THE FOREIGN POLICY DECISION-MAKER SIMULATION[1]

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Keywords and phrases: decision-making, simulation models, graph theory, cognitive psychology, foreign policy

I. MAJOR ELEMENTS OF THE MODEL

The major theoretical presupposition of our model of foreign-policy decision-making is that the beliefs of the decision-makers are central to the study of decision outputs and probably account for much of the variance in international politics. Beliefs represent both the congealed experiences of the decision-maker and his expectations about the decision environment. In the former sense, they are his decisions about the significance of past "events". In the decision-making process the belief system as a whole acts like a template for receiving and channeling information, and for relating possible policy options to perceptions about the intentions and behavior of other nations, as well as to the policy objectives of the decision-maker.[2]

A decision-maker's belief system is represented in our model as a map of causal linkages between four types of concepts. "Affective concepts" (A-Concepts) refer to immediate policy objectives of a decision-maker; "cognitive concepts" (C-Concepts) denote beliefs of a decision-maker about events which occur in the international system; "policy concepts" (P-Concepts) reflect possible alternatives or options from which a decision-maker selects policy recommendations; and "value concepts" (V-Concepts) are abstract values, such as national security, which a decision-maker tries to satisfy. The linkages between concepts carry either positive or negative valence in order to distinguish the nature of the causal relationships which are perceived by the decision-maker. Taken together, the concepts and the causal linkages between them form a "cognitive map" of a decision-maker's belief system. It is this cognitive map which allows a decision-maker to relate an event or a series of events to policy alternatives and policy objectives.

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[1] This research was supported by grants from the Institute of International Studies, University of California, Berkeley, and the National Science Foundation (Grant GS-36558).

[2] For further discussion of our theoretical approach, see Michael J. Shapiro and G. Matthew Bonham, "Cognitive Processes and Foreign Policy Decision-Making," International Studies Quarterly, 17 (June 1973), 147-174.

Our method of representing beliefs of decision-makers reflects the proposition that decision-makers tend to believe that international events are related causally and thus try to infer causal relationships underlying these events and the actions of other nations, even when there is little or no evidence of a causal nature. A decision-maker's motivation to exercise control over his environment leads him to attribute causal relationships to the behavior of others in the international system.

In our model of foreign policy decision-making five processes are invoked when a decision-maker is confronted with a new international situation which may require a response from his government: initial amplification, a search for antecedents, a search for consequences, a search for policy alternatives, and policy choice.

During the initial amplification process, the decision-maker attempts to place a novel international event or series of events into the context of his experiences. This is a process of relating various components of an international situation to existing beliefs about the nations and actions involved so that the situation can be understood.

At the initial amplification stage of our model, new international developments are introduced into the simulation in order to activate concepts in the decision-maker's belief system. When a new situation is introduced, concepts in the decision-maker's cognitive map which most closely correspond to that situation are "highlighted," and this information is stored for further use. Operationally, initial amplification is accomplished externally through the intervention of the researcher, who codes the event in categories contained in the cognitive mapping. The event is then input in the form of a list of concepts to be highlighted in the cognitive map.

The second decision-making process is a search for antecedents. After the initial amplification, the decision-maker searches his cognitive map for prior causes of the current international situation; for example, the intentions of another state which led it to pursue a policy that caused the new situation confronting our decision-maker. These prior causes appear in cognitive maps as "antecedent paths," consisting of concepts and arrows, which lead to initially highlighted concepts. Once the first concept of an antecedent path has been located, we look for the concept directly prior to it and so on until at last we reach a concept with no perceived prior causes -- the beginning of the antecedent path. At this point we store the antecedent path, suppress the portions of the cognitive map unique to this path and repeat the process to obtain other antecedent paths.

