A Cloud Adoption Decision Support Model Based on Fuzzy Cognitive Maps

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Abstract. Cloud Computing has become nowadays a significant field of Information and Communication Technology (ICT). Both cloud providers and customers invest time and resources in an endeavor of the former to serve effectively the needs of the latter so as to adopt efficiently such cloud services, based their needs. The decision to adopt cloud services falls within the category of complex and difficult to model real-world problems. Aiming to support the cloud adoption decision process, we propose in this paper an approach based on Fuzzy Cognitive Maps (FCM) which models the parameters that potentially influence such a decision. The construction and analysis of the map is based on factors reported in the relevant literature and the utilization of experts' opinion. The proposed approach is evaluated through four real-world experimental cases and the suggestions of the model are compared with the customers' final decisions. The evaluation indicated that the proposed approach is capable of capturing the dynamics behind the interdependencies of the participating factors.

Keywords: Cloud Adoption, Fuzzy Cognitive Maps, Decision Support.

1 Introduction

The adoption of cloud computing is still a major challenge for organizations daily producing and processing information in the context of their working activities, while a constantly increasingly number of companies includes cloud computing in their short or long term planning. A sufficient number of services that are available on the cloud has surpassed infancy and appears to be quite mature and attractive. Many of the major software developers or service providers have already turned their strategy towards cloud services mostly targeting at increasing their market share. On one hand companies-customers need to consider the benefits, risks and effects of cloud computing on their organization in order to proceed with adopting and using such services, and on the other hand cloud computing providers need to be fully aware of customers concerns and understand their needs so that they can adjust and fit their services accordingly.

Although in recent years the research community has increasingly been interested in this field, a review of the literature on cloud computing, and especially on cloud adoption, revealed that there yet no efficient integrated models or frameworks to support decision making process for adopting cloud services on behalf of customers.

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Cloud adoption is a decision involving multiple, conflicting factors with incommensurable units of measurements; therefore, it may be considered as a highly complex process that cannot be satisfied using classical and straightforward methods. Furthermore, the extremely fast-moving nature of the cloud computing environment changes, both to supply and demand, shows how difficult it may be for any procedure to assist the decision making process timely and correctly. This is the reason why a framework or model which supports cloud computing adoption should be quite flexible and dynamically adaptable.

This paper proposes a methodology based on Fuzzy Cognitive Maps (FCM), which attempts to exploit the advantages offered by this model, in such a complex computational environment as that of cloud services. The model is constructed in a systematic manner: Firstly, a study of the most recent and relevant literature on cloud computing and particularly on cloud adoption was performed, through which the identification of all possible factors that influence the final decision was made possible. Next, based on the result of this study a questionnaire was built and distributed to a group of experts so as to capture their knowledge and expertise as regards approving the list of factors already identified and possibly extending the list. In addition, experts were called to define possible relations between factor, the direction of such relations (i.e. form factor A to factor B) and a corresponding weight on a Likert scale. After that, a novel model was developed based on a composite Certainty Neuron Fuzzy Cognitive Map and several hypothetical, as well as real-world scenarios were tested.

The rest of the paper consists of four sections as follows: Section 2 presents related work in the area of cloud computing adoption based on the existing literature and focuses on Computational Intelligent (CI) techniques, such as FCM modeling. In section 3 the methodology of Certainty Neuron Fuzzy Cognitive Maps (CNFCMs) is described, while section 4 introduces the cloud adoption modeling process and discusses and analyses the corresponding experimental results. Finally, section 5 concludes the paper and suggests future research steps.

2 Related Work

Among many definitions of cloud computing, a working definition that has been published by the US National Institute of Standards and Technology (NIST) [5], captured the most common agreed aspects. NIST defines cloud computing as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction." This cloud model promotes availability and is composed of five essential characteristics, three service models and four deployment models as follows:

- Characteristics: on-demand self-service, broad network access, resource pooling, rapid elasticity and measured service.
- Service models: Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as a Service (IaaS).

