An Agent-Based Fuzzy Cognitive Map Approach to the Strategic Marketing Planning for Industrial Firms

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Abstract

Industrial marketing planning is a typical example of an unstructured decision making problem due to the large number of variables to consider and the uncertainty imposed on those variables. Although abundant studies identified barriers and facilitators of effective industrial marketing planning in practice, the literature still lacks practical tools and methods that marketing managers can use for the task. This paper applies fuzzy cognitive maps (FCM) to industrial marketing planning. In particular, agent based inference method is proposed to overcome dynamic relationships, time lags, and reusability issues of FCM evaluation. MACOM simulator also is developed to help marketing managers conduct what-if scenarios to see the impacts of possible changes on the variables defined in an FCM that represents industrial marketing planning problem. The simulator is applied to an industrial marketing planning problem for a global software service company in South Korea. This study has practical implication as it supports marketing managers for industrial marketing planning that has large number of variables and their cause–effect relationships. It also contributes to FCM theory by providing an agent based method for the inference of FCM. Finally, MACOM also provides academics in the industrial marketing management discipline with a tool for developing and pre-verifying a conceptual model based on qualitative knowledge of marketing practitioners.

1. Introduction

Strategic marketing planning is the part of strategic planning that defines the strategies and tactics that form the sequences of activities needed to achieve company missions and objectives, considering the external and internal environments of the company (Byars & Neil, 1987). Strategic marketing planning results in well defined marketing strategies and tactical plans that direct, implement, and control activities. Industrial marketing planning deals with the marketing planning issues of industrial firms (firms that produce industrial products or services), and has been widely implemented to coordinate and control their marketing activities (McDonald, 2002). Formal strategic marketing planning is known to have a positive relationship with the financial and nonfinancial performance of firms, coordinated decision making, and specialization of marketing and distribution activities (Claycomb, German, & Dröge, 2000).

However, strategic marketing planning is a typical example of an unstructured decision making problem due to the large number of variables to consider and the uncertainty imposed on those variables. Compared with consumer marketing planning, the problems in an industrial marketing context are more complicated due to the differences between the two environments. Webster (1995) argues that industrial marketing planning requires more frequent interactions among the functional departments within the firms to handle supply chain coordination issues with partners (functional interdependence); product, engineering, manufacturing, and technical orientation (product complexity); and management of buyer–seller relationships (buyer–seller interdependence). These differences sometimes become barriers to implementing industrial marketing planning; the literature reports that limited understanding of external macro-marketing environmental forces; poor internal communication within the marketing department and between functions, business units, and management tiers; insufficient details in marketing programs or the implementation plan; and insufficient consideration of buyer–seller interactions are just a few examples of such barriers (Dibb, Simkin, & Wilson, 2008; Turnbull & Villa, 1998).

While there are studies that diagnose the barriers to implementing industrial marketing planning, the literature lacks studies that provide marketing managers with practical tools to support the role of industrial marketing planning in overcoming these barriers. This reflects "the relevance problem" (Tranfield & Starky, 1998) in industrial marketing planning research. In other words, the literature lacks Mode 2 research (Nowotny, Scott & Gibbons, 2001) that is multidisciplinary and aims at solving practical problems relevant to industrial marketing managers.

Studies on computerised information systems to support the decision making of marketing managers, sometimes called marketing information systems (MkIS), have been conducted as a research stream in marketing since the 1960s (Cox & Good, 1967; Brien & Stafford, 1968; Goretsky, 1983) and can be considered as examples of Mode 2 research in the marketing discipline. Recently, more advanced forms of MkIS that mainly apply the intelligent information systems to solving various marketing problems – including consumer behavior modelling (Martinez-Lopez & Casillas, 2009), service personalization (Chung, Rust, & Wedel, 2009), and marketing strategy development (Li, Li, He, Ward, & Davies, 2011), among others – are proposed to address the relevance problem in marketing. In particular, Li, Kinman, Duan, & Edwards (2000) compare the pros and cons of different types of MkIS for marketing strategy development. They classify the existing information systems for marketing strategy development into six categories: MkIS (in a narrow sense) that mainly aim to provide operational marketing data to marketing managers; decision support systems (DSS) that focus on supporting decision models and data; executive information systems (EIS) that support strategic decision making by CEOs; expert systems (ES) that support experts with a reusable knowledge base; artificial neural network (ANN)-based systems that have strength in identifying transaction patterns of customers; and fuzzy logic-based systems that can handle fuzzy knowledge in the marketing domain. While each type of IS has a unique advantage for supporting marketing strategy development, the common drawback of the contemporary MkIS in supporting industrial marketing planning is the lack of a supporting group knowledge-building process and what-if analysis. As Turnbull & Villa (1998) argue, the integration of knowledge from the different functional departments involved in industrial marketing channels is one of the critical success factors for industrial marketing planning to reflect the buyer–supplier relationships in the planning process. The existence of a large number of variables to be considered for the planning, due to the additional variables relating to the partners, and the uncertainty imposed on the variables requires collaborative human judgment to identify core variables and the causal relationships among them. The MkIS in the literature have limitations in supporting both collaborative knowledge building and analysis of the impacts from taking different strategies under foreseen economic circumstances.

This paper aims to propose a fuzzy cognitive map (FCM)-based approach to industrial marketing planning. An FCM-based approach is chosen as it allows easy integration of the subjective opinions of experts in different industrial marketing channels and quantification of the degree of haziness in relationships among the variables concerned, thus providing a systematic what-if analysis to compare different scenarios. An FCM represents domain knowledge as a connected network in which nodes represent major concepts (variables such as communication frequency with partners) and arcs between nodes represent causal relationships and the strength of the causality. An FCM evaluation function allows managers to quantify the impact of a change on an independent variable (the number of branches, for instance) to a monitored variable (the total revenue). Features of an FCM for strategic planning include the easy integration of knowledge from different stakeholders and the existence of a systematic propagation algorithm to track the impact of a change across a planning system.

While FCMs have potential within the strategic business planning realm, they have limitations in supporting industrial marketing planning due to their inherent drawbacks. Firstly, in conventional FCMs, all relationships (which are represented as arcs) are fixed during an evaluation. However, in reality, it is not unusual for changes to occur in some of the relationships when the cause-effects are not certain among variables in modelling phase. For example, it is not certain which variables among “win ratio in bids,” “IT investment of clients,” “number of partners,” and “consulting pipelines” will be most affected by presale activities during modelling, or which can change during the model evaluation. Secondly, FCMs lack a time concept that is crucial in many applications. Therefore, FCMs cannot effectively describe the dynamic nature of the causal relationships among concept nodes. Some causes may show an immediate effect while others may take hours, days, or even years. For example, increasing the number of partners will have an instant influence on the partner management activities but a delayed influence on the total revenue of a company. Thirdly, FCM is not the best solution when the number of nodes and arcs increase exponentially, due to the limited cognitive ability of the human brain. Lastly, one crucial drawback of a conventional FCM is that it is usually not reusable for other problems in a domain. The causal relationships among concepts can be reused to model other problems in the same domain; therefore, it is beneficial to have a mechanism to reuse generic relationships to solve similar problems.

The novelty of this study in solving a practical problem (developing a tool to support marketing planning) lies in overcoming the limitations of traditional FCMs in representing the time lag in the causal relationships among concepts that are common in marketing planning, and increasing the reusability of FCMs so that a marketing planning model can be reused later through the integration of agent technology and the FCM. This study also contributes to the industrial marketing management discipline by providing marketing managers with an intelligent system that can synthesise the qualitative expert knowledge of multiple managers in different divisions for collaborative industrial marketing planning. The proposed approach is tested through a real-world industrial marketing planning problem in South Korea.

This study takes a design science approach (van Aken, 2005) to produce a novel MkIS that can be used directly by industrial marketing managers. Design science comprises the aim of designing, implementing, and testing a novel solution for managerial problems. Hevner, March, Park, & Ram (2004, p. 726) define the design science method as including the following activities: identification and clear description of a relevant organizational problem; demonstration that no adequate solution exists; development and presentation of novel artefacts (models, constructs, methods, or instantiations) that address the problem; rigorous evaluation of the artefacts enabling the assessment of its utility; articulation of the value added to the domain knowledge base and to practice; and explanation of the implications for management and practice. A novel artefact that addresses the target managerial problems also is known as a design proposition, which corresponds to a causal research model in explanatory science approach (Romme, 2003). A design proposition links a specific intervention to a specific organizational outcome. In the context of this study, the proposed approach based on FCM is considered as a design proposition (intervention) to improve organizational performance (industrial marketing planning).

