SUBJECTIVE KNOWLEDGE BASES IN CORPORATE POLICY MAKING

Peter M. Milling

Department of Management
Osnabrueck University
D-4500 Osnabrueck, F.R. Germany

ABSTRACT

Intelligent behavior involves subjective variables, it is guided by fuzzy goals and constraints, and it applies multi-valued rules of inference to reach its conclusions. Decision or strategy support systems - in order to serve as reliable tools for testing the consequences of alternative courses of action - must reflect these essential aspects of the problem under investigation.

The paper presents a corporate model designed for the investigation of a firm's resource allocation strategy. It discusses the applicability of fuzzy set theory to computer simulation in general and to System Dynamics in particular. After qualitative variables and fuzzy goals have been explicitly included, the model exhibits improved performance with respect to behavior and acceptance by management.

INFORMATION REQUIREMENTS FOR POLICY SUPPORT SYSTEMS

Computer simulation models used for the support of corporate policy making frequently assume that all the required information is available as numerical data. This attitude has its roots in the origins of control theory and cybernetics. While such a premise is acceptable for science and technology, it is misleading as soon as social systems are considered.

In the social sciences, most information results from mental models, verbal statements or written records. These sources provide qualitative information on which actual decision making is based. They describe how information is turned into action, how management responds to developments in its fields of interest, and they are of prime importance for the conceptualization of formal models supporting corporate policy making. These models must explain the causes of observed and potential behavior modes if they are expected to serve as reliable simulators for the evaluation of improved organizational form and guiding policy.

Modeling qualitative variables has its long and important history in System Dynamics, it may even constitute one of the genuine attributes of the approach. Fuzzy set theory offers a conceptional basis for these efforts and provides empirically testable predicates as to how operations on qualitative variables are to be represented mathematically. Without this fuzzification, policy makers often feel that formal models do not properly reflect the knowledge and the considerations used in the actual decision making processes.

Qualitative information lacks the precision of numerical data, but it generally provides a more accurate description of reality than can be gained from the confinement to statistical time series or correlation coefficients. For the development of causal models of social systems, numerical data are used whenever they are available and an adequate representation of the problem under investigation. They are, however, not the sole and frequently not even the key information source for strategy support systems [2], [4].

The capability of the human mind to process qualitative components and apply multi-valued rules of inference can be precisely modeled by applying Fuzzy Set Theory [1], [3]. Its definition of a gradual - instead of a binary - membership function offers a powerful tool to bridge the gap between qualitative statements in real world description and their quantitative representation in formal models. The availability of corresponding operators leads beyond the limits of traditional binary logic. Fuzzy Set Theory might help to dissolve the seemingly antithetic contradictions between precision and accuracy in social system modeling.

LINKING MODEL PRECISION TO ACCURACY

An application of fuzzy set concepts to computer simulation modeling demonstrates their potential: A consulting firm, employing a rather small number of highly qualified professionals, experienced disturbing fluctuations in its incoming project orders. Since there was strong evidence that the oscillatory behavior had endogenous causes, a model based investigation was initialized.

The firm allocated its manpower resources between the acquisition of new projects and the transaction or completion of those in process. The allocation scheme depended upon the pressure stemming either from the upcoming deadlines for the projects in progress or the threatening shortage in the order backlog. It was assumed that this allocation procedure created the system's annoying behavior modes.

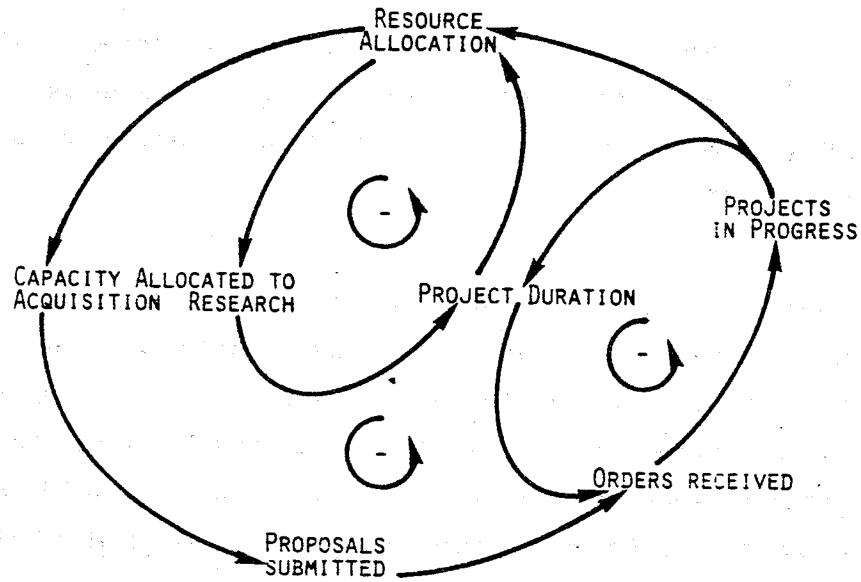

Fig. 1: Causal Diagram
of the Resource Allocation Model

In a first model version, the standard procedure for constructing a policy equation was used to determine the allocation of manpower resources (RA) between acquisition and research activities

$$RA = \Phi \left[\begin{matrix} \text{desired number} \\ \text{of projects} \\ \text{in progress} \end{matrix} - \begin{matrix} \text{actual number} \\ \text{of projects} \\ \text{in progress} \end{matrix} \right] \qquad \langle 1 \rangle$$

