KNOWLEDGE-BASED HEALTHCARE COALITION FORMATION TOOL

END OF PROJECT REPORT

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CONTENTS

A Framework for Cohesive Healthcare Coalition Formation

Yu-N CHEAH[a,1], Yong Han CHONG[b] and Siew Lan NEOH[c]
[a, b] *School of Computer Sciences, Universiti Sains Malaysia, Penang, Malaysia*
[c] *Petronas Nasional Berhad, Petronas Twin Towers, Kuala Lumpur, Malaysia*

Abstract. The mobilisation of cohesive and effective groups of healthcare human resource is important in ensuring the success of healthcare organisations. However, forming the right team or coalition in healthcare organisations is not always straightforward due to various human factors. Traditional coalition formation approaches have been perceived as 'materialistic' or focusing too much on competency or pay-off. Therefore, to put prominence on the human aspects of working together, we present a cohesiveness-focused healthcare coalition formation methodology and framework that explores the possibilities of social networks, i.e. the relationship between various healthcare human resources, and adaptive resonance theory.
Keywords: Coalition Formation, Social Networks, Adaptive Resonance Theory.

1. Introduction

The practice of healthcare and the success of healthcare organisations are highly dependent on the expertise and experience of various healthcare human resources. Although each doctor, nurse or technician is responsible in their respective specialised task, the mobilisation of cohesive and effective groups of healthcare human resource is equally if not more important. Well-established healthcare organisations, while being aware of the need for effective knowledge and human capital management, stand to gain more when cohesive teams or coalitions are formed within the organisation for knowledge and experience-intensive tasks such as surgery and trauma management.

Efforts to define computational frameworks for coalition formation in organisations are actively being pursued, especially from an organisational behaviour or human resource perspective [1]. However, forming the right team in healthcare organisations is not always straightforward especially when human factors come into play. Traditional coalition formation approaches such as Game Theory [2][3][4] and Social-dependence Theory [5][6] have their limitations in view that they are perceived to be 'materialistic' or focusing primarily on competency, performance and pay-off.

To put prominence on the human aspects of working together, we present a cohesiveness-focused healthcare coalition formation methodology and framework. Here, we aim is to explore the potentials of social networks (that focus on the relationship between various healthcare human resources) and adaptive resonance theory (ART).

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[1] Corresponding Author: Yu-N CHEAH, School of Computer Sciences, Universiti Sains Malaysia, 11800 USM Penang, Malaysia. Email: yncheah@cs.usm.my.

2. Overview of the Healthcare Coalition Formation Methodology

Our proposed methodology for healthcare coalition formation consists of two phases (see Figure 1):

1. Coalition Formation: Upon receiving a work request and relevant inputs from the user, this phase checks for the physical availability of human resources and their cohesiveness, i.e. whether or not a particular group of doctors, nurses or technicians can work together effectively and comfortably. This phase not only utilises a straightforward lookup mechanism to check the physical availability of human resources, it also ensures the cohesiveness of a candidate coalition. The latter employs a novel combination of social networks and ART. The result of this phase is a candidate coalition.
2. Scheduling: The available group of employees is checked to ensure that they are available for the duration of the task. If there is a mismatch in the schedule of the employees, an alternative candidate coalition is generated via the coalition formation phase. When the candidate coalition clears the scheduling phase, a finalised coalition is obtained.

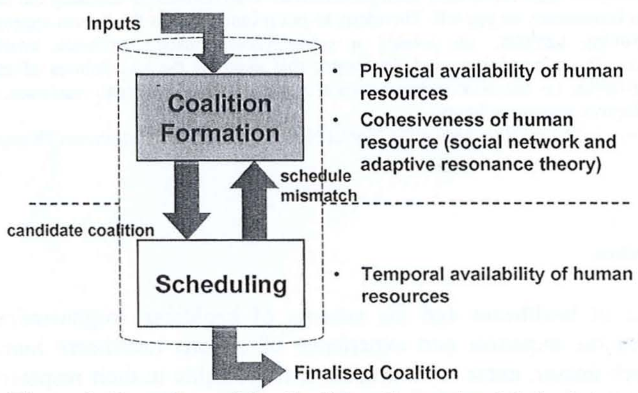

Figure 1: Overview of the Coalition Formation Methodology

Our two-phased methodology can be translated into a framework consisting of the following three layers (see Figure 2):

1. Object Layer: In general, this layer stores various resources. For our purposes, it stores human resource knowledge (e.g. of specialists, nurses, technicians, etc.). This can be viewed as a virtual community of agents represented as nodes, each having its own public and private knowledge. Public (or social) knowledge includes the agent's profile, constraints and schedule; while private knowledge refers to personality, preferences and credibility [7][8].
2. Manager Layer: Three manager components interact with the object layer agents and delivery layer interface to carry out their tasks.
   - Interface Manager: The interface manager receives requests from the user and passes on the relevant inputs to the other manager components to initiate the coalition formation activity. Upon receiving a finalised coalition as the result, the interface manager passes it on to the user.
   - Coalition Manager: The coalition manager carries out the tasks of the coalition formation phase mentioned earlier. It receives the relevant inputs from the interface manager and identifies which human resource agents at the object layer are available to form a coalition. Following this, the coalition agent analyses the social network of the available human resources by determining their relationship values. It then applies ART on the relationship values to produce a candidate coalition.
   - Scheduling Manager: The scheduling manager performs the scheduling phase of our healthcare coalition formation methodology. It checks the candidate coalition for scheduling mismatches. Mismatched human resources are sent back to the coalition manager for other coalition alternatives, while a candidate coalition that does not have mismatched schedules are returned to the interface manager as a finalised coalition.
3. Delivery Layer: This layer is basically the user interface from which the user can submit requests for coalitions with accompanying inputs, and receive the finalised coalition results.

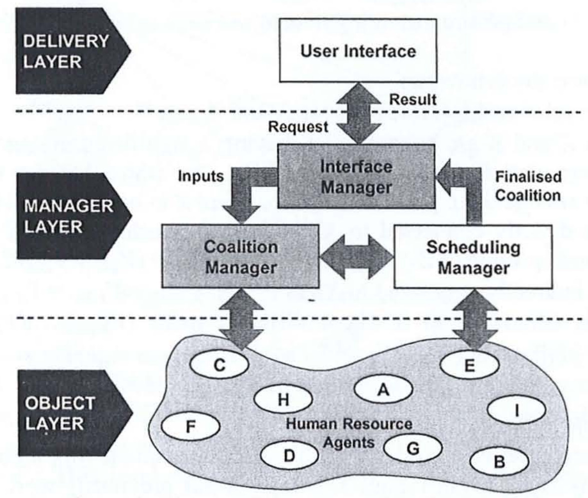

Figure 2: The Coalition Formation Framework

Presently, we aim to focus on the first phase of our coalition formation methodology, i.e. to ensure cohesiveness by employing social networks and ART. The second phase, i.e. scheduling, is beyond the scope of this paper. We now present details of the coalition manager, i.e. the main component for the coalition formation phase.

3. The Coalition Manager

The coalition manager carries out two main functions: social network management and ART.

3.1. Social Network Management

The coalition manager interacts very closely with the human resource agents at the object layer. The community of human resource agents, i.e. doctors, nurses, technicians, etc., is represented as nodes and the relationships between agents are represented as arcs (with corresponding relationship values) (see Figure 3). Their relationships are asymmetrical, i.e. the relationship doctor A has on technician B is not necessarily the same as the relationship technician B has on doctor A, as each agent has its own personality, preferences and credibility. The relationship value an agent has on another agent is a composite value derived from questionnaire-based credibility and personal trait assessments during their past interactions [8][9].

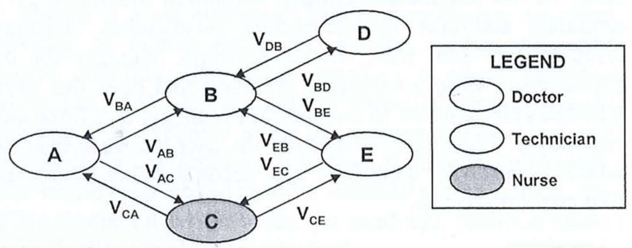

Figure 3: Nodes and arcs representing human resource agents and their relationships

Let us assume the following:

- $V_{X\text{-|-}Z}$ = relationship value between X and Z, and
- agents X and Z are coherent, i.e. having a significant amount of positive or good experience working together, if $V_{X\text{-|-}Z} > e$ (the coherency threshold).

Let us also assume three possible ways for agent Z to be connected to agent X:

1. if Z is directly connected to X ($V_{X\text{-}Z}$ = relationship value of X on Z, $V_{Z\text{-}X}$ = relationship value of Z on X), then $V_{X\text{-|-}Z} = V_{X\text{-}Z} = (V_{X\text{-}Z} + V_{Z\text{-}X})/2$,
2. if Z is indirectly connected to X via Y, then $V_{X\text{-|-}Z} = V_{X\text{-}Y\text{-}Z} = V_{X\text{-}Y} \bullet V_{Y\text{-}Z}$, and
3. if Z is connected to X via n different paths $(V_{X\text{-|-}Z})_1 \ldots (V_{X\text{-|-}Z})_n$, i.e. with multiple indirect connections, then $V_{X\text{-|-}Z} = \dfrac{\sum_{i=1}^{n} (V_{X\text{-|-}Z})_i}{n}$.

As an example, let us consider a healthcare environment with a number of human resources agents as shown in Figure 3. Doctor A has previously worked directly with technician B and nurse C; but not with doctor D or technician E. However, technician B has prior experience working with doctor D and technician E. These result in doctor A being indirectly connected to doctor D and technician E via technician B. Therefore, in order to calculate doctor A's relationship with all colleagues, various direct, indirect and multiple indirect relationships need to be considered.

Table 1 summarises the relationship values for all agents from Figure 3. By default, $V_{X\text{-}X} = 1$; and $V_{X\text{-}Y} = 0$ when $V_{X\text{-}Y} < e$.

Table 1: Relationship values for all human resource agents

Agent	A	B	C	D	E
A	1	$V_{B\text{-|-}A}$	$V_{C\text{-|-}A}$	0	$V_{E\text{-|-}A}$
B	$V_{A\text{-|-}B}$	1	$V_{C\text{-|-}B}$	0	$V_{E\text{-|-}B}$
C	$V_{A\text{-|-}C}$	$V_{B\text{-|-}C}$	1	0	$V_{E\text{-|-}C}$
D	0	0	0	1	0
E	$V_{A\text{-|-}E}$	$V_{B\text{-|-}E}$	$V_{C\text{-|-}E}$	0	1

Having obtained a set of relationship values for each human resource agent in the community, the coalition manager represents each column of Table 1 as a vector $I \equiv (I_1, \ldots, I_M)$, where M is the number of human resource agents in a community. For instance, the vector for agent A is $I_A \equiv (1, V_{A\text{-|-}B}, V_{A\text{-|-}C}, 0, V_{A\text{-|-}E})$. The M number of input vectors serve as inputs for the coalition manager to carry out adaptive resonance to generate the candidate healthcare coalitions.

3.2. Adaptive Resonance Theory

ART is basically an artificial neural network employing unsupervised learning [10]. It is characterised by comparison (input) and recognition (output) fields, a vigilance parameter and a reset module. A basic ART network is shown in Figure 4.

