Fuzzy cognitive maps for dynamic grid service negotiation

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Abstract. The grid is moving from the scientific grid to a pervasive and economic/business grid. Service trading, in which service provider and service consumer negotiate for a mutually acceptable agreement on multi-issues such as service performance, access cost etc., is one of the most important components in building the Economic Grid. In view of Pervasive Grid, a new challenging issue is that participants on pervasive devices usually have limited computational capacity. And it is also desirable that a multi-issue negotiation agreement can be reached as quickly as possible since the wireless communication to exchange the offers is generally unreliable and power-consuming. Hence, an agile, automated, but lightweight multi-issue decision-making model is needed to facilitate service negotiation in Pervasive Grid. More over, existing methods for multi-issue negotiation only regard each issue as a separate issue, though in most of cases, there exist causal relationships between these negotiation issues. In this paper, a decision-making model based on Fuzzy Cognitive Map (FCM) theory is proposed for multi-issue negotiation which takes into account the causal relationships between the negotiation issues. In the proposed model, the causal relationships between the negotiation issues are well represented by FCMs. The service trading is modeled as a dynamic system with interdependent relationships among negotiation issues. The example and experimental results show that the proposed model is lightweight and promising to be employed in Pervasive Grid for multi-issue service negotiations.

Keywords: Service trading, Grid, negotiation, fuzzy cognitive maps

1. Introduction

In the mid 1990s, Ian Foster and Carl Kesselman proposed a distributed computing infrastructure for advanced science and engineering, dubbed “Grid” [14]. This term arose from an analogy with the electricity power grid, or it is to say that data and resources can be delivered seamlessly, transparently and dynamically as needed.

A recent progress in Grid is the introduction of Economic Grid [3]. In Economic Grid, there are some Service Providers that are responsible for offering services for consumption by others. In offering a service, the provider is hoping that it will indeed profit by attracting consumers for the service. There are also some potential Service Consumers that will search for and invoke a particular service, and even compose several services to form a more complex service, to solve a problem. Service trading, in which service providers and consumers meet and try to settle a contract regarding how the service should be performed and how much it costs, is an important component of the effort to build the Economic Grid. However, due to the heterogeneous nature of the Grid environment, service providers and consumers usually have different, even conflicting preference regarding the performance and
cost of the service etc. So service trading is naturally a negotiation process, in which two stakeholders with different preferences try to make a mutually acceptable agreement by the exchange of preference (in the form of offer).

Another recent progress is the introduction of the Pervasive Grid [17], which is essentially a combination of the Grid Computing and Pervasive Computing. Pervasive computing is about devices in everywhere, e.g. in our clothes and in surrounding environment. The increase in the use of mobile devices, coupled with emergence of wireless networking is enabling pervasive computing. It is of no doubt that these two areas are complementary to each other [17]. Some of grid applications involve pervasive computing, e.g. the coupling of sensors to the grid, and signal processing based on data from portable medical devices. Thus the Grid has a more pervasive coupling with the physical world. Meanwhile, some of pervasive applications need the Grid in the background. For example, as portable devices evolve, users can acquire data with higher temporal or spatial resolution, and this increasing volume of data demands the computational power provided by the Grid.

More demands rise when service trading through negotiation in Pervasive Grid is concerned. A major concern is that pervasive devices usually have limited computational capacity, and the wireless communication facilitating offer exchange is generally unreliable and power-consuming. Hence an agile, automated, but lightweight model which can help trading participants reach an agreement as quickly as possible in Pervasive Grid is highly desirable.

However, the Grid community has historically focused on providing infrastructure and tools for secure and reliable resource sharing among dynamic and geographically distributed virtual organizations. Few research efforts have been put in proposing agile decision-making model for service trading participants in Grid. Recently, there are emerging research efforts that try to couple Agent and Grid together [1,6,13,29,33,36,45]. In contrast with Grid community, Agent community has historically focused on the development of concepts, methodologies, and algorithms for autonomous problem solvers that can act flexibly in uncertain and dynamic environments in order to achieve their aims and objectives. As pointed out in [13], for Grid to be effective in its goal to provide seamless, transparent and dynamic resource sharing, it must be imbued with flexible decision-making capabilities provided by agents. And service trading through agent-mediated automated negotiation has been identified as one of the ten promising areas that agent technology and Grid can be integrated to make Grid more agile [13].

In this paper, a lightweight negotiation model based on Fuzzy Cognitive Map (FCM) theory is proposed, which models the trading participants as agents. The example and the experimental results show that this model is promising to be employed to facilitate service trading in Pervasive Grid. The remainder of this paper is organized as follows. Section 2 reviews the related work in negotiation research. The component of the proposed FCM-based model is presented in Section 3. An example of the proposed model is presented in Section 4. Finally Section 5 concludes the paper with a discussion and future work.

