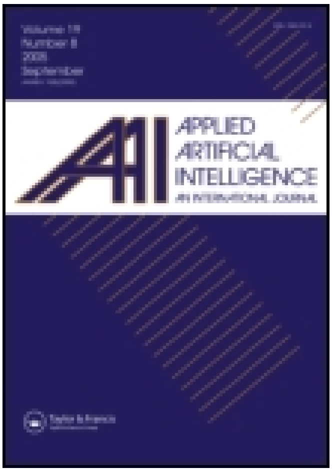

Applied Artificial Intelligence: An International Journal
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/uaai20

SELF-ORGANIZING CONTEXTUALIZED MOBILE WORKFORCE MANAGEMENT WITH COLLABORATIVE ART LEARNING

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Published online: 18 Feb 2007.

Applied Artificial Intelligence, 20:817–847

ISSN: 0883-9514 print/1087-6545 online
DOI: 10.1080/08839510600938110

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SELF-ORGANIZING CONTEXTUALIZED MOBILE WORKFORCE MANAGEMENT WITH COLLABORATIVE ART LEARNING

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□ *With the development in wireless technology and the sophistication in wireless devices, enterprising mobile workforces have grown in recent years. Mobile workforces do not work at a fixed area in a company and they have to visit customers or sell their products in public areas. Therefore, it is important for these enterprises to properly allocate their mobile workforces and leverage their collaborative cooperation. In this paper, we present a novel mechanism, named the collaborative ART learning (CART), which drives social-awareness collaboration between mobile workforces in a public area (e.g., an exhibition center). Because of the characteristics of a pubic working space, this method is situated in a wireless P2P network environment. The mobile workforce peers self-organize dynamically into appropriate collaborative work groups to accomplish tasks on demand. With CART, each peer of a task group receives adjustments of recognized capability levels after the task assigned is completed. CART learns the way to organize fitting collaborative work groups through cycles of problem solving and work force status adapting, leading to continued satisfactory collaborative performance.*

With the advancement of wireless technologies, companies are taking advantage of the efficiencies offered by these new technologies. Companies have or will have a significant number of mobile professionals (more than 20% of their work forces) that will increase from 18% to 42% within a year, and reach 57% within two years (Cutter 2001).

On the other hand, the work force of human teams are often spread among different places. Computer technology and increased network availability have enabled and improved distributed group work of collaboration. *Collaboration refers commonly to a set of participants working together to fulfill a task/service or to produce a product* (Gutwin and Greenberg 2002; Niehaus 1995). A crucial point for successful collaboration is the manner in which

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individual work is related to the group as a whole. The coordination of the contributions of the team members is an important task in supporting distributed group work.

Moreover, awareness-oriented collaboration systems is when users coordinate their work based on the knowledge of what the members of the collaborating group are doing or have done (Bannon and Schmidt 1989). For instance, work space awareness addressed recently in the computer supported cooperative work (CSCW) community (Schleicher et al. 1997; Gutwin and Greenberg 2002) involves *up-to-the-minute* knowledge about where others are working, what others are doing, etc. This information is useful for many of the activities of *real-time collaboration.*

With the rapid growth of mobile workforces the chances and, considerable that mobile work forces of a company need to work together to fulfill situated tasks (services) in real time. This problem is called *contextualized mobile workforce management (CMWM).* For instance, upon encountering a potential buyer of designated needs in a big-scale exhibition, a mobile work force can dynamically trigger the formation of a team of mobile work forces made up of myriad skills (who are at different locations in the exhibition center) to appropriately attend to the buyer in order to gain new business. In other words, *there will be a strong surge of computer and network support for real-time collaborative distributed group work between mobile work forces.*

The current state of the art in CSCW systems or awareness-oriented systems in collaboration primarily unfolds in two directions: communication support for exchanging information at the human level (Schleicher et al. 1997; Malm 1994; Ellis et al. 1991; Johansen, 1991) (as exemplified in Figure 1), and awareness support for capturing and maintaining the knowledge about the state of an environment (in which people interact with and explore the environment) bounded in time and space at the data level (Gutwin and Greenberg 2002; Neisser 1976; Adams et al. 1995; Sohlenkamp and Chwelos 1994; Smith et al. 1998; Roseman and Greenberg 1996; Kraut et al. 2002) (as indicated in Figure 2).

In dealing with the CMWM problem, the aforementioned existing works fall short on the following aspects: social awareness (Greenberg et al. 1996): the information that a person maintains about others in a social context (e.g., degree of acquaintance, their emotional state, or their level of interest, their special skills, etc.), and the mindset in supporting distributed group work (Miles et al. 1993): the approaches employed to facilitate collaboration between distributed group members (e.g., manipulation of shared artifacts).

Most existing relevant works employed a centralized mindset of supporting collaboration between distributed group members (e.g., the client-server approach in wired networks or wireless sensor networks). Consequently, the extent of social awareness that can be achieved is very

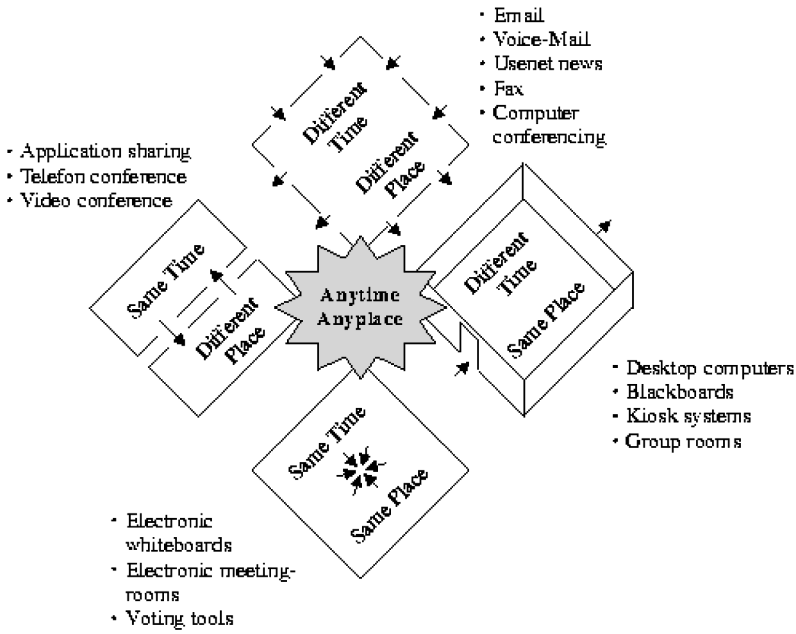

FIGURE 1 Myriad types of CSCW systems for communication support (Schleicher et al. 1997).

limited, owing to the private and individual nature of the social-awareness information. *For the CMWM problem this paper aims to provide a solution characterized by social-awareness enabled and purely distributed mindset (i.e., self-organizing) of collaboration support.*

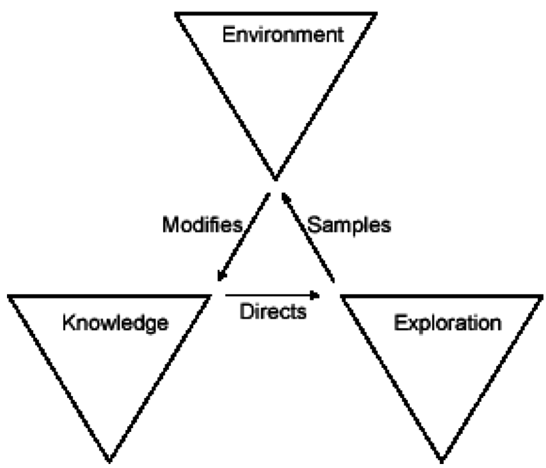

FIGURE 2 The perception-action cycle (Neisser 1976).

THE CMWM PROBLEM

In this section, the definition of the CMWM problem is formulated in terms of its universe and the parts required in the universe.

In a CMWM universe $\beta = (C_{MWS}, S, T, W, R)$, C_{MWS} denotes the collection of mobile M work forces of a company in a designated public work space; S represents a complete skill set (of which each mobile work force may embody only a portion of the N skills in the set); T indicates the company's task ontology in the work space; the $M^* N$ matrix W specifies the strength of skills the work forces embody; the $M^* M$ matrix R denotes the strength of relationships the work forces bear toward one another. The descriptions and representations of the parts of the universe are itemized as follows.

1. Mobile work forces C_{MWS}: The set of M mobile work forces in a designated public work space $C_{MWS} = \{p_1, p_2, \ldots, p_M\}$ together with their availability status.
2. Skill set S: An exhaustive collection of skills $e_1, e_2, \ldots, e_N$ required by the company in the work space.
3. Task ontology T: A taxonomy of task/subtask knowledge required in the work space, where a node of the bottom level is as scrutinized as a skill specified in the skill set. Task ontology helps the decomposition of a task (t_{input}) encountered by a mobile workforce (p_i) into a collection of subtasks $\{t_1, t_2, \ldots, t_K\}$ of different weights $h_1, h_2, \ldots, h_K$ specifying the significance of a subtask to the input task. That is, $p_i \cdot SubTask(t_{input}, T) = [t_1, t_2, \ldots, t_K]$ of the respective weights $h_1, h_2, \ldots, h_K$. Each subtask can be represented eventually as a numeric vector $X(t_j)$ of the N skills (specifying the minimum skill strengths of the N skill required for accomplishing the subtask). That is, $X(t_j) = [x_1, x_2, \ldots x_N]^T$, $x_i \in [0, 1], j = 1 \ldots k, i = 1 \ldots N$.
4. Skill strength matrix W: A collection of M numeric vectors W_j specifying the skill strengths w_{ji} of a mobile workforce p_j over the N skills $(e_1, e_2, \ldots, e_N)$, where w_{ji} is a number raging from 0 to 1 (0 and 1, respectively, represent the minimum and the maximum strength of the designated skill). That is, $W(p_j) = W_j = [w_{j1}, w_{j2}, \ldots w_{jN}]^T, w_{ji} \in [0, 1], j = 1 \ldots M, i = 1 \ldots N$.
5. Relation strength matrix R: An $M^* M$ matrix *of* which an element r_{ji} denotes the relationship strength p_j bears toward p_i. The factors considered in r_{ji} can include their degree of acquaintance, p_j's knowledge of the emotional state of p_i, p_j's knowledge of the level of interest of p_i, p_j's knowledge of the skills of p_i, etc.[1] In this paper we do not model the required factors but presume the existence of the relation strength matrix R that would affect the teaming results when p_i encounters a

task request and seeks potential partnerships to accomplish the given task request.