- Deployment models: private clouds, community clouds, public clouds and hybrid clouds.

Although it is generally accepted that the adoption of cloud services can offer substantial benefits, many organizations are still reluctant to proceed with it. There is a variety of factors that may influence cloud adoption and it is quite important to properly identify and analyze them aiming to assist customers take the correct decision. Equally important in this study, from the vendors' point of view, is to define which factors should possibly change so as to revert a current negative decision. Our research is mainly focused on the SaaS model investigating both the cloud providers' and the customers' sides.

An investigation of the current literature revealed a relatively small number of papers discussing cloud adoption from the perspective of decision making and also current feasibility approaches fall short in terms of decision making to determine the right decision. We introduce a summary of these studies, examining the contribution of each work to the decision making problem.

In [11] a cloud adoption toolkit is presented which provides a framework to support decision makers in identifying their concerns and match them with the appropriate techniques that can be used to address them. In [12] various issues are examined that impede rapid adoption of cloud computing such as cost, compliance and performance. The authors in [8] attempted to contribute to the development of an explorative model that extends the practical applications of combining Technology Acceptance Model (TAM) related theories, with additional essential constructs such as marketing effort, security and trust, in order to provide a useful framework for decision makers to assess the issue of SaaS adoption and for SaaS providers to become sensitive to the needs of users. Wu [9] explores the significant factors affecting the adoption of SaaS by proposing an analytical framework containing two approaches: the Technology Acceptance Model (TAM) related theories and the Rough Set Theory (RST) data mining. In [13], a solution framework is proposed that employs a modified approach named DEMATEL [14] to cluster a number of criteria (perceived benefits and perceived risks) into a cause group and an effect group, respectively, presenting also a successful case study. Even though all of the above techniques contribute a significant piece to this new open research field, they may be classified as "traditional", single layer approaches which examine only a specific part of the problem.

Techniques that combine fuzzy logic and neural networks seem to improve the way the problem is approached by increasing the flexibility of the related models [15],[16]. FCMs were initially introduced and applied in the field of political science [3] and were also utilized for modeling and simulating dynamic systems in different areas of application, such as analysis of electrical circuits, medicine, organization and strategy planning etc. [4][17][18]. In general, FCMs have shown promising results by modeling real-world problems with success and indicating strong ability to capture the dynamics of complex environments. Therefore, we decided to use FCMs in our decision making modeling environment and through the maps we will search for reasonable answers of practical value to both vendors and customers/users of SaaS.

3 FCM Technical Background

An FCM model provides a graphical representation of the knowledge used to describe a given real-world problem in the form of an acyclic graph comprising cognitive states called concepts [1]. Each concept node is characterized by a numeric state, which denotes the qualitative measure of its presence in the conceptual domain. For example, a high positive numerical value indicates that the concept is strongly present in the analysis, enhances or benefits another node, while a negative value prevents or is harmful to another node. Finally, a zero activation value indicates that the concept is not currently active or relevant to the conceptual domain. The FCM works in discrete steps [5]. When a strong positive correlation exists between the current state of a concept and that of another concept in a preceding period, we say that the former positively influences the latter, indicated by a positively weighted arrow directed from the causing to the influenced concept. By contrast, when a strong negative correlation exists, it reveals the existence of a negative causal relationship indicated by an arrow charged with a negative weight. Two conceptual nodes without a direct link are, obviously, independent.

The activation level of each node of the map and the weighted arrows are set to a specific value based on the beliefs provided by a group of experts. Then, the system calculates the activation levels in a repetitive computational sequence at the end of which the model [5]:

- Reaches equilibrium at a fixed point, with the activation levels, being decimals in the interval [-1 1], stabilizing at fixed numerical values.
- Exhibits limit cycle behavior, with the activation levels falling in a loop of numerical values under a specific time-period.
- Exhibit a chaotic behavior, with the activation level reaching a variety of numerical values in a non-deterministic, random way.

