CONCURRENCY AND COMPUTATION: PRACTICE AND EXPERIENCE
Concurrency Computat.: Pract. Exper. 2007; **19**:2067–2090
Published online 19 December 2006 in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/cpe.1143

The potential energy of knowledge flow

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SUMMARY

A knowledge flow is invisible but it plays an important role in ordering knowledge exchange when working in a team. It can help achieve effective team knowledge management by modeling, optimizing, monitoring, and controlling the operation of knowledge flow processes. This paper proposes the notion of knowledge energy as the driving force behind the formation of an autonomous knowledge flow network, and explores the underlying principles. Knowing these principles helps teams and the support systems improve cooperation by monitoring the knowledge energy of nodes, by evaluating and adjusting knowledge flows, and by adopting appropriate strategies. A knowledge flow network management mechanism can help improve the efficiency of knowledge-intensive distributed teamwork. Copyright © 2006 John Wiley & Sons, Ltd.

Received 27 August 2006; Accepted 28 August 2006

KEY WORDS: knowledge flow; Knowledge Grid; knowledge management; knowledge energy; teamwork

1. INTRODUCTION

Effective knowledge management can enhance the creativity and competitiveness of knowledge-intensive teamwork [1–4]. Previous research on knowledge management mainly focused on organizational learning [5–7] and on providing procedures and systems to encourage members

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Contract/grant sponsor: National Basic Research Program; contract/grant number: 2003CB317001
Contract/grant sponsor: National Science Foundation

to communicate [8–10], but seldom considered the efficiency and efficacy of knowledge sharing, especially the routing of knowledge in a geographically distributed team.

The knowledge flow network is a way to formalize and optimize team management by using an approach similar to that of workflow management systems [11,12]. In the knowledge flow process model, introduced in [12,13], *knowledge flow* is the passing of knowledge within a team (e.g. in the form of query-answering, broadcasting and pushing knowledge). A knowledge flow begins and ends at a *knowledge node*. A knowledge node is either a team member, or an agent that can generate, process, and deliver knowledge. A *knowledge flow network* is made up of knowledge flows and knowledge nodes.

The objective of knowledge flow management is to improve the efficiency and efficacy of cooperation in knowledge team. Poor management can waste and even misdirect teamwork. Building knowledge flow networks that only pass the knowledge required for a task is a challenge, particularly for organizations that are geographically dispersed and liable to change. Although the Internet can provide a good means of communication for dispersed teams [14,15], use of email, file sharing, and online blackboards is often ineffective.

The absence of criteria for assessing knowledge flow networks is a major obstacle. For a network to be effective, knowledge must flow to where it is needed—across time and space, and between organizations when necessary.

Potential energy and hydraulic pressure cause water to flow along a river or through pipes. Voltage causes electrical energy to flow through wires. What causes knowledge to flow? What laws govern the knowledge flow? This article explores these questions.

The idea of knowledge energy causing knowledge flow is used here to explore the laws governing the flow, and as criteria for judging its effectiveness. Ways to assess energy are proposed, and their validity is demonstrated by experiments with a prototype knowledge flow management support system. Finally, knowledge flow networking strategies are discussed.

2. KNOWLEDGE ENERGY AND KNOWLEDGE SPACE

2.1. Assumptions

To establish a reasonable research scope, the following assumptions clarify the equality, autonomy, generosity, and simplicity in the object of our research—knowledge flow networks.

Assumption 1. (Equality) Knowledge nodes in a network use similar intelligence to acquire, use, and create knowledge.

We assume that people in an organization are normal in that they are able to generate, use, and spread knowledge. The possibility of extreme intelligence is ignored to simplify the analysis.

Assumption 2. (Autonomy) Knowledge nodes share knowledge autonomously.

We assume that sharing knowledge between nodes is free from outside influence, such as supervisory orders. Thus, we can focus on studying knowledge flow principles and their application when designing particular knowledge flow networks.

Assumption 3. (Generosity) Knowledge nodes share knowledge without reserve.

DOI: 10.1002/cpe

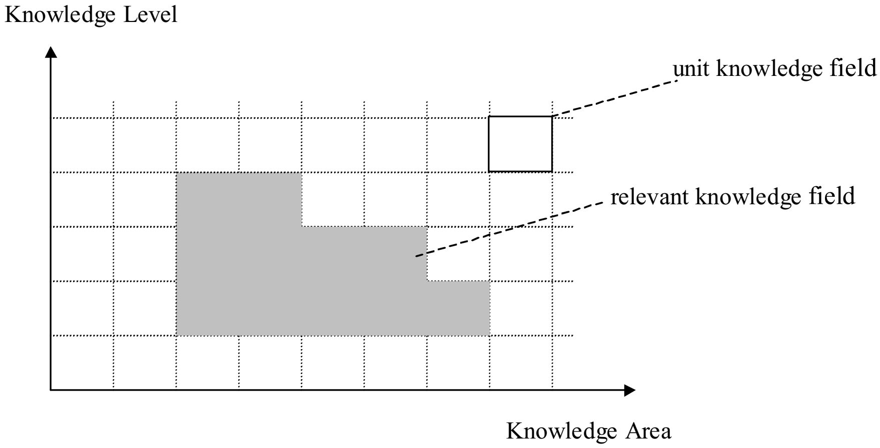


Figure 1. Knowledge area, level and relevant field.

Social and psycological factors influence the effectiveness of a knowledge flow. Here we assume that nodes are willing to pass on knowledge when it is needed. Hesitation, reserve, or deceit will cause poor knowledge flow.

Assumption 4. (Simplicity) The team is cooperative and flat (i.e. peer-to-peer) in organization.

By studying a basic knowledge team we lay the foundation for studying complex teams.

2.2. Knowledge fields

A team usually has knowledge in several application areas or academic disciplines. Knowledge can also be classified into levels (e.g. concepts, axiom, rules, methods, skills, and theory from low to high [16]) in a cognitive hierarchy. Levels are inexact, but when there is uncertainty, team members can use their experience to judge which level knowledge belongs to. Level and area, the two dimensions of knowledge space, specify a *unit knowledge field* (or *unit field*) denoted by $UFd(i, j)$, where i is the area and j is the level. Each unit field has its own knowledge flow network. The *relevant knowledge field* (or *relevant field*) of a task, shown as the grey region in Figure 1, is the union of the unit fields relevant to a task. Teamwork is based on knowledge flow networks in the relevant field.

Nodes need to pass knowledge in every unit field. A knowledge flow network can be defined for every unit field to optimize the flow by avoiding unnecessary flows. Working on a task may involve many such knowledge flow networks. Figure 2 shows a simple example of a team with three members and six networks. The knowledge space has two areas, each with three levels. Arrows of different shades belong to different knowledge flow networks. Knowledge flows in different fields may influence each other by knowledge processing of nodes such as deduction, induction, and analogy [16].