2. Related work

There are three main issues that need consideration when designing negotiation model to facilitate service trading [18]: Trading Model (or Negotiation Protocol), Negotiation Objects and Participants’ Decision-making Model (or Strategy). Negotiation object refers to the range and structure of issues over which the agreement (between service provider and consumer) must be reached. In Grid environment, the negotiation objects are usually multi-issue since providers and consumers are usually negotiating for quality of the service as well as the cost to access a particular service. Related work reviewed in this section focus mainly on the other two issues: Trading model and participants’ decision-making model.

2.1. Trading models

A number of trading models have been studied in existing work [3,25,41]: Commodity Market Model, Posted Price Model, Auction Model and Bargaining (Alternating Offer) Model. Interaction between service providers and consumers in the first three trading models is generally one-way. In contrast, interaction in the bargaining model is usually two-way. In bargaining model, both provider and consumer are allowed to propose offers and counter offers many times to state their preference before an agreement is reached. Pro-

1 In the remainder of this paper, the term agent and participant will be used interchangeably to denote the participant in service trading in Pervasive Grid.
cess of interaction in this model can be presented as Fig. 1 shown in [31].

Figure 1 is a statechart to depict the bargaining model. Entry into the process is through one participant sending an initial propose message leading to a proposed state (Proposed(x) in Fig. 1 means participant x has just proposed an offer). From this state, participants can continuously propose offers (or counter offers) to remain in this state until one of them chooses other actions leading to a closed state. An agreed state is a sub-state of the closed state, which is reached if both participants agree on a proposed offer. A participant is allowed to withdraw from a bargain at any time during the process if it finds an agreement can not be reached, and then bargain reaches the withdrawn state – another sub-state of the closed state. If both participants continue to propose offers but can not reach an agreement even before the deadline of the bargain, it will be closed with a timeout state.

Within the bargaining model, participants have more automated and agile control of their decision-making because participants are free to express what they want and to turn down what are not consistent with their preferences and objectives. Hence it is chosen as the trading model for the Pervasive Grid in this paper.

2.2. Decision-making models

Most of the existing Grid projects focus mainly on setting up an infrastructure to study different trading model in Grid environment, e.g. [3,4]. Few of them focus on working out decision-making model for trading participants in Grid environment. Recently, there are emerging research efforts in this direction.

In [24], a negotiation engine for Grid notification service was presented. Within this engine, both the notification service provider and consumer use a decision-making model derived from negotiation decision functions [10,38], which is a widely used decision-making model employed in many e-Commerce scenarios. Using this engine, notification subscribers (the service consumer) and notification providers can negotiate for mutually acceptable parameters for a set of terms, e.g. price, notification frequency and so on. In [36], Shen et al. listed some decision-making models that are believed to be useful in Grid environment. The authors also proposed a new decision-making model called Discrete Optimal Control Model.

It is generally believed that research of decision-making model in negotiation in agent community can provide insight into the decision-making model design in Grid [13]. There are usually two main lines of researches on participants’ decision-making models in negotiation. The first category is Game-theoretic models, which apply formal analysis (i.e. Game theory analysis) to find out an optimal negotiation strategy of a negotiation given all the possible outcome of the negotiation [18]. In order to carry out the formal analysis of the negotiation process, Game theoretic decision-making models usually make some simplifying assumptions. There are generally two common assumptions [9,18]: (1) complete knowledge of the circumstances in which the game is played and (2) full rationality of the participants. The first assumption implies that the rules of the game and the preferences and beliefs of the players are “common knowledge”. The second assumption corresponds to the need for common knowledge on how players reason. It is believed
that agents maximize their expected payoffs given their beliefs. And it is assumed that agents have infinite computational capacity for their decision-making in negotiation. Furthermore, agents are assumed to have a perfect memory. These assumptions are rarely true in most real world cases. Consequently, these assumptions limit the practical applicability of Game theoretic research directly for designing decision-making model.

One of the contribution of Game theory to the automated negotiation research is that it prescribes some properties to measure particular strategies derived from a given decision-making model [18]. These properties include 1) Pareto efficiency: outcome of the negotiation using a particular strategy must be pareto efficient to all participants. If a negotiation outcome is not Pareto efficient, then there is another outcome that will make at least one participant happier. 2) Stability: stability means that a given decision-making model provides agent with an incentive to behave in a particular way. The best-known kind of stability is Nash Equilibrium: Agent A is using strategy s and its opponent is using strategy s'. If no player can benefit by changing its strategy while the other player keep its strategy unchanged, then these two strategies (s and s') and the corresponding payoffs constitute the Nash Equilibrium.

