An Interpretive Approach to Drawing Weighted and Most Frequent Causal Loop Diagram using ELECTRE III and SUBDUE Methods

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Abstract—The effectiveness of system dynamics is totally influenced by causal loop diagrams. These diagrams have been valued as a tool for representing useful causal structure of systems in order to further stock and flow modeling. The interpretation of concepts and relations makes it difficult to determine the real cause and effect relations of the system. In this paper, an interpretive approach to determining causal loop relationships is developed. This approach uses ELECTRE III and SUBDUE techniques in order to find the most important sources of causal agreement among different stakeholders.

Index Terms—causal loop diagram, system dynamics, Graph-based mining, group model building, soft system dynamics, ELECTRE III, SUBDUE

I. INTRODUCTION

Causal loop diagrams have been used in system dynamics for gaining insights into complex systems. When tackling complicated human activity systems, understanding causal relationship depends on experts' points of view. These experts have different characteristics and work experience that might affect their interpretation about system's causal structure.

In every organization managing means interpreting and reacting to interacting event and ideas of the real world [7]. From this point of view, there is no unique definition of a determine situation, but each individual has his own perspective in defining and interpreting it [9]. The difference is between hard and soft systems thinking. The hard point of view of systems has an "objectivist" that consider problems as independent of individual's point of views and interpretation. The soft systems thinking has a "subjective" that take into consider the importance of participant's perception [10]. It is not always possible for an analyst/expert to recognize and draw different causal relations in a complex system using an "objectivist" approach. It is recognized that there should be no single analyst, but a process of debate should take place among different actors and stakeholders [11].

Vennix's [12] works showed that system dynamics models should be built by a group in a process of group model building. Group model building is discussed by Vennix et al. [13][14][15][19], Vennix [17][18], Luna-Reyes et al. [20], Andersen et al. [21][22], Rouwette et al. [23] and Visser [24].

Lane [25] has argued that system dynamics is very different from hard systems thinking. Even on the basis of the classic texts of Forrester it is less austerely "objective" than is often represented. If one considers recent work by Wolstenholme, Senge and Lane, and the various craft skills that have grown up around the modeling, then it simply cannot be considered as "hard", or "optimizing", or "deterministic."

The organization of the paper is as follows: in the second section, interpretive systems thinking and practice is presented. In the forth to sixth section, three steps of an interpretive approach to drawing causal loop diagrams are depicted.

II. INTERACTIVE SYSTEMS THINKING AND PRACTICE

The interpretive systems approach is frequently referred to as “soft systems thinking” because it gives pride of place to people rather than to technology, structure or organization. In contrast to the functionalist approach, its primary area of concern is perceptions, values, beliefs and interests. It accepts that multiple perceptions of reality exist, and sometimes come into conflict, and wants to help managers and consultants to work successfully in a “pluralistic” environment of this kind.

Interpretive approaches do not assume that organizations are just “human machines” in which people are organized according to their functions, all of which are, geared to some unitary objective. Instead, they assume that people may, rightly or wrongly, fight their own corner rather than be subsumes into some
overarching objective. Thus these approaches make different assumptions about the nature of organizations. Soft approaches stress the importance of organizational and individual learning. They stress that, when people face problematic situations this is a chance for them to learn how to cope with such circumstances in such a way that their performance is improved.

In hard approaches, it is typically assumed that a model is a would-be representation of part of the real world. By contrast, in soft approaches the idea is that models are developed so as to allow people to think through their own positions and to engage in debate with others about possible action.

Some interpretive systems approaches are Interactive Management [26], Social Systems Design [27], Strategic Assumption Surfacing and Testing, Social Systems Science [1] [2], Soft Systems Methodology [3][4][5][6], Soft Systems Thinking [28], Soft Operation Research, Soft Cybernetics, Soft System Dynamics [25].

"Soft systems thinking" is heavily influenced by the “root metaphor” of contextualism. So it is very important to have a common sense about relevant aspects of the nature of problem.

III. OUTRANKING OF CONCEPTS USING ELECTRE III METHOD

This method of decision making deals with inaccurate, imprecise or ill-determination of data. In ELECTRE III [29][30] the outranking relation can be interpreted as a fuzzy relation. There are some definitions and formulas. In this section, we introduce them in short.

To take into imperfect character of the evaluation of actions, ELECTRE III makes use of discrimination (indifference and preference) thresholds.

Discrimination thresholds account for the imperfect nature of the evaluations, and are used for modeling situations in which the difference between evaluations associated with two different actions on a given criterion may either:

- Justify the preference in favor of one of the two actions (preference thresholds, \( p_j \));
- Be compatible with indifference between the two actions (indifference thresholds, \( q_j \)).
- Be interpreted as a hesitation between opting for a preference or indifference between the two actions.

Veto thresholds express the power attributed to a given criterion to be against the assertion “ \( a \) outranks \( b \)”, when the difference of the evaluation between \((g(b) - g(a))\) is greater than this threshold. These thresholds can be constant along a scale or it can also vary.

Credibility index characterizes the credibility of the assertion “ \( a \) outranks \( b \)” and \( a \) \( \triangleright \) \( b \). \( \rho(a \triangleright b) \) denotes this index which is defined by using both concordance index, \( c(a \triangleright b) \), and discordance index for each criterion \( g_j \) in \( F \), that is, \( d_j(a \triangleright b) \).