Following the proposed method, this paper is organized as follows. Section 2 provides the conceptual background regarding FCMs and extended FCMs. Section 3 describes the preliminary design proposition that integrates the agent and the FCM to support industrial marketing planning. In section 4, the approach is applied to a real world industrial marketing planning problem to determine its feasibility. Finally, section 5 discusses the practical and theoretical implications of the study and section 6 concludes the paper.

2. Fuzzy Cognitive Map

A cognitive map was proposed by Axelrod (1976) to represent social scientific knowledge. A cognitive map model is represented by a signed graph that consists of nodes and edges. A node is used to represent a concept of a domain and an edge a causal relationship between nodes. The direction of an edge represents the direction of a causal relationship, which is also called a feedback. A feedback is positive (negative) if an increase in the first variable leads to an increase (decrease) in the second variable. In order to enlarge the scope of cognitive map applications, several variations of cognitive maps have been introduced in the literature. A fuzzified version of the cognitive map - FCM - was first introduced by Kosko (1986). The FCM incorporates fuzzy causality measures in the original cognitive maps, so it provides a flexible, more realistic representation scheme to deal with knowledge.

Fig. 1 (a) shows a part of an FCM that represents the relationships among the marketing concepts of an industrial IT service company. In Fig. 1, the consulting revenue of the company is dependent on the demand for consultant services, which again is affected by the number of partners, the new consulting pipeline, and the install base pipelines. The FCM allows modelers to specify the hazy degrees of causality between concept nodes, as shown in the figure. For example, the number of partners has a negative impact on the demand for consultancy, and the causality is relatively more certain compared with the causality between the new consulting (or install base) pipelines and demand for consultants. The fuzziness can be represented through numbers between −1 and 1 to represent the hazy degrees of causality.

The quantification of the hazy degrees of causality enables causal reasoning through forward and backward chaining. A vector of concept nodes, C^t, represents a system state at time t. The system state at time t+1, C^{t+1}, is derived via the equation:
$C^{t+1} = f\,(C^t \times E)$

In the above equation, E is an adjacency matrix and f is a transfer function. Adjacency matrix, E, is an N × N matrix that represents the causal fuzziness among N concept nodes. In Fig. 1, there are five concept nodes and four causal relationships, and the adjacency matrix of the FCM is represented in segment (b). Three transfer functions are commonly used (Tsadiras, 2008): a sign function, $f_{sign}(x)$, converts evaluation values into either 1 ($x > 0$) or 0 ($x <= 0$) to represent a concept node either activated or deactivated; a trivalent function, $f_{tri}(x)$, into 1 ($x > 0$), 0 ($x = 0$), or -1 ($x < 0$) to represent a concept node that increases, equals, or decreases; and a sigmoid function, $f(x) = tanh(x)$, converts the evaluation into a value between −1 and 1 for a continuous state FCM. The inference of an FCM is a repetitive process of evaluating the equation starting with an initial concept vector (C^0) until the system reaches an equilibrium point at which the system state vector does not change anymore, a limit cycle in which finite states are reached repetitively, or moves into chaotic attractor states instead of stabilizing as in the previous two cases. A discrete state FCM stabilizes to reach an equilibrium point or a limit cycle; the former means that a given state vector reaches the equilibrium state while the latter is a repetitive occurrence of finite states.

This paper summarises existing FCM studies from four perspectives according to the study aims: the application of FCM to solve domain problems; novel ways of construction and inference of FCMs; extending FCMs to meet application-specific requirements; and the study of the integrated multi-agent systems and FCMs.

FCMs have been commonly used in the field of social science, including administrative and management science. Lee, Lee, Kwon, Han, & Yu (1998) applied FCMs to strategic planning simulations, in which the FCMs help decision makers to understand the complex dynamics between a strategic goal and the related environmental factors. Kwahk & Kim (1999) proposed a cognitive map-based method, called two-phase cognitive modelling (TCM), to help organizational members identify potential organizational conflicts, capture core business activities, and suggest ways to support the necessary organizational change. They applied the procedures of the TCM method to a real business process redesign project. The FCM also was applied to business process reengineering (BPR). Xirogiannis and Glykas (2004) describe an attempt to build and operate such a reasoning mechanism as a novel supplement to performance-driven change (PDC) exercises. This new approach proposes utilization of the fuzzy causal characteristics of FCMs as the underlying methodology in order to generate a hierarchical and dynamic network of interconnected performance indicators. Another interesting application of CM is found in Chinese chess (Chen & Huang, 1995). FCMs also have been used in various information systems and information technology areas. Liu (1999) proposed census FCMs (CFCMs) for decision support in geographic information systems (GIS) and generated a CFCM using real census data, human expert knowledge, and quantitative data as a map in GIS.

Schneider, Shnaider, Kandel, & Chew (1998) summarized two drawbacks of conventional FCMs: (1) the lack of a time concept in causal relationships; and (2) concurrency, which requires the simultaneous evaluation of node values in multiple concept nodes. To incorporate the time delay in FCMs, Park & Kim (1995) proposed fuzzy time cognitive maps

(FTCM), in which a relationship is allowed to be attached with time delays. Hagiwara's (1992) extended FCM (E-FCM) was an early effort to incorporate weights having nonlinear membership functions, conditional weights, and time-delay weights. However, existing efforts to handle time delays require dummy nodes in FCMs, increasing the complexity in the inference of FCMs.

In real-world applications, FCMs usually are very large and complex, with large numbers of concepts and arcs. However, existing techniques for constructing and analyzing FCMs are inadequate and sometimes infeasible in practice. Furthermore, as FCMs are sometimes nonlinear systems, different combinations of several inputs to end nodes or initial states may result in new patterns with unexpected behaviours. Thus, systematic and theoretical approaches are required for the analysis and design of FCMs. Buede (1993) also proposed graph operations based upon specifically defined graphical structures and selected qualitative reasoning techniques. Zhang, Liu, & Zhou (2003) introduced a decomposition theory for FCMs, proposing a framework for calculating and simplifying causal inference patterns in complicated real-world applications. Schneider, Shnaider, Kandel, & Chew (1998) described a method for automatically constructing FCMs based on user-provided data. This method consists of finding the degree of similarity between any two variables (represented by numerical vectors), finding whether the relationship between the variables is direct or inverse, and using the fuzzy expert system tool (FEST) to determine the causality among the variables. FCMs can be combined by merging their adjacency matrices with different weighted coefficients that usually represent the beliefs of different human experts (Silva, 1995). Nelson, Nadkarni, Narayanan, & Ghods, (2000) used revealed causal mapping (Narayanan & Fahey, 1990) to understand support expertise in software operations. Jamadagni (2000) suggested and used an object-oriented FCM (OOFCM) to describe a communication network for the purpose of fault and performance monitoring. The OOFCM allows for the reusability of classes through hierarchies and also helps capture dependencies between network entities.

Multi-agent systems (MASs) are distributed problem solving systems that use the collaboration and coordination of autonomous, intelligent agents (Brazier, Dunin-Keplicz, Jennings, & Treur, 1997). One of the major features of MASs that differentiate them from object-based systems (OBSs) is that the interactions among agents take place via asynchronous message exchanges to preserve the autonomy of the agents. Unlike objects that cannot refuse method invocations, agents can refuse or reject service requests delivered through asynchronous messages. FCMs have been adopted in studies to improve the reasoning capability of software agents. Miao, Goh, Miao, & Yang (2001) proposed an agent inference model (AIM) to construct intelligent software agents. AIMs can represent various types of fuzzy concepts, temporal concepts, and dynamic causal relationships among the concepts. They also have the ability to handle feedback and analyse inference patterns across different causal impact models. Rai & Kim (2002) similarly applied FCMs to enhance the reasoning capability of active objects. Maes, Meganck, & Manderick (2005) proposed a multi-agent causal model (MACM) that is an extension of causal Bayesian networks to a multi-agent setting. Instead of a single agent representing an entire domain, several agents that represent their own sub-areas collaborate to represent the entire knowledge of the domain. Each agent has a causal model, determined by an acyclic causal diagram and a joint probability distribution over its observed variables.