DOI: 10.1002/cpe

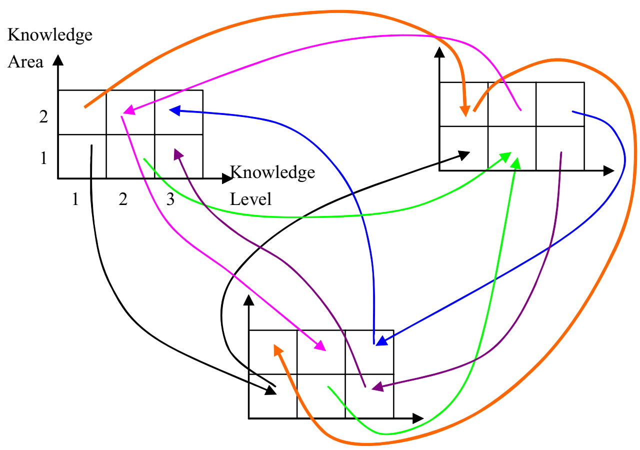


Figure 2. An example with six knowledge flow networks.

2.3. Knowledge energy

Knowledge energy is a parameter that expresses the degree of a node's knowledge and a person's cognitive and creative abilities in a unit field. A node's energy gives its 'rank' in a knowledge flow network. The higher a node's energy, the better it will be at learning, using, and creating knowledge. The knowledge energy in a unit field is estimated by assessing how much relevant knowledge a node contains.

The knowledge energy of a node varies with time and across fields. We use a four-dimensional orthogonal space, *KS*(*knowledge-area*, *knowledge-level*, *knowledge-energy*, *time*), to represent the energy of a node. Any point in the space represents the knowledge energy of a node in a certain unit field at a certain time. At time t, the energy of node u in unit field $UFd(i, j)$ can be represented as $KE(task, u, i, j, t)$. The curved surface in Figure 3 depicts the energy distribution of a node at a time t.

3. KNOWLEDGE FLOW PRINCIPLES

Principle 1. Between any two nodes, knowledge only flows when their energies differ in at least one unit field.

Let u and v be any two knowledge nodes, and $KE(task, u, i, j, t)$ and $KE(task, v, i, j, t)$ be the energies of nodes u and v in $UFd(i, j)$ at time t, respectively. If formula (1) holds, knowledge is likely to flow between u and v.

$$\exists i \exists j \ (KE(task, u, i, j, t) - KE(task, v, i, j, t)) \neq 0 \tag{1}$$

Principle 1 reflects the diversity of people's knowledge. It is the necessary condition for knowledge to flow between nodes.

DOI: 10.1002/cpe

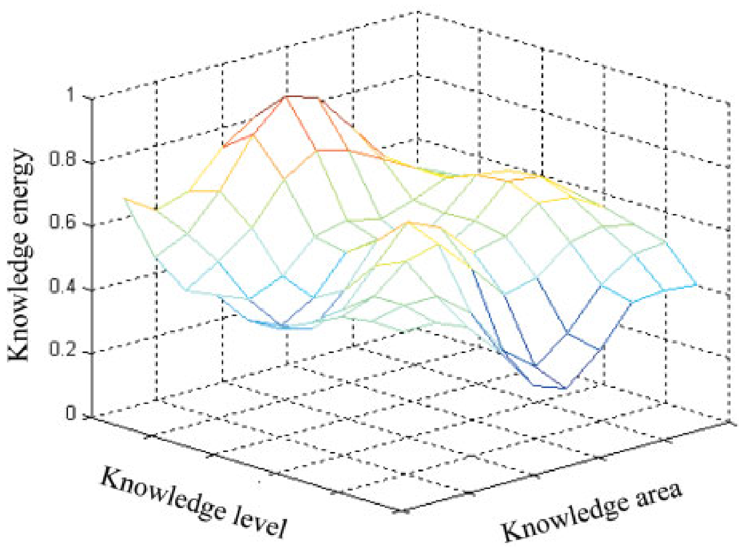


Figure 3. Energy space of a node's knowledge.

Principle 2. A knowledge flow is inefficient if it flows from a low-energy node to a high-energy node.

Let u and v be the two ends of a knowledge flow in $UFd(i, j)$. If formula (2) holds, the flow from u to v is ineffective:

$$\forall t \ (KE(task, u, i, j, t) - KE(task, v, i, j, t)) < 0 \tag{2}$$

Just as water naturally flows from the position with high potential energy to the position with low potential energy, knowledge flows from high-energy nodes to low-energy nodes. Flowing backward needs additional force. Principle 2 asserts that knowledge energy differences constrain effective flow in most cases. Planners of knowledge flow networks must respect this principle to achieve effectiveness [13].

Curves in Figure 4 show energy distributions at seven unit fields of three nodes. The downward pointing arrows represent the directions of effective flow. For example, A → B and B → C is effective at $field_0$, $field_1$, $field_2$, $field_5$, and $field_6$.

When the energy changes at a node, the network may need to be changed to regain efficacy. To improve its position in a competitive team, each node should strive to intensify its knowledge. Team members will thus strive to learn, create, and pass on as much as possible.

Principle 3. Knowledge energy differences always tend to diminish. That is, the following formula holds:

$$\forall i \forall j \ \lim_{t\to\infty} (KE(task, u, i, j, t) - KE(task, v, i, j, t)) = 0 \tag{3}$$

DOI: 10.1002/cpe

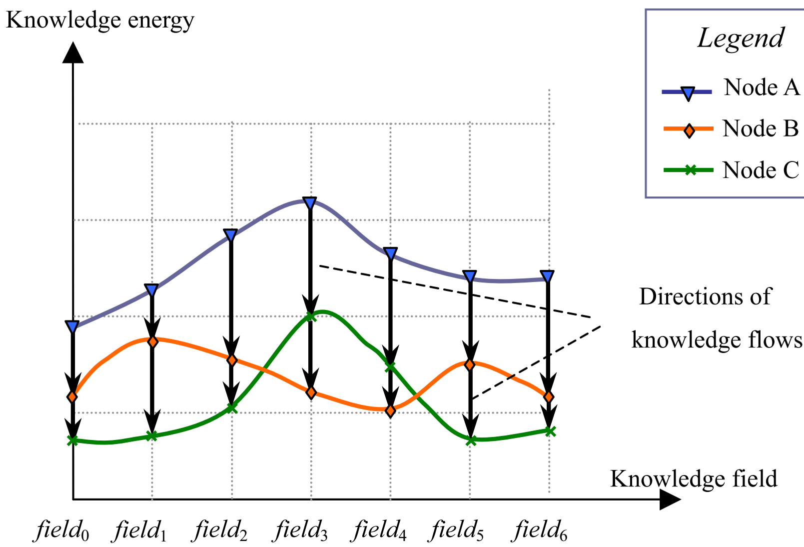


Figure 4. Effective knowledge flow directions at seven unit fields. Knowledge flow directions: $field_0$, $field_1$, $field_2$: A → B → C; $field_3$, $field_4$: A → C → B; $field_5$ and $field_6$: A → B → C.