Due to several reasons, however, this formulation was not considered to be a good representation of actual managerial decision making:

(1) Model output did not satisfactorily reproduce and explain the interactions leading to the observed behavior.

(2) The pressures from elapsed project duration and due results presentation were not given the appropriate attention.

(3) Management felt uneasy defining a crisp value for the "desired number of projects in progress" simply because a model required such an input.

In their actual decision processes, management did not use a definite number to determine whether or not the stock of projects in progress was sufficient. It aimed at maintaining a sufficient level to assure smooth capacity utilization, a broad spectrum of different problems, and a well distributed range of customers. This objective was constrained by the need to keep project duration at a tolerable level to avoid deterring potential customers by expected them to wait unacceptably long for their results.

A MODEL WITH FUZZY GOALS AND CONSTRAINTS

Goal G and constraint C were interpreted as fuzzy sets [1], [5]. Management was striving to assure a sufficient level of "Projects in Progress", which represents the order backlog (goal), and to keep "Project Duration" which is the delivery delay within a tolerable time span (constraint). Despite management's discomfort to define a "desired number of projects in progress", it turned out to be rather easy to reach an agreement on the membership functions $\mu_G(x)$, $\mu_C(x)$ for the two variables, represented in DYNAMO as standard table functions.

The connective "and" in the definition of the set of alternatives forming the decision space was considered to be represented sufficiently well by the intersection of the membership functions. The decision D can be stated as $D = G \cap C$, or

$$\mu_D(x) = \mu_{G \cap C}(x) = \min\, [\mu_G(x),\ \mu_C(x)]. \qquad \langle 2 \rangle$$

The solution x* with the maximal grade of membership represents the optimal decision [4]

$$\mu_D(x^*) = \max \min\, [\mu_G(x),\ \mu_C(x)] \qquad \langle 3 \rangle$$
$$= \max\, [\mu_G(x) \wedge \mu_C(x)].$$

The execution of <3> requires the allocation of manpower either to acquisition or to transaction efforts - depending upon which function is limiting an improved performance.

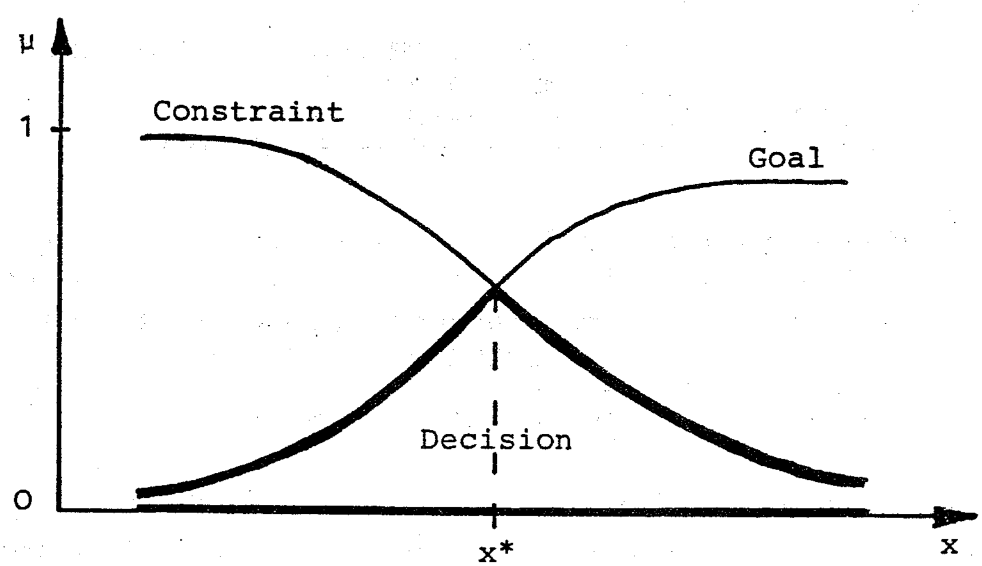

Fig. 2: Decision Space and Optimal Decision

In the case of intersecting membership functions with opposite slopes, the system reaches its optimal state for $\mu_G(x) = \mu_C(x)$. Since the system is a dynamic one, the optimal state - if it is achieved - cannot be sustained by simply maintaining the the current set of parameters. Continuous readjustment in a feedback loop setting is required.