Given the universeβ, the goal of a CMWM problem is to find nearly fittest allocations of mobile work forces for input tasks encountered dynamically by mobile work forces scattering around in a public workspace.

A SOLUTION WITH THE COLLABORATIVE ART LEARNING MECHANISM

Given a CMWM universeβ, this section presents a solution to the problem that is a combination of a wireless peer-to-peer infrastructure that enables self-organizing and a collaborative ART learning approach that generates nearly fittest groups.

The Concepts

The proposed solution to a given CMWM problem is to equip each mobile workforce peer with four functionalities (task managing, peer matching, peer self-organizing, and capability adjusting). Task managing is responsible for decomposing an input task request into a collection of subtasks and delegating the search of the fitting peers to accomplish the subtasks to a certain number of peers. Peer matching is then in charge of the search of winners of fitting peers for a given subtask. Peer self-organizing determines a team of the fittest peers out of those winners associated with the subtasks. Capability adjusting updates the relation strength matrix according to the team's performance.

The execution of each functionality is triggered by the contemporary role played by a peer. There are three types of roles modeled[2] (as shown in Figure 3): *initiator*: a peer that encounters a task request t_{input} in the first place and decomposes the task into a collection of subtasks $t_1, t_2, \ldots, t_K$ (i.e., task managing), determines the fittest peers for accomplishing the subtasks (i.e., peer self-organizing), and accordingly updates its relation strength matrix after the execution of the subtasks (i.e., capability adjusting); (2) *dispatcher*: a peer that is in charge of the search of the winners of the fittest peers for a subtask t_i (i.e., peer matching); and (3) *participant*: any of the mobile work forces p_j in the work space available for the execution of a subtask. A work force, however, can simultaneously assume multiple roles (if necessary).

Each peer can dynamically assume each of the three roles as demanded based on the current status of the work space and its knowledge of social awareness. This is a purely distributed mindset (i.e., wireless peer-to-peer) bearing with social awareness for collaboration support.

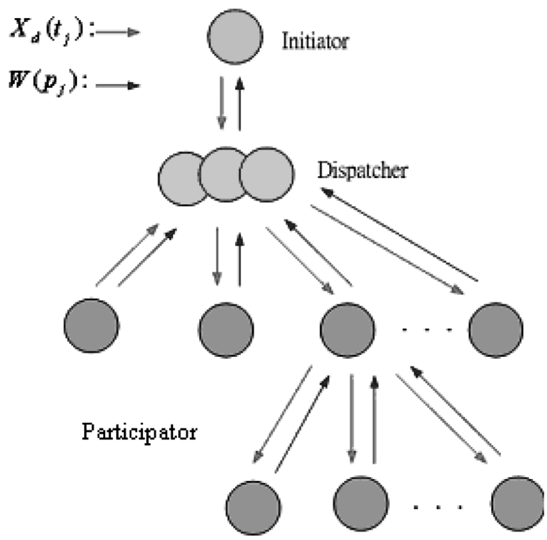

FIGURE 3 The role structure.

Collaborative ART Learning

The four functionalities addressed previously constitute our solution—the collaborative ART learning mechanism (which we'll call CART hereafter). In this section, we briefly review the past research on adaptive resonance theory (ART). In our research, we extend ART by considering peer neurons interrelated interactions and relationships, advancing into a collaborative version of ART (i.e., CART).

ART

The ART network (Grossberg 1976; Carpenter 1977; Carpenter et al. 1992) is a self-organizing network and is based on a "winner-takes-all" competitive principle. It has unsupervised learning ability and adaptive ability for data clustering. ART adapts itself by storing input patterns, and tries to match best the input pattern being fed in at the time. ART is one of the features such as real-time learning, fast adaptive search for best match, etc.

For applications of ART, a work (Jiang and Mair 2002) presented an organizational network for product configuration management within the context of virtual enterprises. In the work, actors can advertise their own skill and knowledge and seek for partners to form dynamic alliances in a community. The connections between different actors who are seeking for partnership are adjusted based on ART so that the management network can exhibit unsupervised learning ability, adaptive ability, and competitive ability. Working in this way virtual enterprises can evolve dynamically and force to improve product quality of each actor and organizational performance of partnerships.

Although inspired by the work (Jiang and Mair 2002), our research makes important advancements with CART. In our research a wide scope of factors are considered in seeking partnerships (such as mobile work force's availability status and social awareness, in addition to their skills), unlike Jiang and Mair (2002), in which only one factor (work force skills) was considered. Moreover, the approach of Jiang and Mair (2002) would result in the same team of work forces (of the best skills) repetitively working on multiple incoming task requests, leaving other work forces idle and, consequently, wasting human resources. *On the contrary, our solution copes with the reality by taking into account the practical factors occurring in a work space and utilizing the work force to a greater extent.*

CART

CART differs from ART mainly in two ways: it relaxes the "winner-takes-all" principle by allowing for multiple winners during each matching, and partner seeking is subsequently accomplished through a heuristic process of collaboration-driven self-organizing given multiple sets of winners, generating nearly fittest groups for tasks.

In this section, the descriptions of CART are unfolded in terms of the presentations of the four functionalities (task managing, peer matching, peer self-organizing, capability adjusting) itemized as follows (assuming a universe β of the CMWM problem is provided as addressed earlier).

- **Task managing**: With task ontology of β, when a mobile workforce p_i (initiator) encounters an input task request (t_{input}), as shown in Figure 4 Task Managing of p_i decomposes t_{input} into a collection of subtasks $\{t_1, t_2, \ldots, t_K\}$, i.e., $p_i \cdot SubTask(t_{input}, T) = [t_1, t_2, \ldots, t_K]$. Each subtask is represented as a numeric vector $X(t_j)$ of the N skills (specifying the minimum skill strengths of the N skill required for accomplishing the subtasks). *With the relationship factor in the relation strength matrix of β, the*

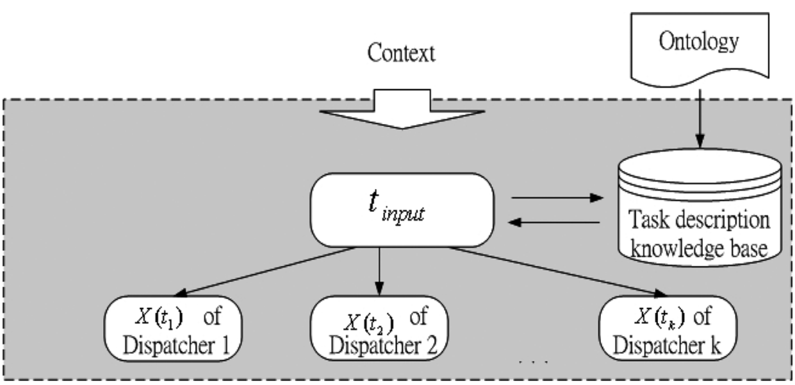

FIGURE 4 The process of task managing.

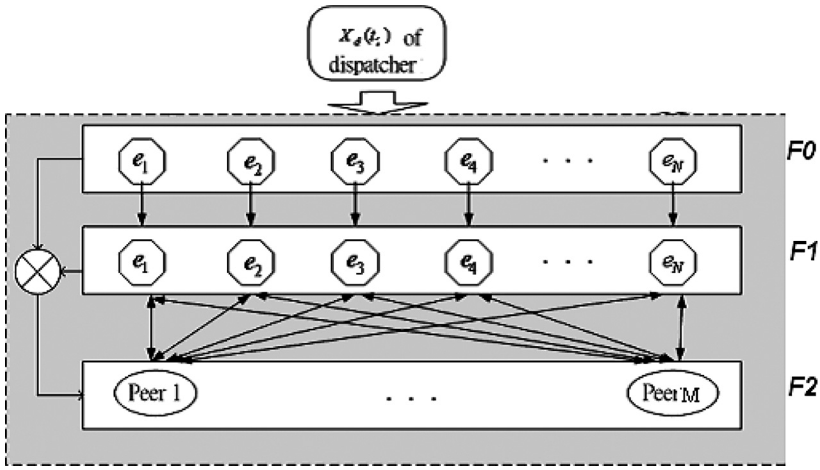

FIGURE 5 The process of peer matching.

search of fitting peers for performing the subtasks is then delegated to K appropriate peers[3] *(dispatchers).*

- **Peer matching**: As shown in Figure 5, a three-layers ART network (similar to the one addressed in Jiang and Mair [2002]) is employed by a dispatched peer to search for fitting candidates for its delegated subtask. The layers F0, F1, and F2 are the input layer, comparison layer, and recognition layer, respectively. The input layer F0 receives a demand $Xd(ti)$ from an initiator. The skill capability of each participator (*provided by β at the beginning and attained from its relation strength matrix afterward*) is accessible in the comparison layer F1 for competence comparison. A competitive process conducted is subsequently by examining the degree of match between the layer F0 and the layer F1 of a participator. If the degree of match between the demand and the capability is higher than a vigilance criterion, the participator that fits the subtask is found and qualified as a winner for the subtask.

