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A Network-Centred Optimization Technique for Operative Target Selection

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Abstract: - The process of accomplishing strategic objectives by concentrating on effects as opposed to attrition-based destruction is known as effects-based operations, or EBO. Finding important nodes in an adversary network is a critical step in the EBO process for a successful implementation. In this paper, propose a network-based method to identify the most influential nodes by combining network centrality and optimization. To determine the node influence, the adversary's network structure is analyzed using degree and between centralities. Given the dynamic nature of the adversary network struct[1]ure and the centrality results, an optimization model that takes resource constraints into account chooses the key nodes. Our findings demonstrate that various network properties, such as between and degree centralities, influence the priorities of nodes as targets, and that using an optimization model yields better priorities with decreasing marginal properties. There is a discussion of the implications for theory and sensible decision-making.

Keywords: Effects-based operations; target selection problem; network centrality; network optimization; integer program

I. INTRODUCTION

In order to achieve the maximum effects of war at the minimum possible costs, organizations in a military sector have introduced new forms of operation. Although there are different forms of new operational concept, one of the most remarkable transformations has been an ongoing shift from objective-based warfare to effects-based operations (EBO). EBO refers to a process for achieving strategic goals by focusing on effects rather than attrition-based destruction [1]. Desired effects in EBO can be accomplished through precise attacks on key targets of adversary systems with minimum risk and destruction.

Since the US forces verified the effectiveness of EBO during the Gulf and Iraq War, scholars and experts on military strategy have paid substantial attention to EBO. While they have made a great deal of progress in defining and developing the concept of, and investigating the applicable war game models for EBO [2, 3], significant gaps still exist in our understanding of EBO. First, previous studies have focused on developing the procedures of and identifying the preconditions for implementing EBO. Although these conceptual works contribute to our knowledge of factors that may underlie EBO, more research attention is needed toward analyzing an adversary's (enemy's) complex network systems. Because the strategic elements of the adversary are linked to each other, analyzing the network structure through which the adversary operates is important for both maximizing desired

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effects and minimizing possible costs of war. Second, several studies have attempted to analyze the adversary's network structure, but have failed to consider various types of network characteristics. They have mainly used degree centrality which implies the extent to which a node (a strategic element of the adversary) is connected to other nodes [4, 5] to analyze the adversary's network structure. However, there are other types of network centralities. Different types of network characteristics provide different bases for assessing the relative importance of nodes [6]. Accordingly, suggest that analyzing various types of network structures provides decision makers with information that is more relevant, more complete, more neutral, and freer from error, and thus, enhances the effectiveness of EBO implementation. Finally, previous research has paid little attention to the dynamic nature of network structures. Some researchers have attempted to select key targets based on the network centrality analysis, but these efforts have not yet been jointly examined the dynamic nature of network structures.

To address these gaps, present an analytic method for selecting key targets to achieve desired effects in EBO. Specifically, adopt two types of network centralities to analyze the adversary's network structure. Considering each node's centrality as its influence value in a network, calculate the contribution of a node to higher level effects. Here, effects can be achieved from the nodes in a lowest level. The nodes in the lowest level have their influence values that affect each other. They also contribute to the effects predefined when organizing unit forces. It denotes this by the contribution of a node. Thus, a node has its influence value as well as its contribution for achieving the desired effects. In addition, develop an optimization model of the target selection problem in EBO, taking the dynamic nature of the adversary network structure into account.

II. LITERATURE REVIEW ON CONCEPTUAL DEVELOPMENT FOR TARGET SELECTION IN EBO

In EBO, physical destruction of an adversary is still important, but only to the extent necessary for supporting the achievement of desired effects [7]. Successful leaders and decision makers have applied principles of EBO to deal with security crises and foreign policy problems throughout history. Recent development of technology has led to more effective and efficient implementation of EBO by providing nearly omniscient intelligence systems and smart weapons enabling pinpoint destruction. Scholars and experts have contributed to the development of EBO by elaborating a detailed process. In general, the process of EBO includes three phases: planning, execution, and assessment [7]. In the planning phase, the most important objective is to define desired effects. To do this, it is necessary to analyze a PMESII system of an adversary: political, military, economic, social, infrastructure, information (see Figure 1). Because nodes which constitute a PMESII system are linked to each other, by analyzing their consecutiveness and network structure, it is possible to identify key nodes. Based on the results of network analyses, actions on key nodes for achieving desired effects are taken by the instruments of national power such as diplomacy, information, military, and economy in the execution phase. After actions on key targets of adversary, it is necessary to conduct a battle damage assessment. In this assessment phase, the focus of assessment should be on the desired effects.