The third process of the simulation, a search for consequences, is an attempt by the decision-maker to anticipate where a situation will lead, if his government does not act. Once the decision-maker has an idea about the prior causes of a situation, he searches for possible consequences for the behavior of other states and his own policy objectives. In a cognitive map consequences appear as paths leading to a decision-maker's policy objectives from concepts which were highlighted during the first two processes, initial amplification and the search for antecedents. The procedure for location "consequent paths" is parallel to the process followed for antecedent paths, except that here the direction of the search is reversed, and we try to find all paths leading from the highlighted concepts rather than paths leading to such concepts.

The fourth process of the model is a search for policy alternatives or options. At this point in the simulation, the decision-maker looks for policy alternatives which are embedded in his explanation of the situation that might give him some control over events in the international system. He hopes that the choice of a policy alternative will lead to changes in events, which as a result, will have a favorable impact on his policy objectives.

Operationally, the search for policy alternatives is quite easily accomplished. After a decision-maker's explanation of a situation has been sorted out, the process continues with a search for all P-Concepts (policy alternatives) which are directly connected to all antecedent and consequent paths. This information is then stored for the next stage.

The choice of a policy alternative from among a number of possible options is the final decision-making process in our simulation. At this point we follow the paths from the possible policy alternatives to the policy values of the decision-maker and calculate which alternative or combination of alternatives will result in maximum gain in values. The signs of the causal linkages are important here, because we must calculate how each policy alternative will affect every policy value to which it is connected. There are, of course, a variety of decision models one can employ to make such calculations. Presently, we employ a lexicographic decision calculus which assumes that the decision-maker first uses his most important policy value to see if the alternatives affect it differently. If this value does not distinguish between alternatives, he then moves to his second ranking value, and so on, until he gets a value which distinguishes one alternative as better than the others. Using this approach, it becomes straightforward to evaluate the perceived impact of all the policy alternatives and to rank them in order of decreasing importance.

II. COMPUTER REPRESENTATION OF THE MODEL

The computer simulation model developed in the course of these investigations of foreign policy decision-making behavior uses digraph theory as its mathematical base. Digraph theory, or the theory of directed graphs, provides convenient matrix techniques for the representation and manipulation of structural relationships and thus enables the computer processing of decision-makers' belief systems.[3]

The cognitive map that represents the subset of a decision-maker's belief system relevant to the foreign policy situation being analyzed is converted to the form of an adjacency matrix. The adjacency matrix A is a square matrix of size n x n where n is the total number of concepts in the corresponding cognitive map. For the purposes of

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[3] Frank Harary, Robert Z. Norman, and Dorwin Cartwright, Structural Models: An Introduction to the Theory of Directed Graphs (New York: John Wiley & Sons, c1965)

our simulation, A is a signed binary matrix. Each element a_{ij} can take on the values +1, 0, or -1; a_{ij} = 1 if the relationship $i \xrightarrow{+} j$ is present in the cognitive map, -1 if the relationship $i \xrightarrow{-} j$ is present in the cognitive map, and 0 otherwise. The diagonal elements a_{ij} are considered to be 0.

The transformation of a cognitive map into its corresponding adjacency matrix is illustrated in Figures 1 and 2. Figure 1 shows a small cognitive map involving eleven concepts and the causal relationships that are perceived to exist among them. Figure 2

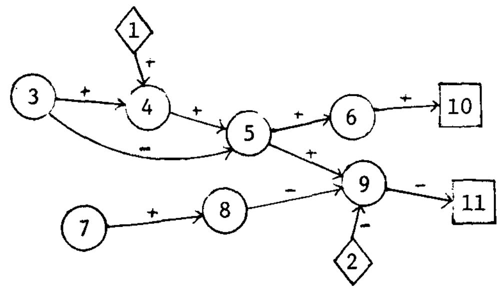

Fig. 1. Illustrative Cognitive Map

Concepts 1 and 2 are Policy Concepts
Concepts 3 through 9 are Cognitive Concepts
Concepts 10 and 11 are Value Concepts

then shows the adjacency matrix that results when the above-stated transformation rules are applied to this illustrative cognitive map.