The required searching steps in peer matching are similar to Jiang and Mair (2002) (but with a slight revision in Step 2) as shown as follows.

1. Calculate $T_j = \frac{|X_d \wedge W_j|}{\alpha + |W_j|}$ for each Participator p_j (W_j is attained from the skill strength matrix of βat the beginning or the relationship strength matrix afterward), where α is a positive integer number called the choice parameter (in prevention of the denominator being zero), $X_d \wedge W_j$ is a vector of which the i_{th}component is equal to the minimum of X_d and W_j, and $|\cdot|$ is the norm of a vector, which is defined to be the sum of its components. In other words, *the comparison layer F1 attempts to classify the subtask into one of the participators in the recognition layer F2 based on its similarity to the skill capability of each participator recognized.*

2. Find participators of the top nc^4 T_j values as the winner candidates. (This is different from the past ART works in which the participator with the maximum T_j value in the layer F2 will be selected as the only winner for the subtask, i.e., winner-takes-all competition).
3. Examine if $SIM_{dj} = \frac{|X_d \wedge W_j|}{|X_d|} \geq \rho, j = 1 \ldots nc$, where $\rho \in [0, 1]$ is the vigilance parameter set by the initiator. In other words, *the skill capability of a winner candidate is sent back to the layer F1 for examining if the similarity between the winner candidate's capability and the required capability is above the vigilance criterion.* A winner candidate is considered as a winner only if it satisfies the vigilance test and thus it is possible to have multiple winners (say m winners).

- **Peer self-organizing**: After receiving K sets of m winners from the K dispatchers, an initiator needs to accordingly, arrange a fittest group of peers that can accomplish the designated k subtasks of t_{input}. In the search for such a fittest group, it might involve a complexity of $O(m^K)$ in the worst case. Accordingly, *CART employs a heuristic to find this fittest group effectively.* The heuristic is detailed as shown in Figure 6 and described as follows.

1. Calculate $\overline{SIM}_i = \frac{SIM_{i1} + SIM_{i2} + \ldots + SIM_{im}}{m}, i = 1 \ldots K$, where $SIM_{i1}, SIM_{i2}, \ldots SIM_{im}$, respectively, denote the vigilance test values of the winners (there are at most m winners) for subtask t_i. ($\overline{SIM}_i$ accordingly indicates the average quality of the m winners associated with the subtask t_i).
2. Self-organize a test group (i.e., a test winner from each winner set associated with t_i) in the following way (also as shown in Figure 6).

   - Calculate $h_I = \frac{h_1 + h_2 + h_3 + \ldots + h_k}{k}$, where $h_1, h_2, \ldots, h_K$ denotes the weights associated with the subtasks $t_1, t_2, \ldots, t_K$ in the first place from task ontology. (h_I then suggests the average expectation of the subtasks.)

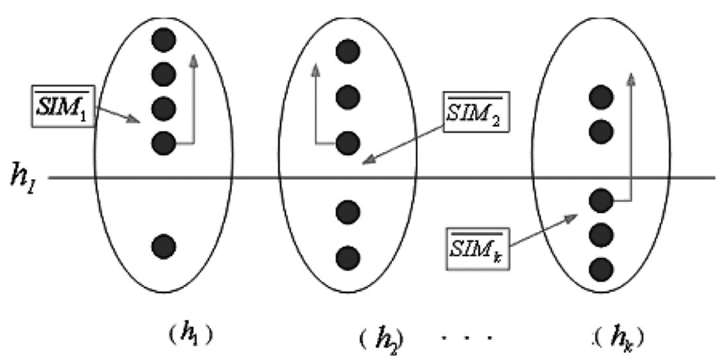

FIGURE 6 The selection of a test winner.

- Select a test winner starting from one of the SIM_{ij} values closest to h_I and greater than h_I (and move in the direction of choices of greater values), if $\overline{SIM}_i > h_I$. (That is, effective and reasonable selections begin with ones that are close to the average expectation.)
- Select a test winner starting from one of the SIM_{ij} values closest to h_I and less than h_I (and move in the direction of choices of greater values), if $\overline{SIM}_i < h_I$. (That is, effective and reasonable selections begin with ones that are close to the average expectation.)
- Rank the selections of the test winners according to the weights of $h_1, h_2, \ldots, h_K$(a bigger weight implies a greater degree of significance in selecting a test winner) and perform the selections in the order specified by the rank.

3. Calculate the fitting value of the test group.
   - Compute $net = \sum_{i=0}^{k} h_i < p_{test}^i >$, where $< p_{test}^i >$ represents the vigilance test value of the test winner p_{test}^i associated with the subtask t_i.
   - Compute $P_o = \frac{1}{1+e^{-net}}$, where $P_o \in [0, 1]$ denotes the fitting value of the test group.

4. Examine if the fitting value of the test group is satisfied (assuming P_h is a fitting threshold set by the initiator).
   - If $P_o \geq P_h$ (i.e., the test group is satisfied), output the fittest group $[p_{OG}^1, p_{OG}^2, \ldots, P_{OG}^k] = [p_{test}^1, p_{test}^2, \ldots, p_{test}^k]$.
   - If $P_o < P_h$, (i.e., the test group is not satisfied), repeat from Step (2).

- **Capability adjusting**: After those subtasks are accomplished by the fitting group $[p_{OG}^1, p_{OG}^2, \ldots, P_{OG}^k]$, the initiator is assumed to evaluate the group by a realistic performance score P_t. With this realistic score, a method of credit assignment is then exerted to adjust the initiator's understanding of the capabilities of the group members. The method is outlined as shown in Figure 7 and detailed as follows.

1. Compute the error function $E(\vec{h}) \equiv \frac{1}{2}(P_t - P_o)^2$, where P_o and P_t denote the expected performance and the realistic performance, respectively.
2. Perform gradient descent on the error function in order to decide the credits of $h_1, h_2, \ldots, h_K$ with respect to the given error, that is, $h_i \leftarrow h_i + \Delta h_i$ and $\Delta h_i = -\eta \frac{\partial E}{\partial h_i} = \eta(P_t - P_o)P_o(1 - P_o) < p_{OG}^i >$. (Please see the Appendix for detailed formula derivation.)
3. Compute the capability adjustments $W_i^{new} = W_i^{old} + l\beta_j X_d$, where $l \in [0, 1]$ is the parameter of learning rate and $\beta_j = \Delta h_j$ is the extent of the adjustment required to finetune the capability.

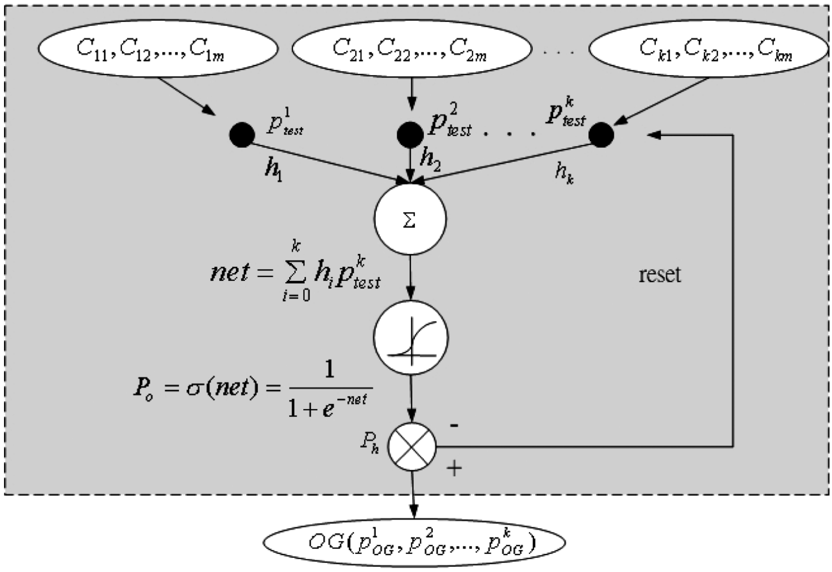

FIGURE 7 The process of peer self-organizing.

Once a fitting group accomplishes a task assigned, the members of the group are available for subsequent incoming tasks or subtasks in the work space and assume different roles, depending on the changing situation contexts.

THE IMPLEMENTATION

The solution platform is implemented with the technology of JXTA (Gong 2001), and with personal Java, which works for handheld devices such as iPAQ. JXTA is a modular platform that provides simple and essential building blocks for developing a wide range of distributed services and applications. Both centralized and de-centralized services can be developed on top of the JXTA platform. JXTA services can be implemented to interoperate with other services giving rise to new P2P applications.

As shown in Figure 8, in our implementation of the distributed infrastructure, the JXTA technology is utilized so as to fulfill the following objectives: enable peers to discover each other across firewalls; empower peers to self-organize into peer groups and to monitor each other remotely; supply peers with various P2P services so as to locate each other and communicate with each other; control the routing of messages over peer communication pipes; and mask the differences of heterogeneous devices so as to allow them to access the service platform seamlessly.

