



Application of a fuzzy cognitive map for impact assessment of transportation projects

Cungki Kusdarjito

*Department of Geographical Sciences
and Planning
University of Queensland*

Phillip Smith

*Department of Geographical Sciences
and Planning
University of Queensland*

Abstract:

This paper proposes the application of a fuzzy cognitive map (FCM), in particular, a FCM based on fuzzy NPN (Negative, Positive, Neutral) logic as an analysis tool for impact assessment of transportation projects.

Many of the social and environmental impact variables of transportation projects are difficult to express in objective quantitative terms. As a consequence, it is common for subjective impact assessment to be carried out by many experts (agents) who have different backgrounds and expertise. In such circumstances, fuzzy set theory offers versatile methods for the representation and analysis of judgements since it can handle incomplete information and uncertain or imprecise data.

A fuzzy cognitive map is a model that represents uncertain causal reasoning both in diagrammatic terms involving edges (causes) and nodes (concepts, variables) and in matrix terms. The main advantage of using a NPN Fuzzy Cognitive Map is that the paths of the impacts can be traced. As a result, the step (iteration) at which the maximum (positive and negative) impacts occur can be determined. A FCM also has an ability to combine judgements obtained from multiple experts.

In this paper, basic concepts of a FCM will be presented together with a computer software implementation, which has been developed for an application to the analysis of the impacts of transportation projects.

Contact author:

Dr Cungki Kusdarjito
Department of Geographical Sciences and Planning
Chamberlain Bld (bld 035)
The University of Queensland
ST LUCIA QLD 4972

Telephone: (07) 3371 7526

Fax: (07) 3365 6899

Email: c.kusdarjito@mailbox.uq.edu.au

Introduction

Transportation planning problems have been characterised in general terms as messy, complicated and not amenable to quantification (Ulengin and Topcu, 1997). As such, systematic analysis is needed to manage them. In particular, many of the social and environmental impacts associated with transportation projects are difficult to assess in objective quantitative terms, though models based on the subjective judgements of multiple experts (agents) have been explored (Roberts, 1976).

Various models are available to evaluate the qualitative impacts of projects including, for example, the *Leopold matrix*, the *judgment impact matrix* (McAllister, 1980), and the *stimuli-impacts diagram* (Nijkamp, 1983). These models use matrices to evaluate the impacts of the projects. However, they do not clearly specify the relations between impacts. For instance, though the Leopold matrix provides a detailed summary of impacts, the information obtained from the matrix is not easy to assess (Holling, 1978). In the judgment impact matrix, the relations between variables are included only to a limited extent. All the impacts of projects on society are directed through the environmental impacts and as a result, there is no provision for the direct impacts of the projects on society. Moreover, the direction of impacts in the judgment impact matrix occurs in one direction only, that is from the impacts caused by a project on the societal system through the environment factors. Consequently, the reverse impact from society or environment to the project may not be determined (McAllister, 1980, Holling, 1978). The stimuli-impacts diagram, may be considered as an extension of the judgment impacts matrix and as such inherits the same limitations.

When the complexity of the impacts is taken into account, *structural modelling* is a simple way to illustrate the impacts (Gerrardin, 1979). The complexity of the impacts refers to the process by which an impact of a project may affect itself either directly or indirectly. In structural modelling nodes represent variables and edges represent causal relations. The underlying mathematics of structural modelling is *graph theory* which represents graphs in terms of matrices. *Cognitive mapping* is a type of structural modelling.

An application of cognitive mapping in the context of transportation planning has been presented by Ulengin and Topcu (1997) who used a cognitive map proposed by Axelrod (1976) and Nozicka (1976) to evaluate the causal relations between impact variables. The causal relations between nodes are derived from the judgments of experts.

In the context of the impact assessment of transport projects, *soft variables* (ie. those unable to be expressed in quantitative terms) are common. Approaches to handling soft variables involve the use of judgements obtained from well-informed experts (agents). Such judgements are considered useful and valuable information for building soft variables in impact assessment. However given that the assessment of projects impacts is based on experts' judgments and that the impacts of transportation projects have been characterised as messy, complicated and non-quantifiable, the classical crisp model of cognitive mapping is also considered insufficient. Thus, a *fuzzy cognitive map* (FCM) is

proposed involving a structural model of the relations between impacts where impacts are expressed as *soft* variables obtained from the experts

In this paper, a FCM is illustrated in the context of analysing the impact of a given transportation project. The basic concepts of a FCM will be presented together with details of a computer software implementation.

Cognitive map

A *cognitive map* (CM) is a type of structural model, in which the causal relations between impacts (variables) are represented in a logical terms by using a matrix and a graph (Axelrod, 1976). The relations between impacts are either positive or negative. The relation is positive if changes in an impacted variable have the same direction as changes in the impacting variable, whereas the relation is negative if changes in an impacted variable have the opposite direction as changes in the impacting variable.

The *adjacency matrix* A is a representation of a CM in matrix form and it represents the direct relation between the impacting and impacted variables (Axelrod, 1976). **Figure 1** shows a simple CM in the context of transportation planning along with its adjacency matrix representation (Ulengin and Topcu, 1997).