Additional fuzzification to FCMs was introduced via Certainty Neuron Fuzzy Cognitive Maps (CNFCM)[2,[7], which allow for various activation levels of each concept between the two extreme cases, i.e. activation or not. The updating function of a CNFCM is the following:

$$A_i^{t+1} = f(S_i^t A_i^t) - d_i A_i^t \tag{1}$$

$$S_i^t = \sum_{\substack{j=1 \\ j\neq 1}}^{n} A_j^t W_{ij} \tag{2}$$

where A_i is the activation level of concept C_i at some time (t+1) or (t), equation (2) is the sum of the weighted influences that concept C_i receives at time step t from all other concepts, d_i is a decay factor, and (3) is the function used for the aggregation of certainty factors.

$$f_{\mathrm{m}}(A_i^t, S_i^t) = \begin{cases} A_i^t + S_i^t(1 - A_i^t) = A_i^t + S_i^t - A_i^t S_i^t, if\ A_i^t \geq 0, S_i^t \geq 0 \\ A_i^t + S_i^t(1 - A_i^t) = A_i^t + S_i^t - A_i^t S_i^t, if\ A_i^t < 0, S_i^t < 0, |A_i^t| \leq 1, |S_i^t| \leq 1 \\ \frac{(A_i^t + S_i^t)}{\left(1 - min(A_i^t, S_i^t)\right)}, otherwise \end{cases} \tag{3}$$

4 Modeling the Cloud Adoption Process

4.1 Model Design

The development of an FCM for modeling the cloud adoption decision-making process was implemented based on two methods: (i) Literature study and (ii) Collection of expert opinion through specially prepared questionnaires followed by interviews. More specifically, a small-scale literature review on the subject was conducted in order to identify a number of factors that potentially influence such a decision which would then be used to form the concepts of our model. Each concept in our model is unique in the sense that no overlaps exist between the interpretation of what each concept represents. For example, concept *Compliance* (C5) focuses on functional requirements rather than the issues of security, the latter being addressed by *Privacy and Confidentiality* concept (C8).

Table 1. Conceptual nodes of the proposed model

Id	Name	Definition
C1	Legal	Cloud adoption compliance with all legislative issues. Ability to adjust when legal requirements grow.
C2	Availability	The amount of time that Cloud Services is operating as the percentage of total time it should be operating.
C3	Security	Security of service: data transfer, data stores, web servers, web browsers.
C4	Cost / Pricing	Operational - Running costs, migration costs etc. Cost benefits from Cloud adoption.
C5	Compliance	Business and Regulatory compliance.
C6	Performance/Processing	Does Cloud adoption perform the process to the desire quality?
C7	Scalability	Ability to meet an increasing workload requirement by incrementally adding a proportional amount of resources capacity.
C8	Privacy/ Confidentiality	Privacy and confidentiality coverage.
C9	Elasticity	Ability to commission or decommission resource capacity on the fly.
C10	Data Access / Import-Export	Access to data in various ways.
C11	Technology Suitability	Does cloud technology exhibits the appropriate technological characteristics to support proposed SaaS?
C12	Hardware Access	Degree of cloud Service accessibility, on local hardware.
C13	Audit ability	Ability of cloud service to provide access and ways for audit.
C14	Exit Process	Guarantee and ensure the output process from provider.
C15	Disaster Recovery	Ability of cloud service vendor to provide the required disaster recovery.
C16	Cloud Adoption	Central concept of the model.

The next step involved identifying a group of experts (3) with strongly related background to the subject (i.e. key personnel in cloud providers). An initial list of concepts was then prepared and the experts were asked to evaluate the list and prompted to add or remove concepts based on their expertise and working experience. The last step included one more round with the experts discussing their comments and reaching to consensus as regards the final list of concepts. These concepts were used to form the nodes of the map and are described in Table 1.