In order to well describe task ontology and the required resources of social awareness in the solution platform we have implemented, the

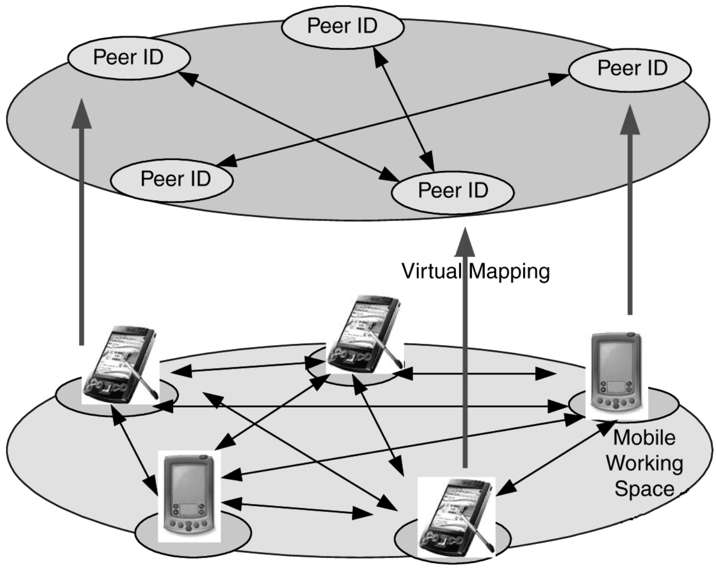

FIGURE 8 A distributed infrastructure empowered by JXTA with P-Java.

resource description framework (RDF)/RDF schema (RDFS) is employed to capture the semantics of the aforementioned resources. RDF (Lassila and Swick 1999) is a standard instituted by W3C for representing resources, which is intended to be a universal format to define and apply meta-data descriptions of web-based resources. Complementary to RDF, the role of the RDFS (Kraut et al. 2002) is to provide information about the interpretation and specify consistency constraints of the statements given in an RDF document. RDFS is regarded as a simpler ontology-based language to be used here.

EVALUATIONS

In this section, we aim to evaluate the qualities of our solution (empowered by the CART mechanism) to the CMWM problem. The envisioned qualities can be investigated by the following *four focus questions.*

- With the learning process of CART, is it true that there is a decreasing trend of the gap between the realistic performance and the expected performance of the fitting groups attained?
- With the learning process of CART, will the perceived capability of a work force be convergent eventually?
- Upon different tasks encountered, will the performance of our solution exhibit the same quality?

- Given a fitting group attained for a given task, how suited do the capabilities of the group members fit the requirements of the task?

This section will begin with a description of our experiment settings, followed by a number of sets of experiments so as to explore the aforementioned focus questions. We will also examine the impacts of certain design parameters to the solution quality, such as the size of the winners (m) and the types of vigilance criterion (ρ) given (i.e., high ρ as 0.9 versus normal-ρas 0.75) and the types of performance scores (P_t) expected (high versus low). Finally, a brief discussion of the evaluations will be furnished.

Experiment Settings

For investigating the performance of our solution, the universe β of a CMWM has to be provided. Without loss of generalization, a simple CMWM problem and a simple β are exerted. This CMWM problem is regarding mobile work forces of an ERP software company in the public work space of a very large software exhibition. Whenever a potential customer (characterized by the size[5] of his/her home business) is encountered by a mobile work force in the first place, an input task is initiated by the mobile work force who subsequently triggers the formation of a self-organized fitting group (of which the members are differentiated by their capabilities) in order to serve the customer. Since there might be commission involved (once the customer becomes a buyer), the relationship factor is considered during the group formation. As follows are the brief descriptions of β.

- Task ontology is represented by a table as shown in Table 1, in which {large, medium, small} denotes the types of the possible input tasks (t_{input}) and {manufacture, marketing, system} represents the possible subtask space $\{t_1, t_2, \ldots, t_K\}$ together with the respective significance weights $\{h_1, h_2, \ldots, h_K\}$. For instance, a "medium" input task can be decomposed into three subtasks {manufacture, marketing, system} with the significance weights {0.6, 0.6, 0.6}, respectively.
- Without loss of generality, the skill space (S) is as well defined as {manufacture, marketing, and system}.

TABLE 1 Task Ontology of β

	Manufacture	Marketing	System
Large	0.8	0.8	0.8
Medium	0.6	0.6	0.6
Small	0.4	0.4	0.4

TABLE 2 An Exemplar of Skill Strength Vector

	Manufacture	Marketing	System	ReadyStatus
Work force 1	0.1	0.6	0.1	1

- The size (M) of C_{MWS} is set to 15 together with the randomly generalized availabilities of the 15 work forces. It is assumed that an occupied work force cannot be allocated to tasks unless he/she becomes available.
- Skill strength matrix (W) is a collection of skill strength vectors $W_j = [w_{j1}, w_{j2}, \ldots w_{jN}]^T, w_{ji} \in [0,1], j = 1 \ldots M, i = 1 \ldots N$. For instance, Table 2 exemplifies such a skill strength vector of the work force 1.
- Relation strength matrix (R) comprises a collection of relationship strength vectors partially exemplified as shown in Table 3, in which the value of an element r_{ji} indicates the summarized relationship from work force p_j to work force p_i by considering their degree of acquaintance and p_j's knowledge of the emotional state of p_i. A complete matrix should also include p_j's knowledge of p_i's interest, p_j's knowledge of the p_i's skill levels, etc.

In addition to the universe β, the other settings of the parameters used in the CART mechanism are also summarized in Table 4. In the simulation, we assume the distribution of the input tasks encountered roughly follows the distribution as shown in Table 5 (i.e., a common perceived business distribution).

The Evaluation Results of the Four Focus Questions (when $m = 1$ and $\rho = 0.9$ and High P_t)

In this section, we give answers to the four focus questions (under the settings of the size of winners (m) and the vigilance criterion (ρ) being set to 1 and 0.9, respectively, and the resulting performance of the attained fitting groups being scored high).

- With the learning process of CART, is it true that there is a decreasing trend of the gap between the realistic performance and the expected performance of the fitting groups attained?

TABLE 3 An Exemplar of the Relationship Element of a Relationship Strength Vector

	Work force 1	Work force 2	......	Work force M
Work force 1	0.8	0.6		0.5

Note: The other portions include Work force 1's understanding of the skill levels of the others, the interests of the others, etc.

TABLE 4 Parameter Settings for CART Learning

Parameter	Value	Description
M	15	Size of C_{MWS}
ρ	0.9 or 0.75	Vigilance criterion: 0.9 if $m = 1$ and 0.75 if $m = 2$
m	1 or 2	Size of the winners associated with a subtask
P_h	0.74	Parameter used in the process of peer matching
α	0.1	Parameter used in the process of peer matching
P_t	High (e.g., 0.82, 0.8) Low (e.g., 0.68)	Realistic performance scores used in the process of capability adjusting
l	0.1	Learning rate in capability adjusting
Service Time	3-4 minutes	The amount of time randomly generated and indicating the time required accomplishing a task assigned in the simulation.
Rounds of trainings	180	CART training cycles

- Figure 9 and Figure 10, respectively, show the trend of the gap between the expected performance and the realistic performance of the fitting groups attained by our solution from the individual aspect and the overall aspect. From both figures, we do observe a decreasing trend of the gap. Moreover, from Figure 9 we find the gap is almost negligible after ten times of task services rendered. This shows that the CART learning can quickly attain good fitting groups so as to achieve the desired performance.
- With the learning process of CART, will the perceived capability of a work force be convergent eventually?
- Due to space limitation, the trends of the learned skill strengths (manufacture, marketing, and system) of only three work forces (Emp1, Emp4, Emp10) are shown in Figure 11. According to the figure, the trend of skill convergence indeed occurs to different skills of different work forces.
- Upon different tasks encountered, will the performance of our solution exhibit the same quality?
- Given the results of a set of 180 cycles of task processing, Table 6 shows the average fitting values (together their standard deviation) attained for the three types of input tasks (12 large tasks, 64 medium tasks, 83 small tasks).[6] These average fitting values are all approximately 0.8 and with

TABLE 5 A Distribution of the Input Tasks

	Rough distribution of the input tasks
Large	20%
Medium	40%
Small	40%

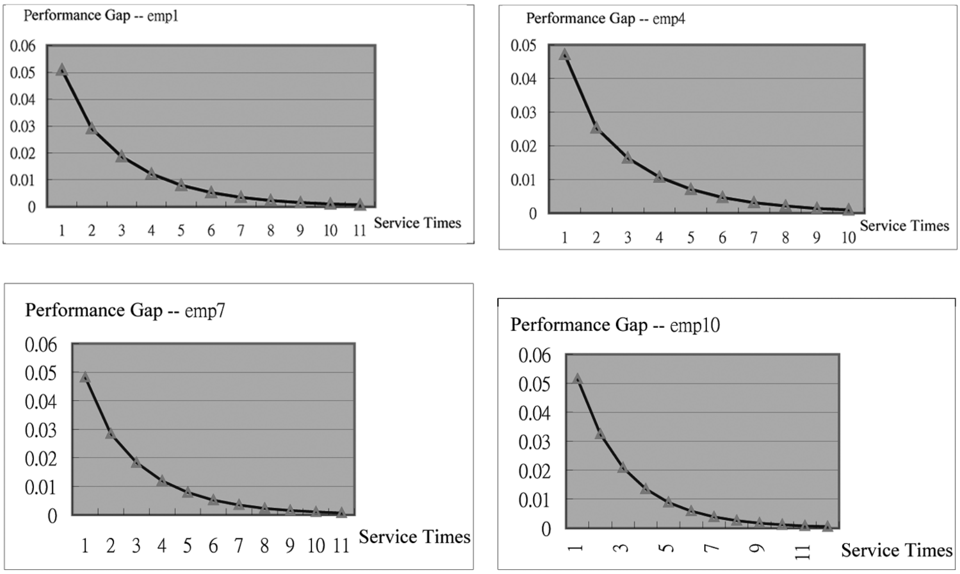

FIGURE 9 Performance gap from the individual aspect.

the deviations approximately 0.01. In other words, our solution generally produces solutions of the same quality to different types of tasks encountered.

- Given a fitting group attained for a given task, how suited do the capabilities of the group members fit the requirements of the task?
- Suppose the skill vectors of the 15 work forces are as shown in Table 7 (that shows Emp1, 2, 3 suit large tasks and Emp4, 5, 6, 7, 8 suit medium task, and Emp9, 10, 11, 12, 13, 14, 14 then suit small tasks).