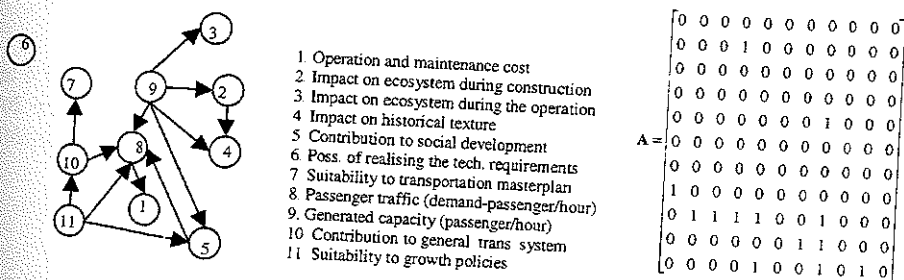


Figure 1 Cognitive map and its adjacency matrix in transportation planning (Ulengin and Topcu, 1997)

Using the adjacency matrix, the calculation process can be easily carried out. When the adjacency matrix is multiplied by itself (using multiplication-rule provided by Axelrod, 1976), the outcome is a matrix which represents the indirect effects of length two from the impacting variables to the impacted variables. For instance, the path $u_1 \rightarrow u_2 \rightarrow u_3$ is a path of length 2, where u_i represents node i in the CM. Mathematically, this statement can be expressed as A^2 . More generally, if the value of powering factor is equal to k (that is A^k), where $1 \leq k \leq n-1$, and n is the number of nodes in the CM, then a path of length k exists from u_i to u_j iff $a_{ij}^{(k)} \neq 0$. The maximum path for an acyclic cognitive map is $n - 1$ (Axelrod, 1976).

The *total effect*, IE, between impacting variable u_i and impacted variable u_j may be expressed as:

$$IE = \sum_{k=1, n-1} A^k$$

Based on this equation, it can be concluded that total effect is a summation of the direct effect ($k=1$) and indirect effects ($k > 1$).

A *reachability matrix* represents the presence of direct and indirect effects from impacting node u_i to impacted node u_j (Nozicka, 1976). A reachability matrix is referred to as the *transitive closure* of the adjacency matrix (Warfield, 1976).

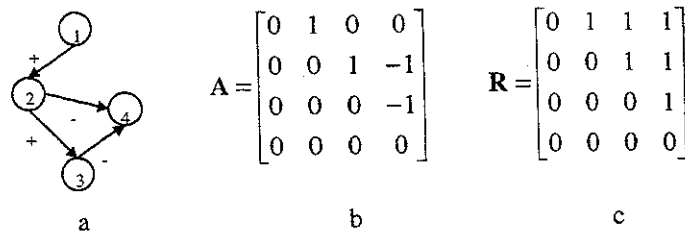


Figure 2 (a) Cognitive map, (b) Adjacency matrix, and (c) Reachability matrix

For instance, the first row of matrix **R** (Figure 2c) represents that nodes 2, 3 and 4 are reachable from node 1. Node 2 is reachable directly from node 1 (see also Figure 2b), while node 3 is reachable from node 1 through node 2. Node 4 is reachable from node 1 either through node 2 or through node 2 and node 3 (Figure 2c).

Fuzzy cognitive map

One of the main drawbacks of the CM using positive or negative signs on edges is the difficulty of determining the total effect values. For example, if there are two directed paths from node u_i to node u_j , one positive and one negative, it is impossible to determine the value of total effect from node u_i to node u_j (Axelrod, 1976).

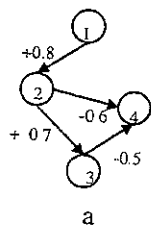
To overcome such a problem, a real value may be used for representing the value of edge between node u_i to node u_j , or alternatively, in terms of fuzzy logic, a fuzzy value. Fuzzy logic is as an extension of boolean logic or crisp logic with membership function $M = [0,1]$ as opposed to $M = \{0,1\}$. The notation $[0,1]$ denotes a membership value in the interval $0 \leq \mu \leq 1$, while the notation $\{0,1\}$ denotes a value of μ equal to 0 or 1. The most frequently used operators in boolean logic (and classical set theory) are the intersection (conjunction, AND), the union (disjunction, OR), and the complement (negation, NOT, COMP). In boolean logic, the AND operator corresponds to boolean multiplication, while the OR operator corresponds to boolean summation. In fuzzy logic, membership is graded, and the conjunction, disjunction and negation should be

defined using, respectively, MIN (\wedge), MAX (\vee) and NOT (\neg) where $\neg A$ has membership function $1 - \mu_A(x)$, ($\mu_A(x)$ representing the degree of membership of x in fuzzy set A) Other extensions for AND and OR operators have been proposed (Yager, 1979; Zimmermann, 1991). t-norm operators and t-conorm (or s-norm) operators prototypically characterise AND and OR, respectively. In decision analysis, the MIN, DOT (algebraic product) and DELTA (bounded difference) operators are common t-norm operators (Kosko, 1986; Zhang *et al.*, 1989; Zimmermann, 1991; Chen, 1995).

NPN (Negative, Positive, Neutral) logic is a generalisation of boolean logic with membership values defined as $M = \{-1, 0, 1\}$ and NPN fuzzy logic is a generalisation of fuzzy logic (and crisp NPN logic) with membership values defined as $[-1, 1]$ (Zhang *et al.*, 1989). Connectives in NPN fuzzy logic are generalisation of those in fuzzy logic.