It is argued that today's marketing managers rarely use marketing models proposed by academics (Martinez & Casillas, 2009) and the lack of proper tools is a reason why marketing managers cannot fully implement systematic marketing planning (Li, Kinman, Duan, & Edwards, 2000). As presented in this section, The FCM is ideally suited to the synthesis and quantification of the subject knowledge of multiple experts for a systematic quantitative analysis. However, a complexity inherent in marketing planning problems requires a new approach to applying FCM. Time delays on the cause–effect relationships between two concepts is common in industrial marketing planning as the time scale of the considered concepts is relatively longer. The incorporation of time delays in the causal relationship between two nodes has been addressed in prior research (Hagiwara, 1992; Park & Kim, 1995), but the use of dummy nodes increases the complexity of the inference of FCMs. Uncertainty on concepts combined with the large number of variables necessary to represent industrial marketing planning problems requires the FCM to be more flexible to allow managers to test different scenarios in the middle of FCM inference, minimising the interruption due to structural changes on an FCM model. However, the FCM literature lacks a systematic way to handle dynamic inference, including ad-hoc relationships (concepts can be associated with other concepts in the middle of an inference). Finally, the reusability of FCMs has been addressed (Jamadagni, 2000), but the granularity of reuse is limited to the object level, and the reuse of relationships that capture patterns of knowledge inference has not yet been addressed.

3. Preliminary Design Propositions: MACOM approach

This section proposes a design proposition (MACOM approach) as a solution to improve the applicability of the FCM to marketing planning problems. The limitations of the current FCM in its application to marketing planning problems were discussed in the introduction section, and this section focuses on the technical details of the design proposition. The design rationale and details of MACOM are provided for verification in later sections. This section corresponds to the research model section of the behavioural science approach.

3.1. Design rationale of MACOM

MACOM is a multi-agent-based FCM evaluation system that meets the additional requirements for marketing planning problems. As argued earlier, marketing planning problems impose a complexity that cannot be resolved by current FCMs. That includes uncertainty and time delay in cause–effect relationships, complexity with a large number of variables, and reusability for similar planning problems. The design principle of MACOM is to consider the evaluation of an FCM as distributed computing by multiple agents that represents the concept nodes of the FCM. An arc between two concept nodes is represented as a direct message communication between two agents.

Modelling an FCM with multiple agents has the following advantages. Firstly, the time lag can be processed efficiently without creating dummy nodes (and therefore more complex FCM structures), which has been done in similar studies to handle the time lag in FCMs. Secondly, the distributed computing nature increases the scalability of FCMs to handle a large number of concept nodes and arcs. Thirdly, defining concept nodes as intelligent agents increases the flexibility of FCM evaluation processes, as the relationships among nodes can be dynamically changed in the middle of the evaluation process. An agent representing a concept node can choose the next event receiver and change weights on each arc based on changes in the business environment. Fourthly, the reusability of FCM knowledge is increased as the generic relationships among concepts (that represent common knowledge in different domains) can be defined as interaction patterns among agents and reused for solving problems in different domains.

3.2 Design artefacts of MACOM

Fig. 2 shows the basic concept and architecture of MACOM.

The MACOM architecture has six major components. The ***interface agent***, located on the user side, is responsible for serving a user in developing an inference of an FCM. The ***coordination agent,*** usually located on the server side, is responsible for setting up a network of node agents that represent the concept nodes of an FCM. The coordination agent also collaborates with interface agents to build an FCM using the reusable relationships in a relationship hub. ***FCM space*** is the artificial space in which the node agents build the FCM and inference takes place. ***Node agents*** represent concept nodes in an FCM. Node agents are usually launched by a coordinator agent at the request of an interface agent. Node agents react to the events that come from other agents (coordinator or node agent) and generate output events to other related agents. An ***event*** is a value with a time variable and direction, which means that it has a vector and is scalar. An event is generated from nodes and moves from one node to another along the linked arc between nodes through message communications between corresponding node agents. Node agents process events considering the time lag specified in the event. The ***relationship hub*** is a knowledge base that has information regarding all nodes and relationships (nodes, arcs, weight value, and time lags). Using this concept, we can dramatically increase the reusability of the FCM model. The relationship hub can have incomplete relationship information that can be specialized during the FCM building stage.

Fig. 3 shows the state transitions of a coordinator and node agent. A coordinator agent starts in the ‘waiting for messages’ state once it is launched, and continuously checks its message queue to process any incoming messages from the interface and node agents. The three major message types from an interface agent that trigger the actions of the coordinator agent include messages requesting a set of relationships for building an FCM, configuring a network of node agents for a given FCM, or making an FCM inference via the communications among node agents. A node agent is created by a coordinator agent to represent an FCM concept node. The first state is ‘initializing’ and involves setting the attributes of the FCM with initial values. This state leads to ‘registering to a coordinator agent (CA)’ in which the node agent registers with the coordinator agent to indicate its successful launch. That step leads to a ‘checking event’ state in which the node agent continuously checks its message queue to process any events delivered to a node agent through messages. The major events that come from a coordinator agent or other node agents are for the inference of the FCM in which the node agent is involved. An event contains the evaluation value of the sender node agent and time lag. The node agent updates its node value using the values in the event and forwards its node value as an event to either linked post-node agents or the coordinator agent if it is the last node agent of the FCM.

Fig. 4 shows how the time lag is processed in MACOM by node agents. In the FCM in Fig. 4 (a), there are time lags in the causal relationships: A → B, B → D, and C → D. Therefore, the evaluations of node values are conducted at different time points. At time 0, the only active node is A, so node agent A evaluates its node value and passes it to a linked successor agent (node agent B). On receiving the value as an event, node agent B compares the time lag with the current time value to decide if the event needs to be processed now. As there is one time lag and the current time is 0, node agent B will store the event in its scheduler. At time 1, the coordinator agent sends all node agents an event that triggers the updating of time values among the node agents. Only node agent B has an event to process at this time and its scheduler will retrieve the event and process it to update its node value. The updated node value will be sent to successor node agents (node agents C and D) as events that again specify the node value of B. Node agent C will receive the event and process it instantly, as there is no time lag on the link between B and C, and will also use the weight value of the link in the calculation of its new node value. On the other hand, node agent D will store the event in its scheduler, as there is a time lag on the link from node B. Fig. 4 (b) summarizes the event processing algorithm of a node agent, and Fig. 4 (c) presents the node values at each time point. Function *f* is an evaluation function employed by each node agent and the function can differ for various node agents, which provides MACOM with more flexibility for the inference of FCMs as compared with other FCM inference mechanisms.

3.3 MACOM simulator

The MACOM simulator helps users develop a MACOM model by reusing relationships in the relationship hub and evaluating the model through agent interactions. The simulator was developed using NetLogo (http://ccl.northwestern.edu/netlogo/), a multi-agent simulation tool. NetLogo helps developers easily implement the graphic user interface as well as conduct a what-if analysis.

The MACOM simulator has three major components. Firstly, the relationship hub builder is implemented based on a Microsoft Excel macro and is used to construct the relationship hub. If we input the FCM adjacency matrix in this builder, it converts the relationship into a format that can be used in the MACOM simulator. Secondly, the relationship hub is a database that stores reusable relationships between nodes as well as between FCMs. An FCM is defined as a record in the database and represented as a tuple of a concept node set (C), a relationship set (R), and context. That is an FCM instance, *fcm* = <C, R, context>. Context is used to provide future users of the FCM with the context information of the FCM, including the problem domain. A relationship is a tuple consisting of cause, effect, and a weight, *r = <cause, effect, weight>,* and is also stored in a database as a record. The relationship hub is queried by a user interface for supporting the FCM building process. Firstly, the user interface guides a user to choose a problem domain. On selection of a problem domain, the user interface lists all FCM models available in the database. The user then can choose a concept and the user interface is enumerated with a list of relationships available in the database. The process is iterated until the user defines an FCM based on the recommended relationships or a new concept and relationships. Finally, the MACOM engine has an agent-based FCM inference logic, with two kinds of transfer functions (1/2 threshold and tanh function) though additional functions can be easily integrated.

