SmartISM

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Interpretive Structural Modeling (ISM) is a technique to establish the interrelationships between elements of interest in a specific domain through experts' knowledge of the context of the elements. Every discipline is expanding its frontier and multiple disciplinary approaches have become essential to solve complex problems. This leads to the study of a large number of constructs of interests simultaneously. These constructs may have been identified in theory or practice. Warfield in the 1970's developed a technique to establish an interrelationship model between variables known as interpretive structural modeling (ISM). The holistic picture of important constructs in the structured form derived from ISM technique helps the practitioners to solve the problem effectively. This technique is widely used due to its simplistic procedure and profound value addition in problem solving in different domains.

Keywords: interpretive structural modeling (ISM) ; reduced conical matrix ; MICMAC (Matrice d'Impacts Croisés Multiplication Appliquée á un Classement (cross-impact matrix mult

1. Introduction

Every discipline is expanding its frontier and multiple disciplinary approaches have become essential to solve complex problems. This leads to the study of a large number of constructs of interests simultaneously. These constructs may have been identified in theory or practice. Warfield [1][2][3][4] in the 1970's developed a technique to establish an interrelationship model between variables known as interpretive structural modeling (ISM). The holistic picture of important constructs in the structured form derived from ISM technique helps the practitioners to solve the problem effectively. This technique is widely used due to its simplistic procedure and profound value addition in problem solving in different domains.

ISM helps in representing partial, fragmented, and distributed knowledge into integrated, interactive, and actionable knowledge. This technique is therefore particularly useful for the areas that are inherently multidisciplinary, such as sustainability. The discipline of sustainability ensures the performance in three areas: economic, social, and environmental, termed as triple bottom line (TBL) [5], while the world undergoes development. Additionally, the literature shows the maximum number of applications of this technique in the area of sustainability.

The search with the quoted keywords of "interpretive structural modeling" on the single database of Scopus yielded 5184 documents. There is an exponential growth in the usage of this technique from 2007 onward; prior to this year articles are around 10 each year starting from 1974. For the year 2007, 46 documents are listed and the numbers are exponentially increasing each successive year to 1200 documents in the year of 2020. With around 36% contribution in articles, India is leading the application of ISM, followed by China, USA, UK, and Iran. Together these five countries contribute around 71% of total articles. This technique is being used in many disciplines in decreasing order, namely business, engineering, computer science, decision science, environmental science, social science, and others.

ISM helps in modeling the variables and brings out the existing interrelationship structure among them. It helps a group of people or decision makers to debate and share their knowledge and achieve consensus on the relationships among the variables. The participants can share their views without any knowledge of mathematical complexity involved in the underlying steps. A computerized program may automate all the graphical and algebraic computation and convert their inputs into a pictorial model consisting of variables along with the relationships among them. The ISM process does not add any information [6] but brings in structural value [7].

In the same time period of the 1970's, another technique known as MICMAC (Matrice d'Impacts Croisés Multiplication Appliquée á un Classement (cross-impact matrix multiplication applied to classification)) was developed by J. C. Duperrin and M. Godet [8]. MICMAC helps in classification of the variables into one of the four categories, namely dependent, independent, linkage, and autonomous variables. ISM coupled with MICMAC becomes a strong tool to visualize the structure of variables along with the interrelationships between them. ISM is also used in several multi criteria decision making (MCDM) techniques such as analytical hierarchy process (AHP) [9], analytic network process (ANP) [10][11][12], technique for order of preference by similarity to ideal solution (TOPSIS) [13][14], decision-making trial, evaluation laboratory (DEMATEL) [15][16], and others.

Implementation of this technique and conduction of brainstorming sessions with experts in previous studies [17][18] led to identification of some key challenges such as variables' identification, selection of decision makers and method of decision making, and unavailability of end-to-end software for ISM and MICMAC. Furthermore, the literature shows erroneous applications of steps of ISM such as wrong reachability matrix [19][20][21][22], wrong transitivity calculations [9][13][16][23][24][25][26][27][28][29][30][31][32][33][34][35][36][37], incorrect level partitioning and wrong structure of the model [31][38][39][40][41][42], and incorrect addition [11][14][43][44][45][46][47][48] or reduction [49][50][51][52] of edges affecting the reachability of variables. An error in an earlier step generally leads to an error in subsequent steps. Similarly, the wrong calculation of transitivity leads to wrong MICMAC diagrams. Therefore, there exists some important issues in implementation of this technique, namely identification of variables, decision makers, expertise and experience of decision makers, method of decision making, and computerization of the steps of ISM. Previous ISM reviews [53][54][55] don't critically analyze the steps of ISM applications in the articles. Similarly, although some automation of the ISM technique has been provided earlier [56][57], there does not exist any end-to-end graphical software that may help in applying this technique and allow the decision makers to focus on sharing knowledge and iterate the ISM technique until a high-confidence consensus model is arrived at. These challenges set the objectives of this research as follows:

- Development of SmartISM, a software tool for ISM and MICMAC using Microsoft Excel and VBA.
- Scoping review of applications of ISM on existing studies to identify application domains, types and numbers of variables studied, composition of decision makers, decision making and data collection techniques, and accuracy of ISM application using SmartISM.

2. ISM and MICMAC Techniques

The interpretive structural modelling (ISM) can be defined as constructs' directional structuring technique based on contextual interrelationships defined by domain experts, utilizing computerized conversion of relations into a pictorial model using matrix algebra and graph theory. It may be explained in the series of steps as follows, which will assist in automating all the processes of the ISM technique.

2.1. Elements or Constructs or Variables

Identification of elements or constructs of the subject being studied is the most important of all activities. Similarly, the establishment of their definition along with the theoretical boundaries or scope is very critical. Elements must be explained with the details of their definition, objectives, and possible indications or measurements. These elements are generally identified by literature review, expert opinions, and/or surveys. Some of the unique approaches have been use of thematic analysis [58], upper echelon theory [11], contingency theory [59], content analysis [52], strengths, weaknesses, opportunities, and threats (SWOT) analysis [30], idea engineering workshop [40][60], and Delphi technique [37][61]. One study [42] has defined the source, understanding, and interpretation for each variable.

2.2. Decision Makers (DMs)

DMs play a very significant role in ISM as the whole process and outcome are dependent upon their input. There are three important aspects for the selection of a group of DMs such as size, expertise, and diversity. The group of DMs should be representative of all of the stakeholders in the domain of the problem. They should have sound experience of domain and expert level knowledge of variables being studied. The literature shows the number of DMs ranging between 2 [62][63] to 120 [64] with a median value of 11, and very few studies [16][30][41][65] have taken DMs from academia, industry, and government together.

2.3. Structural Self-Interaction Matrix (SSIM)

Elements or constructs are interrelated with one of the four relations such as x influences y, y influences x, x and y mutually influence each other, or x and y are unrelated. These relations are almost universally represented by 'V', 'A', 'X', and 'O' characters respectively in the SSIM. These relationships are assigned by DMs based on contextual relationships during pairwise comparison on variables. The number of comparisons is nC2 (mathematical combination), where n is the number of variables in the domain of study. Finally, an n by n matrix is formed with nC2 cells filled with A, V, X, and O symbols and the remaining cells are blank. Most studies have used these standard symbols except few such as [35]. As this is the basic matrix and required for all other steps therefore has been documented in most of the studies except few such as [15][66].

2.4. Reachability Matrix (RM) and Final Reachability Matrix (FRM)

RM is the representation of SSIM in binary form. V, A, X, and O symbols of SSIM are replaced with 1, 0, 1, and 0, digits respectively. At their transposed positions by row with column and column with row, 0, 1, 1, and 0 digits are placed, respectively. The constructs are assumed to influence self, so ones are placed at the diagonal positions. The resultant RM is checked for transitive relations. Transitivity is the basic assumption in the ISM such as if variable x influences y and y influences z then x will influence z transitively. This is second-order or two-hop transitivity whereas generalized transitivity means x is related to z through one or more variables. The transitive relations hence identified are represented in the RM with 1*s to distinguish from original 1s and the resulting matrix is known as FRM. FRM also consists of driving and dependence powers of each variable by counting 1s and 1*s in rows and columns respectively. Very few studies mention usage of some software for transitivity calculations such as [56][57]. However, one of the most frequent reasons for incorrect ISM calculations have been wrong transitivity calculations, such as in studies [9][13][16][23][24][25][26][27][28][29][30][31][32][33][34][35][36][37]. Therefore, this study proposes the use of an established Warshall algorithm [67] for transitivity calculations.