NPN-Fuzzy cognitive map

A NPN-FCM retains all positive and negative impacts, since not all the positive and negative impacts always counteract each other. The edge value between node u_i to node u_j is represented by compound values (u, v) , where $u \leq v$. As a result, the size of the adjacency matrix A becomes $(N \times 2N)$ (i.e. the number of columns is doubled) **Figure 3** illustrates a NPN-FCM.



$$A = \begin{bmatrix} (0 & 0) & (0.8 & 0.8) & (0 & 0) & (0 & 0) \\ (0 & 0) & (0 & 0) & (0.7 & 0.7) & (-0.6 & -0.6) \\ (0 & 0) & (0 & 0) & (0 & 0) & (-0.5 & -0.5) \\ (0 & 0) & (0 & 0) & (0 & 0) & (0 & 0) \end{bmatrix}$$

b

$$R = \begin{bmatrix} (0 & 0) & (0 & 0.8) & (0 & 0.7) & (-0.6 & 0) \\ (0 & 0) & (0 & 0) & (0 & 0.7) & (-0.6 & 0) \\ (0 & 0) & (0 & 0) & (0 & 0) & (-0.5 & 0) \\ (0 & 0) & (0 & 0) & (0 & 0) & (0 & 0) \end{bmatrix}$$

c

Figure 3 (a) NPN-FCM, (b) NPN adjacency matrix, and (c) NPN reachability matrix (transitive closure)

Matrix R in **Figure 3c** represents the value of transitive closure (the MIN (\wedge) operator is used as a t-norm operator to calculate the value of transitive closure). For instance, the first row of matrix R represents the fact that nodes 2, 3 and 4 are reachable from node 1. Node 2 is reachable directly from node 1, and its value is 0.8. Node 3 is reachable from node 1 through node 2 and its value is 0.7. This value is determined by the minimum value of 0.8 ($1 \rightarrow 2$) and 0.7 ($2 \rightarrow 3$). Node 4 is reachable from node 1 through node 2, and its value is 0.6 with a negative sign. This sign is determined from the product of the sign

of edge $1 \rightarrow 2$ and the sign of edge $2 \rightarrow 4$. The value of transitive closure from node 1 to 4 is not determined through node 2 and node 3, since the value of node 4 obtained from this path is -0.5, smaller than -0.6 (in absolute value) obtained from the previous path. When the number of nodes is small this process can be carried out manually using the FCM graph. However, when the number of nodes increases, the value of transitive closure should be determined by "adding" all indirect and direct effect matrices. The indirect effect matrix can be determined by powering the adjacency matrix using NPN fuzzy logic.

When a CM is large and sparse, an *adjacency list* is a more efficient representation involving only the direct effects which exist; that is, if the direct effect between u_i to u_j does not exist, then this relation will not be represented in the adjacency list. As a result, an adjacency list provides a more compact representation than an adjacency matrix (Cormen *et al.*, 1990).

A CM or FCM can be sprouted as a tree, as illustrated in Figure 4. This tree diagram is a representation of the acyclic FCM in Figure 3a. However, when the CM or FCM is cyclic, the number of branches in the tree diagram is essentially infinite and a branch and bound strategy should be adopted to enable a finite spanning (or, sprouting) process. Branch and bound is a technique for pruning a tree such that every branch in the tree need not be examined. This technique may be implemented by using a threshold value such that when the value of vertex is smaller than the threshold value, the sprouting process is terminated for this node (Stephens, 1996).

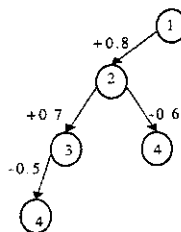


Figure 4 Tree diagram

Chen (1995) used the depth-first search algorithm to determine all possible paths from node u_i to node u_j in the tree. Furthermore, the value of the most effective path is determined from these paths. As its name implies, this algorithm searches deeper whenever possible for every discovered node (Cormen, 1990). However, when the FCM is large, it is more efficient if the search process is directed to determine only the most effective path rather than to evaluate all possible paths from u_i to u_j . The most effective path is determined heuristically by using an extended breadth-first search algorithm. Breadth-first search systematically explores all the "discovered" vertices from a specific

node. More specifically, this algorithm discovers all vertices at distance t from u_i before discovering any vertices at distance $t+1$ (Cormen 1990).

NPN-FCM program

The NPN-FCM program presented below is based on the extended breadth-first search algorithm. The value of impacted nodes is calculated using a selected t-norm operator and then this node is evaluated further to determine whether it should be terminated or not. An adjacency list is used to represent all possible direct effects from impacting variables to the impacted variables. This program evolved from the *Fuzzy Pulse Process* (Kusdarjito and Smith, 1997). Unlike the NPN-FCM program, which uses an adjacency list to represent the direct effect between nodes, the fuzzy pulse process represents the direct effect between nodes as an adjacency matrix.

The NPN-FCM software runs on a PC under the Windows95 (32 bit) environment. It includes a visual interface for input (Figure 5) where the user draws the CM directly.