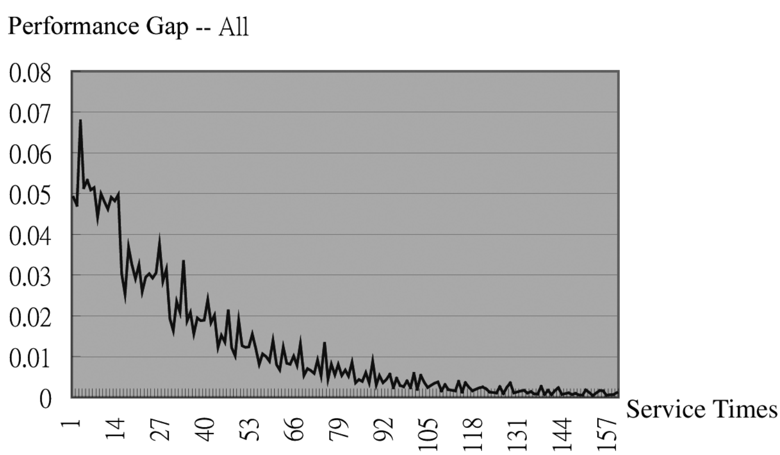

FIGURE 10 Performance gap from the overall aspect.

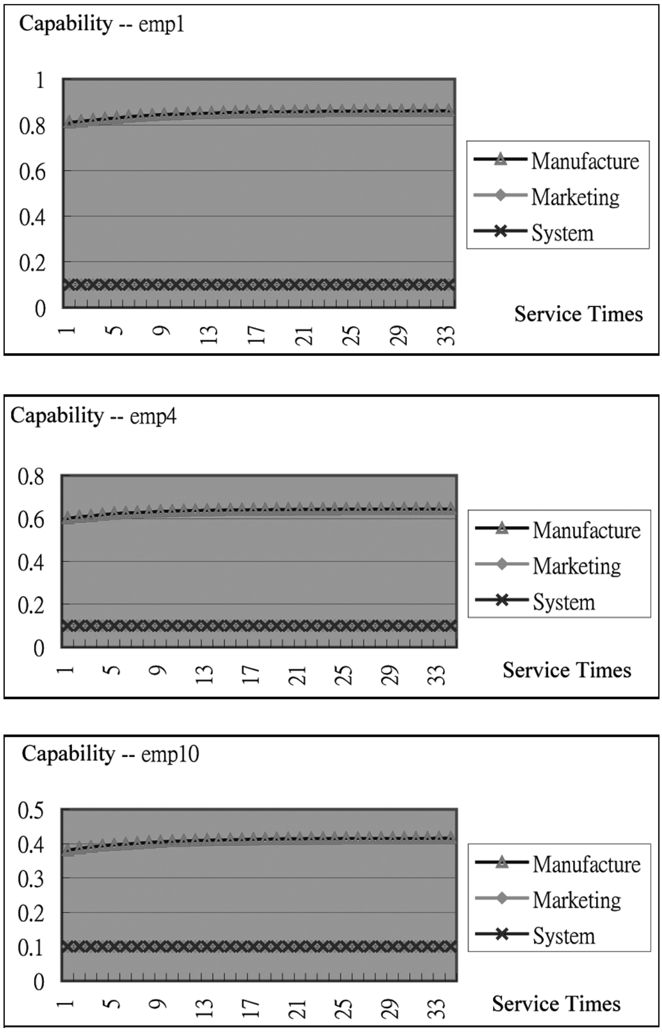

FIGURE 11 Convergent trends of work force skill strengths learned.

- From a macro view Table 8 then shows the results of the work force allocations of the 12 large tasks, 64 medium tasks and 83 small tasks.

  1. From Table 8(a) the task assignments to Emp1, 2, 3 (suitably working for large tasks) are 12 large, 20 medium, and 0 small. The reason behind the assignments of 20 medium is owing to the situations that Emp4, 5, 6, 7, 8, 9 are all busy on medium tasks, while Emp1, 2, 3 are free and qualified for medium tasks (given the fact that there are much more medium tasks than large tasks).

TABLE 6 Performance Results of Three Task Types

	Number of tasks	Average group fitting value	Standard deviation of performance
Large	12	0.80680834	0.011621671
Medium	64	0.809225549	0.013757696
Small	83	0.806090029	0.016289761

Note: There are 21 input tasks of no fitting groups generated due to high vigilance criterion.

2. From Table 8(b) and 8(c) the task assignments to Emp4, 5, 6, 7, 8, 9 (suitably working for medium tasks) are 20–25 medium and 11 (13) small. That is, the majority of the assignments go to medium tasks. There are no assignments of large tasks due to the failing of the vigilance criterion in the situations.
3. From Table 8(d) and 8(e) the task assignments to Emp10, 11, 12, 13, 14, 15 (suitably working for small tasks) are only 25–33 small. There are no assignments of medium or large tasks.

- In order to give a numeric measurement of the allocations (for the purpose of easy comparison), in Table 9 *a simple method of scoring is provided: three points are granted to each correct subtask assignment (i.e., a subtask is assigned to a work force of the exact skill level required); one point is bestowed to each subtask assignment where a work force of higher skill level is assigned to a subtask requiring only lower skill levels; and two points are deducted from the score for the situations where a work force of lower skill level is assigned to a subtask requiring higher skill level.* Accordingly, Table 9 exhibits how a score of 1167, i.e., $345^{*}3+132^{*}1–0^{*}2$, is attained for the total subtask allocations occurring to the processed input tasks. Since the perfect allocations should be of 1431 points, i.e., $(345+132)^{*}3$, the allocations are regarded subsequently with the allocation accuracy rate of 0.82 (i.e., 1167/1431).

For a more detailed view of the workforce allocation (i.e., micro view), Figure 12 shows a fragmented portion of the dynamic view of the detailed task assignments (each task is accomplished within 3–4 minutes and the assigned work forces for the subtask subsequently become free). In Figure 12, tasks are labeled consecutively according to the order in time they are generated and regions of different colors and different stripes represent a variety of types

TABLE 7 Skill Vectors of the 15 Work Forces

Work force	Skill strength vector
Emp1, 2, 3	(0.8, 0.8, 0.8)
Emp4, 5, 6, 7, 8, 9	(0.6, 0.6, 0.6)
Emp10, 11, 12, 13, 14, 15	(0.4, 0.4, 0.4)

TABLE 8 Macro View of Work Force Allocation

	Emp1	Emp2	Emp3
Large	$\boxed{12}$	$\boxed{12}$	$\boxed{12}$
Medium	20	20	20
Small	0	0	0

(a)

	Emp4	Emp5	Emp6
Large	0	0	0
Medium	$\boxed{20}$	$\boxed{23}$	$\boxed{25}$
Small	13	11	11

(b)

	Emp7	Emp8	Emp9
Large	0	0	0
Medium	$\boxed{25}$	$\boxed{22}$	$\boxed{20}$
Small	11	13	13

(c)

	Emp10	Emp11	Emp12
Large	0	0	0
Medium	0	0	0
Small	$\boxed{33}$	$\boxed{27}$	$\boxed{26}$

(d)

	Emp13	Emp14	Emp15
Large	0	0	0
Medium	0	0	0
Small	$\boxed{25}$	$\boxed{31}$	$\boxed{32}$

(e)

of allocations (e.g., different colors denoting different work force capabilities and different stripes indicating tasks requiring different skill levels).

For instance, Task 39 and Task 40 (small tasks) are assigned to Emp10, 11,12 and Emp13, 14, 15, respectively. Task 41 (large task) is assigned to Emp1, 2, 3. Task 42 (small task), however, is assigned to Emp5, 6, 7 (of medium skills) because Emp10, 11, 12 and Emp13, 14, 15 are preoccupied. Task 44 (medium task) is assigned to Emp4, 8, 9. Task 45 (medium task), however, is assigned to Emp1, 2, 3 due to the preoccupations of Emp5, 6, 7 and Emp4, 8, 9. In summary, this dynamic view of task work force allocation exhibits how our solution dynamically achieves situated allocations of work forces to dynamic tasks.

TABLE 9 Allocation Scores

Types of allocations	Allocation number	Weights	Allocation score
Correct allocation	345	+ 3	1035
Allocations of High skills to Low tasks	132	+ 1	132
Allocations of Low Skills to High tasks	0	− 2	0
Total Allocation Score			1167

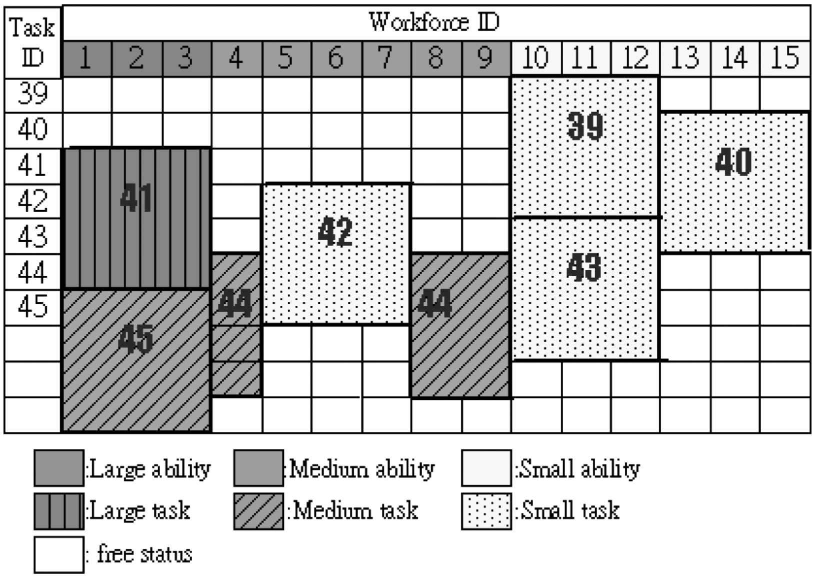

FIGURE 12 Micro view of work force allocation.