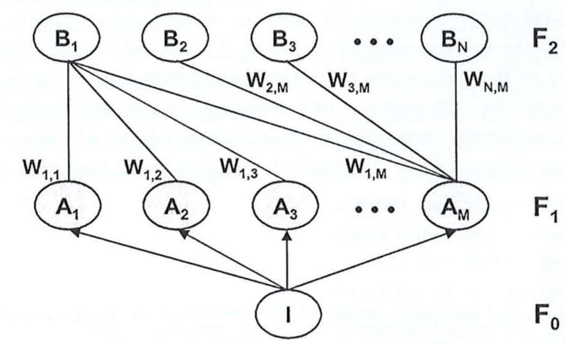

Figure 4: ART network architecture

The coalition manager maintains three levels of ART field activity vectors:

- Level F_0: This level consists of a node which represents the current input vector, I for an agent (obtained from the social network management's relationship value calculation).
- Level F_1: This level consists of as many nodes as there are human resource agents. The F_1 activity vector, i.e. the values of the nodes, is denoted as $A = (A_1, \ldots, A_M)$.
- Level F_2: Nodes at this level represents the candidate healthcare coalitions formed. The F_2 activity vector is denoted as $B = (B_1, \ldots, B_N)$.

Associated with each candidate healthcare coalition node j ($j = 1, \ldots, N$) of F_2 is a vector $w_j \equiv (w_{j1}, \ldots, w_{jM})$ of adaptive weights. The number N, which indicates possible 'slots' for candidate healthcare coalitions, may be arbitrarily large.

The ART network takes input vectors from F_1 and sends them to F_2. In the process, the weights between F_1 and F_2 are updated and the matching process of comparing the relationship value of each F_1 node with the respective weights from the previous cycle would result in certain F_2 nodes to be chosen (representing candidate healthcare coalitions). As more input vectors are put into the network, and as these inputs meet the required vigilance criteria (which determines whether the coalitions are fine-grained or general), the formation of the candidate healthcare coalitions strengthens in line with the concept of establishing resonance.

The human resource agents associated with the same candidate healthcare coalition node in F_2 are deemed coherent to each other and thus, form cohesive candidate coalitions. These candidate healthcare coalitions are then passed on to the scheduling manager that would then ensure the human resource agents, whilst being socially cohesive, are available during the period of the task.

4. Concluding Remarks

In general, our cohesiveness-focused healthcare coalition formation methodology can be viewed as a hybrid methodology that takes into account the human factor in social interactions as well as artificial intelligence techniques such as ART in order to form suitable coalitions for a particular task.

Presently, we have laid out details of the coalition manager. The development of the entire healthcare coalition formation framework is still in progress. The way forward would be to explore details of the scheduling and interface managers. We expect constraint-related techniques as well as evolutionary algorithms [11] to be relevant, especially for the scheduling manager. This would be challenging due to the complex nature of shift work in the healthcare environment. Ultimately, we hope that this framework can be integrated into existing healthcare-related groupware to capitalise on existing human resource profiles that may have already been stored. This can further enhance the quality of coalitions formed in healthcare organisations.

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Healthcare Coalition Formation Using Personal Traits and Adaptive Resonance Theory

Yong Han Chong[1] **Yu-N Cheah[2]**

[1]*School of Computer Sciences, Universiti Sains Malaysia, 11800 USM Penang, Penang, Malaysia*
Tel: +60-4-6533888 ext. 4392, Fax: +60-4-6573335, E-mail: thestep@cs.usm.my

[2]*School of Computer Sciences, Universiti Sains Malaysia, 11800 USM Penang, Penang, Malaysia*
Tel: +60-4-6533830, Fax: +60-4-6573335, E-mail: yncheah@cs.usm.my

Abstract

Traditionally, healthcare-related teams are formed based on the physical availability of healthcare experts that focuses on material benefits. However, we cannot discount the fact that healthcare experts are human and social beings. Therefore, moving away from Game Theory and Social-dependence Theory, we have identified personal traits as a good alternative to be applied on healthcare team or coalition formation efforts due to its 'win-win' characteristics. In this paper, we present a methodology for healthcare coalition formation consisting of two stages: (a) the acquisition and representation of the personal traits of healthcare experts, and (b) the application of adaptive resonance theory in effective coalitions.

Keywords:

Coalition Formation, Personality Traits, Adaptive Resonance Theory.

Introduction

The practice of healthcare, although requires the presence of individual healthcare experts, is very much dependent on the mobilisation of cohesive and effective groups of healthcare experts with different specialisations. Well-established healthcare enterprises, that are equally well aware of the need for effective knowledge and human capital management, stand to gain more when optimum teams are formed within the organisation for knowledge and experience-intensive tasks such as surgery and trauma management.

Traditionally, healthcare-related teams are formed based on physical availability, i.e. healthcare experts are mixed and matched with other team members based on their expertise and availability. However, we cannot discount the fact that healthcare experts are social beings. When a team needs to be formed to carry out a task, individual healthcare experts actually do more that just fulfil a job obligation. They also behave and interact with one another in a way that they can feel comfortable and motivated.

Not many theories have been previously explored in the literature of coalition formation (CF). These are (a) Game Theory that investigates coalition benefits and distribution of payoffs among coalition members [1, 2, 3], and (b) Social-dependence Theory that studies complementing skills and knowledge of coalition members in achieving goals that would be impossible to be achieved independently [4, 5]. However, in addition to these two key CF approaches, and within the healthcare domain, we contend that cohesiveness of healthcare experts working together in a coalition is equally important as it could significantly increase the success of the coalition in performing a health-related task.

Moving away from Game Theory and Social-dependence Theory, which we feel are somewhat 'selfish' in nature, we have identified personal traits as a good alternative to be applied to CF efforts due to its more 'win-win' characteristics. From the Five Factor Model of personal traits in the research on personality [6], personal traits are among the properties of constituent team members that determine the cohesiveness of a coalition. By putting individuals with similar if not identical personal traits together, it is anticipated that the coalitions formed would ultimately prevent or at least minimise internal-conflicts and fractions among members. In this way, better healthcare coalition performance is also expected when compared to teams that are formed merely based on the individual healthcare expert's payoffs/rewards and social-dependency.

In exploring personal traits, there are two major problems we have to deal with:

1. *Personal traits are abstract features that are hard to be measured quantitatively*: A method must therefore be formalised for capturing and representing an individual's personal traits in such a way it can be interpreted computationally.
2. *The number of coalitions that can be formed at any particular time is dependent on the set of individuals available*: An adaptive mechanism capable of accommodating such dynamic behaviour must be formulated so that CF could be done flexibly.

Essentially, the personal traits of an individual are best described by other individuals who know that individual well. Supported by this proposition, we have therefore chosen the feedback approach to address the first problem mentioned earlier whereby healthcare experts (respondents) are required to answer a questionnaire (by giving scores) pertaining to an individual healthcare expert's personal traits. These respondents to the questionnaire have previously interacted closely with the individual healthcare expert in a coalition.

To address the second problem, Adaptive Resonance Theory (ART) [9] was selected for following reasons:

- It can categorise individuals automatically.
- The level of how coarsely or finely it discriminates between individuals in performing the categorisation is controllable.
- If the ART neural network knows a particular individual, its category (or coalition) is recalled immediately. Otherwise, a search will be automatically initiated.
- It can learn any new significantly different individuals automatically.

ART neural network has been widely used for protein/DNA analysis [7] and image processing [8]. It can be effectively applied to form healthcare coalitions. A brief description of ART network is given in the next section.

Adaptive Resonance Theory

Adaptive Resonance Theory (ART) is a type of self-organising neural network, which performs unsupervised batch clustering of input data [9]. Given a set of input patterns, an ART network will attempt to separate the data into clusters.

The dynamics of ART networks consists of the interaction between two layers of processing elements (nodes) in the form of an iterative feedback loop (see Figure 1). The first layer in an ART network, termed F_1, functions as the short-term memory (STM) for the network. The second layer is termed F_2, which is an adaptive layer. The weights between F_1 and F_2 act as the long-term memory (LTM) for the network. Each node in the F_2 layer is a cluster in the set of input patterns and contains the node prototype representing the centre of the cluster. The number of nodes in the F_2 layer grows dynamically as required to cover the input patterns.

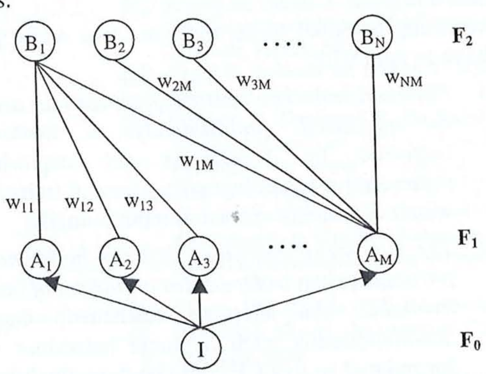

Figure 1. ART Network Architecture

ART dynamics describe an iterative feedback loop between the F_1 layer and the F_2 layer. The resonance in the ART network occurs when the outputs between the two layers, F_1 and F_2, are within some threshold of similarity.

Classical ART networks include ART1, ART2 [10] and Fuzzy ART [11], which were developed by Grossberg. The ART1 network is a binary network, only capable of dealing with binary input patterns, while ART2 and Fuzzy ART are analogue networks. In view that personal traits of an individual are analogue, ART2 is adapted in our efforts to form healthcare coalitions.

A Methodology for Healthcare Coalition Formation using Personal Traits and ART

Our methodology for healthcare coalition formation consists of two stages:

1. *Acquisition and representation of the personal traits of healthcare experts*: This ultimately represents individual healthcare experts.
2. *Application of ART*: This is to cluster the individual healthcare experts (represented by their personal traits) into coalitions.

Personal Traits Acquisition and Representation

The personal traits to be taken into account when forming a coalition are highly dependent on the nature of the task and the social culture of the healthcare organisation. For a generic healthcare organisation and perhaps a surgical department in particular, we propose personal traits such as openness, temperament, confidence, sensitivity, and professionalism.

Let us assume that we have m number of questions to ask for each personal trait and the answer (score) given for each question ranges from 0 to 1 with 1 indicating the highest likelihood of the concerned trait. An example of one of the questions for the temperament trait could be, "The individual maintains composure in difficult situations". The average score, Q^i for a personal trait i is therefore calculated as (1).

$$Q^i = \frac{\sum_{j=1}^{m} q_j^i}{m} \tag{1}$$

where q_j^i is the score given for question j corresponds to personal trait i.

To calculate the average score obtained for a particular trait after a series of feedbacks from different respondents, we adopt (2)

$$I_i = \frac{\sum_{j=1}^{n} Q_j^i}{n} \tag{2}$$

where n is the number of feedbacks.

Finally, after having obtained the respective personal trait average scores of an individual, we represent it as an input vector I (3) to the ART neural network for CF.

$$I \equiv (I_1, \ldots, I_M) \tag{3}$$

where M is the number of personal traits covered by the questionnaire. Note that for our purpose, I represents each healthcare expert and his/her personal traits.