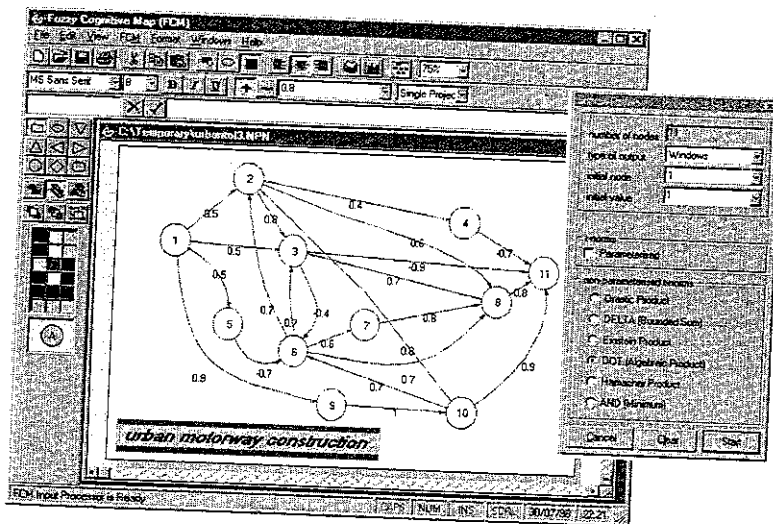


Figure 5 Input interface

Unlike Zhang's method (Zhang *et al* 1989) where the value of initial node is absolutely true ($=1$), the value of initial node in the NPN-FCM program can be chosen from -1 to 1 (except 0). In Zhang's method the calculation is initialised directly by an adjacency matrix and this implies that the initial value is assumed equal to 1 . On the other hand, the calculation in the NPN-FCM program is initialised by a pulse value, and this value can be set for a non-zero value between -1 to 1 . This approach is useful when the impacted node (non-policy variable) is to be evaluated further, for example, evaluating the impact of decreasing the number of vehicle-trips. When the initial value is changed,

the value of impacted nodes will also change, and this condition will influence the interpretation of the result. Moreover, the algorithm used in the NPN-FCM software has greater flexibility to handle t-norms other than MIN (AND), DOT and DELTA, such as Einstein and Hamacher product, and parameterised t-norms (Mizumoto, 1989; Zimmermann, 1991). The function of the t-norm operator in the NPN-FCM program is to calculate the value of an impacted node, u_j , as follows

$$u_j = \text{sign}(u_i)\text{sign}(v_{ij})(|u_i| \otimes |v_{ij}|)$$

where \otimes represents any t-norm such as AND, DOT, DELTA or other t-norms, both parameterised or non-parameterised t-norms. In this equation u_i denotes the value of impacting node while v_{ij} denotes the value of the edge running from the impacting node u_i to the impacted node u_j . The value of v_{ij} can be obtained from the adjacency list. **Figure 6a** and **6b** show t-norm operators available in the NPN-FCM program and the results obtained from these operators can be ordered as follows (Mizumoto, 1989)

Drastic Product \leq DELTA \leq Einstein Product \leq DOT \leq Hamacher Product \leq MIN

Parameterised t-norms are a generalisation of the t-norm operators described above. By selecting the appropriate value for the parameter, the value of the t-norm can be justified accordingly (Mizumoto, 1989; Zimmermann, 1991)

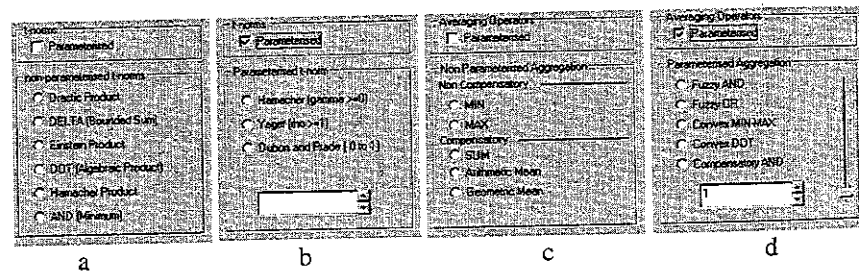


Figure 6 t-norms and aggregation methods available in FCM-NPN program

If the judgment process in cognitive mapping is carried out by multiple experts (as is normally the case), it is necessary to aggregate judgments. With the exception of the SUM aggregation, (summing the positive and negative assertions), the positive and negative judgments are treated separately in NPN-FCM program. Zhang *et al* (1989, 1992) proposed some methods of aggregation, such as

$$\begin{array}{ll} a = -\max(u_1, u_2, \dots, u_m) & \text{and} \quad b = \max(u'_1, u'_2, \dots, u'_n) \\ a = -\min(u_1, u_2, \dots, u_m) & \text{and} \quad b = \max(u'_1, u'_2, \dots, u'_n) \\ a = -\sum (u_i)/m & \text{and} \quad b = \sum (u'_j)/n \\ a = -\sum (u_i c_i)/m & \text{and} \quad b = \sum (u'_j c_j)/n \end{array}$$

The first-three equations assume that each expert has an equal credibility, while the last equation represents that experts have different credibility. Here, m is the number of experts with a negative assertion, while n is the number of expert with a positive assertion, and c_i and c_j are the credibility weight factors assigned to u_i and u_j respectively.

Figure 6c and 6d show the aggregation methods available in the FCM-NPN program. The value of aggregation obtained from the compensated averaging operators will lie between the most optimistic lower bound (MIN) and the most pessimistic upper bound (MAX). Included in the compensatory operators are the arithmetic mean (weighted or unweighted), the harmonic mean, and the geometric mean (Zimmermann and Zysno, 1980, Zimmermann, 1991).

As in parameterised t-norms, a parameterised averaging operator is a generalisation of the averaging operator. The result obtained from the parameterised fuzzy averaging operators will lie in the range between the MIN value and the MAX value (Mizumoto, 1989). Whether the result will approximate the MIN or MAX value depends on the value of parameter (γ), the degree of nearness to the strict logical MIN and MAX (Zimmermann, 1991).

Application of the NPN-FCM program

A hypothetical example in the context of transport project impact assessment will be examined using the NPN-FCM program. A FCM involving a project (urban motorway construction) obtained from a single expert is assumed for ease of explanation (Figure 7).