The DYNAMO equations defining the resource allocation decision RA as function of Sufficient Projects in Progress and Acceptable Project Duration can then be written as

```
RA.KL=DELAY3(MFAPD.K-MFSPP.K,AT)             R  <4>
AT=2                                         P  <4.1>

  RA        RESOURCE ALLOCATION [MAN/MONTH]
  MFAPD     MF ACCEPTABLE PROJECT DURATION [DL]
  MFSPP     MF SUFF. PROJECTS IN PROGRESS [DL]
              MF - MEMBERSHIP FUNCTION
  AT        ADJUSTMENT TIME [MONTHS]


MFAPD=TABHL(MFAPDT,P.K,3,9,2)                A  <5>
MFAPDT=.1/.35/.9/1                           T  <5.1>

  MFAPD     MF ACCEPTABLE PROJECT DURATION [DL]
              MF - MEMBERSHIP FUNCTION
  MFAPDT    TABLE FOR MFAPD [DL]
  P         PROJECTS IN PROGRESS [UNITS]


MFSPP=TABHL(MFSPPT,PD.K,10,18,1)             A  <6>
MFSPPT=1/1/.95/.9/.8/.65/.4/.15/.1           T  <6.1>

  MFSPP     MF SUFF. PROJECTS IN PROGRESS [DL]
              MF - MEMBERSHIP FUNCTION
  MFSPPT    TABLE FOR MFSPP [DL]
  PD        PROJECT DURATION [MONTHS]
```

The time patterns of the values for the membership functions MFAPD and MFSPP over a 100 month period are shown in figure 3. It presents the shifting degrees of goal and constraint fulfillment respectively and the resulting flows in resource allocation between acquisition and research activities.