	1	2	3	4	5	6	7	8	9	10	11	
1	0	0	0	1	0	0	0	0	0	0	0	1
2	0	0	0	0	0	0	0	0	-1	0	0	1
3	0	0	0	1	-1	0	0	0	0	0	0	2
4	0	0	0	0	1	0	0	0	0	0	0	1
5	0	0	0	0	0	1	0	0	1	0	0	2
6	0	0	0	0	0	0	0	0	0	1	0	1
7	0	0	0	0	0	0	0	1	0	0	0	1
8	0	0	0	0	0	0	0	0	-1	0	0	1
9	0	0	0	0	0	0	0	0	0	0	-1	1
10	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	2	2	1	0	1	3	1	1	11

Fig. 2. Adjacency Matrix and Associated Row and Column Sums for the Cognitive Map in Fig. 1.

The adjacency matrix has a number of useful properties.[4] The row sum of the absolute values of the elements of row i gives the <u>outdegree</u> (od) of concept i, that is the number of concepts perceived to be affected directly by concept i. Similarly, the column sum of the absolute values of the elements of column i gives the <u>indegree</u> (id) of concept i, the number of concepts perceived to affect directly concept i. The sum of the indegree and outdegree for concept i gives the <u>total degree</u> (td) of concept i, a useful operational measure of that concept's <u>cognitive centrality</u> in the

[4] <u>Ibid</u>., pp. 17-18.

decision-maker's belief system. Mathematically, these relationships can be expressed as

$$id(i) = \sum_{j=1}^{n} |a_{ij}|$$

$$od(i) = \sum_{i=1}^{n} |a_{ij}|$$

$$td(i) = id(i) + od(i)$$

Applying the total degree criterion for measuring cognitive centrality to the adjacency matrix in Figure 2, concepts 5 and 9 are found to have the highest total degree (4; 2+2 and 1+3 respectively). Examination of the cognitive map in Figure 1 confirms that these two concepts are, indeed, the most central.

Operationally, however, cognitive centrality is not determined on the basis of total degree alone. Some of the perceived relationships in a decision-maker's cognitive map are based on analogies from past events. In such cases, the relational paths between historical events and the affected concepts are also added to the cognitive centrality index. Moreover, since many of our cognitive maps are based on the perceptions of several decision-makers, the possibility of multiple relations between a pair of concepts exists, and such multiple paths are also considered in the computation of cognitive centrality.

The most useful property of the adjacency matrix is that it readily permits the computation of the reachability matrix R. The reachability matrix[5] is a square matrix also of size n x n, each of whose elements r_{ij} is 1 if concept j is reachable from concept i and 0 otherwise. Whereas the adjacency matrix A indicates only direct relationships between concepts, that is concept linkage paths of length 1, the reachability matrix reflects the existence of indirect or deductive relationships as well. Indirect paths, i.e. concept linkage paths of length greater than 1, can be located by raising the adjacency matrix to successive powers. If element $a_{ij}^{(2)}$ of matrix A^2 is non-zero, a path of length 2 exists between concepts i and j; if $a_{ij}^{(2)} = 0$ such a path does not exist.

Figure 3 shows this property of the adjacency matrix; there, the illustrative adjacency matrix is squared to test the existence of paths of length 2. Element $a_{15}^{(2)}$, for example, is non-zero; this reflects the existence of a path of length 2 between concepts 1 and 5. Such a path exists, indeed, in the cognitive map via concept 4.

Similar relationships exist between the matrix A^3 and paths of length 3, the matrix A^4 and paths of length 4, etc. By using boolean addition, the reachability matrix can thus be computed as $R = |A| + |A^2| + |A^3| + \ldots |A^{n-1}|$ since the longest possible path in a cognitive map with n concepts is of length n-1. Computationally, it is

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[5] <u>Ibid.</u>, pp. 117-122.