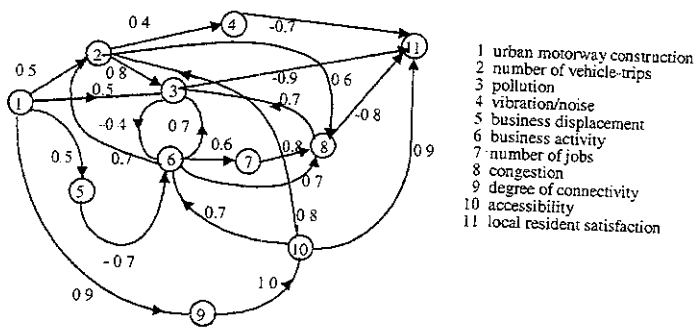


Figure 7 Impact of the urban motorway construction

In the FCM in Figure 7, node 1 represents the construction of an urban motorway project. Node 2 represents the number of vehicle-trips expected to increase as a result of the motorway construction. Node 3 represents pollution levels in the area. Pollution is generated both by traffic and construction activities. As the number of vehicles-trips

increases, noise and vibration will increase and in turn will have a negative affect on local resident satisfaction.

Moreover, road construction activities may affect the viability of existing business activities (Lane, 1978). These impacts are manifest through reduced access of the consumers to businesses or increased access of competitors to consumers. In this hypothetical example, motorway construction may cause displacement of existing businesses (node 5) and in turn will affect the business activities in the region (node 6). The availability of jobs depends on the business activities in the region (node 7). Business activity will also affect the vehicle-trips in the region. The presence of the motorway will increase the connectivity of the region (change of overall physical accessibility) (node 9). Accessibility may be defined as the advantage of places to overcome some forms of friction, such as travel time or distance (Ingram, 1971). Increasing the accessibility of the region will in turn increase the number of vehicle trips. Node 8 represents traffic congestion in the region, and node 11 represents the satisfaction of the local residents. The adjacency list for the motorway construction presented in Figure 7 can be seen in Table 1. The value in parentheses represents the value of edge between impacting node and impacted node. In this example, these values are hypothetical and are representative of a single expert's judgements.

Table 1 Adjacency list for the motorway construction

Impacting Index	Impacted Index	Impacted Index	Impacted Index	Impacted Index
1	2(0.5)	3(0.5)	5(0.5)	9(0.9)
2	4(0.4)	3(0.8)	8(0.6)	
3	6(-0.4)	11(-0.9)		
4	11(-0.7)			
5	6(-0.7)			
6	2(0.7)	3(0.7)	7(0.6)	8(0.7)
7	8(0.8)			
8	3(0.7)	11(-0.8)		
9	10(1)			
10	2(0.8)	6(0.7)	11(0.9)	

The number of nodes in this example is 11 (set automatically by the program), the initial node is 1, the initial value is 1 (default value) and the selected operator is DOT (algebraic product). (Figure 5). There are two options for the output interface. The output in the first option is represented by separated windows, whilst in the second option, the output is compacted into one window using the output manager. In this example, only one policy variable is used, that is an urban motorway construction (Note that it is possible for the user to select more than one policy variable in the NPN-FCM program). As indicated above, the initial value may be set to a non-zero value between -1 and 1. After the CM has been drawn and all options have been selected, calculation can proceed.

Two types of output obtained from the NPN-FCM program are the tree diagram and the "most effective path" from the selected impacting node to the impacted nodes along with their transitive closure values. The tree diagram in the NPN-FCM program is represented in both as a grid and as a true tree diagram (Figure 8).

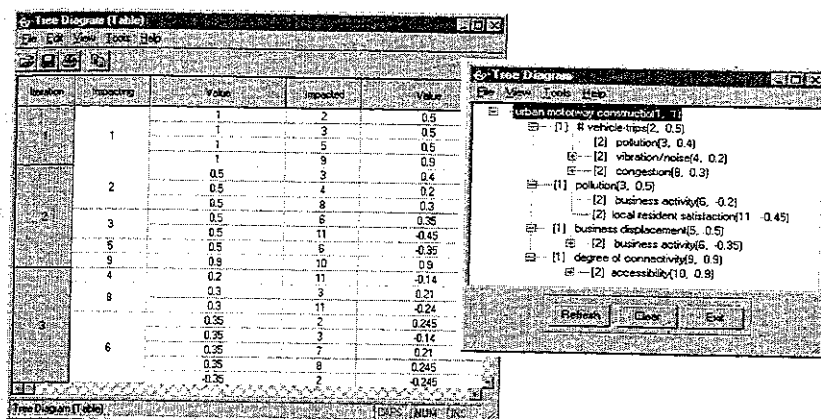


Figure 8 Tree diagram in a grid representation and true tree diagram

In the grid representation, column 1 represents the number of iterations, column 2 represents the name of the impacting node, column 3 represents its value, column 4 represents the name of the impacted node, and column 5 represents its value. In the tree diagram representation, the value in the square bracket [] represents the level of iteration, whilst the values in parentheses () represent the node's index and the value of the impacted node, respectively. A positive sign (+) indicates that this node can be expanded further whereas a negative sign indicates that this node has already been expanded. The absence of any sign indicates that the node is a terminal node.