2.5. Level Partitioning

This is a very important step to develop the hierarchical directional structure among the variables. Reachability, antecedent, and intersection sets are derived for all the variables from the FRM. For a specific variable, a reachability set consists of itself and all the variables it influences, and an antecedent set consists of itself and all the variables influencing it. Thereafter, the intersection set of reachability and antecedent set is calculated. Variables having the same reachability and intersection sets are given the top rank and are removed for the next iteration and the process is repeated until all variables are ranked. Some studies such as [31][38][39][40][41][42] in the literature had incorrect leveling for variables.

2.6. Conical Matrix (CM) and Digraph

CM is row and column wise ordered FRM based on ranks or levels of variables identified in the level partitioning step. Further the levels of each variable are also recorded at the end of row and column in CM. This matrix helps in drawing the digraph to get the first visual output of the hierarchical directional structure of variables. Circular nodes are drawn with variable numbers. Further they are connected with directional edges based upon 1s or 1*s in the CM between pairs of variables. Fewer studies have mentioned CM and digraph [12][20][27][35][65][68][69][70], as the digraph resembles the final model with a lesser number of edges. The importance of the digraph further goes down in automatic calculation of transitivity.

2.7. Reduced Conical Matrix (RCM) and Final ISM Model

Digraph is converted into a final model by replacing the node numbers with names of the variables and representing nodes in the rectangular shapes. Moreover, efforts are made to remove maximum edges from digraph while maintaining the levels and structure of variables and reachability of variables. This is done to improve the readability of the final model. Several studies have committed mistakes at this step either by adding extra edges [11][14][43][44][45][46][47][48] or omitting edges [49][50][51][52] that have affected the reachability of the variables. Therefore, a new algorithm, reduced conical matrix (RCM), has been devised to remove maximum possible edges without affecting structure and reachability of variables, as explained in the fourth section. This RCM is used for making the final ISM model. The final model may further be subjected to validations by different means such as review by DMs, interviews from different sets of participants, or statistical validations.

2.8. MICMAC

MICMAC (Matrice d’Impacts Croisés Multiplication Appliquée á un Classement (cross-impact matrix multiplication applied to classification)) in the simplest terms is a variable classification technique. Variables are mapped onto a two-dimensional grid based on their dependence and driving power values, represented on horizontal and vertical axes respectively. The range of these values is between 1 and total number of variables and the axes are bifurcated at mid-points, resulting in four quadrants numbered anti clockwise. These quadrants classify variables into autonomous, dependent, linkage, and independent categories. The autonomous variables are not connected with the remaining system of variables whereas linkage variables are sensitive and strongly connected with independent and dependent variables. The final hierarchical ISM model coupled with the MICMAC analysis greatly improves the understanding of variables. Therefore, most studies have carried out MICMAC analysis except few such as [19][39][47][71][72].

3. Implementation of ISM

As originally proposed by Warfield [1][2][3][4], the ISM requires its steps to be executed with the assistance of a computer [6]. Some of the more recent studies demonstrate specialized software or routines being developed for ISM. The article [56] mentions the development of the ISM software package in R software. This software package takes the SSIM input in the comma separated (.csv) excel file and provides two outputs in excel file format, namely, "ISM_Matrix" for FRM step to incorporate transitivity calculations and "ISM_Output" for partitioning step to identify the levels of the variables. Similarly, some studies such as [57] have used MATLAB software to calculate the FRM and partitioning steps. The previous studies have attempted to automate FRM and partitioning steps, leading to partial automation of ISM. As pointed out earlier in absence of automation, the final model may introduce errors in edges regardless of correct FRM and leveling, leading to wrong reachability of variables. Further, having all the steps being carried out automatically shows the prompt results to researchers and decision makers for further possible iterations. Therefore, there exists a need to develop an end-to-end graphical software to implement ISM and MICMAC and identify the required algorithms for it.

4. Assessment of ISM Applications

The ISM technique is being applied in a range of domains [53][54][55]. The review article [54] provides 10 different application domains for ISM. It further provides additional parameters such as integration with other MCDM approaches. Similarly the review article [55] identified ISM applications in 14 domains without industry or organizations, 20 industrial sectors, and 4 other areas. Furthermore, among other characteristics, it mentions integration with other MCDM approaches, and the presence of constructs for cost and/or quality. These reviews haven't focused on operationalization of ISM technique. Therefore, there exists a gap to identify the methodology of steps of applications of ISM in the existing articles such as nature and number of variables, compositions of DMs, decision making and data collection techniques, and accuracy of ISM results.