Personal Trait-based CF using ART

Any ART-type neural network can be characterised by its preprocessing-, choice-, match- and adaptation-rules. For our ART neural network for CF, these rules are as follows.

ART Field Activity Vectors: Each ART system includes a field, F_0 whose nodes represent a current input vector and a field, F_1 that receives bottom-up input from F_0 and top-down input from F_2, a field whose nodes represent the active category. The F_0 activity vector is denoted as $I = (I_1, \ldots, I_M)$, i.e. each healthcare expert and his/her personal traits, with each component I_i in the interval [0,1], $i = 1, \ldots, M$. The F_1 activity vector is denoted as $x = (x_1, \ldots, x_M)$. The F_2 activity vector is denoted as $y = (y_1, \ldots, y_N)$. The number of nodes in each field is defined according to requirement.

Weight Vector: Associated with each F_2, category node j $(j = 1, \ldots, N)$ is a vector $w_j \equiv (w_{j1}, \ldots, w_{jM})$ of adaptive weights, or LTM traces. The number N, which indicates coded categories, may be arbitrarily large. Initially,

$$w_{j1}(0) = \cdots = w_{jM}(0) = 0; \tag{4}$$

Each category is said to be uncommitted. After a category is selected for coding, it becomes committed. As shown below (5), each LTM trace w_{ji} is monotonically non-increasing through time, and therefore converges to a limit value.

Parameters: Our ART dynamics are determined by a learning rate parameter $\beta \in [0,1]$ and a vigilance parameter $\rho \in [0,1]$.

Category Choice: For each input I and F_2 node category, j, the choice function T_j is defined by

$$T_j(I) = 1 - \frac{|I - w_j|}{M} \tag{5}$$

where the norm |·| is defined for any M-dimensional vector p as

$$|p| \equiv \sum_{i=1}^{M} |p_i| \tag{6}$$

For simplicity, $T_j(I)$ in (5) is often written as T_j when the input pattern I is fixed.

The category choice is indexed by J, where

$$T_J = \max\{T_j : j = 1 \ldots N\} \tag{7}$$

If more than one index j gives a maximal T_j, the category j with the smallest index is chosen. Thus, nodes become committed in order of j = 1, 2, 3... When the J-th category is chosen, $y_J = 1$, and $y_j = 0$ for $j \neq J$. In choosing the J-th category, the F_1 activity vector x obeys the equation

$$x = \begin{cases} I, & \text{if } F_2 \text{ is inactive} \\ I - w_J, & \text{if the } J\text{-th } F_2 \text{ node is chosen} \end{cases} \tag{8}$$

In other words, here, any J would represent a (potential) coalition of healthcare experts (shown as B_1, ..., B_N in Figure 1), with each healthcare expert represented by his/her own personal trait vector I.

Resonance or Reset: Resonance occurs if the match function of the chosen category meets the vigilance criterion. That is,

$$1 - \frac{|I - w_J|}{M} \geq \rho \tag{9}$$

That is to say, by (7) when the J-th category is chosen, resonance occurs if

$$|x| = |I - w_J| \leq M(1 - \rho) \tag{10}$$

As a result, the healthcare expert I will be incorporated into the chosen J-th category.

Mismatch reset occurs if

$$1 - \frac{|I - w_J|}{M} < \rho \tag{11}$$

That is to say, if

$$|x| = |I - w_J| > M(1 - \rho) \tag{12}$$

then the value of the choice function T_J is set to 0 for the duration of the input presentation to prevent the persistent selection of the same category during the search. A new index J is then chosen by (7). The search process continues until the chosen J satisfies (9).

Learning: Once the search ends, the weight vector w_J is updated using equation (13).

$$w_J^{(new)} = w_J^{(Old)} \frac{n_J}{n_J + n_I}(1 - \beta) + I \frac{n_I}{n_J + n_I}(\beta) \tag{13}$$

where n_I is the number of feedbacks in I while n_J is the total number of feedbacks of all individuals incorporated into category node J. Fast learning corresponds to $\beta = 1$.

Fast-Commit Slow-Recode Option: For efficient coding of noisy input sets, it is useful to set $\beta = 1$ when J is an uncommitted node, and then to take $\beta < 1$ after the category is committed. Having done that would result in $w_J^{(new)} = I$ and category J becomes active for the first time. This option of fast commitment and slow recoding correspond to ART learning at intermediate rates.

Output: After having fed all the available personal trait representations into the ART neural network, individuals incorporated into the same category are deemed to have similar personal traits and thus, would form cohesive coalitions.

Conclusion

Employing a feedback- or questionnaire-based approach in acquiring an individual healthcare expert's personal traits is satisfactorily accurate since the final result is a compilation of opinions from other healthcare experts who have been interacting with, and thus understand, the particular individual. However, this process is time-consuming as one would have to go through a series of close interactions with that individual first before one is ready to answer the personal trait-related questions confidently. Apart from that, it is also a tedious process to answer questionnaires that may become lengthy if other coalition-related personal properties in addition to personal traits are taken into account.

As a next course of action, we are looking into the possibility of acquiring healthcare experts' personal properties, particularly those that would ensure the cohesiveness of a coalition, in addition to personal traits. We are looking forward to define computer simulations of healthcare environment and situations for this purpose. As such, our research on healthcare coalition formation is ongoing. We hope that by forming optimum coalitions or teams for healthcare tasks, patients stand to benefit from the experience and knowledge of healthcare experts, who in turn are motivated to perform due to the cohesiveness of the coalition.

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FORMING COHESIVE COALITIONS USING VIRTUAL SOCIAL NETWORK AND ADAPTIVE RESONANCE THEORY

Yong Han Chong and Yu-N Cheah

School of Computer Sciences, Universiti Sains Malaysia, 11800 USM Penang, Penang, Malaysia

Email: {thestep, yncheah}@cs.usm.my

ABSTRACT

No matter how perfect a coalition is from the aspects of mutual benefits, individual payoffs and knowledge of members, it will still fail to meet expectations if internal conflicts arise. Realizing the importance of a harmonious and cohesive atmosphere in promoting seamless cooperation between coalition members, we propose an agent-based coalition formation approach that leverages on virtual social network and Adaptive Resonance Theory (ART) from artificial neural networks (ANN) to form cohesive coalitions. In virtual social network, relationship values of the agents are obtained. The relationship values are then passed on to the ART-ANN to determine cohesive coalitions.

KEYWORDS

Coalition formation, Virtual social network, Adaptive Resonance Theory.

1. INTRODUCTION

Synergy or the phenomenon that 'the sum is greater than the parts' is what coalition formation is all about. A coalition is formed to achieve a goal that cannot be achieved by an individual person and to yield a benefit that is higher than the sum of benefits if it was pursued individually. However, this is only true when all the relevant elements are configured appropriately, which among others, include coalition members' resource contributions, individual payoffs, mutual benefits and the very main topic of our interest – cohesiveness among coalition members.

In the following sub-sections, we will introduce and explain current approaches for coalition formation, the nature of coalition formation problems, and the purpose and contribution of our research. In section 2, we provide a representation of the social networks between agents in a community and the method to derive a set of relationship values for each agent. The ART (Adaptive Resonance Theory)-artificial neural network (ANN) is then presented in Section 3 to group the agents into cohesive coalitions based on their respective derived relationship values. To conclude, we point out some potential features and future work.

1.1 Current approaches for coalition formation

A few relevant theories and critical work to warrant the successful formation and running of coalitions have been reported in the literature of computer science. The following are some popular approaches:

- *Game Theory*, from the field of economics, investigates coalition benefits and distribution of payoffs among coalition members to ensure stability [Ketchpel, 1994; Shehory & Kraus, 1996; Klusch & Gerber, 2002].
- *Social-dependence Theory*, from social sciences, studies the importance of skills and knowledge of coalition members in achieving goals that would otherwise be impossible to achieve alone [Conte & Sichman, 1995; Sichman & Demazeau, 2001].
- *Trust-based coalitions* identifies reputable agents, perceived at the time of evaluation, to form quality coalitions [Breban & Vassileva; 2002].

1.2 Research problems

Problems in coalition formation research largely stems from the fact that humans are unique and intelligent beings. We have our very own distinctive personalities and attitudes as a result of real-life experiences and learning. Inter-personal problems that lead to conflicts in a coalition can occur when unique individuals are put together in a group to pursue a common goal [Kim & College, 1998]. The situation becomes worse if certain individuals become emotional and consequently, cause the coalition to fail in its objectives.

While many current theories and approaches have addressed the computational aspects of coalition formation and have included the characteristics of individuals as factors in forming coalitions, coalition formation researchers have yet to incorporate coherent agents as yet another factor for coalition formation in an open system to ensure the cohesiveness of a coalition.

1.3 Objectives and contribution

We believe that the true potential and the knowledge possessed by coalition members would only be best capitalized in a conducive environment. Hence, our objective is to develop a coalition formation approach that would naturally reflect the cohesiveness among agents in a community so that agents that have the potential of working together coherently could be identified implicitly without requiring an in-depth analysis of the agents' behavior. Our main contribution is therefore the selection and grouping of agents that have the potential to get along well with each other to form cohesive coalitions, using virtual social network and ART-ANN.

2. VIRTUAL SOCIAL NETWORK

Apart from being unique, humans are, by nature, social beings. Everyone has a social network consisting of friends, relatives and even enemies. From social science literature, it is argued that the personality of an individual, apart from being genetically attributed, is also largely influenced by people whom that individual closely interacts with [Feld, 1981]. In other words, it makes sense to say that an individual usually gets along and only gets along well with people who, to a certain extent, think and behave like him or her. It is this natural phenomenon that provides us with the idea of using social network to identify groups of people believed to have the potential of forming cohesive coalitions.

2.1 Social network representation

Each agent in a virtual community is represented as a node and the relationships a particular agent has with other agents are depicted by the arcs between nodes. The relationship is asymmetrical whereby the value of the relationship agent X has on an agent Y does not necessary mean the same for agent Y on agent X. Therefore, two agents that have a relationship would have two different arcs to represent their respective valuations or relationship value of each other.

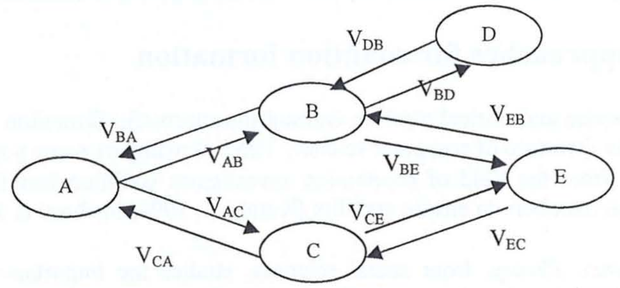

Figure 1. Social network representation of a virtual community

2.2 Our virtual social network approach

Let us assume the following:

- agents X and Z are coherent if $V_{X\text{-}|\text{-}Z} > \mathrm{e}$, e = activation value, and
- $V_{X\text{-}|\text{-}Z}$ = relationship value between X and Z.