In the first iteration, the impacting node is equal to the initial node and the value of impacting node is the initial value set by the user (see Figure 5). Furthermore, destination nodes (impacted nodes) obtained by sprouting node 1 are nodes 2, 3, 5, and node 9 (see also Figure 8, Figure 9 and Table 1). These impacted nodes along with their values are represented in column 4 and column 5 of the first iteration in Figure 8. None of these nodes should be terminated, since the first iteration represents the direct effect between the impacting node and impacted nodes.

In the second iteration, the impacted nodes obtained from the first iteration become new impacting nodes, and these new nodes should be sprouted further as in the first iteration. For instance, node 2 can be sprouted into node 3, 4 and 8, node 3 can be sprouted into node 6 and 11, node 5 can be sprouted into node 6, and node 9 can be sprouted into node 10 (Figure 8 and Figure 9). Further, in the second iteration, impacted node 3 (value = 0.4) obtained from path 1→2→3 and node 6 (value = -0.2) obtained from path 1→3→6 should be terminated, since these nodes will no longer determine the most

effective path in the next (third) iteration. Node 3 (value = 0.4) should be terminated because its value is smaller than that of node 3 (value = 0.5) obtained from the path 1→3 in the first iteration. The reason for pruning path 1→2→3 is that if node 3 (value = 0.4) is sprouted further, the result is only a duplication of the sprouting tree obtained from node 3 (value = 0.5) in the previous iteration but with the smaller values. Node 6 (value = -0.2) from path 1→3→6 should be terminated since the value of this node is smaller than that of node 6 (value = -0.35) obtained from path 1→5→6.

It can be seen that the value of node 3 is compared with the value of the same node in the previous level of iteration, while the value of node 6 is compared with the value of the same node in the same level of iteration. Another terminal node is node 11 (value = -0.45). Node 11 is a terminal node because this node is a sink node, which means that edges are directed only to this node. No edge is sprouted from node 11. Since node 3 (value = 0.4), node 6 (value = -0.2), and node 11 (value = -0.45) have been terminated, the new impacting nodes for the third iteration are determined by nodes 4 (value = 0.2), 8 (value = 0.3), 6 (value = -0.35) and 10 (value = 0.9).

A complete tree representation based on the result in Figure 8 can be seen in Figure 9

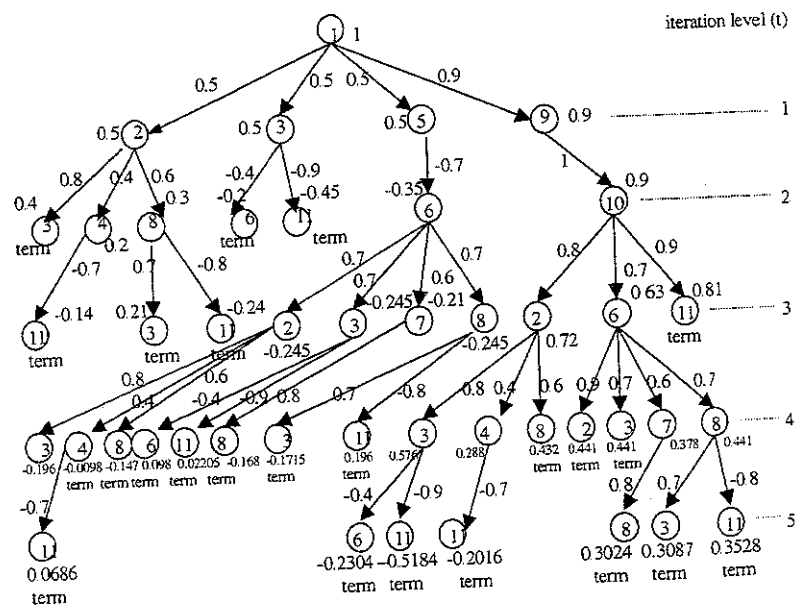


Figure 9 Complete representation of the tree diagram in Figure 8

Based on the result in Figure 9, the maximum impact (both for negative and positive impacts) can be easily determined. The maximum impacts, both for positive and negative paths, can be determined by examining all the available values for a given node in Figure 9. For example, for node 3:

$$\text{MIN}(-0.245, -0.196^*, -0.1715^*) \Leftrightarrow -(\text{MAX}(|-0.245|, |-0.196^*|, |-0.1715|)) = -0.245$$

For the maximum negative path, this value is derived from path $1 \rightarrow 5 \rightarrow 6 \rightarrow 3$ ($t = 4$). The asterisk represents that this value is a terminal node, and this node will not determine the most effective path (except for a sink node, for example is node 11, where no new node is directed from the sink node), and t represents the step or level of iteration. The maximum value for the positive path (for node 3) is determined by:

$$\text{MAX}(0.5, 0.4^*, 0.21^*, 0.576, 0.441^*, 0.3087^*) = 0.576$$

This value is derived from path $1 \rightarrow 9 \rightarrow 10 \rightarrow 2 \rightarrow 3$ ($t = 4$). Finally, the values obtained from these paths (negative and positive) are equal to the value of a transitive closure of node 3 from node 1, that is $(-0.245, 0.576)$, represented as a compound value.