	1	2	3	4	5	6	7	8	9	10	11
1	0	0	0	0	1	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	1
3	0	0	0	0	1	-1	0	0	-1	0	0
4	0	0	0	0	0	1	0	0	1	0	0
5	0	0	0	0	0	0	0	0	0	1	-1
6	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	-1	0	0
8	0	0	0	0	0	0	0	0	0	0	1
9	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0

Fig. 3. Adjacency Matrix in Fig. 2. Squared to Test the Existence of Paths of Length 2

rarely necessary to raise A to the (n-1)th power since such long paths rarely exist; it is only required to raise A to a power k such that $A^k=0$. Once this point is attained, no additional non-zero reachability matrix elements will be located. The full reachability matrix for the illustrative cognitive map is shown in Figure 4.

	1	2	3	4	5	6	7	8	9	10	11	
1	0	0	0	1	1	1	0	0	1	1	-1	6
2	0	0	0	0	0	0	0	0	-1	0	1	2
3	0	0	0	1	-1	-1	0	0	-1	-1	1	6
4	0	0	0	0	1	1	0	0	1	1	-1	5
5	0	0	0	0	0	1	0	0	1	1	-1	4
6	0	0	0	0	0	0	0	0	0	1	0	1
7	0	0	0	0	0	0	0	1	-1	0	1	3
8	0	0	0	0	0	0	0	0	-1	0	1	2
9	0	0	0	0	0	0	0	0	0	0	-1	1
10	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	2	3	4	0	1	7	5	8	30

Fig. 4. Reachability Matrix and Associated Row and Column Sums for the Cognitive Map in Fig. 1.

For the purposes of the simulation, the reachability matrix is treated as a signed binary matrix, where the sign of each non-zero element r_{ij} is the product of the signs of the individual paths of length 1 that make up the path between concepts i and j. If the sign of the relationship between a pair of concepts differs when computed over different paths imbalance is said to exist. In such a case, the sign of r_{ij} in the reachability matrix is the sign obtained when the computation is performed over the geodesic, that is over the path between i and j of minimum length. The imbalance still exists, though, and needs to be considered subsequently in the simulation.

The computation of row and column sums of the absolute values of the elements of R gives other useful measures analogous to the outdegree and indegree of the adjacency matrix. The row sum of R for row i specifies the total number of concepts reachable from from concept i, while the column sum for column i gives the total number of concepts from which concept i can be reached.

After the adjacency and reachability matrices are constructed, the simulation of a given foreign policy event can begin. The event is input in the form of an initial list of concepts to be highlighted in the cognitive map. From these initially highlighted concepts, a full highlight vector is constructed by the process of indirect highlighting. All concepts from which an initially highlighted concept can be reached lie on potential explanatory antecedent paths and are so identified in the highlight vector. Similarly, all concepts which can be reached from an initially highlighted concept lie on potential consequent paths and therefore are also indirectly highlighted. These operations are performed by consulting the columns and rows, respectively, of the reachability matrix. Concepts not highlighted, initially or indirectly, in the highlight vector will play no explanatory role in the problem under analysis; such concepts can therefore be eliminated for the time being from both the adjacency and reachability matrices. Policy concepts will be used in the selection and evaluation of relevant policy options but do not play an explanatory role; as a result they are also temporarily removed from the adjacency and reachability matrices.

If, in the illustrative cognitive map, concept 5 is initially highlighted because it reflects some important aspect of a foreign policy problem under analysis, then concepts 3 and 4 would be indirectly highlighted because they lie on potential antecedent paths and concepts 6, 9, 10 and 11 would be indirectly highlighted because they lie on potential consequent paths. Concepts 7 and 8 are not highlighted and will therefore not play a role in the explanation-finding process; neither will concepts 1 and 2 which are policy concepts.

The highlighted concepts and the perceived relationships among them form the subset of the decision-maker's belief system from which explanations will be deduced; the analysis of this remaining network is the central part of the model. This consists of six steps:

search for antecedent paths;
search for consequent paths;
formulation of alternative explanations;
selection of the preferred explanation;
search for relevant policy options; and
evaluation and ranking of relevant policy options.