It argues that there are optimal priorities of nodes that maximize desired effects in EBO. It can identify key nodes and estimate each node's contribution to higher level effects based on the two types of network centralities and the influence values. However, this information is insufficient to select key targets and predict the likelihood and the extent of desired effects.

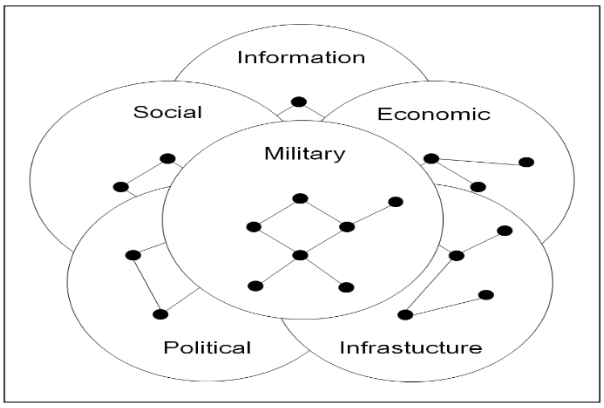

Figure 1. Enemy systems of systems [8]

This is because nodes in an adversary network interact with each other through their links, and thus, changes of the influence values of nodes due to actions or direct attacks lead to the changes of the adversary network, links among nodes, and each node's contribution to higher level effects. These changes will also increase the possibility of the changes in the priority of key targets. Thus, it is important to consider the dynamic nature of network structures resulting from attacks on some nodes as well as network centralities and influence values when selecting key targets in EBO.

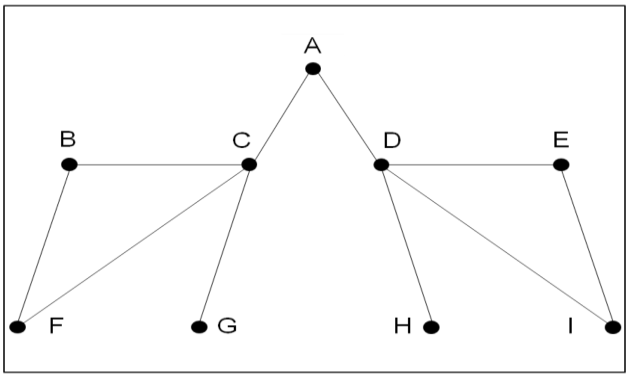

Figure 2: Enemy network example

III. PROPOSED METHODOLOGY

3.1 Concept of analyzing network centrality

Researchers on network view the characteristics of nodes as arising from links and the network structure made up of all links within a network [11]. From a network perspective, network structures and network positions that nodes occupy provide both opportunities and constraints on nodes [12, 13]. Network position can be explained by the concept of network centralities [6, 14]. In this study, adopt degree centrality and betweenness centrality. Degree centrality refers to the extent of direct links of a node to other nodes [4, 5]. Nodes with high degree centrality have more opportunities to access important resources, which, in turn, provide chances to acquire valuable resources, information, status, and power [15]. Betweenness centrality refers to the extent to which a node lies between the paths connecting other nodes of a network together. Nodes with high betweenness centrality are in a good position to play roles as brokers [4]. The focal nodes in central betweenness positions are likely to have greater power and influence because brokerage positions provide nodes with opportunities to access diverse resources and information, and to control the flow of resources and information [12]. Accordingly, nodes with high network centrality (degree centrality and betweenness centrality) have opportunities to get diverse resources and information from other nodes and to exercise power, and thus, can be regarded as highly influential nodes.

3.2 Data

In this study, use the EBO network data of Yaman & Polat [10] to identify the node influence values for selecting key nodes as targets. They construct an EBO network for the operation of NATO (the North Atlantic Treaty Organization) to stabilize a country, and they measure the influence values of nodes in this EBO network via a fuzzy cognitive map (FCM) approach. An FCM is a methodology used to model complex systems under the idea on fuzzy logic and neural networks [12]. As shown in Figure 3, the structure of the network consists of three layers. The highest-level layer represents a strategic objective. Nodes in the second-level layer are three main effects (A, B, and C) to achieve the strategic objective. In the bottom-level layer, there are 12 nodes. These nodes play a crucial role in achieving the strategic objective successfully by utilizing the three main effects. As indicated by links in the figure, each node in the bottom-level layer not only contributes to one of the three main effects, but is connected to other bottom-level nodes.