From the description in **Figure 9**, it can be seen that the algorithm developed here seeks the maximum negative and positive values of the impacted nodes at every level of iteration, and skips all the non-maximum nodes (i.e. terminal nodes). This implies that at a specific level of iteration, all non-terminal nodes available at that level represent the maximum values (negative or positive) of the impacted nodes. As a result, when the (either, negative or positive) impacts occur can be traced qualitatively before the FCM reaches the stable condition (i.e. transitive closure)

Figure 10 shows the output of the hypothetical example calculated by the NPN-FCM program presented as text (in rich text format (rtf) accessed by most word processors) and as a graph. This text output represents all possible "most effective paths" (if any), both positive and negative, from the impacting node to the impacted nodes. The header shows the type of path (positive or negative), origin node (in this case node 1), initial value (node 1), and the operator used in the calculation (DOT operator). The graph representation shows all the values of transitive closure for every impacted node (if any).

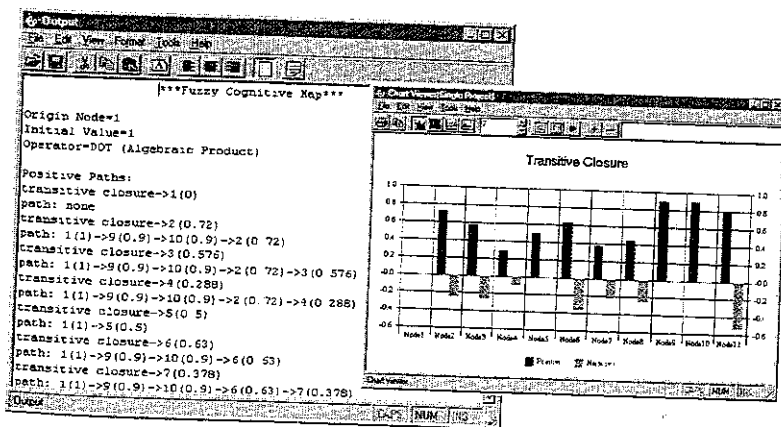


Figure 10 Output interface

Table 2 shows the summary of the result obtained from NPN-FCM programs presented in Figure 10.

Table 2 The value of transitive closure and the most effective path

Destination Node	Transitive Closure	Negative Path	Positive Path
1	(0 0)	-	-
2	(-0.245 0.72)	1→5→6→2	1→9→10→2
3	(-0.245 0.576)	1→5→6→3	1→9→10→2→3
4	(-0.098 0.288)	1→5→6→2→4	1→9→10→2→4
5	(0 0.5)	-	1→5
6	(-0.35 0.63)	1→5→6	1→9→10→6
7	(-0.21 0.378)	1→5→6→7	1→9→10→6→7
8	(-0.245 0.441)	1→5→6→8	1→9→10→6→8
9	(0 0.90)	-	1→9
10	(0 0.90)	-	1→9→10
11	(-0.5184 0.81)	1→9→10→2→3→11	1→9→10→11

Interpretation

Based from this example, it can be concluded that the construction of an urban motorway has a direct effect on displacing business activity (1→5) and increases the degree of connectivity (1→9) of the region. Increasing the degree of connectivity will in turn increase the accessibility of the region (1→9→10). Through node 9 (accessibility), the urban motorway construction has three effects in the region. Firstly, increasing accessibility in the region caused by motorway construction will affect positively on the business activity (1→9→10→6). Secondly, it will increase the number of vehicle-trips (1→9→10→2), and finally, it will impact positively on the local resident satisfaction (1→9→10→11).

Moreover, the improvement of the accessibility in the area will cause business activity to increase (1→9→10→6) and this activity will provide the local communities with more jobs (1→9→10→6→7). However, this activity also leads to the traffic congestion in the region (1→9→10→6→8). When the number of vehicle-trips increase, pollution levels will also increase (1→9→10→2→3) as well as noise and vibration (1→9→10→2→4).

Urban motorway construction also generates unintended impacts. Motorway construction will cause business displacement and in turn will cause business activity to decrease (1→5→6). Although this unintended effect of motorway construction on business activity in turn will reduce the pollution level (1→5→6→3) and congestion (1→5→6→8), this is not a desirable way to alleviate these impacts (pollution and congestion). Furthermore, though a positive impact of urban motorway construction on local resident satisfaction is intended (1→9→10→11), there is an unintended impact

from path $1 \rightarrow 9 \rightarrow 10 \rightarrow 2 \rightarrow 3 \rightarrow 11$, and this negative impact is determined by node 3 (pollution)

It is also possible to trace the impact in FCM from each level of iteration (see **Figure 12**). For example, consider node 11 (local resident satisfaction). As indicated above, urban motorway construction has both a positive impact and an unintended impact on the local resident satisfaction. This unintended impact occurs in two steps. The first unintended impacts occurs from path $1 \rightarrow 3 \rightarrow 11$ at $t=2$, where t represents the level of iteration, while the second unintended impacts occurs from path $1 \rightarrow 9 \rightarrow 10 \rightarrow 2 \rightarrow 3 \rightarrow 11$ at $t=5$. The first unintended impacts is caused by the pollution generated directly from the activity of urban motorway construction, while the second one is caused by the pollution generated by an increasing number of vehicle-trips. As a result, policies should be focused on how to alleviate the pollution level that will affect residents both from the construction activity and from the motorway when constructed