The usual steps of using the MACOM simulator are as follows. In the first step, a user needs to enter the relationship information for the concepts. At this point the user does not need to know all potential FCM models, which means that drawing the complete FCM model is not necessary. In the second step, the user presses the ‘setup’ button and the simulator uploads all relationships from the relationship hub. In the third step, the user selects the initial node values using the slides and starts the simulation by pressing the ‘start’ button, with the user analysing the results in the following step. If the user wants to conduct a what-if analysis, s/he introduces dynamic conditions to the FCM and repeats Steps 3 and 4. The simulator provides three types of what-if simulation, as described in the following paragraphs.

Dynamic-weighting. A user can change the weights on arcs from a fixed value to interval values to compare the impacts of weight value changes in the given interval. For example, the code ‘dynamic-weight 4 5 0.3 0.8’means that the weight of the link between nodes ‘4’ and ‘5’ can have a value in the interval [0.3, 0.8].

Dynamic-relationship. A user can change the direction of the arcs between two nodes. For example, code ‘dynamic-node 3 [[4 5] [4 6]]’ will trigger the interface agent to ask the coordinator agent to report the impact of changing the arc sets from (3→4 & 3→5) to (3→4 & 3→6).

Free-node. A user can set a node as a free node that can be related to all other nodes in the middle of simulation. The simulator will arbitrarily create links to other concept nodes with a given causality value and report how each change will impact the whole FCM. This is to allow a marketing manager to link the free node with other concept nodes to determine which course of causal route produces the best performance of the dependent variables. For example, a command ‘Free-node 5 0.6’ will change node 5 to a free node. The simulator will report the differences when node 5 is related to other nodes with the causality value of ‘0.6’.

4. Experiment

This section applies the design proposition detailed in Section 3 to a real world marketing planning problem to test the feasibility and generality of MACOM. For this purpose, this section introduces a marketing planning problem that reflects the complexities argued in the introduction section and shows how the proposed MACOM can be applied to the problem, overcoming the complexities.

The MACOM simulator was applied to a marketing planning scenario for software service company ‘A’ (the company name is anonymized upon their request). The company is a South Korean branch of a worldwide IT solution provider whose headquarters are located in the United States. The company has a wide spectrum of IT solutions, including database management systems (DBMSs); enterprise resource planning (ERP); middleware solutions like Java, business intelligence tools, and service oriented architecture (SOA) tools; server and storage systems; and industry-specific solutions for the healthcare, insurance, and high tech industries. Due to the large number of solutions offered, the company has very complex partner networks, and the effective management of such partner networks is one of the key success factors of the company. Therefore, their marketing planning requires the consideration of a large number of variables, and judging the impact of a variable on their revenue is not an easy task.

To apply the MACOM approach to support their marketing planning, five managers from sales, consulting, support line of businesses (LOBs), and the finance department were invited to the experiment.

Knowledge acquisition from multiple experts was already proposed in the literature (Mittal & Dym, 1985) to avoid potential pitfalls from relying on a single expert. In the experiment, the partial information gathering is performed via four steps: raw data elicitation, consensus, elicitation of draft relationships, and quantification of the relationships.

In the first step, interviews were conducted with managers for raw data elicitation through an open interview technique. For example, respondents were asked to enumerate concepts that came into their mind when they heard the term 'sales cost'. The second step was to derive consensus among the managers on the extracted concepts from the interviews. In this step, a full list of concepts from all managers was sent back to each manager and they were asked to select the concepts they agreed with. The third step concerned eliciting draft relationships among concepts via a survey among the managers. All concepts extracted in the previous step were listed and the managers were asked to draw arrows between the concepts attached with a '+' or '−' sign that represented a positive or negative relationship respectively. At the last step, the managers were asked to quantify the level of causal relationships as well as the time delay.

The developed FCM is shown in Fig. 5. The definition of each construct in the causal map is presented in Table 1. We used five scale measurement values for each construct as 'significantly increased' (0.9), 'increased' (0.5), 'no change' (0), 'decreased (−0.5), 'significantly decreased' (−0.9). Table 2 shows the causality weights on the relationships of the FCM, and Table 3 shows the time lags on the relationships. We define 0 as immediate impact, 1 as around a three-month time lag, and 2 as more than a six-month time lag. Initially, managers were individually asked to provide the weight and time delay values on each relationship. All managers were then invited to a face-to-face meeting to resolve any conflicting value information.

For the inference of the FCM, we used the current business circumstances of company ‘A’ as the first input, which is summarized in Table 4. This company has not been successful in recent large deals in the market and their market share has decreased as compared with the previous quarter. Economic indicators show that the economic trend of the sector is likely to show positive growth. The number of presales activities, such as giving presentations to clients, has recently increased. The total number of in-progress projects has also increased as compared with the previous quarter, as did revenue from the consulting LOB.

The simulation results for the current business circumstance are shown in Fig. 6. The revenue from the consulting LOB will increase rapidly within 6 to 9 months, but the total revenue will decrease and will be not be recovered within one year. The revenue from the licensing LOB will decrease in the next few quarters and this status will not change if there are no other changes in the business situation presented in Table 4. Although company ‘A’ is a total IT solution provider, their revenue comes mainly from sales of software licenses, such as ERP, CRM, and DBMSs. However, the simulation results show a decreasing trend for license sales in the future. Therefore, the company needs to find a new marketing strategy that can increase their licensing sales revenue.

A ‘what-if’ simulation was conducted to assess the impact of increasing the weight on the relationship between the number of partners and the license pipeline to 0.5; the simulation results are displayed in Fig. 7. We can see that the revenue from license sales is expected to increase within 6 to 9 months. If the company increases the number of partners who can implement the software of company ‘A’ and earn revenue from this delivery, then the revenue from license sales can be increased. Thus, the company needs to develop a new marketing program that can increase the number of new partners. However, if this result is analysed from the consulting LOB’s perspective, the partner of the license sales LOB would be the competitor of the consulting LOB – if the partners provide consulting or software package implementation services to the client, then the consulting LOB may lose their new opportunities. The revenue from the consulting LOB may decrease temporarily from the effect of the increased number of partners, but the increased number of partners will be helpful for recovering the company’s total revenue.

Another simulation was conducted to see the impact of changes on the install base strategy. A large number of customers have already adopted the software of company ‘A’, and these customers are called ‘install base customers’ to distinguish them from new customers. These customers provide another source of revenue for the company, as enterprise software packages such as ERP and CRM are upgraded regularly at additional costs. The upgrades of such systems are usually conducted every 3 to 5 years and the customers sometimes purchase additional modules they did not have in the initial adoption or previous upgrades. If the company increases the number of pipelines for ‘install base customers’, then the business forecast may change, as shown in Fig. 8. The increase in the number of install base pipelines affects both consulting revenue and license revenue. Therefore, company ‘A’ needs to have more sophisticated customer relationship management programs for ‘install base customers’.

The fourth simulation was conducted to analyse the impact of increasing the weight of the relationship between the number of partners and the software license pipeline. Utilization of the partners would be a good way to overcome the limited number of employees in sales, as most of the company’s partners have informal personal relationships with their clients. Using a ‘dynamic-weight’ code, the weight between the number of partners and the license pipeline is changed from 0 to 0.9. The results showed a positive growth trend in license revenue and total revenue as the relationship between the number of partners and license pipeline increases. The last simulation is for the presales activity of company ‘A’. The results showed that presales activity affects only the demand for presales consultants. However, if the company engages in more aggressive presales activities to affect other factors, then the business situation would change.

Finally, as shown in Table 5, eight scenarios were simulated to see the effectiveness of the ‘dynamic-node’ in the MACOM simulator. The results of the simulation show that if the company has aggressive presales activity that can affect other factors such as the win ratio in bids, IT investment of client, number of partners, and consulting pipeline, then the revenue from consulting and license sales would increase rapidly. However, the relationship between presales activity and partner numbers may reduce revenue from the consulting LOB.

Based on the simulation results, the company could derive the following insights for their marketing planning:

- partnering programs need to be further developed,
- more sophisticated CRM programs are required for 'install base customers', and
- the promotion of presales activities is required.