Let us also assume three possible scenarios for a particular agent, Z:

1. if Z is directly connected to X (V_{XZ} = relationship value of X on Z, V_{ZX} = relationship value of Z on X), then $V_{X\text{-}|\text{-}Z} = V_{X\text{-}Z} = (V_{XZ} + V_{ZX})/2$,
2. if Z is indirectly connected to X through Y, then $V_{X\text{-}|\text{-}Z} = V_{X\text{-}Y\text{-}Z} = V_{X\text{-}Y}.V_{Y\text{-}Z}$, and
3. if Z is connected to X through n different paths $(V_{x\text{-}|\text{-}z})_1 \ldots (V_{x\text{-}|\text{-}z})_n$, then $V_{X\text{-}|\text{-}Z} = \dfrac{\sum_{i=1}^{n} \left(V_{X\text{-}|\text{-}Z}\right)_i}{n}$.

As an example, we calculate the relationship value for agent A (based on Figure 1):

Evaluate neighbor of A: $V_{A\text{-}|\text{-}C} = V_{A\text{-}C} = (V_{AC} + V_{CA})/2 > \mathrm{e}$ (Agent A and C are coherent) (1)

→ Evaluate neighbor of C: $V_{C\text{-}|\text{-}E} = V_{C\text{-}E} = (V_{CE} + V_{EC})/2 > \mathrm{e}$ (Agent C and E are coherent) (2)

→ Evaluate neighbor of E: $V_{E\text{-}|\text{-}B} = V_{E\text{-}B} = (V_{BE} + V_{EB})/2 > \mathrm{e}$ (Agent B and E are coherent) (3)

→ Evaluate neighbor of B: $V_{B\text{-}A} = (V_{BA} + V_{AB})/2 > \mathrm{e}$ (Agent B and A are coherent) (4)

$V_{B\text{-}|\text{-}D} = V_{B\text{-}D} = (V_{BD} + V_{DB})/2 < \mathrm{e}$ (Agent B and D not coherent)

$$V_{A\text{-}B\text{-}E\text{-}C} = V_{A\text{-}B}.V_{B\text{-}E}.V_{E\text{-}C} = (4).\ (3).\ (2) \quad (5)$$

$$V_{A\text{-}C\text{-}E\text{-}B} = V_{A\text{-}C}.V_{C\text{-}E}.V_{E\text{-}B} = (1).\ (2).\ (3) \quad (6)$$

$$V_{A\text{-}B\text{-}E} = V_{A\text{-}B}.V_{B\text{-}E} = (4).\ (3) \quad (7)$$

$$V_{A\text{-}C\text{-}E} = V_{A\text{-}C}.V_{C\text{-}E} = (1).\ (2) \quad (8)$$

$$V_{A\text{-}|\text{-}B} = [(4) + (6)] / 2$$

$$V_{A\text{-}|\text{-}C} = [(1) + (5)] / 2$$

$$V_{A\text{-}|\text{-}E} = [(7) + (8)] / 2$$

Table 1 summarizes the relationship values for all agents from Figure 1 after the above calculations are repeated for the other agents.

Table 1. Relationship values for all community agents

Agent	*A*	*B*	*C*	*D*	*E*
A	1	$V_{B\text{-}|\text{-}A}$	$V_{C\text{-}|\text{-}A}$	0	$V_{E\text{-}|\text{-}A}$
B	$V_{A\text{-}|\text{-}B}$	1	$V_{C\text{-}|\text{-}B}$	0	$V_{E\text{-}|\text{-}B}$
C	$V_{A\text{-}|\text{-}C}$	$V_{B\text{-}|\text{-}C}$	1	0	$V_{E\text{-}|\text{-}C}$
D	0	0	0	1	0
E	$V_{A\text{-}|\text{-}E}$	$V_{B\text{-}|\text{-}E}$	$V_{C\text{-}|\text{-}E}$	0	1

By default, $V_{X\text{-}X} = 1$ and $V_{X\text{-}Y} = 0$ when $V_{X\text{-}Y} < \mathrm{e}$. Having obtained a set of relationship values for each agent in the community, we represent each set as an input vector (9) to the ART-ANN for coalition formation.

$$I \equiv (I_1, \ldots, I_M) \quad (9)$$

where M is the number of agents in a community. For instance, the input vector for agent A is $I \equiv (1,\ V_{A\text{-}B},\ V_{A\text{-}C},\ 0,\ V_{A\text{-}E})$.

3. GROUPING POTENTIALLY COHESIVE COALITIONS USING ART

Any ART-ANN can be characterized by its preprocessing-, selection-, match- and adaptation-rule, where selection and match define the search cycle for a fitting prototype [Jain et al., 1999; Carpenter & Grossberg, 1998; Fausett, 1994]. For our ART-ANN, these rules are as follows.

ART Field Activity Vectors: These consist of (a) a field F_0 whose nodes represent a current input vector, I for an agent (obtained from our virtual social network approach), a field F_2 whose nodes represent the active group and consists of group nodes, and (c) a field F_1 that receives bottom-up input from F_0 and top-down input from F_2.

The F_0 activity vector is denoted as (9) with each component I_i in the interval [0, 1], $i = 1,3\ ,M$. The F_1 activity vector is denoted as $x = (x_1,3\ ,x_M)$. The F_2 activity vector is denoted as $y = (y_1,3\ ,y_N)$. The number of nodes in F_0, M is defined according to the number of agents in the community.

Weight Vector: Associated with each group node j $(j = 1,3\ ,N)$ of F_2 is a vector $w_j \equiv (w_{j1},3\ ,w_{jM})$ of adaptive weights. The number N, which indicates coded groups, may be arbitrarily large. Initially

$$w_{j1}(0) = \cdots = w_{jM}(0) = 0 \tag{10}$$

Then, each group node j is said to be uncommitted. After a group node j is selected for coding, it becomes committed.

Parameters: Our ART dynamics are determined by a learning rate parameter $\beta \in [0,1]$ and a vigilance parameter $\rho \in [0,1]$.

Group Node Selection: For each input I and group node j of F_2, the choice function T_j is defined by:

$$T_j(I) = 1 - \frac{|I - w_j|}{M} \tag{11}$$

where the norm $|\cdot|$ is defined for any M-dimensional vector p as

$$|p| \equiv \sum_{i=1}^{M} |p_i| \tag{12}$$

For notational simplicity, $T_j(I)$ in (11) is written as T_j when the input pattern I is fixed.

The group node selected for coding is as shown in (13) and indexed by J,

$$T_J = \max\{T_j : j = 1 \ldots N\} \tag{13}$$

If more than one index j gives a maximal T_j, the group node j with the smallest index is chosen. Thus, nodes become committed in order (j = 1, 2, 3, ...). When the J-th group node is selected, $y_J = 1$ and $y_j = 0$ for $j \neq J$. In a group node selection system, the F_1 activity vector x obeys the equation

$$x = \begin{cases} I & \textit{for group nodes of } F_2 \textit{ that have not yet been committed} \\ I - w_J & \textit{if the J-th group node of } F_2 \textit{ has been committed} \end{cases} \tag{14}$$

Resonance or Reset: Resonance occurs if the match function of the selected group node meets the vigilance criterion. That is,

$$1 - \frac{|I - w_J|}{M} \geq \rho \tag{15}$$

That is to say, when the J-th group node is selected by (11), resonance occurs if

$$|x| = |I - w_J| \leq M(1 - \rho) \tag{16}$$

If (16) is true, then the corresponding agent of I is associated with the selected J-th group node. Mismatch reset occurs if

$$1 - \frac{|I - w_J|}{M} < \rho \tag{17}$$

That is to say, if

$$|x| = |I - w_J| > M(1 - \rho) \tag{18}$$

then the value of the choice function for T_J is set to 0 for the duration of the input presentation to prevent the persistent selection of the same group node during the search. A new group node J is then selected by (13). The search process continues until the selected J satisfies (15).

Learning: Once the search ends, the weight vector w_J is updated according to the equation

$$w_J^{(new)} = w_J^{(Old)} \frac{n_J}{n_J + 1}(1 - \beta) + I \frac{1}{n_J + 1}(\beta) \tag{19}$$

where n_J is the total number of relationship value sets that have been factored in by group node J. *Fast learning* corresponds to β = 1. Each adaptive weight w_{ji} is monotonically non-increasing through time and therefore, converges to a limit value.

Output: After having fed the relationship value sets of all agents in the community into the ART-ANN, the agents associated with the same group node are deemed coherent to each other and thus, have the potential of forming cohesive coalitions.

4. CONCLUSION

In this paper, we have presented the idea of exploiting virtual social network to identify coherent agents, i.e. agents that have the potential of working together cohesively in a coalition. In this way, we avoid using the questionnaire method that normally requires the respondent to answer a long list of questions to evaluate his or her personality. However, the limitation of our approach is that the agents in a community must engage with each other in a series of interactions first so that a social network can be constructed before it can be utilized.

Following that, we proposed the use of ART to group potentially coherent agents. By the use of ART, we are able to group agents automatically with the ability to control the group granularity at a desired level as well as to learn new groups dynamically.

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CREDIBILITY-CHART AND DUAL-MEMORY REFERENCING FOR ROBUST AND EFFICIENT AGENT SEARCH IN COALITION FORMATION

Yong Han Chong Yu-N Cheah

e-mail: thestep@cs.usm.my e-mail: yncheah@cs.usm.my
School of Computer Sciences, Universiti Sains Malaysia, 11800 USM Penang, Penang, Malaysia

Key words: Coalition formation, Agent search, Credibility

ABSTRACT

Substantial work has been devoted in applying (1) game theory for forming stable coalitions that yield maximum benefit for all agents, and (2) dependency theory for acquiring the necessary resources to form a coalition. However, certain assumptions made in these two approaches are impractical in the real world. For instance, the efforts of game theory that intend to produce stable coalitions are vulnerable when being applied in an open environment where agents are allowed to join and leave a coalition at will and where offers for better rewards in other coalitions arise from time to time. On the other hand, the social reasoning mechanism in dependency theory that requires each agent to have knowledge of all other agents in a community is just as infeasible for real world implementation. Hence, in this paper, we will explore two viable solutions to overcome the above weaknesses by analysing the agents' long-term credibility trends in order to form sustainable coalitions and by leveraging on an economical yet robust mechanism to search for potential coalition members.

I. INTRODUCTION

The "capability of an individual is limited but when multiple individuals are being coalesced to work cohesively, the resulting synergy and impact could be just amazing" [1]. This is the underlying motivation that drives most of the research work in Coalition Formation (CF). Most research work in the literature has also progressed along the lines of two models, i.e. the *utility-based* and *complementary-based* models [1].

The *utility-based model* aims to form a coalition structure with the objective of maximising the profits of the team, e.g. by using game theory, and then deciding how to distribute the benefit among coalition members [2]. On the other hand, the *complementary-based model* follows the principle that each party complements each others' skills and therefore enhances the power (success rate) of teamed agent to accomplish the goals [3]. However, when these two broadly studied models are being taken in the context of an open multi-agent environment such as those in e-commerce, certain assumptions become unrealistic and invalid due to the following reasons:

- A coalition that is deemed stable by game theory at the time of formation may not last long in a dynamic environment [4]. For instance, the emergence of new opportunities in terms of better pay-off for agents may cause a current coalition to not satisfy the pareto-optimal condition. As the result, the short-lived stability of a coalition may incur higher cost as new members need to be recruited more frequently for substitution.
- In a real world setting, agents should be allowed to join or leave a coalition at will or to join more than one coalition at a time. For example, a multi-national company may form coalitions with companies from different countries to bid for big projects around the world at the same time. Such a scenario however, contradicts the assumption made by game theory where agents can only join one coalition at a time [2].
- The social reasoning mechanism based on dependency theory by the complementary-based model requires each agent to maintain explicit models of all other agents in the community [3]. This is very costly in terms of information maintenance and storage, especially in an open environment where the number of agents is enormous and fluctuates over time.
- Apart from that, the identification of potential coalition members by referring to the agent models that an agent has, as in the social reasoning mechanism, does not provide a viable 'entry point' for new agents that intend to form coalitions and which have yet to have any knowledge about other agents in the community.