Based on the final concept list, the experts were again asked to complete a questionnaire concerning the causal relationships between the nodes of the map and the weights involved, i.e. the degree to which concepts influence each other. The influences were fuzzified using eleven linguistic variables : "negatively very high", "negatively high," "negatively medium," "negatively small," "negatively very small," "neutral," "positively very small," "positively small," "positively medium," "positively high," "positively very high". For simplicity's sake, these variables were encoded in a Likert scale corresponding to integer values within range [-5, 5]. At the same time for each defined relation, the experts would have to declare the value of confidence of their answers by using integer values in range [0, 5] which corresponded to six linguistic variables: "zero", "small", "medium", "high", "very high". The experts' ranking was then combined with their answers in a weighted average scheme and the relationships of the node in the model were represented by the normalized weight matrix shown in Table 2.

Table 2. Causal relationships and weight values between conceptual nodes on a Likert scale from 1 (very low) to 5 (very high) positive and negative - Row influences column.

	C1	C2	C3	C4	C5	C6	C7	C8
C1		0	-2	5	0	3	0	-3
C2	0		0	5	2	0	0	4
C3	-3	0		5	0	-4	0	5
C4	5	5	5		5	5	5	5
C5	5	4	-3	5		0	0	-2
C6	1	0	-2	5	3		0	-4
C7	5	0	0	5	2	3		0
C8	0	2	0	5	4	-3	0	
C9	5	0	-2	5	3	4	0	0
C10	4	3	2	5	2	3	5	3
C11	0	4	-5	4	4	0	0	-4
C12	0	2	-3	5	4	2	0	0
C13	0	5	3	5	4	2	0	2
C14	0	4	0	5	0	0	0	0
C15	0	2	0	5	0	2	0	0
C16	-3	0	-3	5	-3	-3	5	0

Table 2. *(Continued)*

	C9	C10	C11	C12	C13	C14	C15	C16
C1	0	4	3	0	2	0	0	5
C2	0	0	-3	4	4	0	2	4
C3	0	4	-4	-3	-4	0	0	5
C4	3	5	5	5	5	0	5	-5
C5	0	2	4	4	4	2	4	5
C6	3	3	0	0	0	2	0	5
C7	2	5	0	0	0	0	0	5
C8	-2	3	-4	-3	-3	0	0	5
C9		5	0	0	0	0	0	5
C10	4		4	4	4	0	4	5
C11	0	4		0	5	0	0	4
C12	0	4	1		2	0	0	4
C13	0	2	0	2		0	0	3
C14	0	0	0	0	0		0	5
C15	0	5	3	0	0	0		5
C16	0	4	0	0	0	0	0	