Yaman & Polat [10] provide a good causal network structure related to EBO, and their approach for obtaining node values and link weights through FCM should be of special interest. Our study basically employs their network structure and dataset. However, it performs additional analyses through several centrality concepts, and further, selects the targets that maximize desired effects using an optimization model.

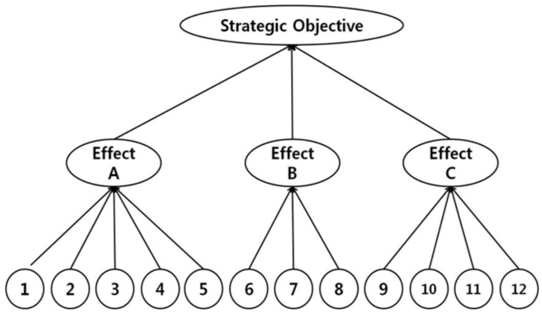

Figure 3. An EBO network for the operation of NATO [10]

3.3 Measure

Degree centrality captures the number of links a focal node has in a network. In order to compare the results of degree centrality analysis and betweenness centrality analysis, it normalizes degree centrality by dividing degree centrality scores by the maximum possible degree. According to data representation, a network can be classified into binary or valued network. A link weight in a binary network only takes 0 or 1, depending on whether the link exists. On the other hand, a valued network can take continuous link weights to represent the degree of link. In the case of valued networks, degree centrality depends on the group size and maximum link strength as well as the number of links [4, 5]. Thus, degree centrality is calculated according to the following formula:

Degree centrality of node $j = \sum_{j=1}^{n} \frac{w_{ij}}{w_{max}(n-1)} \times 100$ (1)

Where w_ij is the weight of the link between node i and j, w_max is a maximum link value, n is a network size (the total number of nodes), and the possible maximum network centrality is 100.

Betweenness centrality captures the sum of the fraction of shortest paths between two nodes that pass through a focal node. As with degree centrality, normalize betweenness centrality by dividing betweenness centrality scores by the maximum possible betweenness. Of the several measures of betweenness centrality, take flow betweenness centrality because our network data comprise valued types of links [11]. compute betweenness centrality using Ucinet program [12].

For non-symmetric network data, the in-directed link is the link received by a focal node and the out-directed link is the link initiated by a focal node. Because network data in this study is non-symmetric, it analyzes an in-directed network and an out-directed network separately, and then aggregates them.

Table 1. Link weights (w_ij) of the Network represented by node-node adjacency matrix

	1	2	3	4	5	6	7	8	9	10	11	12
1	0	0.2517	0.0465	0.3372	0.1869	0.7766	0.0853	0.2070	0.8321	0.8321	0.1026	0.0220
2	0.1392	0	0	0.4065	0.2189	0.0092	0.4483	0.0103	0.8276	0.8210	0.3735	0.0355
3	0.1175	0.0547	0	0	0	0.1956	0.1168	0.0485	0.0064	0	0	0
4	0	0.0003	0.0107	0	0.0659	0	0	0	0	0.1346	0	0
5	0	0	0	0.0064	0	0	0	0	0	0	0	0
6	0.0037	0	0.0037	0	0	0	0.7072	0.1528	0.0119	0.0057	0.4480	0
7	0.0004	0.0659	0.0011	0	0	0.5445	0	0.0034	0.1391	0.0733	0.1577	0
8	0	0	0	0	0	0.0614	0.1414	0	0.0024	0	0.0570	0
9	0	0.0725	0	0	0	0.0003	0.1491	0	0	0.0296	0.0414	0.0181
10	0	0.0048	0.0179	0	0	0	0.0519	0	0.2706	0	0.0630	0.0945
11	0	0	0	0	0	0	0.0623	0	0	0.0017	0	0
12	0	0	0	0	0	0	7	8	9	10	11	12

IV. OPTIMIZING TARGET SELECTION

In order to choose which node(s) to target when considering EBO, it can give ranks to nodes simply prioritizing them according to these values. For instance, node 2, 7, and 4 based on the betweenness centrality results are not necessarily the best three targets choose, because destroying the highest betweenness centrality positions does not always guarantee the most desired effects. This yields the need of further evaluating the influence values of nodes under the dynamic nature of network structure.