Therefore, in our work, we aim to achieve following objectives:

- To design a robust and cost-effective mechanism to search for potential coalition members. Agents possessing skill and experience in specific fields must be made accessible for identification by other agents at minimum cost.
- To devise a reliable tool to form stable coalitions in a dynamically changing environment. Consistent and highly credible agents must be easily identified as they are more committed to stay longer in a coalition.

Bearing the above objectives, we propose the following solutions:

- *Leveraging on an agent's long-term credibility trend for coalition member selection*: When taking the long term prospect, the agent's payoff and coalition's benefit should not be the only factors determining the stability of a coalition, not to mention in a dynamically changing environment. Rather, we contend that the credibility of an agent, that encompasses qualities such as reliability, trust, commitment, skill, experience and many others that one may deem important for the achievement of a goal but hard to be quantified, is playing an equivalently important role, if not more [5][6]. Consequently, when the credibility factor is taken into account in addition to the monetary factor as in game theory, the risk of suffering from coalition instability would then be equally distributed.

- *Providing a public and thus centralised facility for the community of agents to search for potential coalition members in addition to their personally established social network*: By doing so, we would be able to (1) lessen the storage burden that each agent has to bear in maintaining the models of all agents in the community as only information of certain agents that are deemed important will be kept, (2) allow new agents that have no knowledge about others, i.e. empty personal social network or allow agents with limited or inadequate personal social networks to utilise the public facility for potential coalition member recommendation, and (3) allow an agent to either select its preferred coalition partners or recommend them to other agents after its personal social network is established over time in the community.

The remainder of this paper is structured as follows. Section II summarises the specific approaches adopted in the utility-based and complementary-based CF models, as well as a trust-based CF approach. The methodology of our approach is then presented in Section III followed by a detailed discussion of the relevant concepts in Section IV. We then conclude the paper with a brief outlook on future work in Section V.

II. RELATED WORK

Utility-based coalition formation methods aim at building stable coalitions. Many coalition formation algorithms today rely on chosen game-theoretic concepts for pay-off division within coalitions. The Shapley-value [4] payoff division method is calculated by looking at the order in which a coalition could have been formed and the individual coalition member's averaged marginal contribution across all the different formation possibilities. The Core [3] payoff division method entails allocations in cooperative games in such a way where no subgroup within a coalition can do better by deserting the coalition. The Kernel [7] payoff division method avoids forming any coalition containing an agent that can actually obtain more payoff when another agent within the same coalition is removed but without the corresponding payoff being reduced.

Apart from the utility-based models, there is a complementary-based model that makes use of dependence-theory, i.e. social reasoning mechanism [1]. In this model, an agent is required to calculate its dependency on other agents in order to identify whether its goals are achievable and plans are feasible. An agent is said to be dependent on another if the latter can help/prevent him to achieve one of its goals. To do this, an agent needs to have a complete and correct representation of each other so that agents that are more susceptible to accept a proposition of coalition can be identified and thus coalesced.

In addition to payoff division and agent-dependency, trust relationship has also been identified as another crucial factor in determining the success of a coalition. The trust-based coalition formation mechanism [8] extends the concept of temporary coalitions to long-term coalitions formed by both customers and vendors based on their current trust evaluation on each other. This mechanism is shown to bring stability to the system (in the number of coalitions and in the overall dynamics) as well as provide the customer agents increased benefits after a period of time. The mechanism also reduces the communication overhead between agents that subsequently makes it scalable for large numbers of agents and interactions.

III. MEDTHODOLOGY

The research efforts for this paper were centred on the task of forming coalitions in an open environment constituted by autonomous agents, in particular (a) the search for potential coalition members, (b) the selection of credible agents to form coalitions, and (c) the credibility assessment of coalition members. Figure 1 illustrates our research methodology followed by the tenets of our proposed strategy for coalition formation.

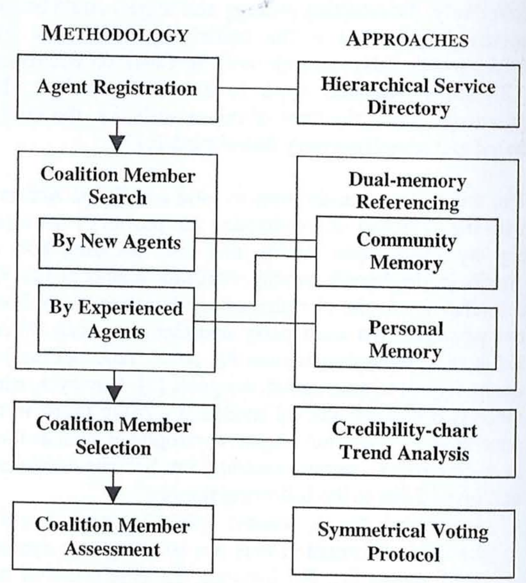

Figure 1. Research methodology

1. *Registration of newcomers*: Agents that wish to join a community must register its services to a public facility called the *hierarchical service directory*. An agent is allowed to register more than one services that it can provide to the community.
2. *Potential coalition member search*: When an agent has a goal that it cannot achieve alone, it must form a coalition and search for the potential members in the community. The search mode is dependent on the agent's personal social network, i.e. *personal memory*. If the agent is a newcomer and its personal memory is empty, then it must seek recommendations from the *community memory*. On the other hand, if that agent has past coalition experience with other agents and its personal memory is populated, it can then directly reach the agents which it knows can provide the required services. In cases where the personal memory is insufficient to cover all the agents, it can still turn to the community memory for help.
3. *Coalition member selection*: Having identified potential agents that could provide the necessary services, the selection of the final agents to form a coalition will be done by analysing the long-term trend of their *credibility charts*.
4. *Coalition member assessment*: Members in a coalition are given opportunities to evaluate each other under certain conditions using the *symmetrical voting protocol*. As a way to encourage the agents to take part in the assessment, the evaluation process is made easy by requiring the agents to answer only one simple yet comprehensive question.

IV. RELEVANT CONCEPTS

In this section, the relevant concepts mentioned in the methodology, namely the hierarchical service directory, the personal and community memories, credibility-chart trend analysis and symmetrical voting protocol will be further discussed.

Hierarchical Service Directory

This directory is a hierarchical structure reflecting the actual organisation and classification of services that exist in the real world, from the most generic to the most specific. For each category of services, agents offering the relevant services are kept and sorted by the disciplinary weight they have. The disciplinary weight ranges from 0 to 1 and indicates how well-versed the corresponding agent is in that particular category of service and it is independent on the number of services being offered by each agent. The resulting service directory is meant as a database to support the functioning of the community memory.

Dual-memory Referencing

When an agent in a community has a goal, where the plan to achieve that goal makes it dependent on other agents, there are two possible ways that it can get to the necessary agents, i.e. by referring to the personal memory or the community memory.

- *Personal memory*: Each agent has a personal memory populated with information of the top n most credible/awful agents in the community that it has coalesced with before. Among the information of agents captured here are the details of how to reach them when their services are needed and their respective credibility-charts constructed from a series of past coalescing experience via the symmetrical voting protocol. As such, the personal memory that expands from time to time would act as a social network to help an agent to (1) reach its preferred agents faster for future coalitions, (2) avoid coalescing with the same poor-performing agents again, (3) reduce the size and thus the cost of storage as the number of agents in the memory has been capped, and (4) enable agents to recommend their favourite agents to other agents that have failed to get the necessary agents from their own personal and community memory. For agents that have newly joined a community, they are assumed to have an empty personal memory.
- *Community memory*: This is a centralised repository storing information of services offered by all agents in the community and their respective credibility-charts. This memory is accessible by those who have insufficient knowledge about the services offered by the community of agents and their respective credibility valuations. Thus, for new agents, the community memory would serve as an 'entry point' to look for the necessary agents should a coalition is to be formed. On the other hand, for agents whose personal memory failed to facilitate the search for the necessary agents due to insufficient social network coverage, the community memory would provide a viable alternative to do so. With the community memory, agents that are in need of services from others would know where to obtain them and this will significantly decrease communicational and computational costs when searching for agents in a large community [9]. Furthermore, it also reduces the individual agent's memory requirement and avoids data redundancy by having a centralised repository.

Credibility-chart Trend Analysis

By analysing an agent's long-term credibility-chart (see Figure 2), the direction in which the agent's credibility is heading to can be easily recognised. In this way, agents charting a credibility downtrend can be identified and subsequently discarded even when their current credibility valuation is positive. This is to avoid from recruiting coalition members with decreasing credibility that would threaten the long-term stability of the coalition. On the contrary, agents with increasing or at least consistently positive credibility would be highly sought after for forming a coalition. This method, that provides an overview of the course of the agents' credibility, would offer a more accurate solution for selecting coalition members in comparison to methods that are merely based on a current value [8].

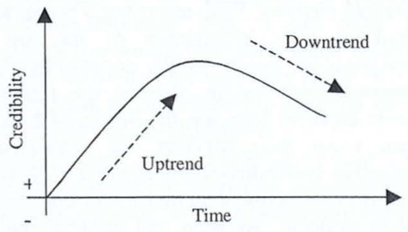

Figure 2. Positive credibility but with downtrend

In addition to that, by selecting agents with increasing or consistently positive credibility valuation, it is anticipated that the ultimate coalition formed would be able to last longer or suffer from a lower turnover rate at most. Consequently, the cost of advertising and searching for replacement agents would be cut down substantially.

Symmetrical Voting Protocol
By symmetrical voting, whenever an agent initiates a vote casting exercise on another agent, the other agent would be allowed to cast a vote in return on the initiating agent. The vote carries an answer rating that ranges from -1 to 1 for the question: "Would you like to work with [agent name] again?" with -1 indicating the unlikeliness and 1 the otherwise. For every vote being cast, it will be updated and reflected on the corresponding agent's credibility-chart that resides in the voting agent's personal and community memory.

There are three conditions that would allow an agent to initiate a vote:

- *When the common goal of the coalition is achieved*: Coalition members would cast their votes to reflect their latest credibility valuation on each other.
- *When a coalition is deserted by an agent*: An agent can leave a coalition if it does not get along well with the coalition or receives a better offer from other coalitions.
- *When an agent is discarded from a coalition*: An agent can be discarded by a coalition if the majority of the coalition members agree to do so.