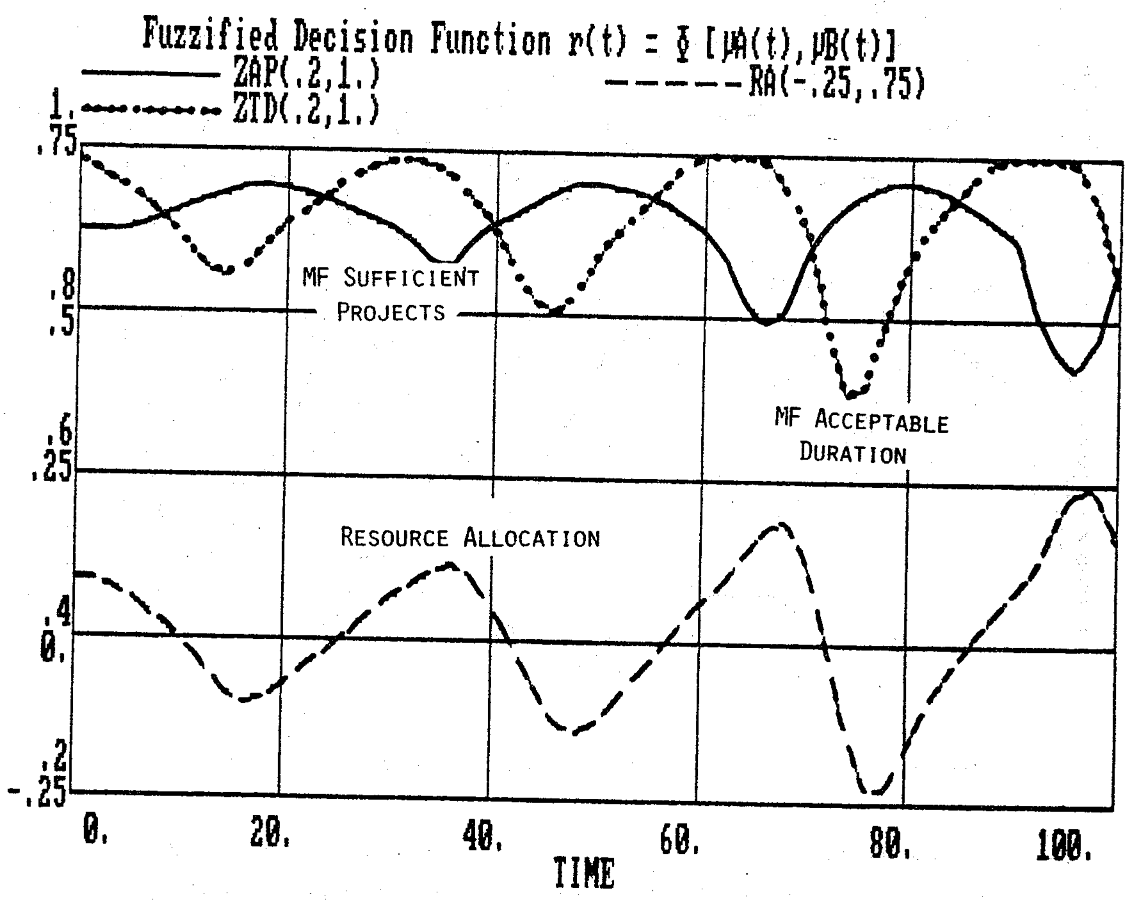

Fig. 3: Time Pattern
of the Fuzzified Decision Function

Figure 4 reflects the Level of Satisfaction as it varies with the achieved performance of the system's "hard facts": the stock of Projects in Progress and the capacities devoted either to acquisition efforts or to actual research activities.

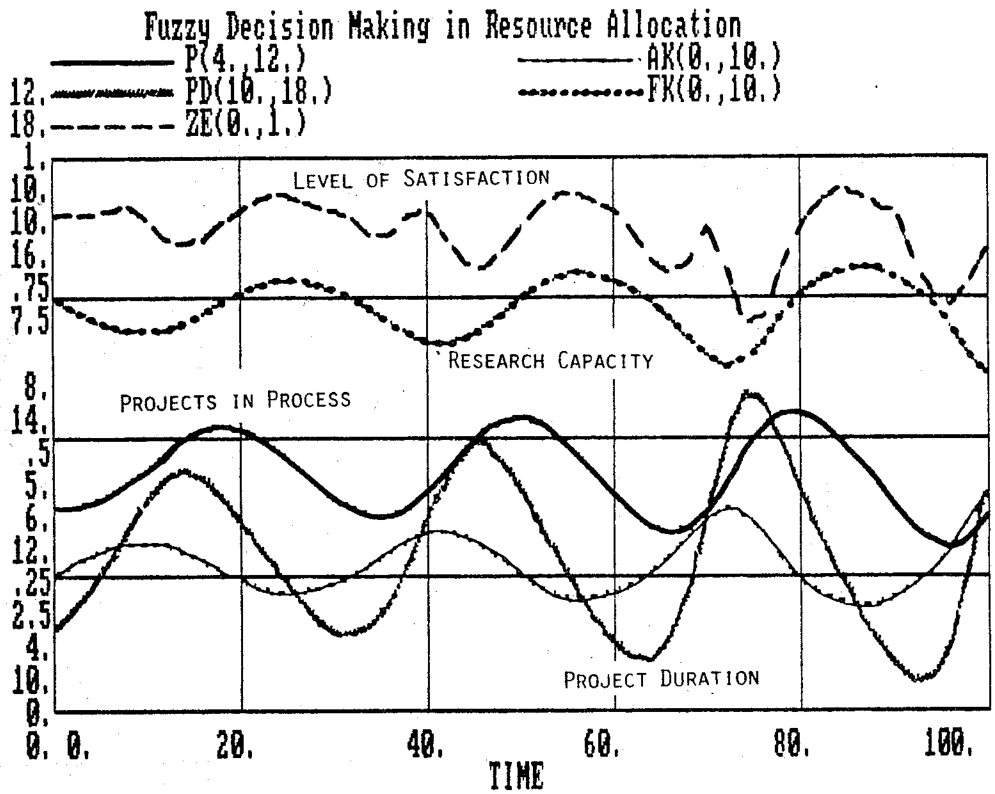

Fig. 4: Behavior of the Resource Allocation Model

This fuzzified version of the model was considered by management to be a structurally valid representation of reality. Its behavior captured the characteristic fluctuations which initiated the study. Model analysis indicated the interactions of the pursued objectives and explained how information delays and amplifications in actions taken caused the observed time pattern. The insights gained from this investigation provided the basis for an improved allocation policy.

REFERENCES

[1] Bellman, R.E. and L.A. Zadeh, "Decision Making in a Fuzzy Environment", Management Science, Vol. 17 (1970), pp. B141-B164.

[2] Forrester, J.W., "Lessons from System Dynamics Modeling", Proceedings of the 1986 International Conference of the System Dynamics Society, J. Aracil, J.A.D. Machuca, M. Karsky eds., Sevilla 1986, pp. 1-16.

[3] Milling, P.M., "Applying Fuzzy Logic to the Representation of Managerial Decision Making Processes", Cybernetics and Systems: Present and Future, J. Rose ed., Lytham St. Annes 1987, pp. 712- 716.

[4] Morecroft, J.D.W., "Strategy Support Models", Strategic Management Journal, Vol. 5 (1984), pp. 215-229.

[5] Zimmermann, H.-J., "Description and Optimization of Fuzzy Systems", International Journal of General Systems, Vol. 2 (1976), pp. 209-215.