Another category is AI-based models, whose goals are to work out a computationally workable solution to find an acceptable strategy in the negotiation rather than the optimal strategy. In contrast, those common assumptions in Game theoretic research are not necessary in the field of AI. AI approaches to negotiation, the focus lies more on finding workable rather then optimal strategies. The connection between AI approaches and Game Theory is important: AI techniques can be used to develop practical decision-making models and algorithms; while game theory can provide valuable managerial insights and formal analysis of the strategy derived from a particular strategy. Researchers have applied many AI techniques for designing decision-making models for negotiation participants:

Heuristic models: One major means of overcoming the aforementioned limitations of Game theoretic models is to use heuristic methods. Such methods acknowledge that there is a cost associate with computation and decision-making and seek to produce a good, rather than optimal solution [18]. Some typical examples of such line of work are [10–12,32,38].

CSP (Constraint Satisfaction Problem) based models: Negotiation can be viewed as a searching problem that agents try to find a joint space of the possible acceptance ranges and then locate a solution (i.e. agreement) from this joint space. One of the widely used techniques to solve such searching problem is Constraint Satisfaction Technique. In CSP-based models, each negotiation issue is taken as a variable; preferences are encoded as constraints for particular variable; and the objective of the negotiation is to find a solution in which all the preferences of different agents are satisfied. Some typical examples of such line of work are [5,22,23,26].

Machine Learning based model: It is intuitive to think that participant will be more successful in negotiation if it has the ability to “learn” its opponent’s behavior from historical encounters with the opponent, and make adaptive counter-actions based on the extracted information. This desirability agrees with the goal of Machine Learning to some extent [28]. Early attempt to incorporate learning techniques to decision-making model is using Bayesian Learning [2,48,49]. Case-based reasoning (CBR) is another type of learning technique being used in negotiation [50]. Reinforcement learning is another technique be used to facilitate learning in negotiating agents [35,46]. However, there is a well-known dilemma in above methods that it has to deal with the exploitation and exploration trade-off [44]. And it also requires many thousands of iterations to converge.

The decision-making models reviewed here provide valuable references when designing decision-making model. However, to the best of our knowledge, there is little work to date that has been reported to study the relationship and influence between different negotiation issues directly. As Jenning and Wooldridge pointed out, existing multi-issue negotiation are typically extensions of single issue models [11,12]. And few of them are suitable for pervasive devices in Pervasive computing due to the heavy computation. A novel light-weight decision-making model for trading participants in Pervasive Grid is presented in next section, which studies the relationship and influence between negotiation issues directly.

This paper is the first attempt in extending Fuzzy Cognitive Maps as a decision-making model. Compared with existing decision-making models, the proposed model has some other obviously desirable advantages: Firstly, our FCM based model can model multiple negotiation issues’ influence on one another. Most related work (e.g. [11,12,26]) assumes that the multiple negotiation issues is independent of each other, but in real case, these issues often depend on one another. Therefore, in the proposed model, Fuzzy Cognitive Maps are used to effectively represent such de-
3. A FCM-based decision-making model for Grid services

As discussed before, three main issues need to be considered when service trading (through negotiation) is concerned: negotiation objects, trading model, and participants’ decision-making model. As mentioned earlier, negotiation objects in Grid environment is usually multi-issues. This section mainly focuses on the other issues.

Having chosen the bargaining model as the trading model, the next step is to design a decision-making models for participants. As mentioned earlier, Pervasive Grid context has a number of characteristics, which demands more challenging requirements for the decision-making model. The decision-making model in Pervasive Grid should be lightweight, and should be able to adapt to dynamic setting and reduce offer exchange numbers.

A decision-making model based on Fuzzy Cognitive Map (FCM) is proposed. At each round, a negotiation agent first calculates a proposal using FCM inference process. Then the agent evaluates the proposal of its negotiation opponent: if its opponent’s proposal is better than its proposal generated before, the agent accepts its opponent’s proposal and negotiation finishes; otherwise, the agent sends its proposal to its opponent and negotiation proceeds to the next round.

3.1. Theoretic background of Fuzzy Cognitive Map

Fuzzy Cognitive Map (FCM) is a modeling and analyzing tool for complex dynamic systems. It is first proposed by Bart Kosko [20, 21]. Concept and weight are two important components of FCM. Concept represents all the factors that describe the main behavioral characteristics of the system. Weight denotes the causal relationship between the concepts representing the causal relationships that exist among concepts.

FCM can be represented by a graph, which is a signed graph with feedback, consisting of nodes and arcs. Nodes represent concepts and are marked as ellipses. Nodes are connected by signed and weighted arcs representing the weights between concepts. Figure 2 gives an example of the graph representation of FCM.