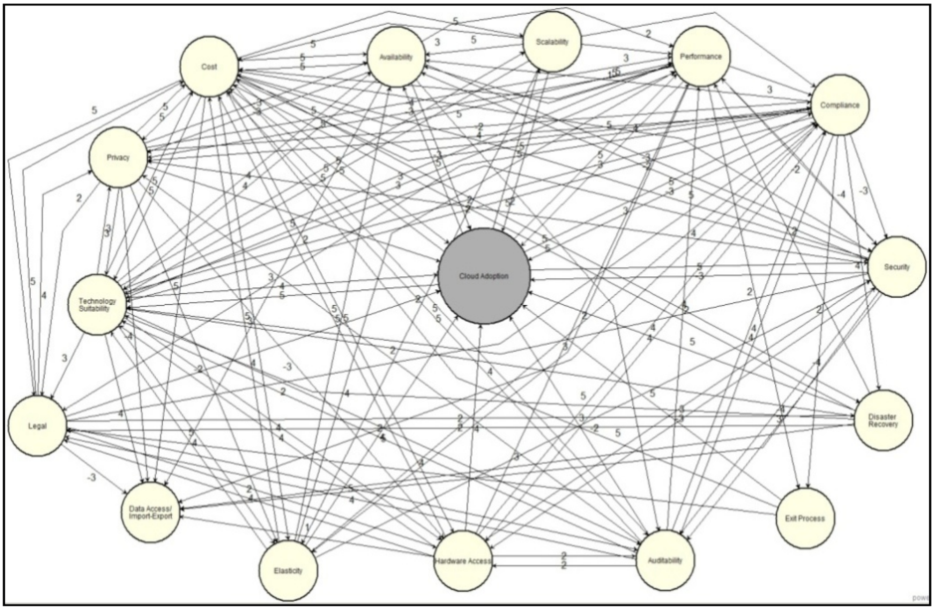

Fig. 1. The cloud adoption CNFCM model

Fig. 1. presents a graphical representation of the map. It is obvious that the structure of the map is quite complex, with 141 total number of connections between nodes. The map is initialized by setting values to the concepts (activation levels) so as

to reflect the different scenarios being considered. Each scenario represents a certain situation under modeling as this is described through the activation levels, with the aim being to study the evolution of these levels as follows: After a sufficient number of iterations, if the map succeeds to reach equilibrium at a fixed point, then the final values may be further studied. The most important value is that of the central concept of the map, while at the same time the final values of the rest of the concepts may also provide useful information to decision makers and assist in reaching to important conclusions.

4.2 Experimental Results

Aiming to test and evaluate the performance of the proposed model, two hypothetical scenarios were first conducted representing the so called “extreme cases”, that is, a situation where everything would be in favor of cloud adoption (positive scenario) and the opposite case (negative scenario). The target was to reach to equilibrium under known situations and assess the performance of the model proving that the model behaves correctly and as expected to. Next, the map was tested on a number of real-world scenarios, that is, cases collected from real customers of three international cloud services providers with the aid of the same experts that were utilized to construct the map. The two extreme scenarios and the real-world cases experimentation are described below. In all experiments the map was executed for 250 iterations and the results were assessed first to inspect whether they reached equilibrium and then to examine the value of the concept of interest (that is, cloud adoption).

Scenario 1: Positive Case

This case assumes an ideal environment where the cloud services offered perfectly match a customer’s needs. Thus, the initial values for each concept were chosen so that they reflect this ideal setting and guide the central concept of interest to a positive value. Following the same logic with linguistic variables as in the case of relationships between the concepts, the initial activation levels for this scenario were defined as listed in Table 3.

The map was executed using the activation level values of Table 3 and the normalized form of the weights listed in Table 2, transformed in the range [-1, 1]. As shown in Figure 2(a), the model reaches an equilibrium state and thus inference is possible. The basic finding here is that the map behaves correctly and leads the central concept of interest to the positive value of 0.795. This means that the model correctly recognized the positive environment and suggested that a decision in favor of cloud adoption should be taken based on the values “read” in the concepts and the current influences between the nodes.

Scenario 2: Negative Case

Working in the same way as with the positive scenario, appropriate initial values for each concept were chosen this time to guide the central node to a negative value. The initial activation levels for the negative scenario are shown in Table 4.

Table 3. FCM initial activation level values of the concepts for the positive scenario

Concept	Linguistic Value	Numerical Value	Normalized Value
C1	positively high	4	0.8
C2	positively high	4	0.8
C3	positively high	4	0.8
C4	negatively high	-4	-0.8
C5	positively high	4	0.8
C6	positively high	4	0.8
C7	positively high	4	0.8
C8	positively high	4	0.8
C9	positively high	4	0.8
C10	positively high	4	0.8
C11	positively high	4	0.8
C12	positively high	4	0.8
C13	positively high	4	0.8
C14	positively high	4	0.8
C15	positively high	4	0.8
C16	zero	0	0

Table 4. FCM initial activation level values of the concepts for the negative scenario

