Level:

1) Node 3.4 - Execution speed
2) Node 3.7 - Non-programmed decision facilities

Original weights

Row \ Col	1	2
1	1.000	8.000
2	0.125	1.000

Table 5 : Node 2.4 Model's Degree of Correspondence to Real System

Links from Lower Level:

1) Node 3.2 - Model flexibility
2) Node 3.5 - Physical, information, and control components
3) Node 3.6 - Primitive modeling constructs
4) Node 3.7 - Non-programmed decision facilities

Original weights

Col / Row	1	2	3	4
1	1.000	0.143	0.143	0.125
2	7.000	1.000	4.000	0.500
3	7.000	0.250	1.000	0.333
4	8.000	2.000	3.000	1.000

Table 6 : Node 3.1 Formal Modeling Structures/ Modeling Methodology

Links to Lower Level:

1) Node 4.1 - Conventional modeling approach

2) Node 4.2 - New modeling paradigm

Original weights

Col / Row	1	2
1	1.000	0.143
2	7.000	1.000

Table 7 : Node 3.2 Model Flexibility

Links from Lower Level:

1) Node 4.1 - Conventional modeling approach

2) Node 4.2 - New modeling paradigm

Original weights

Col / Row	1	2
1	1.000	0.333
2	3.000	1.000

Table 8 : Node 3 Output Provisions

Links from Lower Level:

1) Node 4.1 - Conventional modeling approach

2) Node 4.2 - New modeling paradigm

Original weights

Col / Row	1	2
1	1.000	0.333
2	3.000	1.000

Table 9 : Node 3.4 Execution Speed

Links from Lower Level:

1) Node 4.1 - Conventional modeling approach

2) Node 4.2 - New modeling paradigm

Original weights

Col / Row	1	2
1	1.000	5.000
2	0.200	1.000

Table 10 : Node 3 Physical, Information, and Control Components

Links from Lower Level:

1) Node 4.1 - Conventional modeling approach

2) Node 4.2 - New modeling paradigm

Original weights

Col Row	1	2
1	1.000	0.111
2	9.000	1.000

Table 11 : Node 3 Primitive Modeling Constructs

Links from Lower Level:

1) Node 4.1 - Conventional modeling approach

2) Node 4.2 - New modeling paradigm

Original weights

Col Row	1	2
1	1.000	0.333
2	3.000	1.000

Table 12 : Node 3 Non-programmed Decision Facilities

Links from Lower Level:

1) Node 4.1 - Conventional modeling approach

2) Node 4.2 - New modeling paradigm

Original weights

Col Row	1	2
1	1.000	0.143
2	7.000	1.000

The next step in the AHP procedure was the calculation of the relative weights of the decision elements. A set of spreadsheets are developed and are used to calculate the weights for each of the above matrices along with matrix consistencies. Then, after checking on the consistencies, and reassesing the assigned matrix values in an iterative manner, these relative weights are aggregated through a series of matrix calculations to yield a solution to the problem. Table 13 shows the resulting final weights.

Table 13 : Final Weights

Conventional simulation approaches	0.203
New simulation approach	0.797

The results of final weights obtained from AHP clearly indicate that the new simulation approach is preferrable to the conventional approach in terms of the aspects and criteria considered in the AHP study. The conclusion reached in this AHP study coincides with Beaumariage's (1990) results for object-oriented modeling approach, which were obtained using a different set of factors/criteria.

4 SUMMARY AND CONCLUSIONS

The example system modeled for validation of the formalism and the software developed shows the potential of the framework, even though the manufacturing system modeled is a simple one and the software is a prototype. This new approach allows the simulation analyst to collect and analyze certain types of data such as performance of different non-programmed control schemes and/or objects, and information processing capabilities of different entities and/or hierarchical levels. Traditional simulation modeling approaches do not allow studying various aspects of typical decision problems using a multi-criteria analysis. The formalism and the modeling methodology also dictate a uniform model. This indicates that different model developers who conceptualize a system in the same structured manner can come up with almost identical models. In contrast, the highly acclaimed and so called flexibility of the traditional approaches result in different models for the same real system if different model developers are involved in the model building process.

The final weights obtained from the AHP study is due to significant advantages provided by the new simulation approach. The formal structures provide the basic constructs for modeling information, control, and physical aspects of the system independently and simultaneously, which is a considerable improvement over the traditional approach. The interactive use of several knowledge-bases during the simulation allows more realistic and versatile representation of real systems.

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