V. CONCLUSION

In this paper, we reviewed the application of game theory, dependency theory and trust relationship between agents in coalition formation. We realise the importance of selecting coalition members not based only on the current valuation but also the credibility trend it is in if an efficient and long-lasting coalition is desired. In order to do this, we proposed the analysis of long-term credibility charts of agents. Also, we have highlighted the significance of having more than one medium to facilitate the search of potential coalition members. To enable this, a dual-memory referencing mechanism is presented. Here, the idea is to introduce a new mechanism to search, select and evaluate potential coalition members based on information kept in the community memory and the individual agent's personal memory. The motivation for this approach is to save computational resources and to gain coalition formation robustness. By selecting members based on the agents' long-term credibility trend, we expect the eventual coalitions to be more stable, cost-effective and competent in achieving its goals.

We plan to implement this new mechanism in a Java-based multi-agent system. Methods for evaluating the agents' benefits in terms of cost and time are being developed. Experiments for verifying and analysing the coalition's stability are also planned. Meanwhile, we envisage that the proposed techniques would lead towards more effective and efficient coalition formation systems.

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APPENDIX B: APPLICATION SCREENSHOTS

KNOWLEDGE-BASED HEATLHCARE COALITION FORMATION TOOL

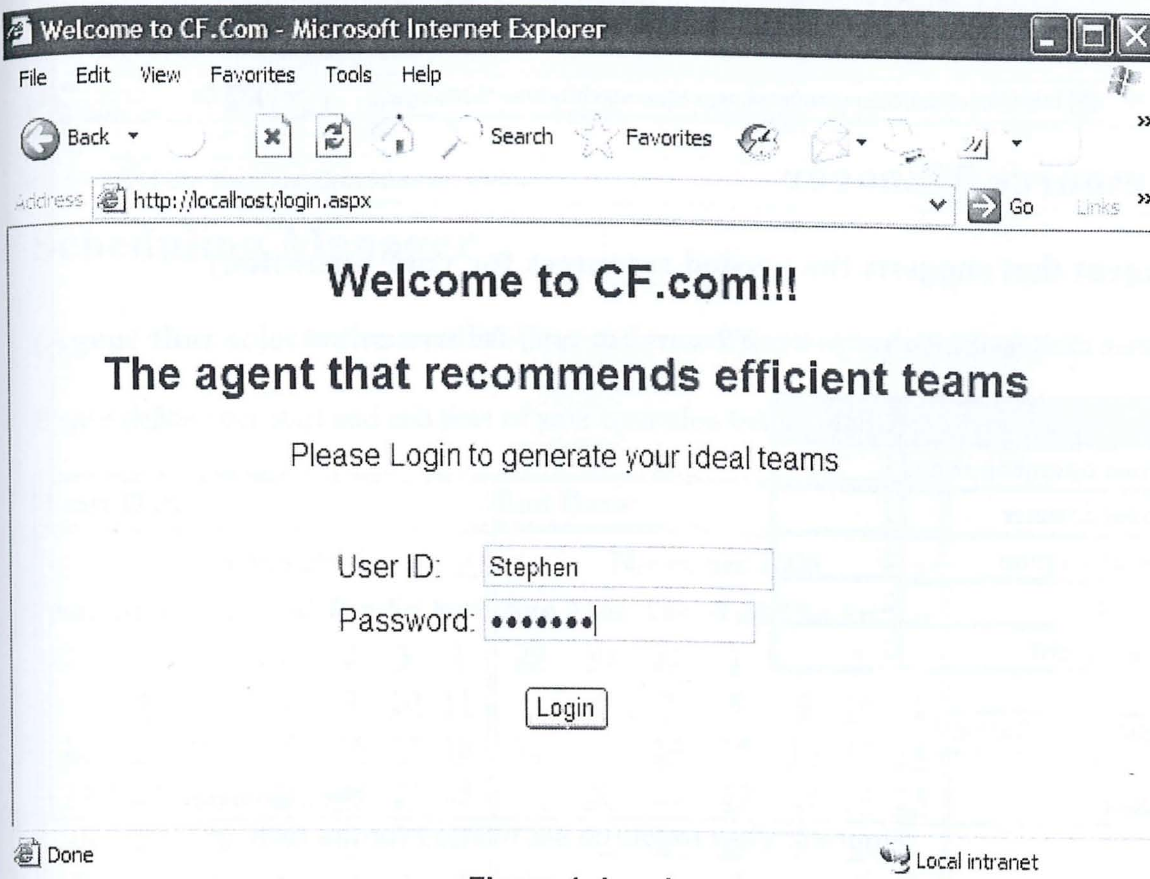


Figure 1: Log-in screen

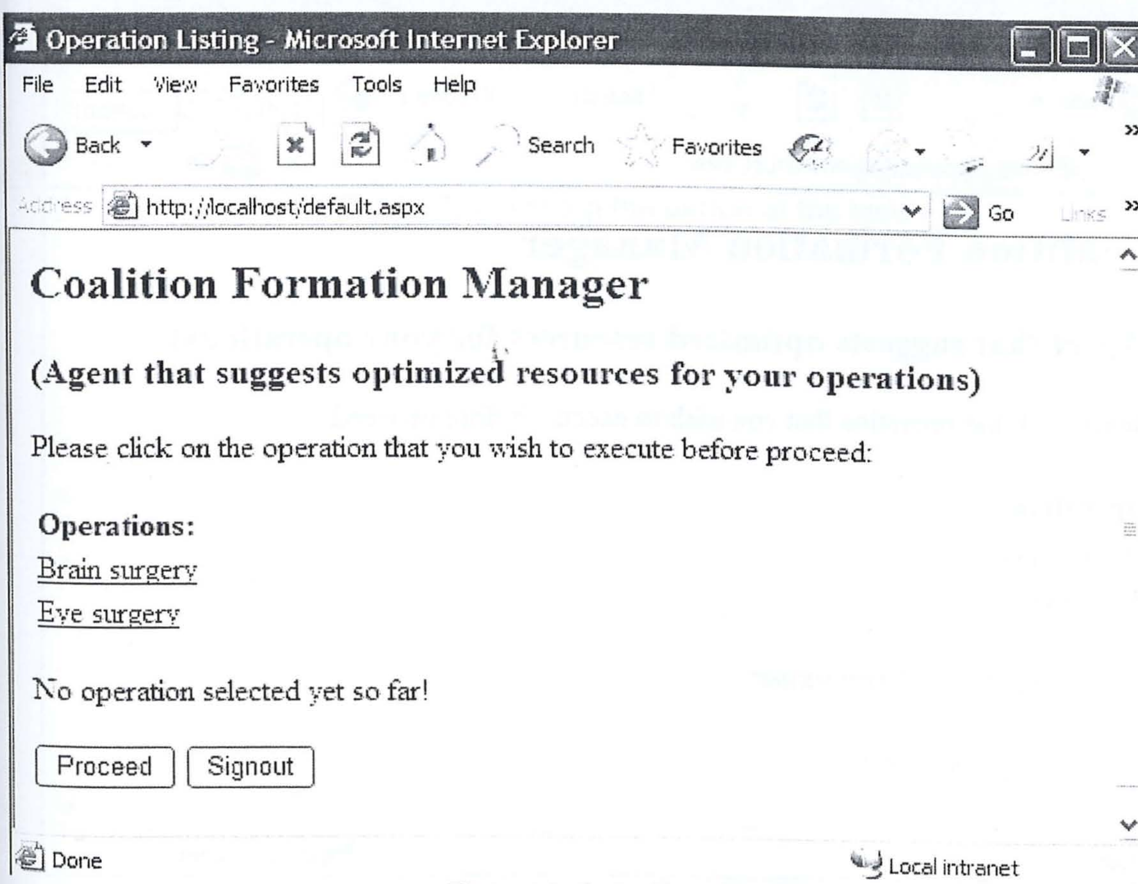


Figure 2: Selection of task

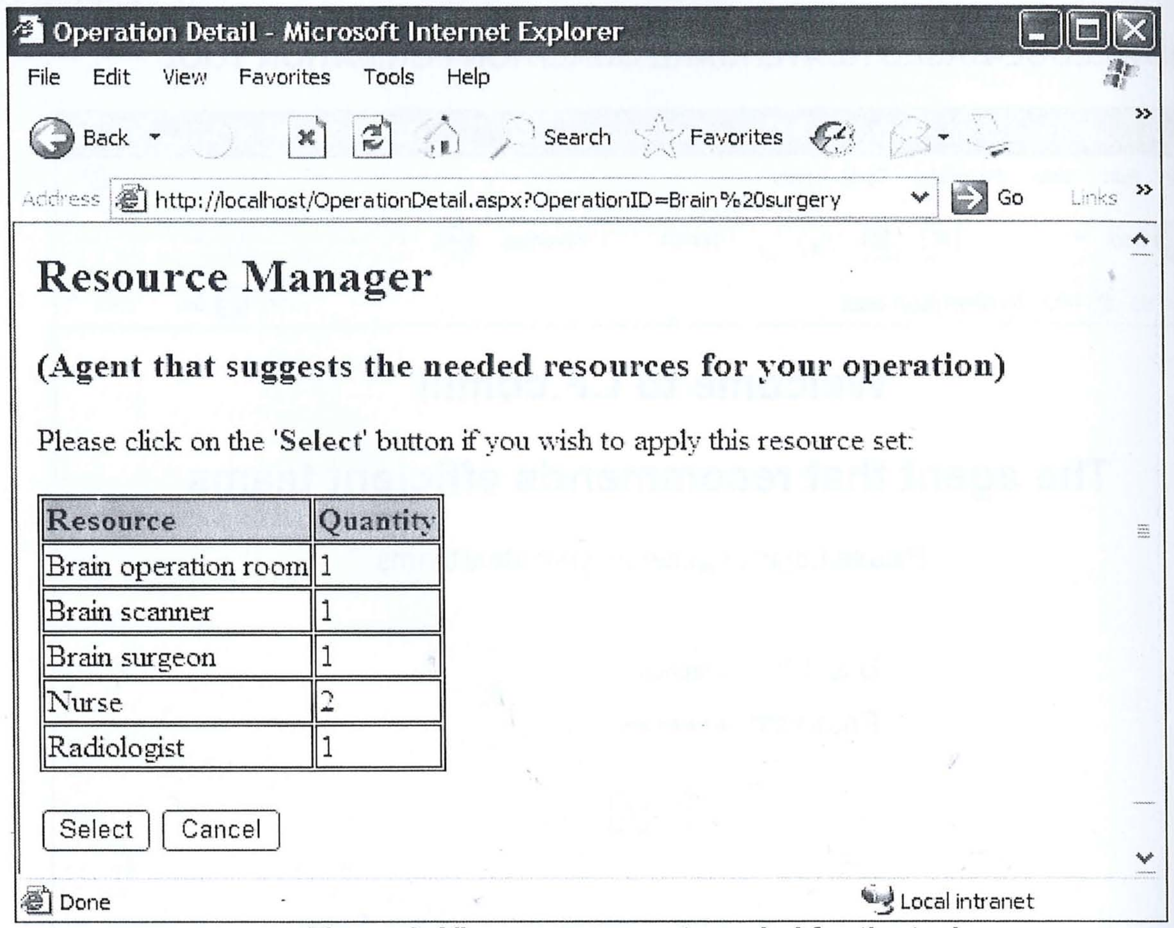


Figure 3: View resource set needed for the task

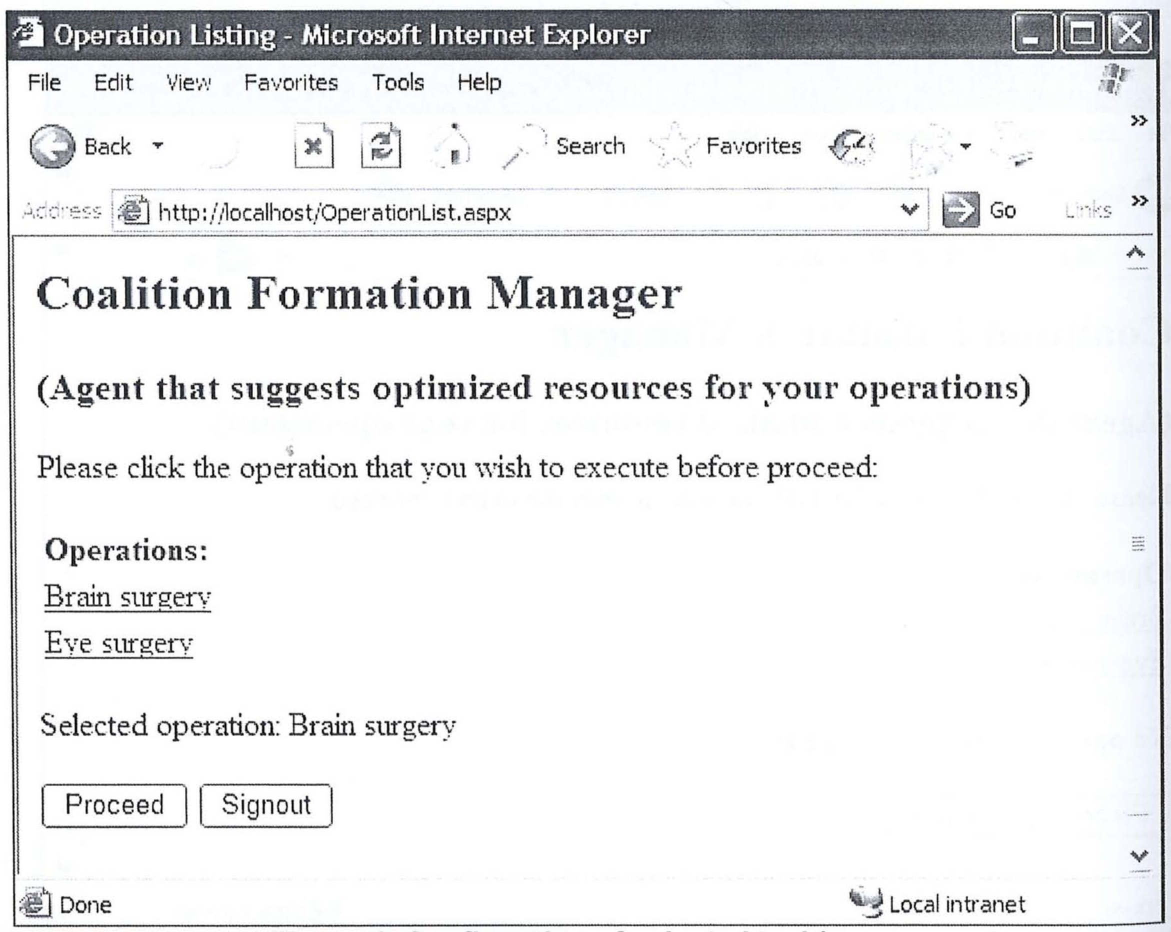


Figure 4: Confirmation of selected task/resource set