The search for antecedent paths involves the identification of the various linear sequences of concepts leading to the concepts externally highlighted to reflect the present situation. Antecedent paths are located by starting with the initially highlighted concepts and, for each, searching the respective column of the adjacency matrix to identify the immediately antecedent concepts. If there are several immediately antecedent concepts, the one with the highest cognitive centrality is chosen as the best next step in the path; this procedure directs the search to the most complex and hence most central region of the cognitive map. Once the second concept of the path has been chosen, the adjacency matrix is searched for the concept directly antecedent to it with the highest cognitive centrality. This procedure is followed until a concept with no antecedents is reached; this concept with an indegree of 0 marks the beginning of this antecedent path. At this point all relationships unique to this antecedent path are removed from the adjacency matrix. The same procedure is then followed to locate the next possible antecedent path and so forth until gradually the entire set of antecedent relationships in the adjacency matrix is fully reduced.

At this point the full set of antecedent paths has been identified. Each path is now tested to ascertain whether at least one of the relationships on the path is perceived as historically supported. If no historical support exists, the path is suppressed. In this manner the set of antecedent paths is reduced to the set of plausible antecedent paths which is then stored.

Applying this algorithm to the illustrative cognitive map will result in the location of two antecedent paths, (3-4-5) and (3-5), when concept 5 is the initially highlighted concept.

The search for consequent paths is performed in an analogous manner. This time, however, the search is for concepts which lead away from the initially highlighted concepts. The rows of the adjacency matrix are now used to locate directly consequent concepts and the choice among several directly consequent concepts is again resolved by the cognitive complexity criterion. The construction of a consequent path proceeds until a concept with no consequents is reached; this concept, usually a value concept, with an outdegree of 0 marks the end of this consequent path. At this point, the relationships unique to this consequent path are removed from the adjacency matrix and the search procedure is performed iteratively until the full set of consequent paths has been identified. The historical support test is not applied to consequent paths, since consequent paths refer to developments which might occur at some point in the future. The set of consequent paths is thus identical to the set of plausible consequent paths.

The illustrative cognitive map with concept 5 initially highlighted will yield two consequent paths when this algorithm is applied; these are (5-6-10) and (5-9-11).

From the full set of plausible antecedent and consequent paths, one or more explanations can be derived. The number of explanations available depends on the number of unique mutually inconsistent sets of antecedent and consequent paths that exist. Inconsistency, in this sense, is identical to imbalance. If the sign of the perceived relationship between two concepts when determined over one path differs from the sign obtained over another path, imbalance is present and the paths belong to two separate inconsistent explanations, of which one will be accepted and the other suppressed.

Explanation selection is accomplished in the model with the aid of a path balance matrix P. If a plausible antecedent paths and b consequent paths were located, then the path balance matrix P is a square matrix of size $c \times c$, such that $c = a + b$. Matrix P is binary with each element $p_{ij} = 1$ if paths i and j are mutually balanced and $p_{ij} = 0$ if they are imbalanced. Entries on the main diagonal equal 1 by definition. The matrix is symmetric, because the balance relationship is symmetric (i.e. if i balances j then j balances i). The balance relationship is not transitive, however, since, if i balances j and j balances k, it does not necessarily follow that i balances k. For this reason, each element of P above the main diagonal, p_{ij}, has to be uniquely determined by examining the subnetwork of relationships among the shared concepts on paths i and j. If paths i and j share less than two concepts, imbalance is not possible and p_{ij} is set to 1.

The path balance matrix may then be used to identify all sets of antecedent and consequent paths which form balanced consistent explanations. The model predicts that the explanation that will be preferred by the decision-maker will be the one with the highest cognitive centrality. The cognitive centrality of explanation k is defined in the model as

$$cc_k = \sum_{i=1}^{n} (cc(i)\ x_{ik})$$

where n is the total number of concepts, cc(i) is the cognitive centrality of concept i, and x_{ik} is a boolean variable with a value of 1 if concept i is present in explanation k and 0 otherwise.