There are two types of concepts in FCM: cause concepts, and effect concepts. The direction of the weight shows which concept causes the other concept: the weight always emanates from the cause concept and points to the effect concept. As shown in Fig. 2, weight $w_{12}$ starts from $C_1$ and points to $C_2$. So, $C_1$ is the cause concept of $C_2$ (effect concept) connected by $w_{12}$. A concept can be the cause concept of a causal relationship and at the same time the effect concept of another causal relationship. For example, in Fig. 2, $C_1$ is the cause concept of $C_2$ connected by $w_{12}$, while it is the effect concept of $C_3$ connected by $w_{31}$.

Every concept and weight has a value, which is termed concept state value and weight value respectively. The concept state value shows the current status of the concept, and the weight value expresses how strongly the cause concept influences the effect concept. Both the concept state value and weight value take values in the interval $[-1, 1]$ or $[0, 1]$. The state value of a particular node, denoted by $A_i$, can be calculated by multiplying the state values of all its causal nodes with the weights between pairs of related nodes. The sum of the products is the input of a threshold function, which serves to restrict unbound state values to a strict range. The threshold function can be bivalent, trivalent or sigmoid:

\[
\begin{align*}
\text{Bivalent:} & \quad T(x) = \begin{cases} 1 & x \geq t \\ -1 & x < t \end{cases} \\
\text{Trivalent:} & \quad T(x) = \begin{cases} 1 & x > t \\ 0 & x = t \\ -1 & x < t \end{cases} \\
\text{Sigmoid:} & \quad T(x) = \frac{1}{1 + e^{-\lambda x}}
\end{align*}
\]

The calculation of a concept state value in FCM is as follows:

\[
A_j(t) = T \left( \sum_{i=1}^{n} (A_i(t-1) + w_{ij}) \right)
\]

where $n$ is the number of the concepts; $A_j(t)$ denotes the new state value of the concept $C_j$ at time $t$; $A_i(t-1)$ denote the old state value of concept $C_i$ at time $t - 1$;
$w_{ij}$ represents the weight from concept $C_i$ to $C_j$; and $T$ is the threshold function.

Weight value can be either positive, negative, or zero. A weight value $w_{ij}$ is positive (negative) means that the state value of the effect concept $C_j$ changes proportionately (inversely) with state value of the cause concept $C_i$. And the absolute value denotes the strength of the corresponding causal relationship. $w_{ij} = 0$ means that there is no causal relationship between the two concepts.

Values of all the concepts in a FCM are usually written in a notion of vector: $A = [A_1, A_2, \ldots, A_n]$. And all weights values are organized together in an $n$ by $n$ matrix ($n$ denotes the number of the concepts), which is called connection matrix. Connection matrix is usually used to represent a FCM instead of the graph-like representation like Fig. 2. With the representation of the concept values as vectors and weight values as connection matrices, the calculation in Eq. (4) can be viewed and implemented as simple matrix multiplication operation.

After modeling the dynamic system as combination of concepts and weights, FCM is able to analyze the equilibrium of the dynamic system. FCM analyzes the equilibrium of a particular system by FCM inference process. The FCM inference process is carried out by calculating new state values of concepts using (4) iteratively until a stable pattern is derived (during the inference process, it is possible that some certain concept is set to a fix values). There are two possible kinds of stable pattern for a particular system: the system settles into a limit cycle, or the system reaches an equilibrium state. Concept values and weight values as connection matrices, the calculation in Eq. (4) can be viewed and implemented as simple matrix multiplication operation.

3.2. Modeling the negotiation context with FCM

Generally speaking, decision-making usually refers to the process of selecting a particular action in a given situation. In the scenario of service trading through negotiation, there are two possible actions, to accept an offer or to reject an offer. For rejection action, agent may also need to decide what to propose as a counter offer rather than merely reject an offer.

Service trading can be viewed as a dynamic system with interdependent relationships among negotiation issues. For instance, the cost for the usage of the business forecasting service will increase as the level of prediction increases. If a received offer is not acceptable, the offer-receiver will change the values of corresponding issues to generate a more advantageous offer for itself. There also exist trade-off relationships (trade-off means accepting less of one thing in order to get more of something else) between pairs of issues.

For example, if service consumer considers an offer to be unacceptable, it will then increase the level of

![Fig. 2. Concepts and weights in FCM.](image-url)
prediction to generate a more advantageous offer. And as a trade-off to the increase in the level of prediction, it will decrease the requirement on the response time. As this simple example shows, service trading process can be considered as a dynamic system, and FCM, as tool for causal analysis tool, is an appropriate modeling tool.

Since different agents usually have different preferences over the negotiation issues when negotiating, the negotiation context has different reflection in different agent’s mental state. Agent’s mental state includes agent’s preference over different negotiation issues, the received offer, its evaluation of the offer, and its possible counter-offer. The environment in Pervasive Grid is changing quickly, which also influences agent’s decision-making. In order to make agent adaptable to the quickly-changing environment, the perceived environment information is also included in agent’s mental state.