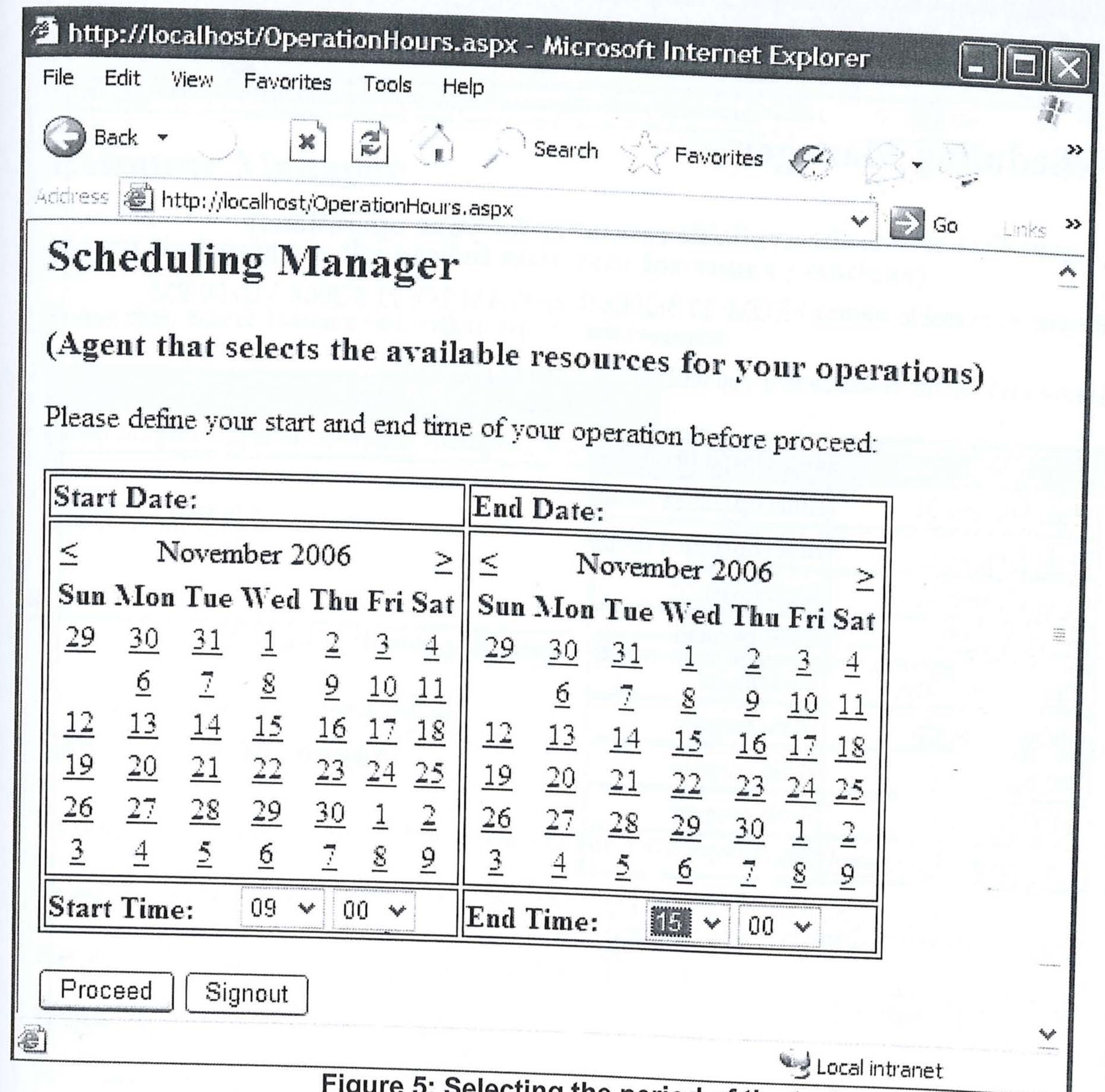


Figure 5: Selecting the period of the task

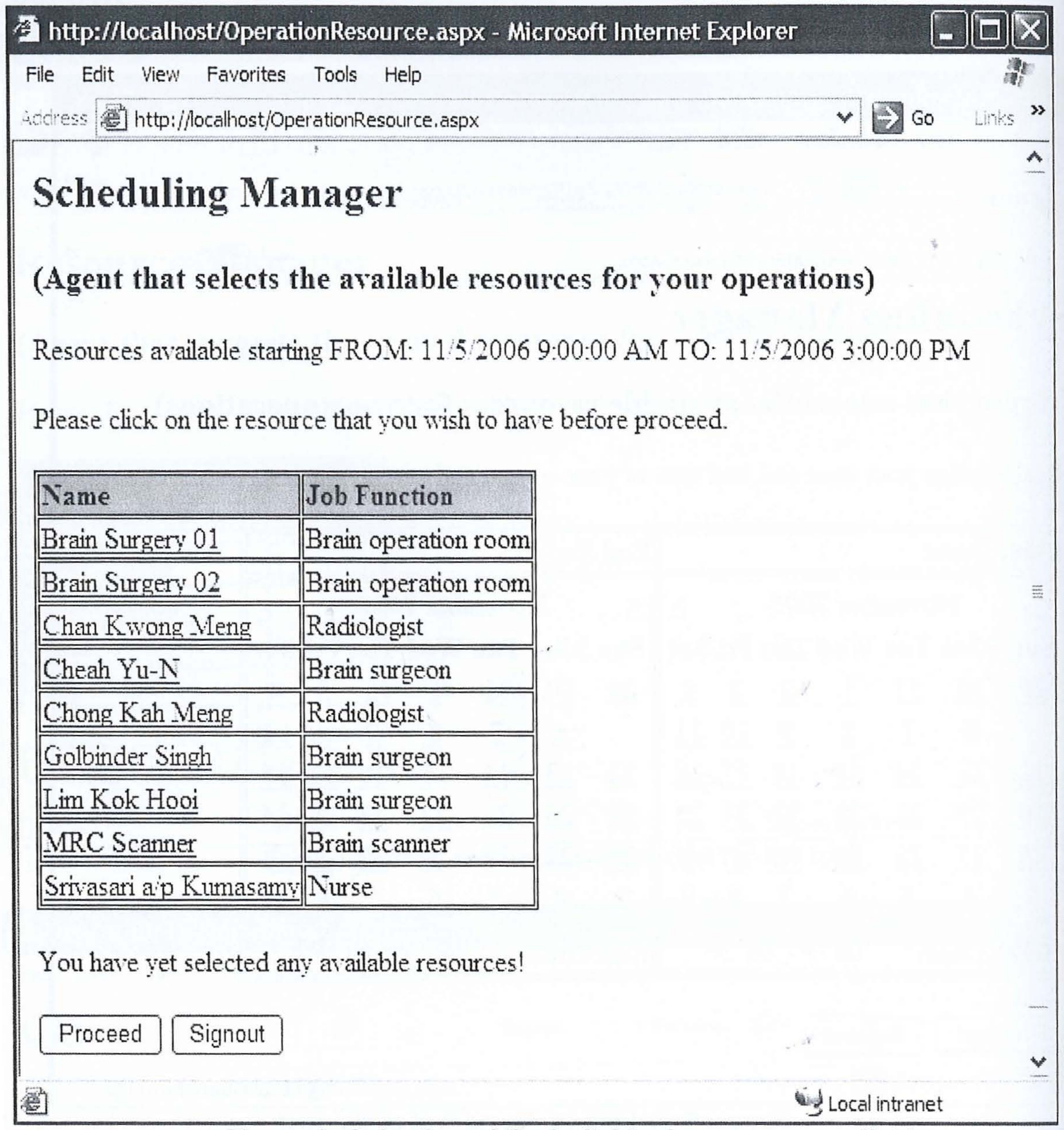


Figure 6: Selection of the individual resources available

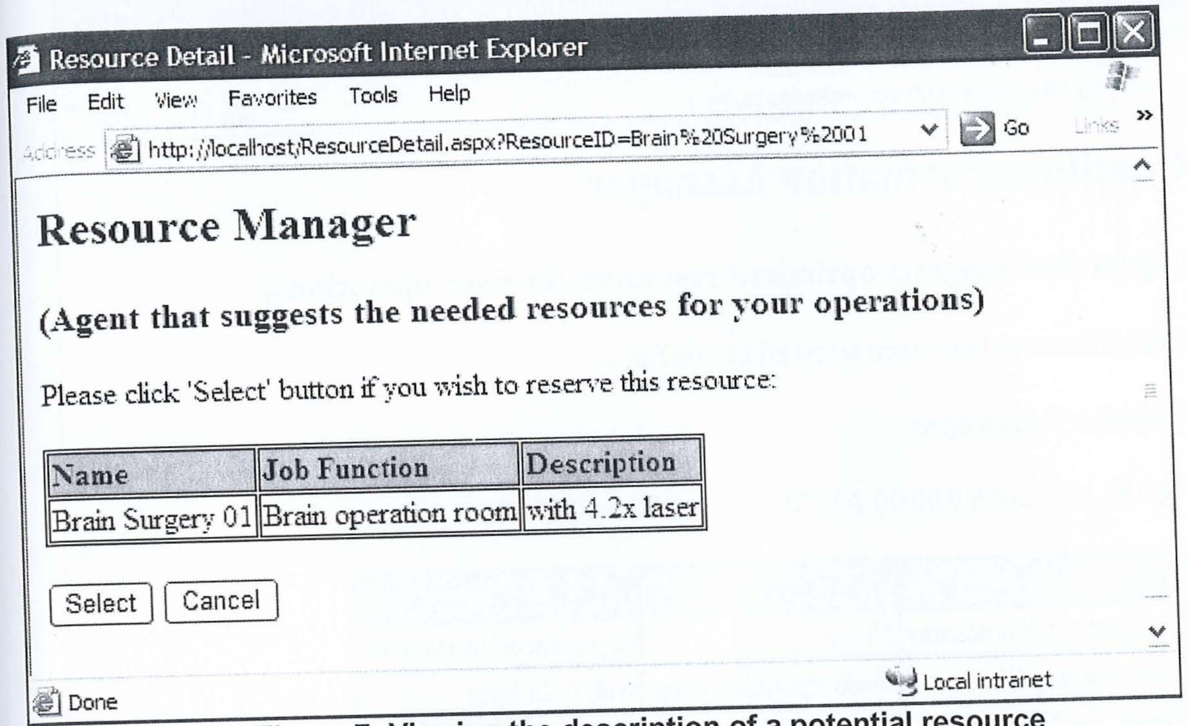


Figure 7: Viewing the description of a potential resource

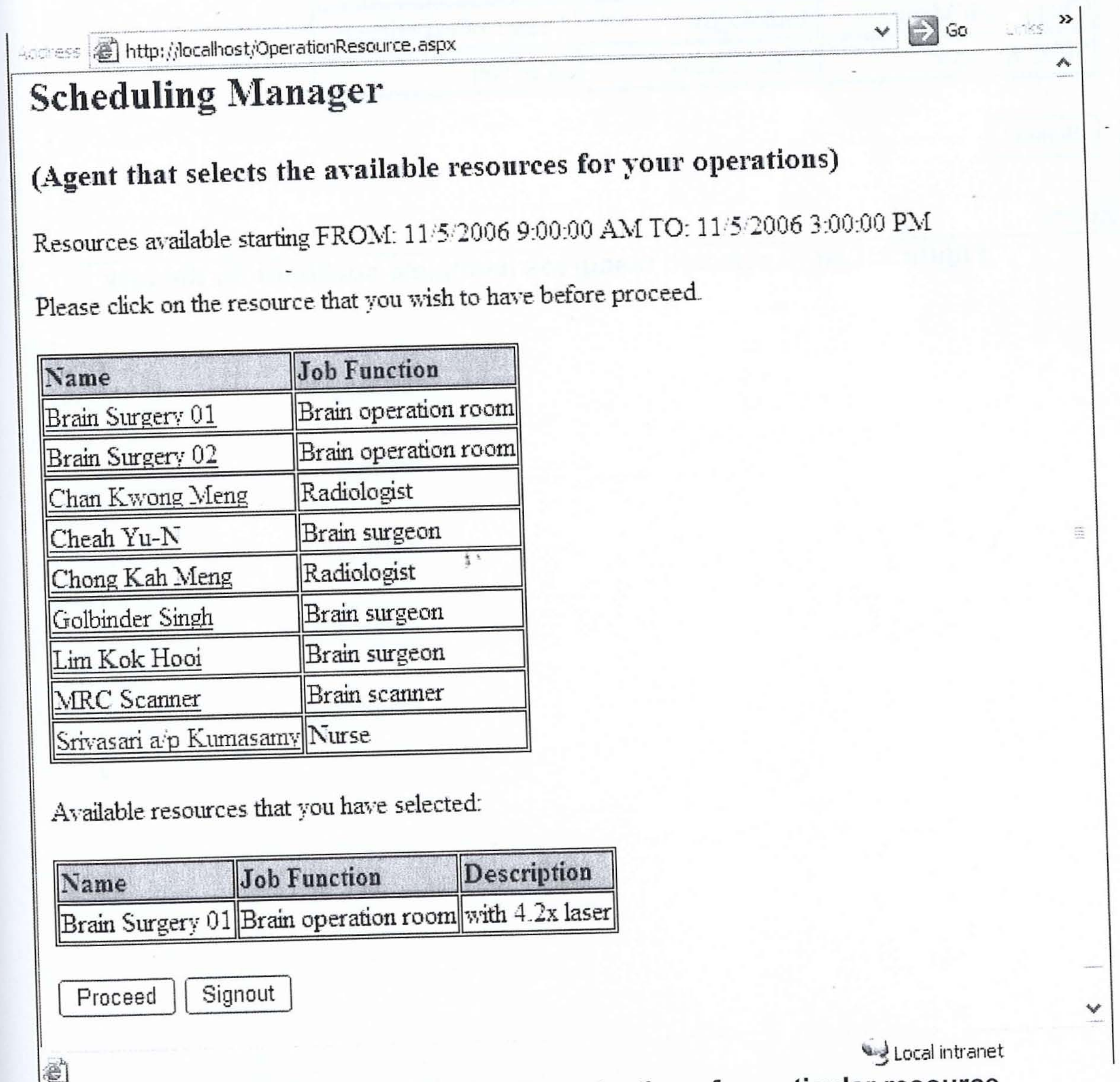
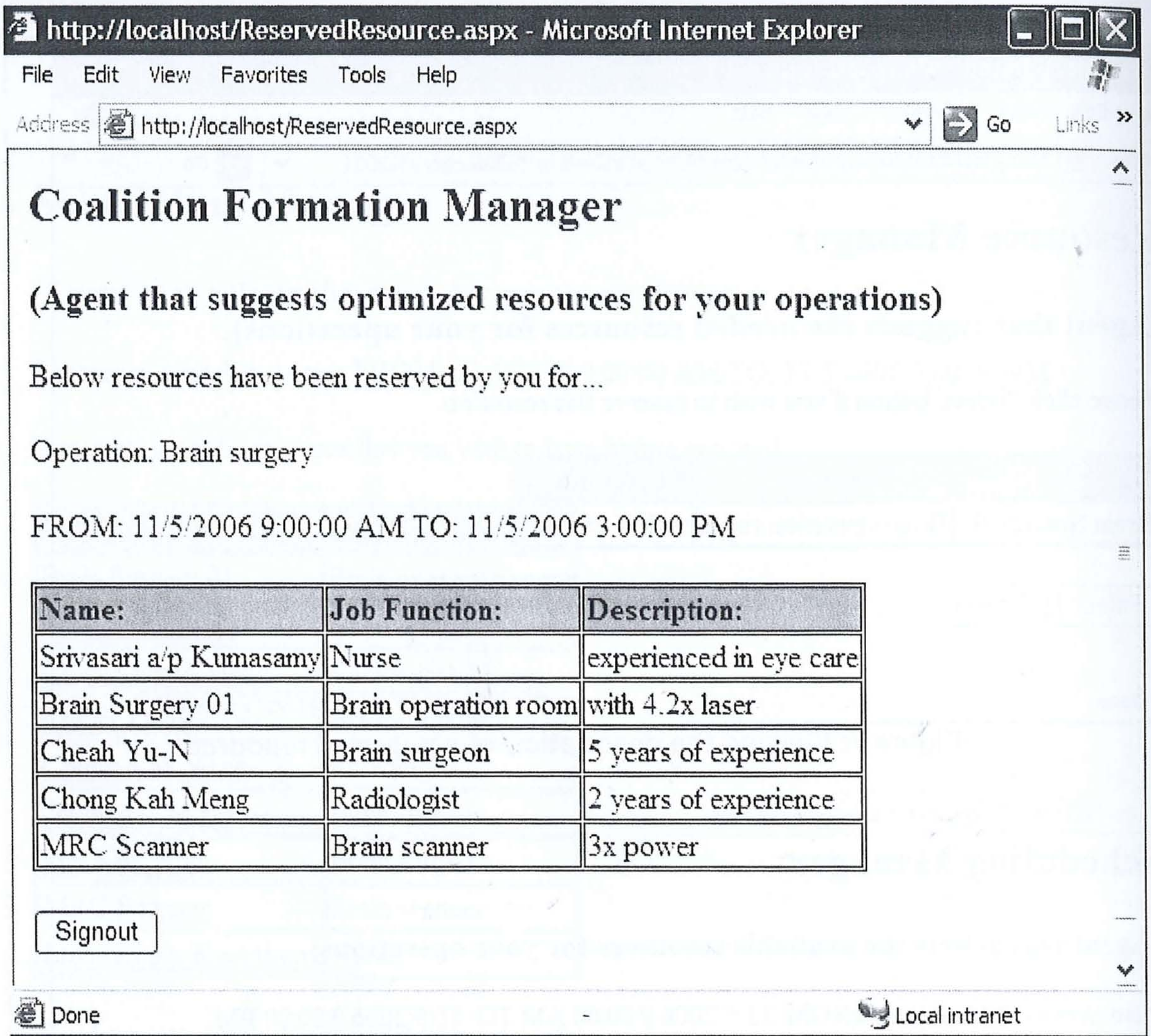


Figure 8: Confirming the selection of a particular resource



Coalition Formation Manager

(Agent that suggests optimized resources for your operations)

Below resources have been reserved by you for...

Operation: Brain surgery

FROM: 11/5/2006 9:00:00 AM TO: 11/5/2006 3:00:00 PM

Name:	Job Function:	Description:
Srivasari a/p Kumasamy	Nurse	experienced in eye care
Brain Surgery 01	Brain operation room	with 4.2x laser
Cheah Yu-N	Brain surgeon	5 years of experience
Chong Kah Meng	Radiologist	2 years of experience
MRC Scanner	Brain scanner	3x power

Signout

Figure 9: List of selected resources (complete coalition) for the task