The experiment showed how the MACOM approach can help industrial marketing managers to analyse different marketing strategy options through what-if analysis supported by a MACOM simulator. Even though the MACOM was applied to a specific marketing planning problem in this paper, it is a generic framework that can be applied to other problems that have similar characteristics. For example, the marketing manager of company 'A' was confronted with the typical difficulties of industrial marketing planning that mainly arise from the complexity of the inter-relationships between internal variables and the supplier–buyer relationship variables. The increased number of partners who sell the company's software license had a negative relationship with the revenue of its own consulting LOB. The FCM turned out to be a useful tool to integrate the knowledge of different functional divisions of the company to identify the major variables and depict the inter-relationships among those variables. Secondly, the experiment also showed how marketing managers can handle uncertainty in the modelling phase through dynamic node and dynamic weight concepts of the MACOM simulator in the middle of evaluation of the FCMs. In this experiment, the dynamic node (presale activity in Table 5) and dynamic weight (weight on the relationship between the number of partners and the software license pipeline) concepts were effective to evaluate the overall impact to the system when modelling parameter values (the weights on relationships and the relationships between nodes) are uncertain. The uncertainty in the modelling phase is not a unique feature of marketing planning problems and does exist in other areas; MACOM can be applied to such problem domains as well. Thirdly, the time delay on cause–effect relationships have been effectively adopted in the evaluation of FCMs through the intelligence of agents that represent the concept nodes. In the experiment, the managers of company 'A' were invited to express their opinion on time delays on identified cause–effect relationships and then made agreements on these delays through face-to-face discussion. The time delays were incorporated in the evaluation of the FCM by the agents that represent the corresponding concept nodes. The agent-based mechanism to process a time delay in MACOM is generic and can be applied to any FCMs that contain time delays on cause–effect relationships.

5. Discussion and Implications

As shown in the experiment, the practical implications of the MACOM approach for marketing managers are as follows. Firstly, the advantage of an FCM-based approach to marketing planning in terms of integrating expert knowledge from different functional departments was demonstrated. As argued by Webster (1995), the interdependence of functional departments for the provision of industrial products and services is one of the differences between industrial and consumer marketing planning. For company 'A', the identification of major variables that affect the total revenue of the company and causal relationships among them requires the consideration of opinion from different functional managers. In the experiment, an FCM was used to share the knowledge on marketing planning among managers in different functional departments. The four-stage approach taken in the experiment allowed the functional managers to share their own opinion on marketing planning and adapt it while comparing with those of other managers. An FCM was used to represent the marketing planning knowledge of the functional managers and collaborative enhancements.

Secondly, industrial firms have to consider a large number of variables for marketing planning due to additional variables in the relationship with their partners, and this is further complicated for company 'A' as they have partners who sell the company's software licenses while the company has their own consulting department. Though the two LOB activities contribute positively to the total revenue of the company, there are interaction effects between the two activities and analysing the impact of each activity in a changing business environment is not easy via traditional marketing planning tools. An FCM allows managers to specify the strength of causal relationships among the concepts as well as the causal directions, and its inference mechanism enables the managers to conduct what-if analysis to quantify the impact of a change on the concept node. The FCM-based approach provides an opportunity for marketing managers to build a knowledge map that includes a large number of variables and to conduct a quantitative analysis to analyse various scenarios. In addition, artificial neural networks (ANNs) and fuzzy systems have been integrated for marketing planning (Li, 2000). However, such an approach requires a significant quantity of historical data for the learning of the system, while the MACOM approach in this paper doesn't require such data but requires the expert knowledge of the marketing managers and therefore can be applied to problem domains where historical data is not available.

Thirdly, the MACOM approach provides marketing managers with greater flexibility for the simulation of various scenarios for marketing planning. It is imperative to have diverse what-if analysis on a given FCM for marketing planning as the development of an FCM is based on the subjective opinions of managers across different departments. In MACOM, each concept node is represented by an intelligent agent that can decide the direction of causal impact to the next concept node agent, and therefore the what-if analysis in MACOM does not require the rebuilding of the FCMs from the beginning for a change on relationships among concept nodes as well as the direction of the causal relationship.

Finally, though the MACOM architecture was implemented as a stand-alone NetLogo application, the architecture can also be applied to implement a web-based knowledge sharing system in solving marketing problems for a company. In this case, the coordinator agent and relational hub are located in server-side and interface agent on client-side like web browsers. The interface agent launched on a web browser conducts interaction with users to support the FCM building process. The interface agent can interact with the relational hub in the process by listing generic relationships for a given problem. For inference of an FCM, the interface agent interacts with the coordinator agent that performs the evaluation of the FCM in collaboration with node agents and returns results back to the interface agent to be shown to the users.

The MACOM approach in this paper can be considered as a management theory (Van Aken, 2005) that explains how an FCM can be applied to solving marketing planning problems. Van Aken (2005) distinguishes management theory from organizational theory by referring to the former as the output of descriptive science and the latter as the output of solution-oriented research. According to his perspective, organizational theory explains how and why certain organizational phenomena occur, while management theory explains how an intervention can improve managerial performance. In marketing discipline there are few research efforts that provide novel design propositions to help marketing managers make better decisions. Chung, Rust, & Wedel (2009) developed a novel design proposition based on an adaptive personalization system for customized digital music player services. Their learning algorithm to identify user preference on music listening is a generative mechanism and can be applied to other information service provision. Similarly, Ansari, Essegaier, & Kohli (2000) propose a recommendation system based on a hierarchical Bayesian approach to enhance the accuracy of recommendations for products. Martinez-lopez & Casillas (2009) also develop a design proposition for extracting consumer behaviour knowledge using a genetic fuzzy system on electronic commerce data. The novelty of their design proposition is the method of integrating an evolutionary computing based learning method (genetic algorithms) with fuzzy systems, which has strength in representing domain knowledge in a flexible way. Their proposed system, MkMSS, defines technological rules that can be applied to other similar domains to imply a management theory.

The MACOM approach in this study showed how the FCM theory can be applied to solve industrial marketing planning problems. In particular, the complexity imposed in industrial marketing planning, such as uncertainty in the direction of relationships between concepts, time delays in cause–effect relationships, and the large number of variables to be considered, requires an advanced method for the inference of FCMs and a MACOM approach shows how an FCM can be applied to the problem of overcoming such challenges. The technological rules implied in the design proposition of MACOM form a generative mechanism that can be applied to the marketing planning of different industrial organizations. The technological rules that define how an agent plays the role of a concept node in an FCM were designed to overcome dynamic inference, including change of causal relationship and causal weights, and time lags, which are essential for supporting marketing planning. The design is novel as it provides a better way of solving a domain problem. For example, the existing approach for handling a time lag in FCM involves creating dummy nodes between the time lagged concept nodes (Park & Kim, 1995). However, this approach has a scalability problem, as the number of concept nodes increases as the total time lag increases. The agent-based mechanism adopted in MACOM does not affect the total number of concept nodes, so there is no increased complexity of an FCM. Also, the flexibility of inference is increased as the inference decision is distributed over the agents that represent the concept nodes of an FCM. Compared to traditional inference mechanisms which take a centralized approach (for example, Liu, 1999; Hagiwara, 1992) for FCM inference, the distributed nature of the multi-agent system adopted in MACOM allow the impact of a change on an FCM to be minimized through local adaptation by affected agents.

In summary, MACOM is an enhanced way of solving marketing planning problems and can be further extended for solving other similar problems such as strategic business planning.

Finally, this paper is one of few efforts in the industrial marketing research domain to apply intelligent systems technology to solving strategic marketing planning problems. According to Li, Kinman, Duan, & Edwards (2000), more than 50% of marketing managers were not satisfied with their current computer based systems for strategy development and the major reasons of the dissatisfaction turned out to be “limited support capabilities and the inability to couple analysis with managers’ intuition and judgement (p. 569)”. The MACOM approach proposed in this paper is one of the efforts to fill the gap through FCM. MACOM allows marketing managers to integrate their intuition and judgement on cause–effect relationships among variables existing in target domain problem as an FCM and to evaluate the consequences of a given scenario. Further, the what-if analysis functionality of the MACOM simulator allows marketing managers to test different scenarios by adjusting their initial intuition and judgement during the evaluation of the FCM. MACOM also provides academics in the industrial marketing management discipline with a tool for developing and pre-verifying a conceptual model based on qualitative knowledge of marketing practitioners. Researches based on positivism require developing a research model to derive a set of hypotheses for identified research questions to be verified through a data set. The major tasks in developing a research model include defining major variables and their cause–effect relationships. While in many cases research models are derived through literature reviews and researchers’ own judgement, it is also common to base a research model on the qualitative knowledge of practitioners or other scholars. FCMs can be used for integrating and representing domain knowledge from multiple scholars and/or practitioners to develop research models.