If knowledge in the unit field $UFd(i, j)$ flows between two nodes, and if they share their knowledge without reserve, then the flow will be from the higher energy node to the lower energy node. Thus their energy in $UFd(i, j)$ will differ less and less as the knowledge flows. This effect will be clear in a closed environment when no knowledge flows into the team from outside. In this case, all nodes will end up with similar knowledge in the long term. Then the result is stagnation under principles 1 and 2. To avoid stagnation, a team should learn from outside continually rather than only pass knowledge inside.

Depreciation can be neglected over short spans of time or if it is slow enough. In this case, energy will not decrease.

Let $KE(task, u, i, j, \Delta t)$ be the change in energy of node u in $UFd(i, j)$ over a time $\Delta t > 0$. $KE(task, u, i, j, \Delta t)$ is non-negative. So,

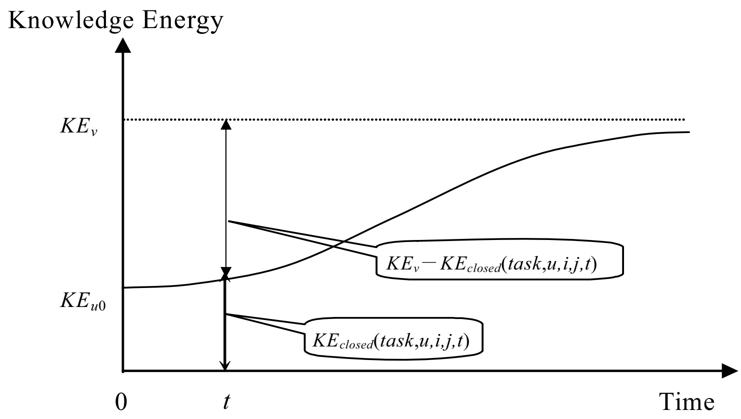
$$KE(task, u, i, j, \Delta t) = KE(task, u, i, j, t + \Delta t) - KE(task, u, i, j, t) \geq 0 \quad (4)$$

4. A MODEL OF KNOWLEDGE ENERGY

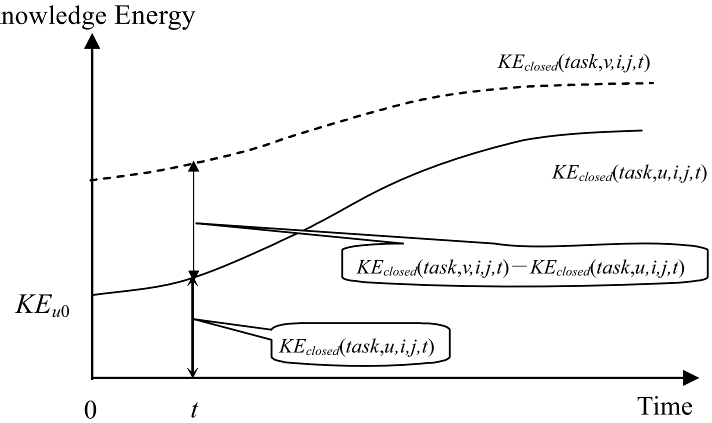
4.1. Computing energy in a closed environment

Let node v be the only predecessor of node u, and u the only successor of v. We first discuss the case where the knowledge energy of node v is a constant (shown in Figure 5(a)). In this case, the following statements about the energy of node u in unit field $UFd(i, j)$ at time t, denoted as $KE_{\mathrm{closed}}(task, u, i, j, t)$, can be derived from the following assumptions.

DOI: 10.1002/cpe



(a)



(b)

Figure 5. Knowledge energy change of node u: (a) when the knowledge energy of node v is a constant; (b) when the knowledge energy of node v changes with time.

(1) $KE_{\text{closed}}(task, u, i, j, t)$ increases monotonically.
(2) $KE_{\text{closed}}(task, u, i, j, t)$ tends to its predecessor's knowledge energy when the time is long enough (see Principle 3). So the final value of $KE_{\text{closed}}(task, u, i, j, t)$ is the energy of its predecessor, that is, $KE_v = KE_{\text{closed}}(task, v, i, j, 0)$.
(3) $KE_{\text{closed}}(task, u, i, j, t)$ increases in direct proportion to its own value, and to the proportion of its difference from that of its predecessor to the value of the predecessor, that is, to $(KE_v - KE_{\text{closed}}(task, u, i, j, t))/KE_v$. Thus, the larger the node's energy, the more rapidly it increases. Also, the more energy node u has yet to gain, the faster the gain.

DOI: 10.1002/cpe

A nonlinear differential equation, Equation (5), follows from the above analysis and the traditional logistic models [17], where λ is the proportionality coefficient and KE_{u0} is the initial knowledge energy of u:

$$\begin{cases} \dfrac{\mathrm{d}KE_{\text{closed}}(task, u, i, j, t)}{\mathrm{d}t} = \lambda\left(\dfrac{KE_v - KE_{\text{closed}}(task, u, i, j, t)}{KE_v}\right)KE_{\text{closed}}(task, u, i, j, t) \\ KE_{u0} = KE_{\text{closed}}(task, u, i, j, 0) \end{cases} \tag{5}$$

The solution to Equation (5) is as follows:

$$KE_{\text{closed}}(task, u, i, j, t) = \frac{KE_v}{1 + (KE_v/KE_{u0} - 1)\,\mathrm{e}^{-\lambda t}} \tag{6}$$

When the energy of the source node v changes with time (shown as the dashed curve in Figure 5(b)), the energy of u changes after its predecessor node v. The energy of node v in unit field $UFd(i, j)$ at time t is denoted by $KE_{\text{closed}}(task, v, i, j, t)$, and the nonlinear differential equation, Equation (5), is now given by the following:

$$\begin{cases} \dfrac{\mathrm{d}KE_{\text{closed}}(task, u, i, j, t)}{\mathrm{d}t} \\ \quad = \lambda\left(\dfrac{KE_{\text{closed}}(task, v, i, j, t) - KE_{\text{closed}}(task, u, i, j, t)}{KE_{\text{closed}}(task, v, i, j, t)}\right)KE_{\text{closed}}(task, u, i, j, t) \\ KE_{u0} = KE_{\text{closed}}(task, u, i, j, 0) \end{cases} \tag{7}$$