Moreover, from Table 10 the percentage of input tasks being served and not being served with our solution is 87%[7] (i.e., 159/180) and 13% (i.e., 21/180), respectively. That is, the service rate is high with respect to high vigilance criterion.

The Evaluation Results of the Four Focus Questions (when $m = 2$ and ρ is 0.75 and High P_t)

In this section, we give the results to the four focus questions (under the settings of the size of winners (m) and the vigilance criterion (ρ) being set to 2 and 0.75, respectively, and the resulting performance of the attained fitting groups being scored high).

- With the learning process of CART, is it true that there is a decreasing trend of the gap between the realistic performance and the expected performance of the fitting groups attained?

TABLE 10 Percentages of Tasks Served

	Number of tasks	Percentage
Tasks not served	21	13%
Tasks served	159	87%
Number of Total Tasks	180	100%

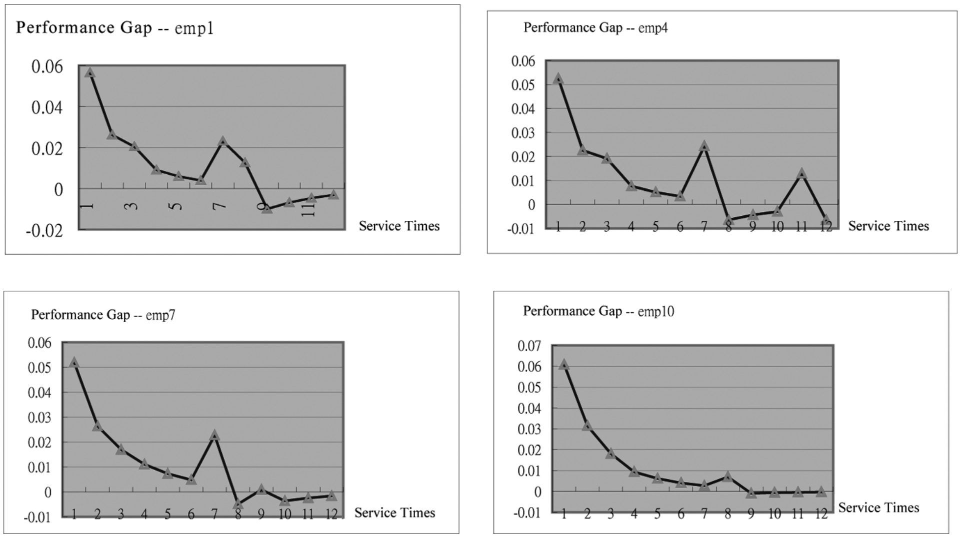

FIGURE 13 Performance gap from the individual aspect.

Figure 13 and Figure 14, respectively, show the trend of the gap between the expected performance and the realistic performance of the fitting groups attained by our solution from the individual aspect and the overall aspect. From both figures, we indeed observe a decreasing trend of the gap (in light of the existence of few lumps). Moreover, from Figure 13 we find the gap is almost negligible after ten times of task services rendered. This shows that CART learning quickly attains a good fitting group so as to achieve the desired performance.

- With the learning process of CART, will the perceived capability of a work force be convergent eventually?

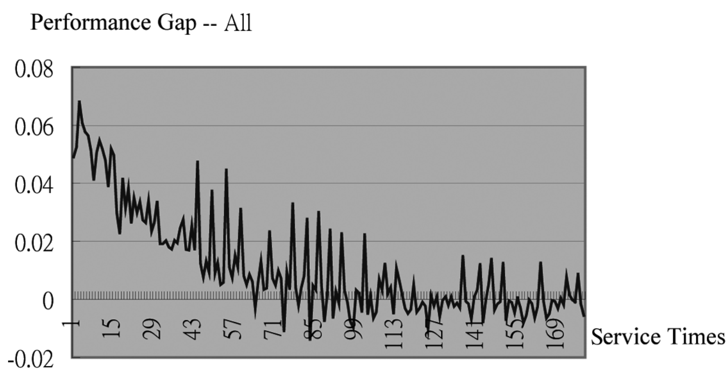

FIGURE 14 Performance gap from the overall aspect.

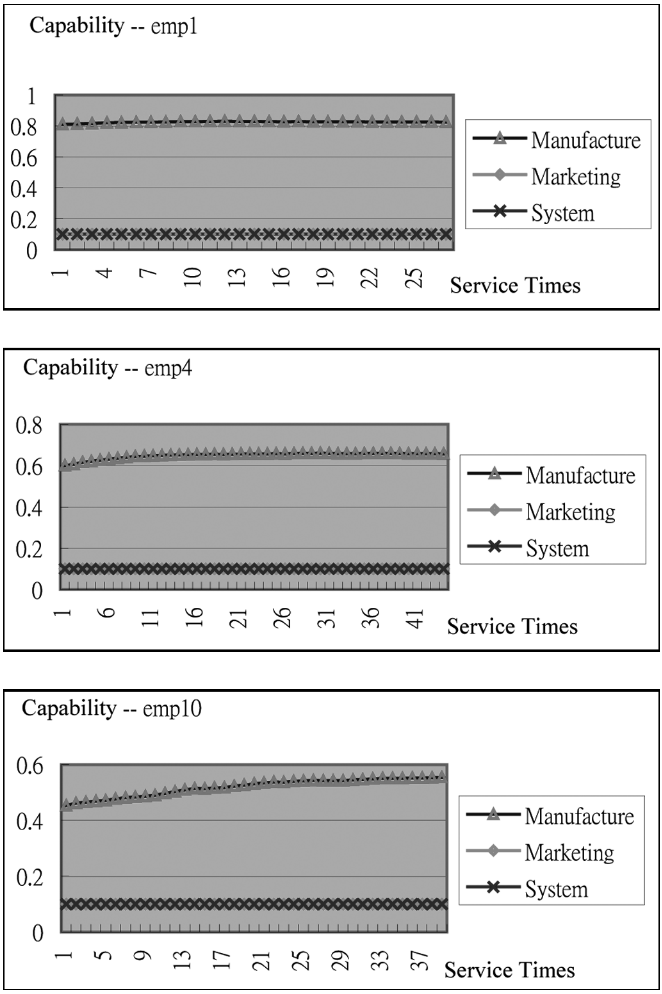

FIGURE 15 Convergent trends of work force skill strengths learned.

Due to space limitation, the trends of the learned skill strengths (manufacture, marketing, and system) of only three work forces (Emp1, Emp4, Emp10) are shown in Figure 15. According to the figure, the trend of skill convergence indeed occurs to different skills of different work forces.

TABLE 11 Performance Results of Three Task Types

	Number of tasks	Average group fitting value	Standard deviation of performance
Large	26	0.786856568	0.022623917
Medium	85	0.801767038	0.022973817
Small	67	0.811997089	0.016919644

Note: There are two input tasks of no fitting groups generated.

TABLE 12 Macro View of Work Force Allocation

	Emp1	Emp2	Emp3
Large	$\boxed{9}$	$\boxed{9}$	$\boxed{9}$
Medium	17	17	17
Small	0	0	0

(a)

	Emp4	Emp5	Emp6
Large	7	8	10
Medium	$\boxed{22}$	$\boxed{21}$	$\boxed{22}$
Small	14	13	8

(b)

	Emp7	Emp8	Emp9
Large	10	9	8
Medium	$\boxed{21}$	$\boxed{19}$	$\boxed{20}$
Small	9	12	15

(c)

	Emp10	Emp11	Emp12
Large	0	0	0
Medium	25	28	26
Small	$\boxed{13}$	$\boxed{11}$	$\boxed{13}$

(d)

	Emp13	Emp14	Emp15
Large	0	0	0
Medium	0	0	0
Small	$\boxed{31}$	$\boxed{31}$	$\boxed{31}$

(e)

- Upon different tasks encountered, will the performance of our solution exhibit the same quality?
  Given the results of a set of 180 cycles of task processing, Table 11 shows the average fitting values (together their standard deviation) attained for the three types of input tasks (26 large tasks, 85 medium tasks, 67 small tasks). These average fitting values are around 0.78–0.81 and with the deviations around 0.023. In other words, our solution generally produces solutions of the same quality to different types of tasks encountered.
- Given a fitting group attained for a given task, how suited do the capabilities of the group members fit the requirements of the task?
  Suppose the skill vectors of the 15 work forces are as shown in Table 7 (that shows Emp1, 2, 3 suit large tasks and Emp4, 5, 6, 7, 8 suit medium tasks, and Emp9, 10, 11, 12, 13, 14, 14 then suit small tasks).
  From a macro view Table 12 then shows the results of the work force allocations given 12 large tasks, 64 medium tasks, and 83 small tasks;

  1. From Table 12(a) the task assignments to Emp1, 2, 3 (suitably working for large tasks) are 9 large, 17 medium, and 0 small. The reason behind the assignments of 17 medium is owing to the situations that

Emp4, 5, 6, 7, 8, 9 are all busy on medium tasks, while Emp1, 2, 3 are free and qualified for medium tasks (given the fact that there are many more medium task than large tasks).

2. From Table 12(b) and 12(c), the task assignments to Emp4, 5, 6, 7, 8, 9 (suitably working for medium tasks) are 19–22 medium and 9–15 small. That is, the majority of the assignments go to medium tasks. However, there are 8–10 assignments of large tasks due to a lower vigilance criterion of 0.75 being exerted in the situations. Moreover, the lower vigilance criterion makes Emp4, 5, 6, 7, 8, 9 busier (i.e., capable of executing medium tasks or large tasks), resulting in a greater chance of executing medium tasks for Emp1, 2, 3 (when they are free). This also accounts for why Emp1, 2, 3 execute more medium tasks than large tasks, as shown in Table 12(a).
3. From Table 12(d) and 12(e), the task assignments to Emp10, 11, 12 and Emp13, 14, 15 (suitably working for small tasks) are 11–13 small and 31 small, respectively. There are no assignments of medium tasks to Emp13, 14, 15. However, there are 25–28 assignments of medium tasks to Emp10, 11, 12 due to Emp4, 5, 6, 7, 8, 9 being busy and also a lower vigilance criterion.