6. Conclusion

This paper proposed a novel design proposition for industrial marketing planning based on FCMs. The novelty of the design proposition lies in the technological rules that detail how agent technology can be integrated with FCMs to overcome the limitations of traditional FCMs in supporting industrial marketing planning. A MACOM approach allows marketing managers to consider time lags in causal relationships among major concepts in marketing planning. It also facilitates the analysis of the impacts of changes in an FCM, as a result of increased flexibility due to the distributed agent interactions that are core for the analysis. A MACOM simulator with a user-friendly interface was developed to support the building and execution of simulation models based on a MACOM approach. A MACOM approach was applied to a real world industrial marketing planning problem to show the feasibility and usefulness of the approach.

This study also has a limitation. The proposed design proposition, MACOM, has been tested via only one case therefore the generalization of the proposed approach needs to be considered carefully.

The study is one of a small number of efforts that apply a design science approach to solving industrial marketing planning problems, and future research directions include an approach to integrating FCMs with other quantitative approaches to improve the precision of planning results. For example, data mining techniques can be used to identify a causal relationship and its strength from historical data on marketing planning and FCM inference can be used for the simulation to analyse different scenarios.

Acknowledgment

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Figures and Tables

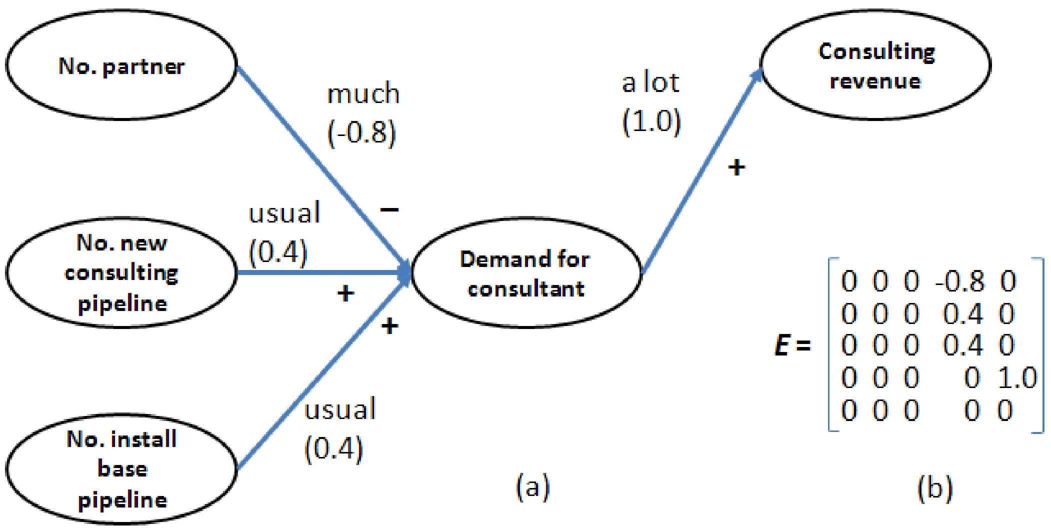


Fig 1: An example FCM and its adjacency matrix

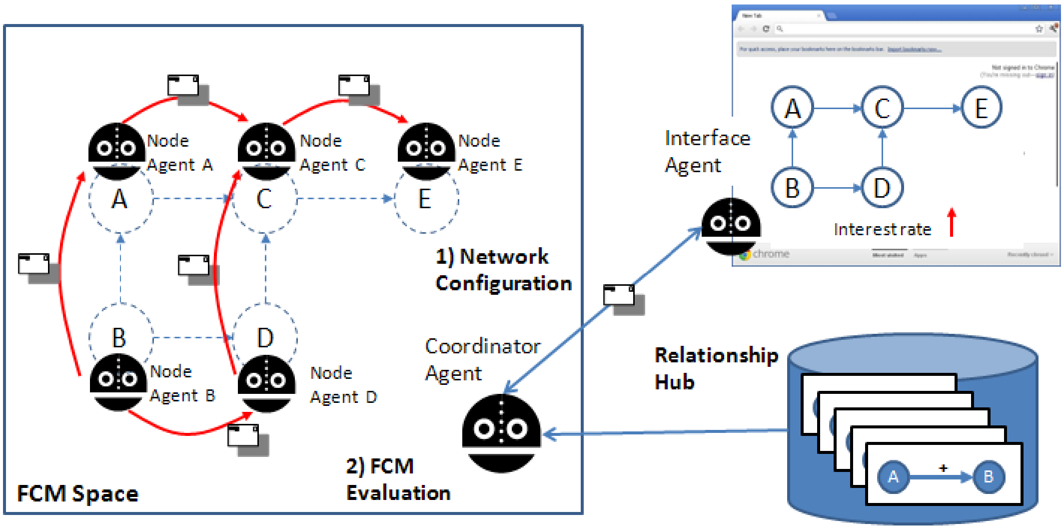


Fig 2: MACOM concept and architecture

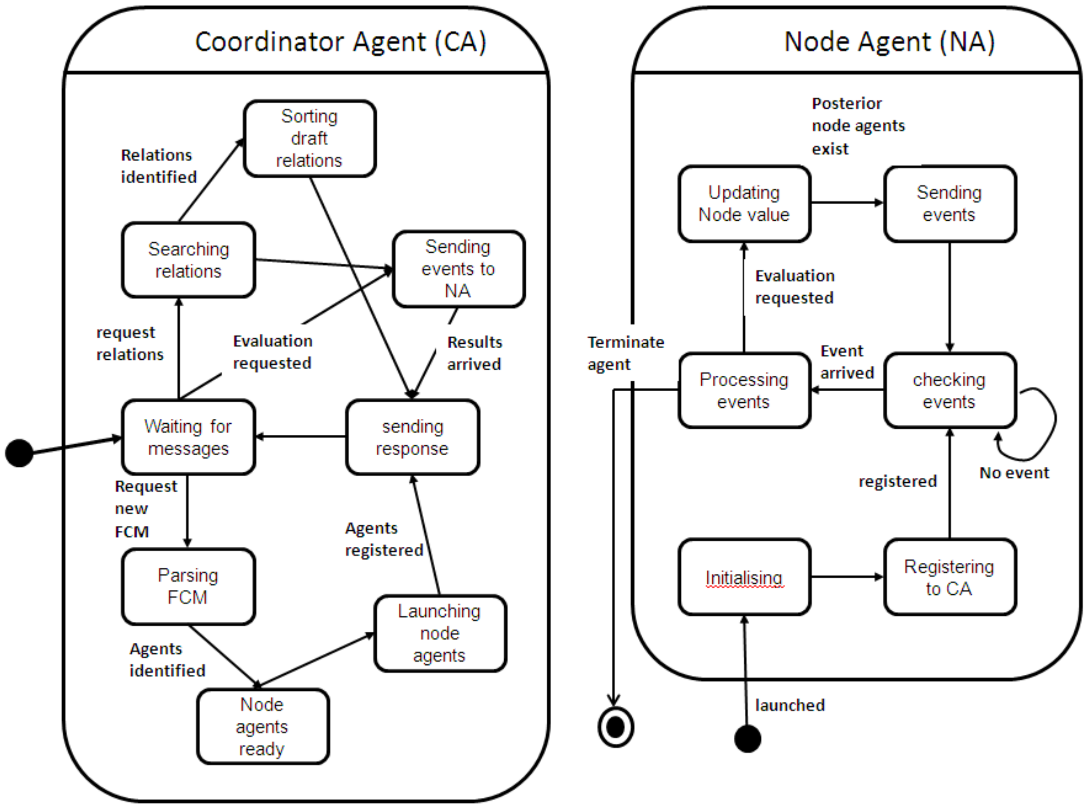
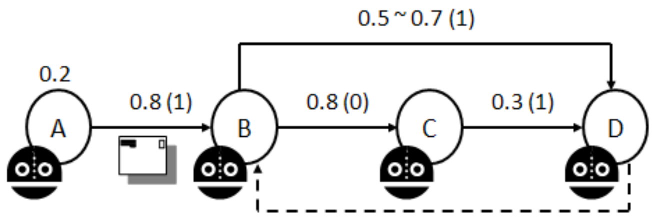