4.1 Node influence values

Let v_i be the initial influence value of node i. An initial value is taken from one of the centrality results. As seen in Table 2, there are three types of initial influence values: degree centrality, betweenness centrality, and their aggregated centrality. It independently uses each as our initial value, in turn. Now, introduce our decision variables as follows:

$$x_i = \begin{cases} 1, & \text{if node } i \text{ is selected as a target,} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Suppose that attacking node i results in p_i (where 0≤p_i≤1, for all i) amount of damage to node i, i.e., compared to the initial influence value of node i, its remaining value becomes v_i (1-p_i) after damaged. For simplicity, may set damage to be identical to all nodes, e.g., p_i=p for all i. Now, involve our decision variable to this form. Due to its characteristic that it takes 0 or 1, v_i (1-p_i x_i) leads to an appropriate resulting value. Thus, when x_i=1, the corresponding node value becomes v_i (1-p_i). Otherwise, it maintains its initial value v_i.

To take interaction between nodes into account, employ the notion of an FCM approach. Originally, Kosko [13] has introduced to explain the relationships between the elements of complex systems or networks, and it has been widely used to a variety of fields (e.g., engineering applications, strategic planning, information technology, decision-making, etc.). The main idea is on that a certain node's effect is based on its neighboring nodes that are incoming to that node, and its influence value can be calculated via the sum of all incoming node with the proportion of the corresponding link's weight. Mathematically, this can be expressed as:

$$v_i = f\left(\sum_{j=1}^{n} w_{ji} v_j\right) \tag{3}$$

where function f can vary depending on the problems but usually sets to be bivalent, trivalent, logistic, or sigmoid [10]. Here, w_ji indicates the weight of link (j,i). As a variant, Yaman & Polat [10] propose the following way by involving its own value into calculation:

$$v_i^{new} = v_i^{old} + (1 - v_i^{old}) \sum_{j=1, j \neq i}^{n} w_{ji} v_j^{old} \tag{4}$$

This implies that initial node value plus incoming node values with the corresponding link's weight can create a new value of the node. Note that in their approach all node values range from 0 to 1, and the sum of incoming node values are only reflected by the amount of complementary value of itself (1-v_i^old) in order to ensure the resulting value is still in [0, 1]. Prior to this approach, Koulouriotis et al. [22] suggest a simpler version of node influence evaluation as:

$$v_i^{new} = v_i^{old} + \sum_{j=1, j \neq i}^{n} w_{ji} v_j^{old} \tag{5}$$

in which incoming node values are no more rescaled by (1-v_i^old), and thus, the new influence value can be obtained by adding incoming node values with weights to its own initial value. Based on these approaches, employ Equation (1) as our influence value evaluation. Then, an initial influence value of node i can be achieved via

$$v_i + \sum_{j=1, j \neq i}^{n} w_{ji} v_j \tag{6}$$

Now, include our decision variables on whether to attack node i to this value calculation. Then, the final value of node i is

$$V_i(x) = v_i(1 - p_i x_i) + \sum_{j=1, j \neq i}^{n} w_{ji} v_j \left(1 - p_j x_j\right) \tag{7}$$

It define this as V_i (x), whose value depends on decision variable x=(x_1,x_2,⋯,x_n) and accordingly depends on its neighbour's damages. Let J be the set of all nodes, and i and j be an element of set J, i.e., i,j∈J. There are 12 nodes in our EBO network on the lowest-level as in Figure 1. In addition, it define J_i as the subset of J whose elements are the incoming nodes to i. Using these sets and indices, Equation (2) can be rewritten:

$$V_i(x) = v_i(1 - p_i x_i) + \sum_{j \in J_i} w_{ji} v_j \left(1 - p_j x_j\right) \tag{8}$$

4.2 Optimization models for selecting nodes

The final influence value of node i, V_i (x), contributes to three main effects in the network, and this value changes as its neighbors' functionality. To deal with this, now attempt to select which nodes to be our targets based on an optimization model expressed as a mathematical form. As mentioned earlier, use x_i as our decision variables defining whether or not node i is selected as a target.