When constructing the FCM to represent agent’s mental state, negotiation issues are taken as concepts, which are called issue concepts. It is assumed that both service provider and consumer are concerned with the same set of issues and this set is unchangeable after the negotiation starts. There is also one special node, which represents agent’s evaluation for the offer. Agent makes its decision mainly based on the value of this concept. It is called the decisional concept. Agents’ preferences over different issues are represented by the weights between the issue concepts and the decisional concept; while the trade-offs are represented by the weights connecting different issues directly.

All the perceived environmental information, such as the utilization of CPUs and available memory, are also included in the constructed FCM. And these factors are called environmental concepts in order to distinguish from the issue concepts. Different agents can have different set of environmental concepts, because they may perceive different environmental factors. The influence that the environmental concepts exerted on the decision-making is represented by the weights between the environmental concepts and decisional concept.

In the course of service trading, only values of issue concepts are to be included in offer or counter offer. Other parts of the mental state, such as values of the environmental concepts, decisional concept, and weights, are kept as agents’ private information.

3.3. Evaluation of received offer

When agent receives an offer, agent will evaluate it first.

By using the FCM, the evaluation of the offer is basically the calculation of the state value of the decisional concept. So the received offer is evaluated by applying Eq. (4) one time.

Before using Eq. (4) to evaluate the offer, the state values of the issue concepts need to be calculated. As discussed before, the state values of issue concept denotes the degree of that corresponding issue. One way to measure the degree of an issue concept is mapping the real value of the issue into a member value of a fuzzy set in [0, 1].

The mapping of value of the negotiation issue is determined as follows: firstly, find the possible value space of the particular concept, say \( V_i \); secondly, the maximum value in \( V_i \) is mapped to 1, that is \( Max(V_i) \Rightarrow A_i = 1 \); thirdly, the minimum value in the \( V_i \) is mapped to 0, that is \( Min(V_i) \Rightarrow A_i = 0 \); and lastly, other values in the \( V_i \) are mapped by applying following formula:

\[
A_i = \frac{v - Min(V_i)}{Max(V_i) - Min(V_i)}
\]  

3.4. Action selection

After the evaluation of the received offer, agent makes the decision whether to accept it or not. Many existing negotiation models usually set a fix acceptance criterion: if the evaluation is larger than this criterion, agent accepts the offer; otherwise, agent rejects it and proposes a counter offer.

As discussed before, Grid environment is dynamic and volatile. Hence, it is desirable that agent’s acceptance criterion is flexible. In the proposed model, a more flexible acceptance criterion is applied:

If the evaluation of the received offer is not less than the evaluation of the counter offer the agent is ready to send back, the agent will accept the offer. Otherwise, a counter offer is generated and is sent back. For example, agent \( B \) sends an offer, say \( O_b \), to agent \( A \). Agent \( A \)'s evaluation of \( O_b \) is \( U_b \). The counter offer that Agent \( A \) is ready to send is \( O_a \). Agent \( A \)'s evaluation for \( O_a \) is \( U_a \). If \( U_b \geq U_a \), then Agent \( A \) will accept \( O_b \); otherwise, it will offer \( O_a \) to Agent \( B \).

But what is the counter offer an agent is ready to send? In the proposed model, the counter offer is derived from the stable state derived by the FCM inference process. Before carrying out the inference process, state values of the concepts need to be set: state values of issue concepts are set as discussed in Section 3.3; state values of the environmental concepts are set by the perception of the environment, e.g. through query
to Index Service provided by Globus; and state value of the decisional concept is set to be the evaluation of the received offer just calculated in Section 3.3.

The criterion to determine whether a stable state is reached is:

\[ |A_i(t+1) - A_i(t)| < e \]  

(6)

where \( e \) denotes an error level which keeps the changes of state value of all concepts as small as possible. As the error level \( e \) becomes smaller, it will need more steps of inference to derive a stable state. In the proposed model, the sigmoid threshold function \( T(x) = \text{Fout!} \) is applied. By applying this threshold function, mental state of agent is guaranteed to reach a stable state.

After the FCM reaches the stable state, state values of the issues concepts are to be mapped back to real value using Eq. (5) reversely.

### 3.5. Weight assignment

From above discussion, it is noted that the weights between concepts play an important role in the proposed model. In the proposed model, the weights are assigned using a Case-based reasoning method. The case base is organized according to the environmental concepts values. And agents try to retrieve similar negotiation context from the case base when negotiating in a new situation based on the environmental concepts values. There are two scenarios when assigning weights in the propose model.