Fig 3: The state transition diagrams of the coordinator and node agents



(a)

t	A	B	C	D
0	0.2	b_0	c_0	d_0
1	0.2	$b_1=f(b_0,0.8)$	$c_1=f_c(c_0,f_b(b_1,0.8))$	d_0
2	0.2	b_1	c_1	$d_2=f_d(d_1, f_b(b_1,0.5 \sim 0.8), f_c(c_1,0.3)$

(c)

```
Event evt;
Vector inp, out;
Schedule schd;
Time t = 0;
Time_Delay  td=0;
...
Set evt = getEvt(t);
If evt.type == INPUT_ARRVD
   inp = evt.getArg("INPUT");
   td = getTimeDelay(evt.sender)
    if (td ==0)
       myvalue = f(myvalue, inp);
    else
       schd.add(evt);
Else If evt == CLOCK_TICK
    t = evt.getArg("TIME");
     schd.process(t);
```

(b)

Fig 4: (a) An example FCM showing time lags; (b) Algorithm to process an event by node agents; (c) Node values in different time lags

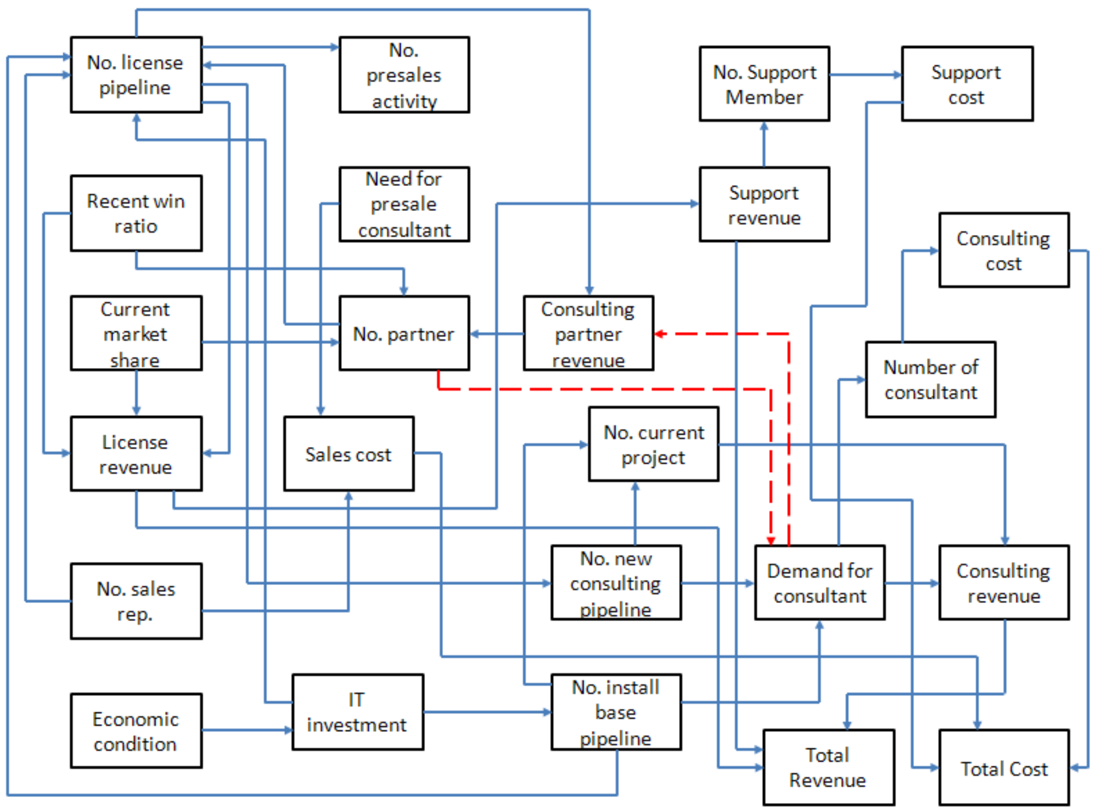


Fig 5: An FCM that describes the business impact of 'A' company

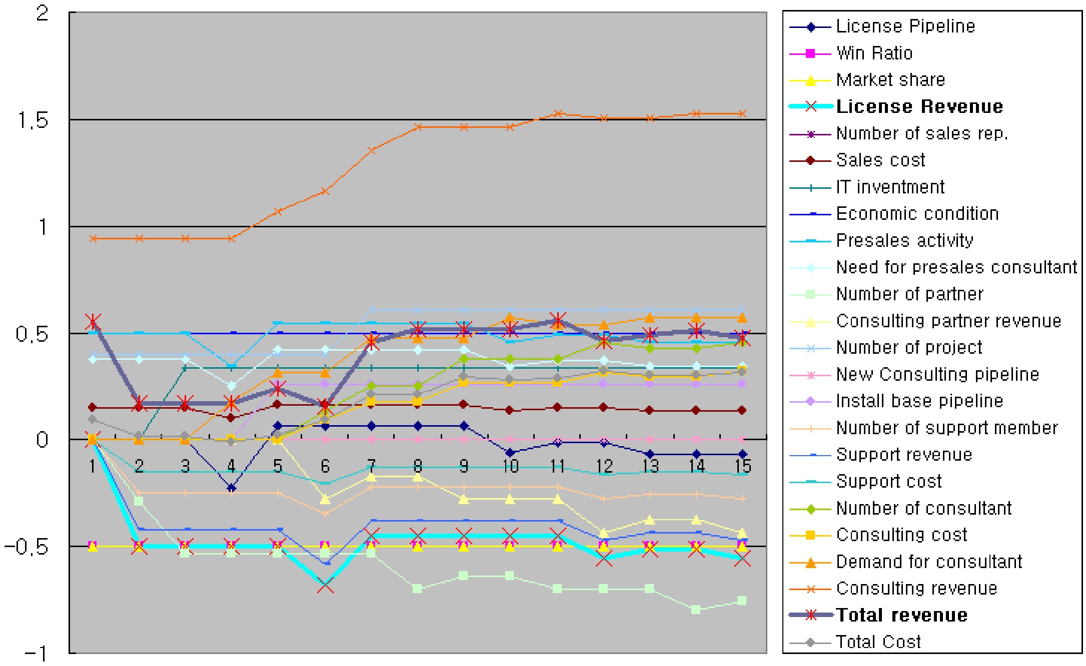


Fig 6: Simulation result for as-is business situation

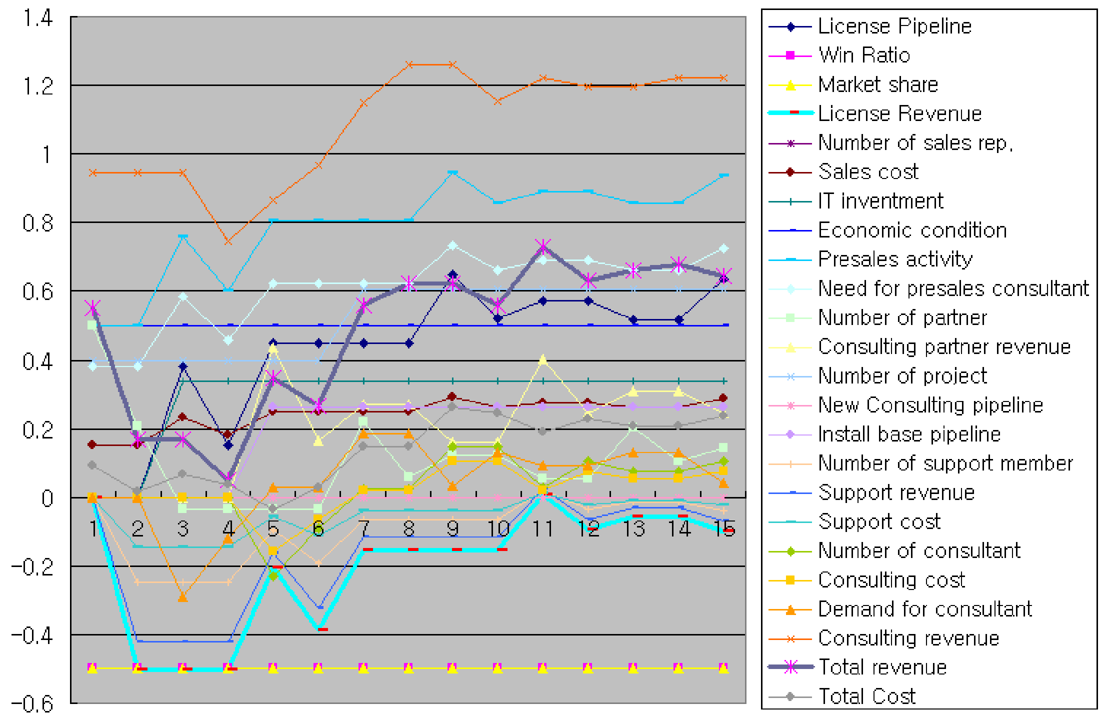


Fig 7: What-if simulation results for the change of partner strategy

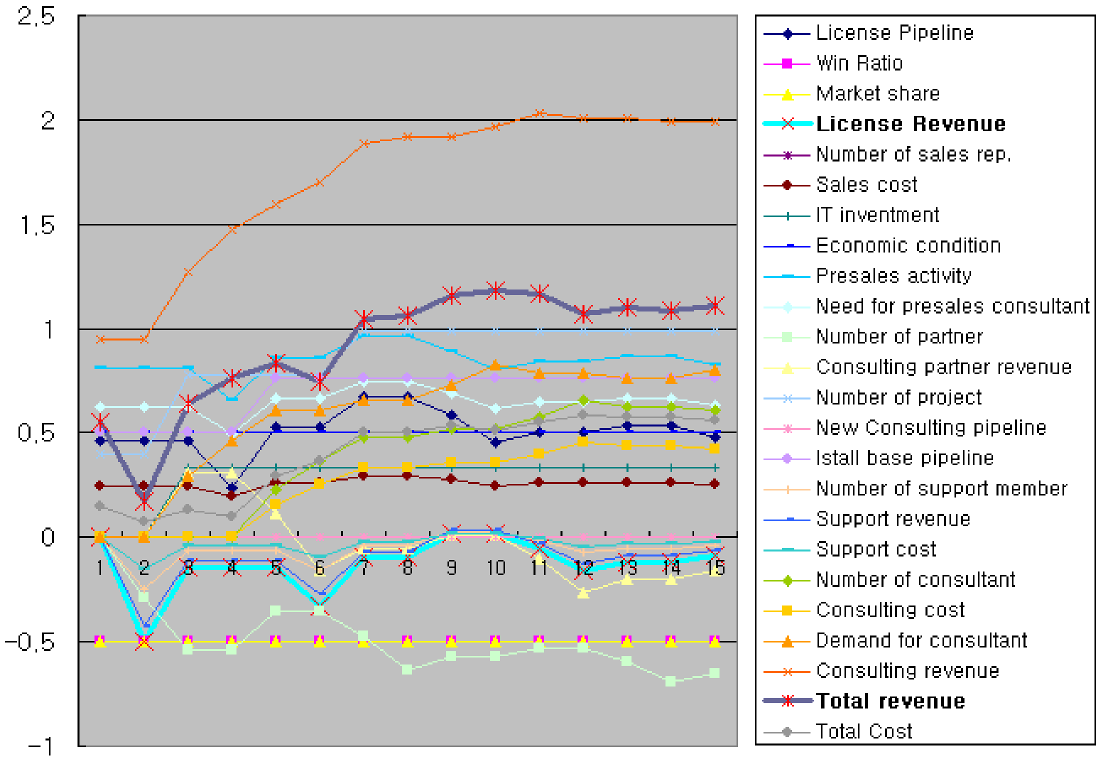


Fig 8: What-if simulation results for install base strategy

Table 1: Concept nodes for marketing planning casual map of ‘A’ company

No	Construct	Explanation
1	License pipeline	Number of license sales pipeline in CRM
2	Win ratio	Recent deal win ratio:
3	Market share	Market share of S/W license
4	License revenue	Revenue from S/W license sales
5	Number of sales rep.	Salesman number
6	Sales cost	Cost of sales LOB
7	IT investment	Total volume of IT investment of clients
8	Economic condition	Economic condition of local territory
9	Presales activity	Presales activity such as presentation
10	Need for presales consultant	Need for presales consultant
11	Number of partner	Number of S/W implementation partners
12	Consulting partner revenue	Revenue volume of implementation partner
13	Number of project	Current number of projects in progress
14	New consulting pipeline	New consulting pipeline
15	Install base pipeline	Consulting pipeline from install base client
16	Number of support member	Number of members in support LOBs
17	Support revenue	Revenue from support sales
18	Support cost	Cost of support LOB
19	Number of consultant	Number of consultants
20	Consulting cost	Cost of consulting LOB
21	Demand for consultant	Demand for consultant
22	Consulting revenue	Revenue from consulting sales
23	Total revenue	Total revenue of local branch
24	Total cost	Total cost of local branch

Node Number		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
License Pipeline	1	0,0	0,0	0,0	0,8	0,0	0,0	0,0	0,0	0,7	0,0	0,0	0,7	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Win Ratio	2	0,0	0,0	0,0	0,7	0,0	0,0	0,0	0,0	0,0	0,0	0,5	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Market share	3	0,0	0,0	0,0	0,4	0,0	0,0	0,0	0,0	0,0	0,0	0,6	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
License Revenue	4	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,9	0,0	0,0	0,0	0,0	0,0	0,8	0,0
Number of sales rep.	5	0,4	0,0	0,0	0,0	0,0	0,6	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Sales cost	6	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,6
IT inventment	7	0,7	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,8	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Economic condition	8	0,0	0,0	0,0	0,0	0,0	0,0	0,7	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Presales activity	9	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,8	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Need for presales consultant	10	0,0	0,0	0,0	0,0	0,0	0,4	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Number of partner	11	0,4	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	-0,6	0,0	0,0	0,0