The general solution to Equation (7) is as follows:

$$\begin{cases} KE_{\text{closed}}(task, u, i, j, t) = \dfrac{1}{C_1\,\mathrm{e}^{-\lambda t} + \lambda\,\mathrm{e}^{-\lambda t}\int_0^t \mathrm{e}^{\lambda t}/KE_{\text{closed}}(task, v, i, j, t)\,\mathrm{d}t} \\ KE_{u0} = KE_{\text{closed}}(task, u, i, j, 0) \end{cases} \tag{8}$$

where C_1 is a constant. We can get a particular solution by replacing $KE_{\text{closed}}(task, v, i, j, t)$ in Equation (8) with an appropriate expression. For example, in a closed environment suppose we have a team composed of three nodes a, b, c, where node a is the predecessor of b, and b is the predecessor of c. Suppose $KE_{\text{closed}}(task, a, i, j, t)$ is a constant KE_{a0}. Then we can obtain the knowledge energy of b by using Equation (8) as follows:

$$KE_{\text{closed}}(task, b, i, j, t) = \frac{KE_{a0}}{1 + (KE_{a0}/KE_{b0} - 1)\,\mathrm{e}^{-\lambda t}}$$

Furthermore, the knowledge energy of c can be obtained by

$$KE_{\text{closed}}(task, c, i, j, t) = \frac{KE_{a0}KE_{b0}}{KE_{b0} + (KE_{a0} - KE_{b0})\lambda t\,\mathrm{e}^{-\lambda t} + ((KE_{a0} - KE_{c0})KE_{b0}/KE_{c0})\,\mathrm{e}^{-\lambda t}}$$

DOI: 10.1002/cpe

4.2. Computing energy in an open environment

In an open environment, a knowledge node can acquire knowledge from outside its team as well as from within.

Let $KE_{\text{open}}(task, u, i, j, t)$ (in abbreviation $KE(u, t)$) be the knowledge energy of node u in $UFd(i, j)$ at time t in an open environment. Its increase is composed of energy gained within the team (denoted as $KE_{\text{in}}(u, t)$) and that from outside (denoted as $KE_{\text{out}}(u, t)$). Thus,

$$KE(u, t) = KE(u, 0) + KE_{\text{in}}(u, t) + KE_{\text{out}}(u, t) \tag{9}$$

In an open environment, nodes that have higher energy could gain more knowledge and their energy would grow faster. The rate of increase in $KE_{\text{out}}(u, t)$ is proportional to the energy of u, $KE(u, t)$. Furthermore, when the energy of predecessor v is higher than that of node u, $KE_{\text{in}}(u, t)$ can be computed as in a closed environment.

From this, we can obtain the following nonlinear differential equations, where λ and δ are the proportionality coefficients and KE_{u0} is the initial energy of u:

$$\begin{cases} \begin{cases} KE(u, t) = KE(u, 0) + KE_{\text{in}}(u, t) + KE_{\text{out}}(u, t) \\ \dfrac{\mathrm{d}KE_{\text{out}}(u, t)}{\mathrm{d}t} = \delta KE(u, t) \\ \dfrac{\mathrm{d}KE_{\text{in}}(u, t)}{\mathrm{d}t} = \lambda\left(\dfrac{KE(v, t) - KE(u, t)}{KE(v, t)}\right)KE(u, t) \\ KE_{u0} = KE(u, 0) \end{cases} & \text{if } KE(v, t) - KE(u, t) > 0 \\ \begin{cases} KE(u, t) = KE(u, 0) + KE_{\text{in}}(u, t) + KE_{\text{out}}(u, t) \\ \dfrac{\mathrm{d}KE_{\text{out}}(u, t)}{\mathrm{d}t} = \delta KE(u, t) \\ \dfrac{\mathrm{d}KE_{\text{in}}(u, t)}{\mathrm{d}t} = 0 \\ KE_{u0} = KE(u, 0) \end{cases} & \text{if } KE(v, t) - KE(u, t) \leq 0 \end{cases} \tag{10}$$

The general solution of Equation (10) is as follows:

$$\begin{cases} \begin{cases} KE(u, t) = \dfrac{1}{C_2\,\mathrm{e}^{-(\delta+\lambda)t} + \lambda\,\mathrm{e}^{-(\delta+\lambda)t}\int_0^t \mathrm{e}^{(\delta+\lambda)t}/KE(v, t)\,\mathrm{d}t} \\ KE_{u0} = KE(u, 0) \end{cases} & \text{if } KE(v, t) - KE(u, t) > 0 \\ KE(u, t) = KE_{u0}\,\mathrm{e}^{\delta t} & \text{if } KE(v, t) - KE(u, t) \leq 0 \end{cases} \tag{11}$$

where C_2 is a constant. By replacing $KE(v, t)$ in formula (11) with the appropriate expression, we can get the solution of $KE(u, t)$.

Using the results of this section, we can compute changes in a node's knowledge energy in a closed or an open environment from its initial energy, from its learning ability, and from its predecessor's energy.

DOI: 10.1002/cpe

Table I. Scale for pairwise comparisons in the judgment matrix.

Scale for *KE*	Knowledge comparison	Explanation
1	Equal	Two nodes are equally energetic
3	Moderately greater	One node is moderately more energetic than the other
5	Much greater	One node is much more energetic than the other
7	Very much greater	One node is very much more energetic than the other
9	Dramatically greater	One node is extremely more energetic than the other
2, 4, 6, 8	Intermediate values	Judgment values between the above
Reciprocals		If v is the judgment value when h is compared to k, then $1/v$ is the judgment value when k is compared to h

5. KNOWLEDGE ENERGY ASSESSMENT

Knowledge can be explicit or tacit. Explicit knowledge is linguistic and therefore relatively simple to express and easy to encode. Tacit knowledge comes from experience and intuition, and is therefore much harder to express and encode [6,18]. Explicit knowledge is easy to assess objectively and statistically. However, tacit knowledge is difficult to assess, as it is often subconscious [19].

One way to evaluate a node's knowledge energy is to involve experts in the area being assessed, i.e. reputable people who are qualified professionals or have considerable experience in the area. For example, eminent scientists could be invited to assess research teams and experienced teachers to assess e-learning teams. Our solution is as follows.

The experts examine the objective and subjective materials of each node in the network. The former includes information about the node's local repository, and the latter includes results of questionnaires, self-evaluation, colleagues' evaluation, and achievement assessment. Although a node's tacit knowledge and cognitive and creative abilities are difficult to assess, they can be reflected by the subjective materials. A node with more knowledge always shows better performance and a node with greater ability always receives a better evaluation.