Table 13 gives a numeric measurement of the allocations and also shows how a score of 676 is attained for the total subtask allocations occurring to the processed input tasks. Since the perfect allocations should be of 1575 points, the allocations are regarded subsequently with the allocation accuracy rate of 0.43 (i.e., 676/1575).

For a more detailed view of the work force allocation (i.e., micro view), Figure 16 shows a fragmented portion of the dynamic view of the detailed task assignments. For instance, Task 104 and Task 105 (medium tasks) are assigned to Emp4, 5,9 and Emp6, 7, 8, respectively. Task 106 (medium task) is assigned to Emp1, 2, 3 because Emp4, 5, 6 and Emp7, 8, 9 are preoccupied. Task 107 (small task) is assigned to Emp13, 14, 15 (of small skills). Task 108 and Task109 (large task) are assigned to Emp4, 5, 9 and Emp6, 7, 8 because Emp1, 2, 2 are preoccupied. Task 110 (medium task), however, is assigned to Emp10, 11, 12 due to the preoccupations of Emp4, 5, 9 and Emp6, 7, 8. In sum, this dynamic view of task work force allocation exhibits

TABLE 13 Allocation Scores

Type of allocations	Allocation number	Weights	Allocation score
Correct allocation	272	+ 3	816
Allocations of High skills to Low tasks	122	+ 1	122
Allocations of Low Skills to High tasks	131	− 2	− 262
Total Allocation Score			676

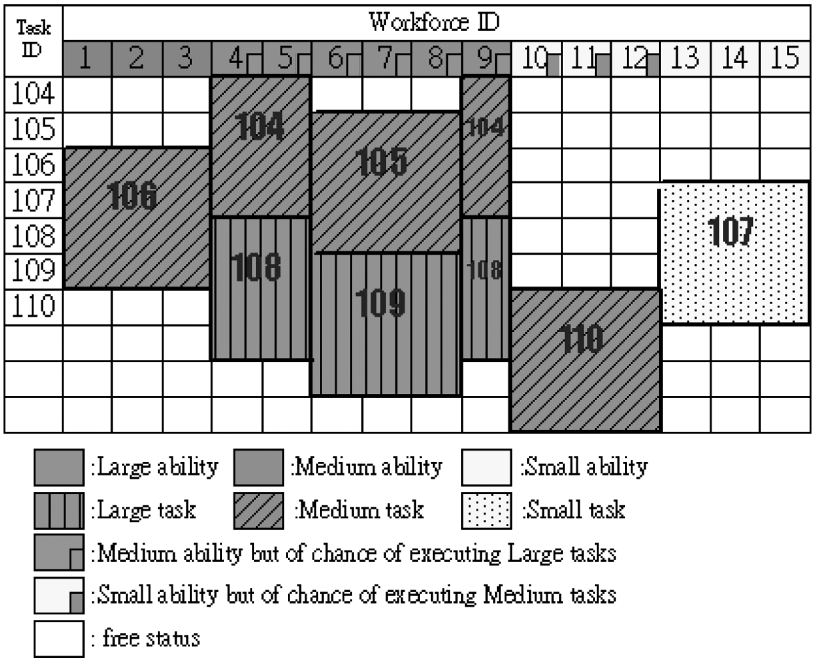

FIGURE 16 Micro view of work force allocation.

how our solution dynamically achieves situated allocations of work forces to dynamic tasks.

Moreover, from Table 14 the percentage of input tasks being served and not being served with our solution is 99%[8] (i.e., 178/180)and 1% (i.e., 2/180), respectively. That is, the service rate is very high with respect to a lower vigilance criterion.

The Evaluation Results of the Four Focus Questions (when P_t is Low)

This section aims to examine if our solution also works well when the realistic performance of the attained fitting groups P_t is low ($P_t = 0.68$), unlike the investigations constructed previously (where the realistic performance of the attained fitting groups is high, i.e., $P_t > 0.8$). Without loss

TABLE 14 Percentages of Tasks Served

	Number of tasks	Percentage
Tasks not served	2	1%
Tasks served	178	99%
Number of Total Tasks	180	100%

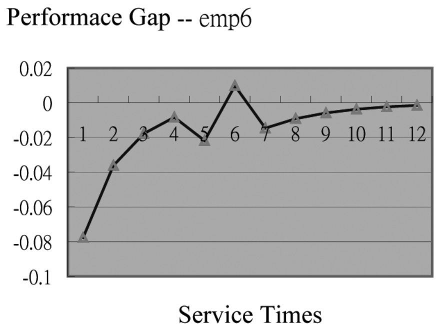

FIGURE 17 Performance gap of an individual work force.

of generality, the settings of this set of experiments are as follows: the *size of* $C_{MWS} = 12$, the *number of input tasks* $= 150$, $m = 1$, and $\rho = 0.9$. By working well for our solution in this situation, we mean the convergent capability of work forces will accordingly be degraded appropriately (if the original capabilities are overestimated). As follows are the brief evaluation results.

Figure 17 and Figure 18, respectively, show the trend of the gap between the expected performance and the realistic performance of the fitting groups attained by our solution from the individual aspect and the overall aspect. From both figures, we indeed observe a decreasing trend of the gap (in light of the existence of few lumps). Moreover, from Figure 17, we find the gap is almost negligible after ten times of task services rendered. This shows that CART learning quickly attains a good fitting group, so as to achieve the desired performance.

From Figure 19 the trends of the learned skill strengths (manufacture, marketing, and system) of an individual work force are shown in Figure 19. According to the figure, the trend of skill convergence indeed occurs to different skills of different work forces.

From Table 15 the percentage of input tasks being served and not being served with our solution is 65% (i.e., 98/150)and 1% (i.e., 52/150), respectively. That is, the service rate is low with respect to a high vigilance

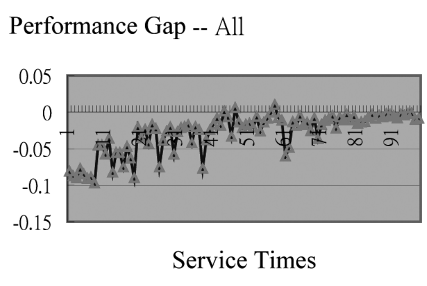

FIGURE 18 Performance gap of the overall work forces.

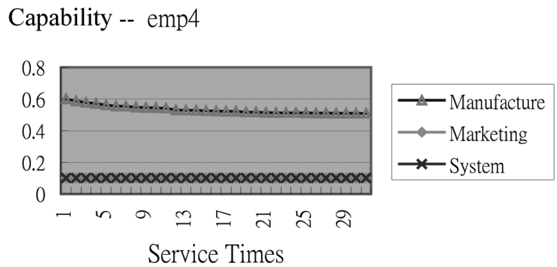

FIGURE 19 Convergent trend of the capability learned.

criterion and low realistic performance. This is owing to the situations that, as time goes by, work forces of small skill level become unable to service small tasks. Work forces of medium skill level become unable to service medium tasks, but can service small tasks. Work forces of large skill level become unable to service large tasks, but, medium or small tasks. Consequently, there are 52 tasks not being served. *In short, our solution can service learn to downgrade the capability of a work force if the reality performance of the work force is lower.*

Discussion

Cross-examining the results attained from previous sections (of features $m = 1$ and $\rho = 0.9$ and of features m $= 2$ and $\rho = 0.75$) , we have the following observations.

Considering correct work force allocation as briefed in Table 16(a), the settings of $m = 1$ and $\rho = 0.9$ outperform those of m $= 2$ and $\rho = 0.75$ (82% versus 43%). On the other hand, the settings of m $= 2$ and $\rho = 0.75$ outperform those of $m = 1$ and $\rho = 0.9$ (99% versus 87%) as far as percentage of tasks served is concerned (as briefed in Table 16(b)). Accordingly, it is believed that our solution works best as follows.

- If a high level of correction is desired in work force allocation, the number of winners (m) should be lower and the vigilance criterion (ρ) should be higher.

TABLE 15 Percentages of Tasks Served

	Number of tasks	Percentage
Tasks not served	52	35%
Tasks served	98	65%
Number of Total Tasks	150	100%

TABLE 16 Brief Cross-Examinations of the Evaluation Results

(a)	
	Rates of Correct Work Force Allocation
m = 1 and $\rho = 0.9$	82%
m = 2 and $\rho = 0.75$	43%
(b)	
	Percentage of Tasks Served
m = 1 and $\rho = 0.9$	87%
m = 2 and $\rho = 0.75$	99%

- If a high level of service percentages is desired in tasks served, the number of winners (*m*) should be higher and the vigilance criterion (ρ) should be lower.

In light of the aforementioned differentiations, our solution is of the features itemized as follows.

- A solution to the CMWM problem should be characterized by a social-awareness enabled and purely distributed mindset (i.e., self-organizing) of collaboration support.
- A solution should learn to know the realistic capabilities of peers and accordingly deploy appropriate workforce allocation for serving tasks collaboratively.
- A solution should adapt to the dynamic changes of the environment in terms of the status of work forces and input tasks.