The first scenario is that agent successfully retrieves similar case from the case base. In this case, the weights in the newly-constructed FCM are instantiated with the values in the retrieved similar case.

The second scenario is that there is no similar case available. In this case, default weights will be assigned. The default weights are assigned based on agents’ preferences. To specify how much one concept influences another, people often use linguistic terms, such as \{highest, very high, high, a bit high, average, a bit low, low, very low, lowest\}. Agents do not need to specify explicitly the default value of the strength of the relationship between pairs of concepts. Agent only needs to specify the strength of the relationship using such linguistic terms as all these linguistic terms can be mapped into a value in the range \([0, 1]\). In this scenario, these linguistic terms are mapped to \{0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1\} correspondingly.

In summary, the decision-making process of the participant goes as follows:

Step 1: Measure the degrees of issue using Eq. (5);

Step 2: Evaluate the offer by applying Eq. (4) one time;

Step 3: Set value for each concept (including the issue concepts, environmental concepts, and decisional concept) in the FCM and then start the FCM inference process;

Step 4: Calculate new concepts state values using Eq. (4); it should be noted that state values of environmental concepts are always clamped to the original values before the inference process since agent can not change the environment but can only perceive it;

Step 5: If the condition in (6) is not met, loop back to Step 4;

Step 6: Otherwise, FCM reaches the stable state. State values of issue concepts at this stable state are mapped back to real values using Eq. (5) reversely. This is the counter offer that agent is ready to send;

Step 7: If the state value of the decisional concept derived at Step 6 (it is the evaluation of the counter offer) is less than the evaluation of the received offer, agent accepts the received offer. Otherwise agent will send back the counter offer.

### 4. Experimentation

An experiment on the illustrative example introduced in Section 3 is presented in Section 3.1 to show how the proposed model works. The lightweight property of the proposed model is shown in Section 3.12.

4.1. The technical description of the illustrative example

There are 3 issues open for negotiation between the service provider and consumer for the business forecasting service: level of prediction, response time, and cost of the service access. So in both agents’ constructed FCMs, there are three common issue concepts: \( C_1 \): Level of prediction; \( C_2 \): Response time; \( C_3 \): Cost of the service.

Each agent also has a decisional concept, which is called overall satisfaction: \( C_4 \): Overall satisfaction.

Other than the issue concepts and decisional concept, agents also have a number of environmental concepts in the constructed FCMs. Different agents have different set of environmental concepts. For service provider, factors as CPU utilization and available memories will affect the performance of the service. Thus these
two concepts will affect service provider’s decision-making. To make scenario simpler, in this example, only CPU utilization ($C_5$) is included as environmental concept.

The service consumer resides on a pervasive device and uses wireless network for communication with service provider in the Pervasive Grid. When the underlying wireless network is not reliable, consumer may be willing to accept any acceptable offer to terminate the negotiation early; whereas if it is reliable, consumer may try to wait and search for the best offer to maximize its payoff. Hence, in consumer’s constructed FCM, QoS $^2$ of the wireless network ($C_5$) is included as an environmental factor.

After choosing the set of concepts, weights are assigned to the relationships between concepts to represent its preference over different issues and influences exerted by the environmental concepts.

Take all the concepts and weights together, service provider’s FCM constructed before the negotiation starts is shown in Fig. 3.

The FCM can be presented in a matrix form:

$$W = \begin{bmatrix} 0 & 0 & 0 & 0.5 & 0 \\ 0 & 0 & 0 & -0.5 & 0 \\ -0.4 & 0 & 0 & -0.7 & 0 \\ -0.5 & 0.3 & 0.6 & 0 & 0 \\ 0.7 & -0.4 & -0.5 & 0 & 0 \end{bmatrix}.$$

![Fig. 3. FCM presentation of the provider’s mental state.](image)

In this example, reaching an agreement quickly is of higher priority as it is believed that the wireless communication is much more power-consuming than the computation in pervasive device. Based on the experimental results, the $\lambda$ value is chosen to be 3, and error level $e$ is chosen to be 0.0001.

Now suppose that service provider starts the negotiation by sending out the first offer. The offer is represented in a format like “I can provide you the prediction for future two days with a response time of 1 second. And you need to pay $180 for this service.” This offer can be converted in a notion of vector by taking every real value of the negotiation issues as the vector elements. The offer is $[2, 1, 180]$ after the conversion.

Service consumer’s acceptable range for the level of prediction is from one day to seven days; consumer’s acceptable range for the response time is from 0.001 second to 10 seconds; and its acceptable range for the cost of service is from 90 to 200.

After applying Eq. (5), service consumer maps the offer to $[0.1667, 0.09991, 0.81818]$. After evaluation using Eq. (4) the evaluation of this received offer is 0.16547.