The experts compare the materials to rank nodes' knowledge energies. Based on the materials, experts in area i can assess the energy for each unit field $UFd(i, j)$, $j = 1, 2, \ldots, n$. As the comparison of two nodes is much easier to perform than assessing nodes individually, the experts make pairwise comparisons of energy using the scale shown in Table I. The results of the comparisons are put into a judgment matrix, in which an element a_{hk} gives the scaled energy difference between nodes h and k. If nodes $h$and k have equal knowledge energy, then $a_{hk} = 1$; if the knowledge energy of h is higher than that of k, then $a_{hk} > 1$; otherwise $a_{hk} < 1$.

From an expert's judgment matrix, we can compute its eigenvector, in effect the maximum latent root $\lambda_{\max}$, to rank the nodes based on their energy. We take the eigenvector values as giving the relative energies of the nodes, not the absolute energies. The expert then evaluates one node in the team to obtain an absolute energy, and we compute absolute energies for the other nodes on that basis.

With such results from s experts in each knowledge area i, we get a vector $m_p = (m_{i1p}, m_{i2p}, \ldots, m_{ijp}, \ldots, m_{inp})$, $j = 1, 2, \ldots, n$, $p = 1, 2, \ldots, s$, for every node as its energy in area i. Here, element m_{ijp} represents a node's knowledge energy in $UFd(i, j)$ as evaluated by expert p.

DOI: 10.1002/cpe

Table II. The average stochastic consistency index.

	Nodes								
	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

However, when experts make pairwise comparisons, there may be inconsistencies. For instance, if element $a_{12} = 2$, $a_{23} = 5$, and $a_{31} = 3$ (this means that, among the nodes, 1 is moderately more energetic than 2, 2 is much more energetic than 3, and 3 is moderately more energetic than 1), the pairwise comparisons are inconsistent. Complete consistency is difficult to maintain, especially when the team is large, because when dealing with intangibles human judgment is inevitably inconsistent. Judgement matrices must be nearly consistent otherwise the pairwise comparisons will be invalid. Using each others' matrices, experts can greatly improve consistency. The consistency of each matrix is assessed to judge whether the comparison results are reasonable or need to be improved.

The stochastic consistency index of the judgment matrix, *CI*, is given by

$$CI = \frac{1}{n-1}(\lambda_{\max} - n) \tag{12}$$

The average stochastic consistency index, *RI*, an experimental value given in [20], is shown in Table II.

The stochastic consistency ratio (*CR*) is

$$CR = \frac{CI}{RI} \tag{13}$$

If $CR < 0.1$, the judgment matrix is taken to be consistent and the energy evaluations of the experts are considered reasonable. Otherwise, the judgment matrix is reviewed and adjusted until $CR < 0.1$.

When a team is large, we can divide it into distinct groups with fewer than eight nodes, but where one node belongs to all groups to act as a computational bridge. The experts' pairwise comparisons within each group lead to their relative energy vectors. Estimating the absolute energy of the bridge node allows an absolute energy to be calculated for every other node in the team as a whole.

The energy vectors in knowledge area i of one node calculated from the experts' comparisons are gathered into the following matrix:

$$\mathrm{M} = \begin{bmatrix} m_{i11} & m_{i21} & \cdots & m_{in1} \\ m_{i12} & m_{i22} & \cdots & m_{in2} \\ \vdots & \vdots & \vdots & \vdots \\ m_{i1s} & m_{i2s} & \cdots & m_{ins} \end{bmatrix}$$

To amalgamate all of the experts' estimated results for a node's knowledge energy in each unit field, we average each column of numbers, $m_{ij1}, m_{ij2}, \ldots, m_{ijs}$, and obtain the mean $\bar{m}_{ij}$ and standard

DOI: 10.1002/cpe

deviation d_{ij} $(j = 1, 2, \ldots, n)$ as follows:

$$\bar{m}_{ij} = \frac{1}{s}\sum_{p=1}^{s} m_{ijp} \tag{14}$$

$$d_{ij} = \sqrt{\frac{1}{s}\sum_{j=1}^{s}(m_{ijp} - \bar{m}_{ij})^2} \tag{15}$$

Thus we obtain vectors $\bar{m}_i = (\bar{m}_{i1}, \bar{m}_{i2}, \ldots, \bar{m}_{in})$ and $d_i = (d_{i1}, d_{i2}, \ldots, d_{in})$. Here, $\bar{m}_{ij}$ is the mean value of one node's knowledge energy in unit field $UFd(i, j)$ given by all of the experts, and $\bar{m}_i$ is the vector that denotes its knowledge energy at all levels in area i.

All the data, including M, $\bar{m}_i$, and d_i, are sent to all the experts who confirm their estimates and also give a measure of their confidence in the result. Therefore we obtain two matrices: $R_{n\times s}$ and $e_{n\times s}$. The element r_{ijp} of $R_{n\times s}$ is the ultimate result of expert p in $UFd(i, j)$ and e_{ijp} in the matrix $e_{n\times s}$ the confidence in this result. We limit the confidence e_{ijp} to [0, 1]. The confidence $e_{ijp} = 1$ if the expert is absolutely certain of the result; $e_{ijp} = 0$ if completely bewildered. The confidence rests on the available resources and information, the sufficiency of proof evidence, and the experience of the expert.

Let $R^*_{ij} = \{k : e_{ijk} \geq \lambda, k = 1, 2, \ldots, s\}$, where λ is a given threshold value, $0 < \lambda < 1$, then

$$\bar{R}_{ij} = \frac{1}{|R^*_{ij}|}\sum_{k\in R*_{ij}} r_{ijk} \tag{16}$$

where $|R^*_{ij}|$ is the number of those elements in R^*_{ij}. That is, all the r_{ijp} whose confidence e_{ijp} is less than λ will be neglected. We then compute the mean of the rest. We have $\bar{R}_{ij}$ as the value of the energy in $UFd(i, j)$ of node u: $KE_u(task, u, i, j, t)$, Ke_{uij} for short. After the estimations in all areas are finished, we have a matrix KE_u representing the overall energy of node u:

$$KE_u = \begin{bmatrix} Ke_{u11} & Ke_{u21} & \cdots & Ke_{um1} \\ Ke_{u12} & Ke_{u22} & \cdots & Ke_{um2} \\ \vdots & \vdots & \vdots & \vdots \\ Ke_{u1n} & Ke_{u2n} & \cdots & Ke_{um} \end{bmatrix}$$

For simplicity, the data are organized as a series of values corresponding to knowledge areas. Let w $(task, i, j)$ be the weight on the level axis for accomplishing the task, such that $\sum_{j=1}^{n} w(task, i, j) = 1$. Ordinarily, high-level knowledge contributes more to accomplishing the task, so the weight for higher levels is greater. Then, the energy of area i of a node can be computed as follows:

$$KE_a(task, u, i, t) = \sum_{j=1}^{n} w(task, i, j)Ke_{uij} \tag{17}$$

So the energy of node u is represented by an M-tuple:

$$\langle KE_a(task, u, 1, t), KE_a(task, u, 2, t), \ldots, KE_a(task, u, m, t)\rangle$$

Now we define $KE_n(task, u, t)$ as the general energy of node u in time t when it completes a task. Let w $(task, i)$ be the weight on the area axis for completing a task, such that $\sum_{i=1}^{m} w(task, i) = 1$.