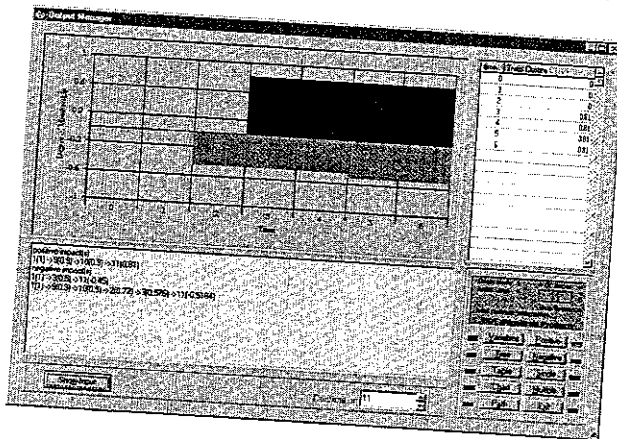


Figure 12 Subjective time representation

Conclusion

NPN Fuzzy Cognitive Map (and computer software implementation) has been proposed in this paper for evaluating the impact of a transport project (here, motorway construction). The algorithm used in this program is more efficient and more flexible than the original approach proposed by Zhang *et al* (1989, 1992). The program uses an adjacency list rather than adjacency matrix. As a result t-norms other than MIN (AND), MAX (OR), and DELTA can be evaluated easily. Moreover, computer execution time is reduced since only the actual direct effects are represented in the adjacency list.

The program is more straightforward than Chen's methods (Chen, 1995) in that, rather than examining all possible paths from an impacting node to impacted nodes and selecting the most effective path from these available paths, this algorithm determines the most effective (maximum and minimum) path heuristically.

In a policy analysis, knowing the path of the impact can be used as guidance to alleviate or eradicate unintended impacts of projects since the variables that cause these impacts can be easily traced. As a result, policy can focus on these variables. Moreover, by using a FCM based on NPN logic, it can be predicted when (in qualitative terms) an unintended impact (if any) occurs. Thus an unintended impact may occur before or after an intended impact. It is possible that a given project initially yields a high value for an intended impact followed by a more significant (higher value) unintended impact.

Acknowledgment

The first author acknowledges AUSAID sponsorship for study at the University of Queensland

References

- Axelrod, R (1976) The analysis of cognitive maps, pp 55-73 of Axelrod, R (ed) *Structure of Decision: The Cognitive Maps of Political Elites* New Jersey: Princeton University Press
- Cormen, T H, Leiserson, C E, and Rivest, R L (1990) *Introduction to Algorithms* New York: McGraw-Hill
- Chen, S M (1995) Cognitive-map-based decision analysis based on NPN logics *Fuzzy Sets and Systems* 71, 155-163
- Dubois, D and Prade, H (1982) A class of fuzzy measures based on triangular norms: a general framework for the combination of uncertain information *Fuzzy Sets and Systems* 8, 43-61
- Gerradin, L A (1979) Structural modeling, including temporal dimension as an aid to study complex system governabilities and to foresees unforecastable alternative futures *Technological Forecasting and Social Change* 14, 367-385
- Holling, C S (1978) *Adaptive Environmental Assessment and Management* New York: Wiley
- Ingram, D R (1971) The concept of assessability: a search for an operational form *Regional Studies* 5, 101 - 109
- Kosko, B (1986) Fuzzy cognitive maps *International Journal Man-Machine Studies* 24, 65-75
- Kusdarjito, C and Smith, P (1997) *Fuzzy Pulse Process*, Unpublished manuscript, Department of Geographical Sciences and Planning, University of Queensland

Application of NPN Fuzzy Cognitive Map for Transport Projects

- Lane, J E (1978) Environmental considerations in transport project assessment: the need for additional research *Australian Road research*, 36 - 38
- Mizumoto, M (1989) Pictorial representations of fuzzy connectives, Part 1: cases of t-norms, t-conorms and averaging operator *Fuzzy Sets and Systems* 31, 217-242
- Nijkamp, P (1983) Qualitative Spatial Input Analysis pp 79-90 of Chatterji, M, Nijkamp, P Lakshmanan, T R Pathak, C R (eds) *Spatial, Environmental and Resource Policy in the Developing Countries* Hampshire: Gower Publishing
- Nozicka, G J Bonhan, G M and Saphiro, M J (1976) Simulation techniques pp 349-359 of Axelrod, R (ed) *Structure of Decision. The Cognitive Maps of Political Elites* New Jersey: Princeton University Press
- Roberts, F S (1976) *Discrete Mathematical Models with Application to Social, Biological, and Environmental Problems* Englewood Cliffs: Prentice Hall
- Stephen, R (1996) *Visual Basic Algorithm* New York: John Wiley and Sons
- Ulengin, P and Topcu, I (1997) Cognitive map: KBDSS integration in transportation planning *Journal of Operational Research Society* 48, 1065-1075
- Warfield (1976) *Societal Systems: Planning, Policy and Complexity* New York: John Wiley and Sons
- Yager, R R (1979) A measurement-informational discussion of fuzzy union and intersection *International Journal Man-Machine Studies* 11, 189-200
- Yager, R R (1980) On a general class of fuzzy connectives *Fuzzy Sets and Systems* 4, 235-242
- Zhang, W R Chen, S S Bezdek, J C (1989) Pool2: A generic system for cognitive map development and decision analysis *IEEE Transaction on Systems, Man, and Cybernetics* 19(1), 31-39
- Zhang, W R Chen, S S Wang, W and King, R S (1992) A cognitive-map-based approach to the coordination of distributed cooperative agents *IEEE Transactions on Systems, Man and Cybernetics* 22, 103-113
- Zimmermann, H J and Zysno, P (1980) Latent connectives in human decision making *Fuzzy Sets and Systems* 4, 37-51
- Zimmermann, H J (1991) *Fuzzy Set Theory and Its Application* Boston: Kluwer Academic Publisher