5. Development of SmartISM Using Microsoft Excel

This section explains the functions and features of VBA to develop SmartISM, an end-to-end graphical software to automate processes of ISM and MICMAC.Firstly, the SSIM matrix defined by DMs is entered in Excel, and serves as the basic input for other steps of ISM. For n variables, the size of SSIM will be n by n. DMs will compare n(n + 1)/2 or ${}^{n}C_2$ unique pairs of variables and assign one of the relationships using symbols V, A, X, or O, as explained earlier. Thereafter, eight VBA macros will derive matrices of RM, FRM, CM, and RCM; level partitioning; and draw diagrams of digraph, final model, and MICMAC. RM is a binary form of SSIM using conversion rules for V, A, X, and O as explained earlier and keeping 1s at the diagonal positions of the matrix. RM also contains the driving and dependence powers for each variable.The second function FRM requires calculation of transitive relations among variables. For manual calculation, RM can be visualized as a digraph with variables representing nodes and 1s in the RM representing the directed edges. By tracing different paths, transitive relations can be identified. For a large number of variables the process would be tedious and leads to errors, whereas a simple Warshall algorithm [67] for transitive closure can be used to automate it. This algorithm results in generalized transitivity if applied in-place, otherwise it will give second-order or two-hop transitivity. Transitive relations are marked with 1* in FRM. Moreover, the 1s and 1*s are counted in rows and columns to calculate the driving and dependence powers respectively for each variable.The next step is to calculate the ranks of the variables through level partitioning. A new matrix LP is defined with five columns namely elements (Mi), reachability set R(Mi), antecedent set A(Mi), intersection set R(Mi)∩A(Mi) and level, and n rows. For a specific variable Mi in FRM, non-zero cells in the row comprise its reachability set and their corresponding identifiers are kept in the LP row of the same variable Mi. Similarly, non-zero cells in the column comprise its antecedent set and their corresponding identifiers are kept in the LP row of the same variable Mi. The intersection sets are calculated for all variables and variables having the same reachability and intersection sets are given first rank. In the next iteration, identifiers of all the ranked variables are removed from reachability, antecedent, and intersection sets. Again, variables having the same reachability and intersection sets are given the second rank and iteration continues until all the variables are ranked. The iteration results may be copied in one Microsoft Excel Sheet.Once the variables are ranked, a digraph can be developed easily by positioning the variables as per their ranks with the help of CM. CM is row and column wise sorted FRM as per variables' ranks or levels. Directed edges can be drawn between variables as per non-zero cells in the CM. Two shape objects Oval and Connector are needed to automate the drawing of digraph. Positing of ovals needs to be carefully assigned, as there can be multiple ovals in one level. The simplest way to identify the needed objects in drawing is to auto record a macro and draw a sample. Afterwards, the macro can be manually edited and static names of the objects can be made dynamic for easy handling in the loop structures of VBA. The final model represents variable names in the rectangular boxes in place of their identifiers in ovals and tries to remove maximum possible transitive links from the digraph. Transitive reduction is a technique to reduce the number of transitive links. Transitive reduction is complicated, specifically for the directed cyclic graphs, and the algorithm may even distort the structure of the digraph. Therefore, an algorithm was designed to develop a reduced conical matrix (RCM) that removes maximum links without changing the structure of digraph and reachability of elements. The main logic is to remove incoming links from second lower-level variables from the CM and results in RCM. RCM was used to draw automated final ISM model using Rectangle and Connector shape objects, as in the following pseudo code.Lastly, a macro was written to draw a MICMAC diagram. The basic input for this diagram was the dependence and driving powers of variables from FRM. This was the longest macro as it required many shape objects such as Line, Connector, Rectangle, Oval, and Textbox. However, it didn't require any special algorithm to be used. Nevertheless, logic to initiate, aggregate, and draw different objects based on number of variables, and dependence and driving powers in a specified space, required careful arrangement.For the details of the functions the pseudo codes have been provided in the paper and also for demonstration of SmartISM a video has been attached.

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