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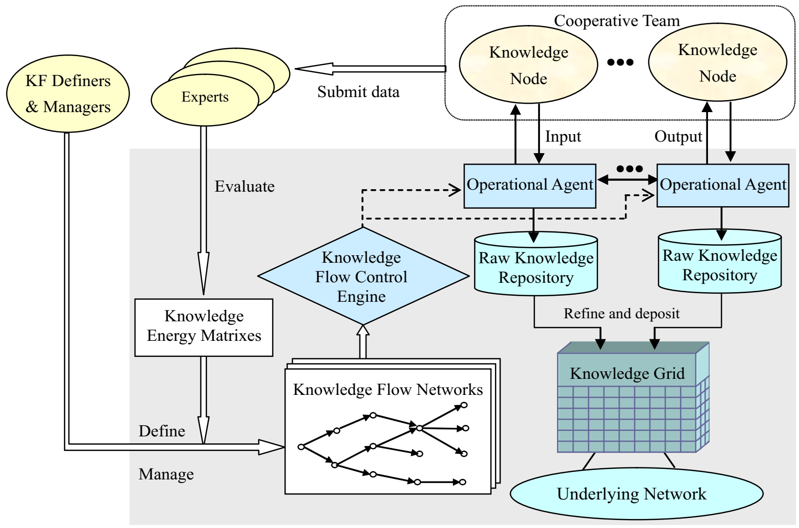

Figure 6. General architecture of the knowledge flow management system.

We compute KE_n $(task, u, t)$ as follows:

$$KE_n(task, u, t) = \sum_{i=1}^{m} w(task, i) KE_a(task, u, i, t) \tag{18}$$

Thus, we have values for the energy of node u in a unit field $KE_u(task, u, i, j, t)$ in a certain area $KE_a(task, u, i, t)$ and its overall knowledge energy $KE_n(task, u, t)$.

6. A KNOWLEDGE FLOW MANAGEMENT SUPPORT SYSTEM

The proposed principles and methods can help implement a knowledge flow management system that provides team members with an interface for coding their knowledge and a means for passing knowledge on. The system organizes the knowledge flow network using workflow process patterns and the distribution of the knowledge energy in the team, passes knowledge from node to node, collects knowledge, processes data and case documents, tracks the contribution and use of knowledge, and assesses node energies.

The general architecture of the system is shown in Figure 6. The solid arrows denote knowledge flow, and the dotted arrows denote control information flow between the control engine and the operational agents. As they work, nodes (team members) record and receive knowledge through operational agents. Each agent receives knowledge and delivers it to its node, collects its node's new knowledge, passed or created, and delivers it to successor nodes. The control engine saves the structure of knowledge flow

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networks, monitors their operations, and directs agents to pass knowledge appropriately along the links of the networks. When a node creates knowledge, its agent collects it. The agent passes this knowledge on under the direction of the control engine. The agent of any successor takes the knowledge in and passes it to its node and its node's successors. At the same time, the system stores the new knowledge in its repository as raw knowledge, and after refining it is passed to the Knowledge Grid (Resource Space Model) to accumulate for use in later tasks [16,21].

The left-hand part of Figure 6 shows how knowledge energy is evaluated and how knowledge flow networks are formed and managed. Experts or their agents evaluate node energies and provide them in matrices. Professionals use the matrices according to the needs of the task when they define knowledge flow networks. The system maintains the predecessor and successor relationships between nodes and controls the knowledge flows. Once the knowledge flow networks are in use, the energy matrices can be changed after re-evaluation by experts or by computation as described above. Knowledge flow networks can be adjusted by the managers when necessary.

To enable our system to run on different platforms, the Resource Description Framework (RDF) [22] is adopted to represent the elements of knowledge flows, including the sender, the receiver, and the knowledge ID information, as follows:

```
<rdf: RDF>
  <rdf: Description ID="KnowledgeFlowID">
    <area> KnowledgeArea </area>
    <level> KnowledgeLevel </level>
    <sender> knowledgeNodeID </sender>
    <receiver> knowledgeNodeID </receiver>
    <KFcontent>
      <rdf: Bag>
    <rdf: li>
      <content>knowledgeID</content>
    </rdf: li>
    . . .
    <rdf: li>
      <content>knowledgeID</content>
    </rdf: li>
      </rdf: Bag>
    </KFcontent>
  </rdf: Description>
</rdf: RDF>
```

The knowledgeIDs in the content tags point to descriptions that hold the required attributes and content. A description of knowledge with time, task, originator, group, area, level, topic, and content can be represented as follows:

```
<rdf:RDF>
  <rdf:Description ID="KnowledgeID">
    <time> Time </time>
```