As in our EBO network, there is a single highest-level node representing a strategic objective that an adversary pursues. To achieve the strategic objective, there are three main effects on the second highest-level. It denote these effects by node A, B, and C. Since these three nodes are also affected by 12 lowest-level nodes, their post-values can be expressed as V_A (x),V_B (x), and V_C (x), respectively. As an attacker, wish to minimize their effects by targeting some of the lowest-level nodes in order to lessen their strategic objective achievement. Based on this underlying idea, attempt to minimize the sum of these three post-values after take action through decision variables x=(x_1,x_2,⋯,x_n). This yields the following objective function:

$$\text{Minimize: } V_A(x) + V_B(x) + V_C(x) \tag{9}$$

In our EBO network, node A is influenced by node 1 through 5, node B by node 6 through 8, and node C by the others. Taking this into account,

$$V_A(x) = \sum_{i=1}^{5} r_i V_i(x) \tag{10}$$

$$V_B(x) = \sum_{i=6}^{8} r_i V_i(x) \tag{11}$$

$$V_C(x) = \sum_{i=9}^{12} r_i V_i(x) \tag{12}$$

where r_i is a contribution rate of node i. Contribution rates from each node to effect are provided by Yaman & Polat [10] as in Table 3.

Table 2. Results of network centrality analyses

Node	Degree Centrality	Betweenness centrality	Aggregated centrality
1	21.53	11.90	33.43
2	20.43	16.16	36.59
3	3.38	8.12	11.50
4	5.25	12.33	17.58
5	2.61	2.36	4.97
6	15.95	9.77	25.73
7	15.01	14.62	29.63
8	3.74	4.10	7.83
9	13.12	7.44	20.55
10	13.12	10.96	24.07
11	7.14	3.16	10.31
12	0.93	0.86	1.79

Table 3. Contribution rate (r_i) from the lowest-level nodes to effects A, B, and C

node	A	node	B	node	C
1	0.90	6	0.50	9	0.95
2	0.80	7	0.65	10	0.70
3	0.80	8	0.75	11	0.15
4	0.35			12	0.15
5	0.30				

Now, consider the situation under which are not able to attack all of adversary's nodes, but to do some of them, and thus, should make a decision on which nodes to select for attack in order to minimize the adversary's effects subject to the following cardinality constraint:

$$\sum_{i=1}^{12} x_i \leq k \tag{13}$$

where k is an integer value can set that depends on our available weapon resources (e.g., guns or missiles). This constraint implies that the number of attacks is limited by k. The underlying assumptions of this model are 1) there is a single type of means of attack, and 2) it is not allowed to attack multiple times for a single target. It provides a final version of our optimization model formulated as an integer program in the following:

$$\text{z}^* = \min \sum_{i=1}^{12} r_i V_i(x) \tag{3a}$$

$$\text{s.t.} V_i(x) = v_i(1 - p_i x_i) + \sum_{j \in J_i} w_{ji} v_j \left(1 - p_j x_j\right), \forall i \tag{3b}$$

$$\sum_{i=1}^{12} x_i \leq k \tag{3c}$$

$$x_i \in \{0,1\},\ \forall i \qquad 0020\text{(3d)}$$

In sum, Equation (3a) minimizes the sum of main effects of the adversary, Constraint (3b) refers to the influence value evaluation for each node in a recursive way by considering all other nodes, and Constraints (3c) – (3d) clarify disallowance of attacking more than availability and multiple time attacks under a single type of means.

4.3 Computational results

It shows the performance of our optimization model through computational experiments, using the EBO network as in Figure 1 with the link weights (w_ij) in Table 1. Our optimization model (3) requires several experimental settings. First, an initial influence value of node i, v_i, is adopted from degree centrality and betweenness centrality obtained in Section 3. It set up three different values for v_i: 1) degree centrality, 2) betweenness centrality, and 3) aggregate centrality (degree centrality plus betweenness centrality), so that it can compare the node priorities and effects with the ones determined via optimization model. Finally, decreasing proportion compared to its initial node value (p_i) is set to be 0.8 for all nodes identically. In Constraint (3c), use the value of k from 1 to 12, in turn. This enables to see the node priorities (or, rankings) to minimize the adversary's effects.

It show the resulting node priorities by solving the optimization model and compare these with the priorities simply obtained from centrality measure in Table 4.