The concordance condition will be:

\[
c(a \triangleright b) = \sum_{j \in F^S} w_j + \sum_{j \in j^0} q_j w_j
\]

Where,

\[
\varphi_j = \frac{g_j(a) + p_j(g_j(a)) - g_j(b)}{p_j(g_j(a)) + q_j(g_j(a))}
\]

And concerning the coalition of criteria in which \( a \) \( \triangleright \) \( b \)

\[
J^S = \{ j \in J : g_j(a) + q_j(g_j(a)) \geq g_j(b) \}
\]

Concerning the coalition of criteria in which \( b \) \( \triangleright \) \( a \)

\[
J^Q = \{ j \in J : g_j(a) + p_j(g_j(a)) < g_j(b) \}
\]

To define the value of the discordance index, we admitted that this value grows in proportion to the difference \( g_j(b) - g_j(a) \). This index can be presented as follows:

\[
d_j(a \triangleright b) = \begin{cases} 1 & \text{if } g_j(b) \geq g_j(a) + v_j(g_j(a)) \\ 0 & \text{if } g_j(b) \leq g_j(a) + p_j(g_j(a)) \\ v_j(g_j(a)) - p_j(g_j(a)) & \text{otherwise} \end{cases}
\]

The credibility index is defined as follows:

\[
\rho(a \triangleright b) = c(a \triangleright b) \prod_{j \in J \setminus (J^S \cup \{ a \triangleright b \})} \frac{1 - d_j(a \triangleright b)}{1 - c(a \triangleright b)}
\]

When \( d_j(a \triangleright b) = 1 \), it implies that \( \rho(a \triangleright b) = 0 \), since \( c(a \triangleright b) < 1 \).

Thus the definition of \( \rho(a \triangleright b) \) is based on the following main ideas:

a) When there is no discordant criterion, the credibility of the outranking relation is equal to the comprehensive concordance index.

b) When a discordant criterion activates its veto power, the assertion is not credible at all, thus the index is null.

For the remaining situation in which the comprehensive concordance index is strictly lower than the discordance index on the discordant criterion, the credibility index becomes lower than the comprehensive concordance index, because of the opposition effect on this criterion.

IV. MINING OF FREQUENT PATTERNS FROM CAUSAL LOOP DIAGRAM USING SUBDUE

Graph-based modeling has emerged as a powerful abstraction capable of capturing in a single and unified framework many of the relational, spatial, topological, and other characteristics that are present in a variety of datasets and application areas [31]. A number of researchers have developed data mining algorithms that work with graphs in many different fields such as link analysis [32][33][34], semantic web [35], behavioral modeling [36][37], VLSI reverse engineering [38].

SUBDUE [39] is a technique that can discover interesting and useful Approximate substructure patterns in structural data which is based on minimum description length [40]: principle and optional background
knowledge. Subdue uses a variant of beam search for its main search algorithm, as summarized in Figure 1. It grows a single vertex incrementally by expanding a node in it. At each expansion it searches for the best total description length: the description length of a pattern and the description length of the graph set with all the instances of the pattern condensed into single nodes. SUBDUE performs approximate matching to allow slight variations of substructures, thus supporting the discovery of approximate substructures.

SUBDUE’s search is guided by the MDL principle given in Eq. (1), where $DL(S)$ is the description length of the substructure being evaluated, $DL(G \setminus S)$ is the description length of the graph as compressed by the substructure, and $DL(G)$ is the description length of the original graph. In this technique, the best substructure is the one that minimizes compression ratio:

$$\text{Compression} = \frac{DL(S) + DL(G \setminus S)}{DL(G)} \quad (1)$$

Step 1: Drawing causal loop diagram for each individual. In this step, a skilled interviewer individually draws causal loop diagrams for each stakeholder after a deep interview.

Step 2: Working with diagrams (Identifying the root metaphor). After drawing causal loop diagrams for each individual, they should be analyzed. In order to start analyzing, the first step is to identify the key concepts from diagrams. These key concepts will be used in further workshops.

V. DRAWING INDIVIDUAL CAUSAL LOOPS

Suppose that we have five people that all of them have knowledge about an issue and with use of an expert interviewer, their drawing of causal loop diagram are presented as below.

VI. DETERMINING KEY CONCEPTS

According to interviewee causal loops, we have five adjacency matrixes which rows and columns show concepts. Table 1 shows the deference and indifference thresholds which is equal for all interviewees (criteria).

<table>
<thead>
<tr>
<th>Criterion (i)</th>
<th>0 ≤ i ≤ 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>q</td>
<td>1</td>
</tr>
<tr>
<td>p</td>
<td>3</td>
</tr>
</tbody>
</table>

TABLE I.
THE DIFFERENCE AND INDIFFERENCE THRESHOLDS

By using ELECTRE III/IV software, we calculate the preference of alternatives (concepts). The result is represented in figure 1.
As the figure is shown, D is the most preferable concept. After that, A and B are preferable but they are indifferent to each other. In the end, C and E are the least preferable concepts.

VII. FINDING THE MOST FREQUENT CAUSAL LOOPS

By using SUBDUE open source software, if we let SUBDUE’s threshold value to be 0.5 then the resulted graph is depicted by Figure 3.

Figure 2 – Frequent causal relationships detected by SUBDUE

Figure 3 shows the most frequent causal relationships from every other five causal loop diagrams with threshold 0.5. Using this causal loop diagram and the preferences of concepts from ELECRE III method, the final weighted most frequent causal loop diagram is drawn (Figure 4).

Figure 3 – Final causal loop diagram drawn by SUBDUE and weighted by ELECTRE III

VIII. CONCLUSION

System dynamics modelers look forward to an approach for drawing causal loop diagrams which can consider different perceptions of people. Hence, we have developed an interpretive approach. With the proposed approach, the complex causal relationships between concepts are discovered. Key concepts are identified using ELECTRE III, and then a most frequent graph is discovered by SUBDUE. It is now possible to draw the system’s final weighted most frequent causal loop diagram.

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