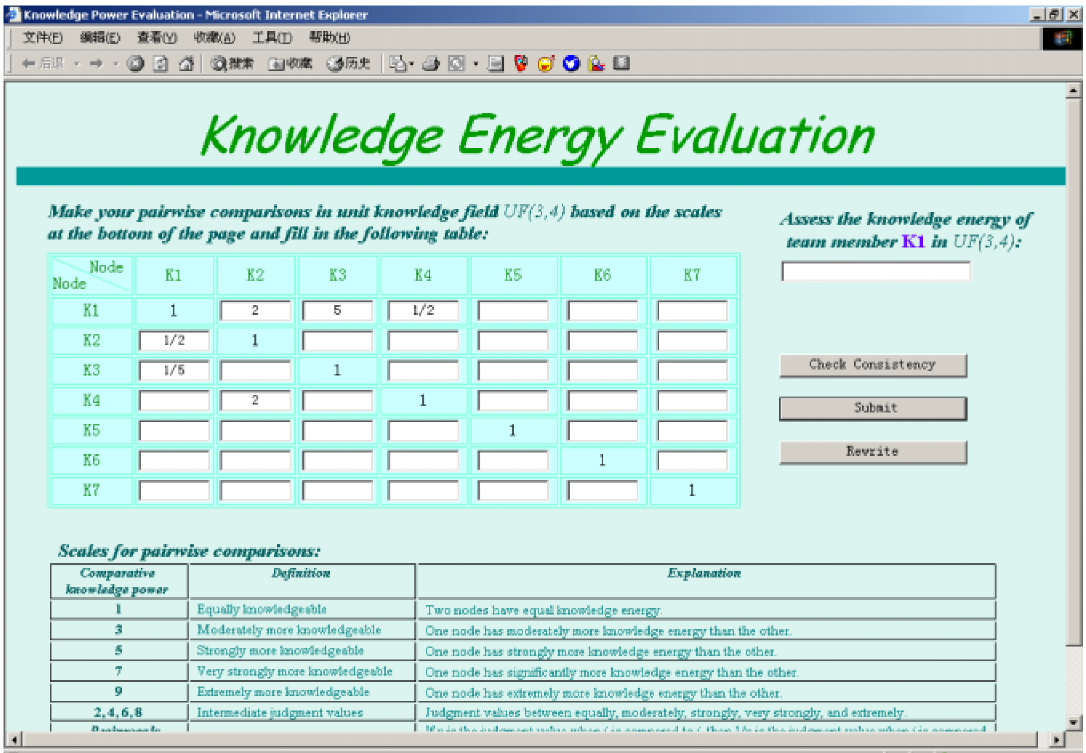

Figure 7. Interface for knowledge energy pairwise comparisons.

```
  <task> TaskName </task>
  <originator> knowledgeNodeID </originator>
    <group> groupID </group>
    <area> KnowledgeArea </area>
    <level> KnowledgeLevel </level>
    <topic> KnowledgeTitle </topic>
  <content> KnowledgeContent </content>
  </rdf:Description>
</rdf:RDF>
```

Figures 7 and 8 show the prototype interfaces for energy evaluation. Experts in a unit field make pairwise comparisons between nodes and put their results into the table in the middle part of Figure 8. After checking consistency by pressing the ‘Check Consistency’ button, they can submit the results if they check out; otherwise, some adjustment should be made. The estimated results of all experts are

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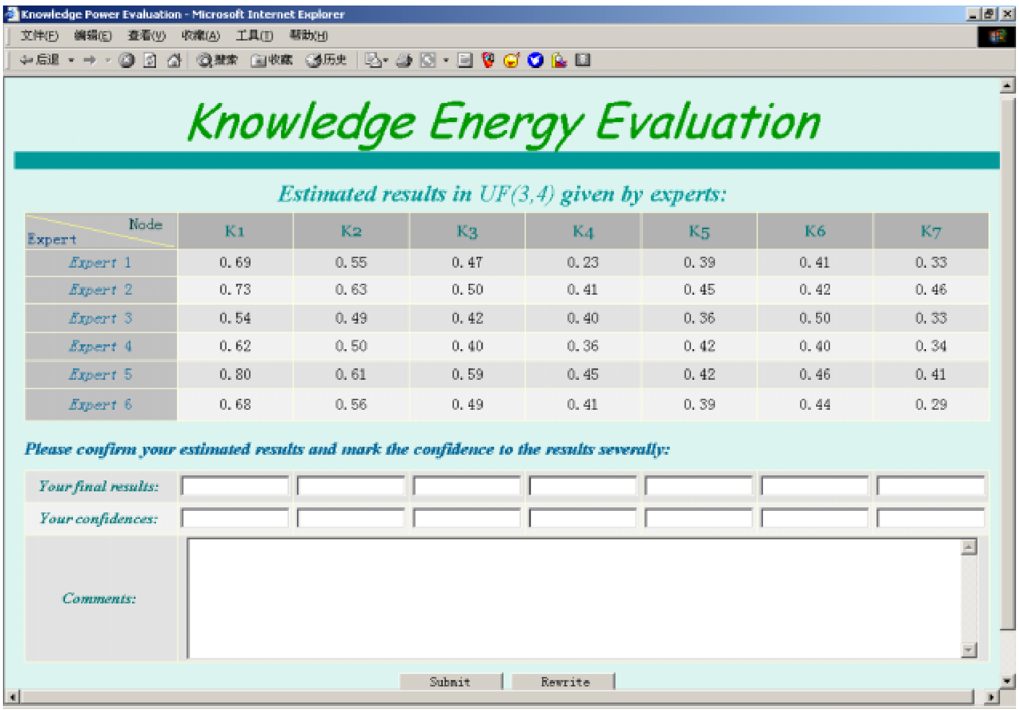

Figure 8. Interface for final knowledge energy evaluation.

given in the table shown in the middle part of Figure 8. Experts can confirm or amend their results and also give confidence levels to the final results. The energy of the nodes can be computed by averaging the final results with confidence level higher than a specified threshold value.

Figure 9 depicts the interface of the knowledge flow definition tool. Designers can use the tool to design a knowledge flow network and specify the properties of its nodes. The node energies, shown in the table at the bottom left-hand side of Figure 9, can help in designing an effective knowledge flow network. Once the network is defined, its effectiveness should be verified as described above.

7. EXPERIMENT

The idea of knowledge flow was tested by selecting experimental groups and recruiting experts, providing group members with different learning conditions, and then tracking their knowledge energy over a period of time (10 weeks).

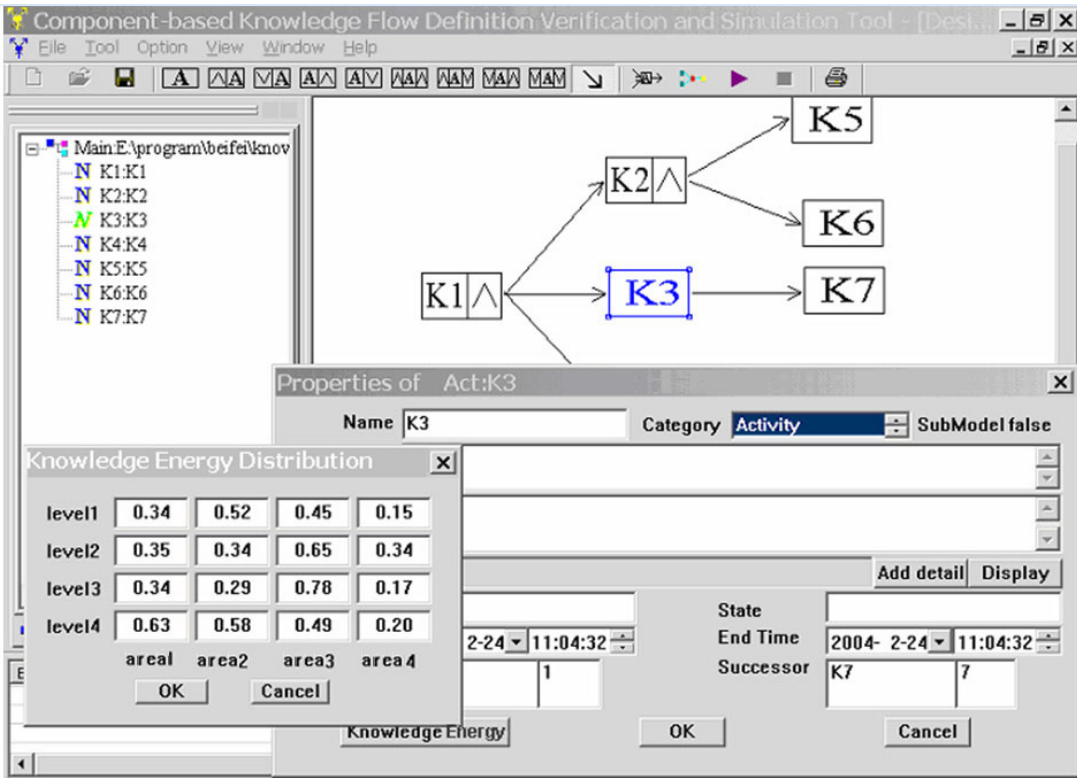

Figure 9. The knowledge flow network definition tool.