Now service consumer needs to calculate the next counter offer it is ready to send. Values for the issue concepts ($C_1, C_2, C_3$) are $[0.1667, 0.09991, 0.81818]$. Assume that after parameterization QoS ($C_5$) of the wireless network is set to 0.9. Values of all concepts in the FCM held by service consumer to represent its mental state are $[0.1667, 0.09991, 0.81818, 0.16547]$.  

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$^2$It is assumed that QoS has already been parameterized from some characteristics of the network, e.g. bandwidth, range, frequency of disconnections.
Now service consumer starts the FCM inference process to calculate the counter offer. After 20 inference iterations, FCM reaches the stable state. Then state values of $C_1$, $C_2$ and $C_3$ are the degree of the corresponding negotiation issues that will be included in the next counter offer. Evaluation of this counter offer is the new state value of the decisional concept, which is 0.44116.

Because $0.1654 < 0.44116$, evaluation of the received offer is less than the evaluation of the counter offer service consumer is ready to send. So service consumer rejects the offer and proposes the counter offer. Degrees of $C_1$, $C_2$ and $C_3$ [0.688803, 0.3356, 0.3645] are mapped back to real values to generate the counter offer by Eq. (5) reversely. That is [5.1282, 3.3567, 130.0947].

Service provider will then carry out the same process: evaluates the offer, and carries out FCM inference process to determine whether to accept the offer or to generate a counter offer. Service provider’s acceptable range for the level of prediction is from one day to seven days; acceptable range for the response time is from 1 second to 60 seconds; and its acceptable range for the cost of service is from 150 to 300.

Service provider receives the offer [5.1282, 3.3567, 130.0947]. After mapping, degrees for the issue concepts are [0.68003, 0.03994, 0]. Evaluation of this offer is 0.23531. Suppose now the degree of CPU utilization is 0.1. Now the service provider starts the inference process to calculate the counter offer.

After 24 iterations of inference, a stable state of the FCM is derived: [0.70127, 0.31804, 0.30198, 0.48478, 0.1]. Evaluation of the counter offer ready to be sent is the state value of the decisional concept at this stable state, which is 0.48478.

Because $0.23531 < 0.48478$, evaluation of the received offer is less than the evaluation of the counter offer service provider is ready to send. So service provider rejects the offer and proposes the counter offer. Degrees of $C_1$, $C_2$ and $C_3$ are “unmapped” to generate the counter offer by using Eq. (8) reversely. That is [5.2076, 19.7644, 195.2963].

Then a new round of encounter starts. Exchanges of offers and counter offers will continue until a mutually acceptable agreement is reached between the service provider and the consumer. The complete negotiation process is shown in Table 1.

At the 10th offer exchange, provider’s evaluation of the received offer is larger than the evaluation of next counter offer it is ready to send, so provider accepts this offer. An agreement is reached at the 10th offer exchange.

4.2. The lightweight property

As discussed earlier, the decision-making model for service trading participants in Pervasive Grid must be lightweight and helps participants to reach an agreement more quickly. In the proposed model, the lightweight-ness is measured by the iteration of inference before a counter offer is derived; and how quickly an agreement is reached is measured by the times of the offer exchanges in the course of the negotiation.

The decision-making process is also controlled by the value of $e$ in Eq. (6). As mentioned before, as the error level $e$ becomes smaller, it will need more steps of

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*One round of encounter in the course of negotiation contains at most two times of the offer exchange: agent $A$ sends an offer to agent $B$, and agent $B$ sends an counter offer as agent $B$ chooses not to accept the offer.*
Table 1
A complete negotiation process

<table>
<thead>
<tr>
<th>Offer exchange Round</th>
<th>Received offer</th>
<th>Evaluation of the received offer</th>
<th>Evaluation of next counter-offer</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (provider → consumer)</td>
<td>2</td>
<td>1</td>
<td>180</td>
</tr>
<tr>
<td>2 (consumer → provider)</td>
<td>5.1282</td>
<td>3.3567</td>
<td>130.0947</td>
</tr>
<tr>
<td>3 (provider → consumer)</td>
<td>5.2076</td>
<td>19.7644</td>
<td>195.2963</td>
</tr>
<tr>
<td>4 (consumer → provider)</td>
<td>3.5982</td>
<td>2.4731</td>
<td>128.446</td>
</tr>
<tr>
<td>5 (provider → consumer)</td>
<td>4.9245</td>
<td>19.3516</td>
<td>200.8157</td>
</tr>
<tr>
<td>6 (consumer → provider)</td>
<td>2.9907</td>
<td>5.0758</td>
<td>145.1825</td>
</tr>
<tr>
<td>7 (provider → consumer)</td>
<td>5.8745</td>
<td>10.1918</td>
<td>258.4351</td>
</tr>
<tr>
<td>8 (consumer → provider)</td>
<td>5.5422</td>
<td>1.2643</td>
<td>160.5565</td>
</tr>
<tr>
<td>9 (provider → consumer)</td>
<td>6.2523</td>
<td>5.0425</td>
<td>226.0517</td>
</tr>
<tr>
<td>10 (consumer → provider)</td>
<td>2.2311</td>
<td>5.376</td>
<td>139.6909</td>
</tr>
</tbody>
</table>

Fig. 5. Average inference iterations to derive a counter offer.