Table 4. Optimal priorities of nodes compared to centrality measures. Here, Opt. indicates optimal priorities and Cen. Indicates centrality-based priorities

	Degree-based				Betweenness-based				Aggregate-based			
	Selected node		Remaining value		Selected node		Remaining value		Selected node		Remaining value	
Prior -ity	Opt.	Cen.	Opt.	Cen.	Opt.	Cen.	Opt.	Cen.	Opt.	Cen.	Opt.	Cen.
1st	1	1	149.4	149.4	2	2	117.4	117.4	1	2	272.3	277.0
2nd	2	2	103.6	103.6	1	7	85.9	103.5	2	1	188.6	188.6

3rd	6	6	87.9	87.9	7	4	72.1	98.8	7	7	160.5	160.5
4th	7	7	73.6	73.6	6	1	63.0	67.4	6	6	136.6	136.6
5th	9	9	61.7	61.7	10	10	53.9	58.3	10	10	116.7	116.7
6th	10	10	50.9	50.9	3	6	46.3	49.2	9	9	98.0	98.0
7th	3	11	47.7	49.8	9	3	39.6	41.7	3	4	87.3	91.4
8th	8	4	45.1	47.8	4	9	34.9	34.9	4	3	80.7	80.7
9th	4	8	43.1	45.2	8	8	32.0	32.0	8	11	75.1	79.1
10th	11	3	42.0	42.0	5	11	31.5	31.5	11	8	73.6	73.6
11th	5	5	41.4	41.4	11	5	31.0	31.0	5	5	72.3	72.3
12th	12	12	41.3	41.3	12	12	30.9	30.9	12	12	72.1	72.1

These results imply that depending on the notion of centrality considered, selected targets can vary. In particular, degree centrality and betweenness centrality provide more distinguishable results. However, the goal to disconnect the nodes, which play a crucial role in connecting other high value nodes, may make one choose betweenness centrality based results.

In addition, under a certain centrality, optimal node priorities can be achieved by solving the optimization model, and this definitely outperforms simple centrality-based rankings in terms of the entire network value decrease. Figure 4 shows the remaining values as the number of nodes for target grows large. If the influence value is based on degree centrality, the solution qualities are not so remarkable although achieve optimality for the best target selection. However, when focusing on a betweenness centrality-based influence value, an optimal target selection provides a relatively promising result.

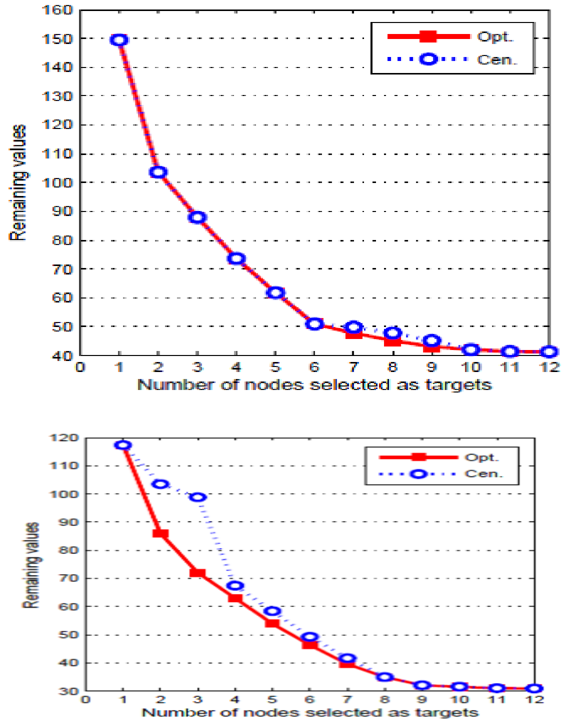

Figure 4. Remaining values of the adversary network as the number of nodes selected as targets grows large: (a) under degree centrality based value (left). (b) Under betweenness centrality based value (right). Here, Opt. indicates optimal priorities and Cen. indicates centrality-based priorities.

V. CONCLUSION

Contextual uncertainty, which arises when there is uncertainty about the available options, their likelihood of occurring, and the possible outcomes associated with each option, should be taken into account when making decisions. The key to managing uncertainty in decision making is to pinpoint, quantify, and examine the variables that are most likely to have an impact on the final result. As a result, since decisions about the implementation of EBO are made in the face of uncertainty, it is essential to arm decision makers with accurate information to support their choices. By adopting two types of network centralities and creating an optimization model that takes into account the dynamic nature of network structures, our study provides an advanced analytical method for identifying key targets to achieve desired effects in EBO. It makes no claims about the comprehensiveness of our method. Having said that, it offers a novel perspective on a topic that has long caught EBO's attention.

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Declaration of Conflicting Interests

The authors declare that there is no conflict of interest.

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