Concept	Linguistic Value	Numerical Value	Normalized Value
C1	negatively high	-4	-0.8
C2	negatively high	-4	-0.8
C3	negatively high	-4	-0.8
C4	positively high	4	0.8
C5	negatively high	-4	-0.8
C6	negatively high	-4	-0.8
C7	negatively high	-4	-0.8
C8	negatively high	-4	-0.8
C9	negatively high	-4	-0.8
C10	negatively high	-4	-0.8
C11	negatively high	-4	-0.8
C12	negatively high	-4	-0.8
C13	negatively high	-4	-0.8
C14	negatively high	-4	-0.8
C15	negatively high	-4	-0.8
C16	zero	0	0

Executing the model using the values for negative the scenario again the map reached equilibrium with its behavior being the one anticipated: the central concept of the map takes the negative value of -0.795 (see Figure 2(b)).

From the above "extreme" scenarios it is evident that the proposed model behaves correctly by recognizing the setting fed and therefore we may now proceed with evaluating its performance on real-world cases.

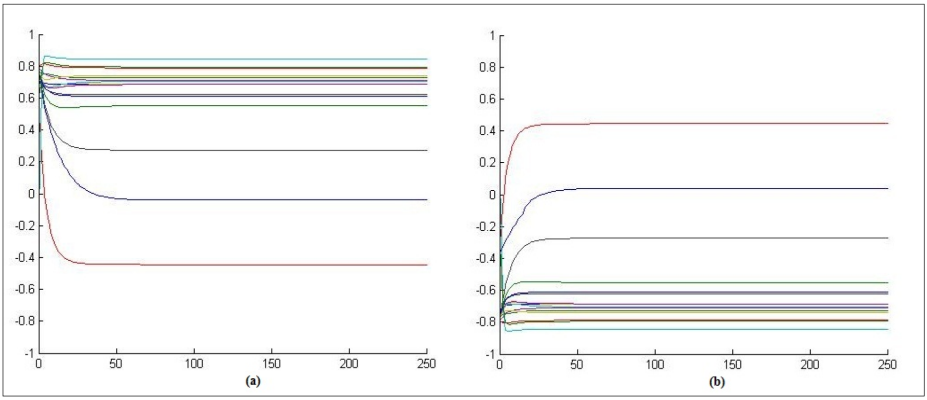

Fig. 2. (a) Positive Case, (b) Negative Case

Real-World Scenarios

As previously mentioned, with the help of cloud providers four different cases were identified: Two customers who decided to proceed with cloud adoption and two cases in which they rejected it. These four cases, along with some related information describing the required cloud services, the size of the organization, the line of business and the final decision regarding cloud adoption, are summarized in Table 5.

Table 5. Brief description of real-world cases

Case	Line of Business	Size (users)	Cloud Services
A	Academic Institution	4500	Mail Server / Mailbox / Mail client
B	Industry	220	Mail Server / Mailbox / Document Management
C	Supplies Industry	85	Mail Server / Mailbox / Mail Client / Document Management
D	Insurance Brokers	125	Mail Server / Mailbox / Mail Client / Custom Business System

A series of interviews was conducted, both with the cloud providers and the customers, so as to identify the initial activation level values for each case separately, which essentially reflected the state of the offered service and the associated factors describing each customer's particular situation at the moment of decision. These initial activation level values for each case are shown in Table 6 in linguistic form, which was found by the people involved in the questionnaires easier to understand and follow.