Fig. 6. Average offer exchange numbers to reach an agreement.

The decision-making process is also controlled by the λ value in the threshold function in Eq. (4). Experiment was conducted to find out how λ value influences the decision-making process. The experiment was carried out as follows: choose different λ value (λ = 1, λ = 2, λ = 3); run the proposed model repeatedly (1000 episodes) with a particular λ value; then record the average iteration of inference to derive a counter offer and the average number of offer exchanges to reach an agreement in different setting (i.e. with different λ value).

Average iterations of inference to derive a counter offer in different settings (λ = 1, λ = 2, λ = 3; ε = 10^{-3}) are shown in Fig. 5. Average numbers of offer exchanges to reach an agreement in different setting (λ = 1, λ = 2, λ = 3; ε = 10^{-3}) are shown in Fig. 6.

It is observed that the average number of inference iteration increases with the increase of λ value, and the average number of offer exchanges decreases with the increase of λ value. In order to make the proposed model lightweight, it is desirable that the average number of inference iteration should be small. Hence, the λ value is expected to be small. However, in order to reduce the number of offer exchanges to reach an agreement more quickly, the λ value is expected to be large. There is a trade-off in the selection of λ value. When implementing the proposed model, λ value can be different based on the priority of these two requirements. It is observed from Fig. 6 that when λ = 2, it generally shows a good balance.

5. Conclusions and future work

The rationale of the proposed model is that: Service trading by nature can be viewed as a dynamic system with multi-negotiation issues and interdependent relationships among negotiation issues that are represented by Fuzzy Cognitive Maps (FCM). If a counter offer is generated before a stable state of the FCM is reached, agent’s mental state is still possible to change. The generated counter offer may not be advantageous for the agent itself or it may not be acceptable for the offer receiver. Most of the existing decision-making models only help agents to see the influence of its current action at the immediate next step. In contrast, the proposed
model enables agents to see the influence of current actions to some steps “further”.

There is some existing work in applying fuzzy logic for decision-making design for negotiation, e.g. [15, 16]. To the best of our knowledge, this paper is the first attempt in studying multi-issue negotiation as a dynamic system and in extending Fuzzy Cognitive Maps as a decision-making model. Compared with the existing decision-making models reviewed in Section 2.2, the proposed model has some desirable advantages:

1. FCM is lightweight in nature. It is fast to converge and only involves simple metrics calculation throughout the inference process.
2. Most existing methods for multi-issue negotiation only regard each issue as a separate issue. However, in most of cases, there do exist causal relationships between these negotiation issues. In this paper, the causal relationships between the negotiation issues were taken into account in our model and FCM is used to reason out stable states while considering such causal relationships.
3. Agent can use fuzzy linguistic terms to specify the preference between different negotiation issues. Agents do not need to specify explicitly their preferences over different negotiation issues in real value.
4. As discussed before, degrees of particular issues are necessary for evaluating an offer using Eq. (4). The proposed model is not constrained to any degree mapping method. Any method to map issue values to degrees can be used. This is rational because after the stable state is derived, the degrees of issue concepts are mapped back to real values using the same method reversely. It is the degrees of the concepts that really matters, but not the mapping method. Thus it makes our model a flexible model, and can works with many mapping method (linear or non-linear).
5. A flexible condition to determine whether to accept an offer or not is introduced. By applying a flexible condition, agent may accept an offer that it has previously turned down since agents’ preferences change with the quick changes of the dynamic Grid environment. The proposed model increases the probability of reaching an agreement.

The experimental results show that with a suitable \( \lambda \) value, counter offer can be derived within a small number of inference iterations and a possible agreement can be reached with a small number of offer ex-

changes. Thus it is shown that the proposed model is a light-weight model and is promising to be deployed in Pervasive Grid.

Currently, the weight values in the constructed FCM are assigned by retrieving similar negotiation scenarios from a case base. Although desirable properties of the proposed model have already been shown by this treatment, this treatment introduces extra overhead for maintaining the case base. Moreover this treatment does not make it easier to apply formal analysis to analyze the efficiency and stability of the proposed model, e.g. Game theoretic analysis. In our future work, a formal way to model the weight will be studied in order to facilitate formal analysis of the proposed model. Then, a formal analysis of the proposed model will also be investigated.

References


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