There were a few recent works (Edwards et al. 2002; Groove Networks 2004; World Street 2004) addressing spontaneous collaboration via wired P2P technologies. However, these work are concerned mainly with issues such as how two people can have an unplanned interaction with one another (e.g., the exchange of current contact information, notes, documents, etc.), i.e., the support of *anywhere* collaboration. This kind of collaboration primarily concerns the "tools" to be interfaced by peers for collaboration (e.g., whiteboard, voice chat, file space, co-browsing, etc.) and the extensibility of the tool set. Nevertheless, the management of mobile work forces addressed in the CMWM problem requires a type of collaboration considering the utilities of grouping. Accordingly, these tool-oriented P2P collaboration systems cannot be applied to the CMWM problem.

CONCLUSION

With the rapid growth of mobile work forces, the chances are considerable that mobile work forces of a company need to work together to fulfill situated tasks (services) in real time. This problem is defined in this paper as the problem of contextualized mobile workforce management (CMWM). In order to supportreal-time collaboration of distributed group work between mobile work forces, this paper presents to the problem a novel solution that is a combination of a wireless peer-to-peer infrastructure that enables self-organizing and a collaborative ART learning approach (CART) that generates nearly fittest work groups.

The CART approach advances traditional ART approaches mainly in two ways: relaxing the "winner-takes-all" principle by allowing multiple winners to be generated during each matching so as to avoid the consequence of wasting human resources, and partner seeking is resolved through a novel heuristics process of collaboration-driven self-organizing so as to generate nearly fittest work force groups for tasks to a greater extent, considering a wide scope of factors (e.g., relationships, interests, work force skills, etc.). In other words, the CART approach better copes with the reality by regarding realistic factors of a work space so as to further utilize work forces.

Unlike existing relevant research, our solution empowered by CART is characterized by a social-awareness enabled and purely distributed mindset (i.e., self-organizing) of collaboration support. Furthermore, our solution learns the realistic capabilities of work forces and deploys appropriate work force allocation for effectively engaging collaboration between work forces, in addition to its capability of adapting to the dynamic changes of the environments.

Future fruitful research directions include the following: the flexibility of work force allocation (e.g., the ability to rearrange the work force allocation in the middle of task execution if the utility of the foreseeable rearrangement is better than that of the original arrangement; the consideration of a wider scope of context attributes (e.g., proximity of work forces, fine granularity of task descriptions, etc.), and the other possible applications of the proposed solution.

REFERENCES

Adams, M., Y. Tenney, and R. Pew. 1995. Situation awareness and the cognitive management of complex systems. *Human Factors* 37(1):85–104.

Bannon, L. J., and K. Schmidt. (1989). Cscw: Four characters in search of a context. In: Globally *Proceedings 1st European Conference on Computer Supported Cooperative Work*, pages 358–372. Sloug, United Kingdom.

Carpenter, C. A. 1977. Distributed learning, recognition, and prediction by ART and ARTMAP neural networks. *Neural Networks* 10:1473–1494.

Carpenter, C. A., S. Grossberg, N. Markuzon, J. H., Reynolds, and D. B. Rosen. 1992. Fuzzy ARTMAP: A neural network architecture for incremental supervised learning of analog multidimensional maps. *IEEE Transactions on Neural Networks* 3:698–713.

Cutter Consortium. 2001. The New Mobile Workforce. *Business-IT Strategies Advisory Service* 4(10):1–4.

Edwards, W. K., M. W. Newman, J. Z. Sedivy, T. F. Smith, D. Balfanz, D. K. Smetters, H. Chi Wong, and S. Izadi. 2002. Using speakeasy for ad hoc peer-to-peer collaboration. In: *Proceedings of the ACM conference on Computer Supported Cooperative Work*, 256–265, New Orleans, Louisiana, USA.

Ellis, C. A., S. J. Gibbs, and G. L. Rein. 1991. Groupware: Some issues and experiences. *Communications of the ACM*, 34(1):38–58.

Gong, L. 2001. *Project JXTA: A Technology Overview*, Sun Whitepaper, http://www.jxta.org/

Greenberg, S., C. Gutwin, and A. Cockburn. 1996. *Using Distortion-Oriented Displays to Support Workspace Awareness*. technical report, Department of Computer Science, University of Calgary, Canada.

Groove Networks Inc. 2004. http://www.Groove.com.

Grossberg, S. 1976. Adaptive pattern classification and universal recoding, I: Parallel development and coding of neural feature detectors and II: Feedback, expectation, olfaction, and illusions. *Biological Cybernetics*, 23:121–134; 187–202.

Gutwin, C. and S. Greenberg. 2002. A descriptive framework of workspace awareness for real-time groupware. *Computer Supported Cooperative Work* 11(3-4):411–446.

Jiang, P. and Q. Mair. 2002. A self-organizational management network based on adaptive resonance theory. In: *Proceedings of the 3rd International Symposium on Multi-Agent Systems, Large Complex Systems, and E-Businesses (MALCEB'2002)*, Erfurt, Germany.

Johansen, R. 1991. Teams for tomorrow. In: *Proceedings 24th IEEE Hawaii International Conference on System Sciences*, pages 520–534. IEEE Comp. Soc. Press.

Kraut, R. E., D. Gergle, and S. R. Fussell. 2002. The use of visual information in shared visual spaces: Informing the development of virtual co-presence. In: *Proceedings of the ACM conference on Computer supported Cooperative Work*, 31–40, New Orleans, Louisiana, USA.

Lassila, O. and R. Swick. 1999. *Resource Description Framework (RDF)*, W3C proposed recommendation, http://www.w3c.org/TR/WD-rdf-syntax.

Malm, P. S. 1994. *CSCW and Groupware: A Classification of CSCW-Systems in a Technological Perspective*, Masters Thesis, University of Tromsø.

Miles, V. C., J. C. McCarthy, A. J. Dix, M. D. Harrison, and A. F. Monk. 1993. Reviewing designs for a synchronous-asynchronous group editing environment. In: *Computer Supported Collaborative Writing*, ed. M. Sharples, 137–160, London: Springer Verlag.

Neisser, U. (1976). *Cognition and Reality*. San Francisco, CA: W.H. Freeman.

Niehaus, R. J. 1995. Evolution of the strategy and structure of a human resource planning DSS application. *Decision Support Systems* 14(3):187–204.

Roseman, M. and S. Greenberg. 1996. TeamRooms: Network places for collaboration. In: *Proceedings of the Conference on Computer-Supported Cooperative Work*, 325–333, New York.

Schleicher, J., M. Koch, M. Bürger. 1997. Workspace awareness for distributed teams. In: *Workshop Coordination Technology for Collaborative Applications*, ed. W. Conen, 199–218, Singapore, Springer: Lecture Notes on Computer Science.

Smith, R., R. Hixon, and B. Horan. 1998. Supporting flexible roles in a shared space. In: *Proceedings of ACM CSCW'98 Conference on Computer-Supported Cooperative Work*, pages 197–206.

Sohlenkamp, M. and G. Chwelos. 1994. Integrating communication, cooperation and awareness: The DIVA virtual office environment. In: *Proceedings of ACM CSCW'94 Conference on Computer-Supported Cooperative Work*, pages 331–343.

WorldStreet. 2004. http://wwWorldStreet.com.

ENDNOTES

1. At the beginning, p_j's knowledge of the skills of p_i is attained from the skill strength matrix. As time goes by, this knowledge will be updated in accord with p_j's interactions with p_i.
2. The so-called role-based administration in which roles are created to reflect various job functions and users are assigned to roles based on their responsibilities and qualifications. (Should the need of a more complex administration be required, role hierarchies can be employed to structure roles to reflect an organization line of responsibilities.)
3. By appropriate peers, we mean peers of good relationships or of the same benefit group, etc.
4. This is a predetermined integer number indicating the number of winner candidates considered in the next phase of the vigilance test.
5. In this paper this size information can be attained either from the RFID tag carried by the customer or from an inquiry by the mobile work force that encounters the customer in the first place.

6. There are 21 input tasks of no fitting groups generated owing to the inability to pass the fitting threshold P_h.
7. Table 6 shows the detailed results of the 159 services (i.e., 12 large, 64 medium, 83 small).
8. Table 11 shows the detailed results of the 178 services (i.e., 26 large, 85 medium, 67 small).

APPENDIX

The derivation of $\Delta h_i = -\eta \frac{\partial E}{\partial h_i} = \eta(P_t - P_o)P_o(1 - P_o)p^i_{OG}$ is attained as follows:

- $E(\vec{h}) \equiv \frac{1}{2}(P_t - P_o)^2$ (the error function)
- Apply gradient descent to the error function:

$$\Delta h_i = -\eta \frac{\partial E}{\partial h_i} \tag{1}$$

$$\begin{aligned}\frac{\partial E}{\partial h_i} &= \frac{\partial E}{\partial net}\frac{\partial net}{\partial h_i} \\ &= \frac{\partial E}{\partial net} < p^i_{OG} >\end{aligned} \tag{2}$$

$$\frac{\partial E}{\partial net} = \frac{\partial E}{\partial P_o}\frac{\partial P_o}{\partial net} \tag{3}$$

$$\begin{aligned}\frac{\partial E}{\partial P_o} &= \frac{\partial}{\partial P_o}\frac{1}{2}(P_t - P_o)^2 \\ &= \frac{1}{2}2(P_t - P_o)\frac{\partial(P_t - P_o)}{\partial P_o} \\ &= -(P_t - P_o)\end{aligned} \tag{4}$$

$$\begin{aligned}\frac{\partial P_o}{\partial net} &= \frac{\partial \sigma(net)}{\partial net} \\ &= P_o(1 - P_o)\end{aligned} \tag{5}$$

$$\frac{\partial E}{\partial net} = -(P_t - P_o)P_o(1 - P_o) \tag{6}$$

Based on Formulas (3), (4), (5).

$\Delta h_i = -\eta \frac{\partial E}{\partial h_i} = \eta(P_t - P_o)P_o(1 - P_o) < p^i_{OG} >$. Based on Formulas (1), (2), (6).