Operationally, the search for the preferred explanation is accomplished within the model in the following manner: the cognitive centrality for each antecedent and consequent path located is computed as the sum of the total degrees of its component concepts. The path with the highest cognitive centrality is selected as the base of the explanation. All other paths are then examined in order of decreasing cognitive centrality with the aid of the path balance matrix to determine whether they are consistent with all paths previously selected as part of the preferred explanation. If so, they are added to the explanation.

When the explanation-finding algorithm was applied to the illustrative cognitive map four antecedent and consequent paths were located:

1 (3-4-5); 2+3+4= 9
2 (3-5); 3+4= 7
3 (5-6-10); 4+2+1= 7
4 (5-9-11); 4+4+1= 9

The cognitive centrality of each path is shown following the identifications of the component concepts. From the five paths the following 4 x 4 path balance matrix is derived:

	1	2	3	4
1	1	0	1	1
2	0	1	1	1
3	1	1	1	1
4	1	1	1	1

This matrix shows that all paths are mutually balanced with the exception of paths 1 and 2. Paths 1 and 2 are inconsistent, since path 1 yields a positive linkage between 3 and 5 while path 2 yields a negative linkage. Applying the preferred explanation search algorithm to this path balance matrix, an explanation consisting of paths 1, 3 and 4 is selected; this explanation has an overall cognitive centrality of 17.

With the preferred explanation identified, the adjacency matrix is reduced by removing from it all non-policy concepts and relationships which are not present in the explanation; policy concept linkages are restored to the adjacency matrix at this time. A final reachability matrix can then be computed and the search for relevant policy options can be performed.

The search for policy options involves the examination of the reachability matrix to determine if, for each given policy concept, one or more concepts which are part of the explanation are reachable. If so, that policy concept is added to the set of relevant policy concepts; otherwise it is discarded as inapplicable.

In our example there are two policy concepts, concepts 1 and 2. Both of these are relevant, since they are adjacent to concepts which are part of the preferred explanation (concept 1 is adjacent to concept 4, while concept 2 is adjacent to concept 9).

The set of relevant policy concepts is evaluated and ranked. Evaluation is performed in terms of the differential impact of the policy concepts on an externally specified and ranked set of high-order value concepts. This operation involves the use of a policy impact matrix V, which is a rectangular matrix of size p x s where p is the total number of relevant policy concepts and s is the total number of the high-order value concepts. V is a signed binary matrix where each element v_{ij} specifies the sign of the perceived effect that policy concept i has on value concept j. Essentially, V is a submatrix of the reachability matrix R and is constructed from it.

The ranking of the relevant policy concepts is then done using a lexicographic decision algorithm. Based on the proposition that decision-makers do not seek to maximize all of their values simultaneously but rather pay selective attention to one high-order value at a time, this procedure involves the iterative classification of the policy concepts into three categories (positive impact, zero impact, and negative impact) with respect to each value concept, starting with the most important value first. Computationally, this is performed by calculating a policy impact index N for each relevant policy concept, such that

$$N_i = \sum_{j=1}^{s} (10^{s-j} v_{ij})$$

where the s value concepts are so ranked that value 1 is perceived as more important than value 2, etc. Selection of the preferred policy, then, involves selection of the relevant policy concept with the highest policy impact index.

In our example, the policy impact matrix is of size 2 x 2 involving 2 policy concepts (1, 2) and 2 value concepts (10, 11):

	10	11
1	1	-1
2	0	1

Policy concept 1 is thus perceived to have a positive effect on value 10 and a negative effect on value 11; policy concept 2 has no perceived effect on value 10 and a positive effect on value 11. If value concept 10 is deemed more important than value concept 11, policy concept 1 would be preferred. If the value rankings were reversed, then concept 2 would become the preferred policy.

The simulation model has been implemented in FORTRAN IVH for the IBM 370 computer system available at The American University Computation Center and in its present form is capable of processing cognitive maps involving up to 200 concepts.