Table 6. Initial activation level values for real world cases

Concept	Case A	Case B	Case C	Case D
C1	positively very high	positively medium	positively medium	positively medium
C2	positively medium	positively medium	positively medium	positively medium
C3	positively medium	positively medium	positively medium	positively medium
C4	negatively very high	negatively small	positively very small	positively high
C5	positively very high	positively medium	positively medium	negatively very small
C6	positively very high	positively medium	positively medium	negatively very small
C7	negatively high	positively very high	positively very high	negatively medium
C8	positively medium	negatively very high	positively very small	positively very small
C9	positively medium	positively very high	positively very high	negatively medium
C10	positively very high	positively medium	positively medium	negatively small
C11	positively very small	positively medium	positively medium	negatively small
C12	positively very small	positively very small	positively very small	positively very small
C13	positively very small	positively medium	positively very small	negatively medium
C14	negatively very small	negatively very small	negatively very small	negatively high
C15	positively very high	positively very high	positively very high	positively very high
C16	zero	zero	zero	zero

The first case involved an academic institution with a medium to large size which requested a comprehensive solution for email services. In that case easily someone can discern from initial activation level values, that the condition was favorable for a positive decision. The second case described a medium industrial organization which requested for some email cloud services and cloud based document management system. The situation of that organization at that moment can be described as positive too. Third case represents another industrial organization which requested a complete email cloud package and also a cloud based document management system. The decision environment seems to be positive. Finally the fourth case involved a medium insurance broker's organization which requested a complete email cloud package and also a cloud infrastructure to fit a heavy tailored made owned system. In that case, someone can hardly make an assessment of the final decision, based on the initial activation values.

The model was executed again for 250 iterations and reached equilibrium in all cases. The outcome of the model for each of the aforementioned cases is given in Table 7 comparatively with the actual decisions that were taken by the customers.

Table 7. Model's decisions compared with real decisions

Case	Our model's decision	Real decision
A	Yes	Yes
B	Yes	No
C	Yes	Yes
D	No	No

At this point a small discussion on the results should be made. It is evident that the model succeeded in matching its estimation or suggestion with the real decision in three out of four cases. More specifically, in cases A and C our model suggested a positive decision achieving a match with the actual decision. Also, in case D the model estimated a negative decision again in agreement with the real decision. Unlike the previous cases the model failed to coincide with the actual decision taken for real case B. We attempted to investigate the reason for this and after consulting our experts it became evident that this customer should have decided positively given the context of his particular needs; nevertheless, despite the fact that the offered cloud package was fulfilling all requirements the decision was turned negative as a result of the stand towards the cloud environment as a technology taken by the responsible persons, something which on one hand it is definitely beyond the scope of this study and on the other suggests that the result was correct in the first place.

5 Conclusions

This paper proposed a new approach, aiming to improve the cloud adoption decision process. We demonstrated how a new model based on Certainty Neuron Fuzzy Cognitive Maps (CNFCMs) can be constructed and applied to face decision making on the cloud adoption problem, taking the advantages offered by using techniques that combine fuzzy logic and neural networks.

The proposed model was experimentally evaluated on two extreme scenarios, an ideal setting in favor of cloud adoption and a completely negative leading to cloud rejection, showing successful performance. This enabled further experimentation with four real-world scenarios collected form experts/developers in the local mobile software industry. The model succeeded in matching its estimation with the corresponding real decisions in three out of four cases. A more detailed investigation for the case where the model “failed” to suggest the decision that was actually taken revealed that this decision was influenced by human and personal factors that are out of the model’s scope and the targets of this research.

Although the results are at a preliminary stage, they may be considered quite encouraging. There are quite a few steps that may be executed in the future so as to enrich and optimize this model. A map analysis, both at a static and a dynamic level, can extract useful information about the behavior of the model. Examples of such an analysis may include the study of the significance of each node in the map by measuring the strength of the connections sourcing by this node, the statistical investigation of a rich number of experimental repetitions using known tests like Pearson correlations, and so on. In addition, more real-world case scenarios could give a helpful feedback for better calibration of the model. Finally, possible expansion of the map will be investigated so as to include more concepts representing better the real cloud environment. Examples of such concepts are the *Return of Investment (ROI)*, *Legislation*, various *Costing Issues* etc. The speed with which current technology evolves underlines the need for periodically studying the model, re-identifying the participating concepts and redefining their causal relationships.

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