Consulting partner revenue	12	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,6	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Number of project	13	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,9	0,0	0,0
New Consulting pipeline	14	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,6	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,6	0,0	0,0	0,0
Istall base pipeline	15	1,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,8	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,6	0,0	0,0	0,0
Number of support member	16	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,6	0,0	0,0	0,0	0,0	0,0	0,0
Support revenue	17	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,6	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Support cost	18	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,5
Number of consultant	19	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,7	0,0	0,0	0,0	0,0
Consulting cost	20	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	1,0
Demand for consultant	21	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	-0,7	0,0	0,0	0,0	0,0	0,0	0,0	0,8	0,0	0,0	0,7	0,0	0,0
Consulting revenue	22	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,6	0,0
Total revenue	23	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Total Cost	24	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0

Table 2: FCM adjacency matrix

Node Number		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
License Pipeline	1				2					0			2												
Win Ratio	2				1							2													
Market share	3				1							1													
License Revenue	4																	0							
Number of sales rep.	5	2					0																		
Sales cost	6																								0
IT inventment	7	2														2									
Economic condition	8							2																	
Presales activity	9										0														
Need for presales consultant	10						0																		
Number of partner	11	2																				2			
Consulting partner revenue	12											2													
Number of project	13																						0		
New Consulting pipeline	14													2								2			
Istall base pipeline	15	0												2								2			
Number of support member	16																		0						
Support revenue	17																0								
Support cost	18																								0
Number of consultant	19																				0				
Consulting cost	20																								0
Demand for consultant	21												2							2			1		
Consulting revenue	22																							0	0
Total revenue	23																								
Total Cost	24																								

Table 3: Time adjacency matrix

No	Construct	Situation	Input Value
2	Win ratio	We have been defeated in recent major deals	−0.5
3	Market share	Recent market share has decreased compared to last quarter	−0.5
8	Economic condition	Various local economic indices show optimistic forecast for economy	0.5
9	Presales activity	Presales activities have increased compared to last quarter	0.5
13	Number of project	Number of project in progress is increasing	0.4
22	Consulting revenue	Revenue of consulting LOB has increased compared to last quarter	0.6

Table 4: Current business circumstance

No	Affecting factors
1	Win ratio
2	IT investment
3	Number of partners
4	New consulting pipelines
5	Install base pipelines
6	Win ratio, IT investment, Number of partners
7	Win ratio, IT investment, New consulting pipelines, Install base pipelines
8	Win ratio, IT investment, Number of partners ,New consulting pipelines, Install base pipelines

Table 5: Simulation scenarios for presales activity