7.1. The experiment procedure

Step 1. Select sample groups. From an existing research team, we selected three groups of three members with different knowledge energies. Figure 10 shows the nodes of such a group within the ellipse. The flow was from A to B to C in each group.

Step 2. Select the knowledge field. After considering the nature of the research team's task and the knowledge ranges of members of the selected groups, two areas were selected: *intelligent agents* and *workflow*. For each area, four levels were defined, from high to low: *concept*, *method*, *skill*, and *theory*. The three groups were evaluated so that the flows could be managed appropriately. For simplicity, we considered only the overall energy of each node and ignored knowledge depreciation.

Step 3. Determine learning strategies. At the beginning of the experiment, the flow was from A to B to C. We set different strategies for passing and learning knowledge for different groups. For group 1, node A did not learn at all, maintaining constant energy. B and C learnt only from the flow. For group 2,

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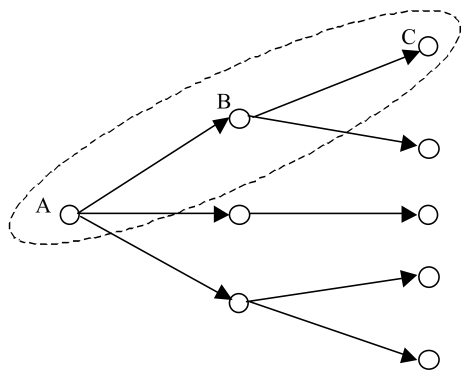

Figure 10. A sample group.

A was allowed to acquire knowledge from outside, but B and C learnt only from the flow. For group 3, all nodes were allowed to learn from anywhere, outside or inside the group.

Step 4. Collect experimental data. At the end of each week of the experiment, the nodes were evaluated by the experts using the method introduced in Section 5. The evaluations are shown in Figure 11.

The evaluations are summarized in Table III.

At the end of the experiment, the three groups submitted their final research reports. Each participant was tested and interviewed to assess their learning, achievements, and abilities. The new valid explicit knowledge that each group added to the repository was measured. The results of these assessments are given in Table IV.

7.2. Analysis of the results

Figure 11 shows that the three groups gradually and similarly increased their knowledge energy in the first three weeks. This was mainly because short-term affects were not very obvious, although different strategies have been enforced. However, after the first three weeks the groups began to exhibit differing behaviour.

Figure 11(a) shows that A learnt very little in the first group, and B and C slowly closed up on A. In a closed environment, as the nodes approached equal energy, the flow became slower and slower. Note that A did increase in group 1, but only slightly, because it was impossible to establish an entirely closed environment in the experiment. The occasional energy decrease can be attributed to knowledge depreciation and the subjective nature of the evaluation.

Figure 11(b) shows that nodes in group 2 increased their energy more smoothly than in group 1. With A acquiring knowledge constantly, B and C had more to learn. The final energies of group 2 were much higher than those in the entirely closed environment. The original energy gaps between nodes were sustained during the experimental period. Hence, group 2 was more efficient in knowledge sharing and learning than group 1.

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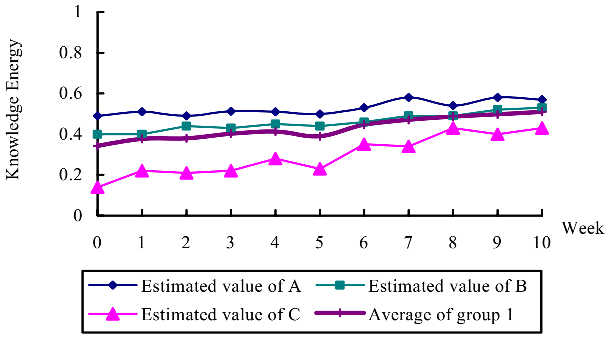
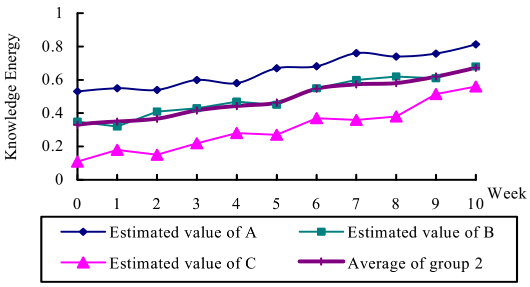
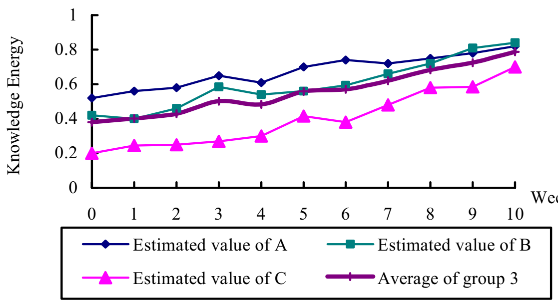


(a)



(b)



(c)

Figure 11. Knowledge energies of the groups change with time: (a) group 1; (b) group 2; (c) group 3.

DOI: 10.1002/cpe

Table III. Comparisons of average knowledge energy.

	Group 1	Group 2	Group 3
Initial value	0.343	0.33	0.38
Final value	0.51	0.673	0.787
Difference	0.167	0.343	0.407

Table IV. Research achievement.

Assessment	Group 1	Group 2	Group 3
Technical report assessment	Bad	Average	Excellent
Interview assessment	Bad	Good	Excellent
New explicit knowledge	26 pieces	42 pieces	74 pieces

For group 3, shown in Figure 11(c), the increment of individual nodes was so different that their ranks changed. After the eighth week, B had become the most knowledgeable node in the team. This was mainly due to the different rates of learning from outside for each node. For efficiency, the flow was changed to B $\rightarrow$ A $\rightarrow$ C. The average increase in energy for this group was by far the highest, making them the most efficient.

The results given in Tables III and IV clearly show that knowledge nodes in an open environment perform better with regards to knowledge learning, sharing, and creation than those in a closed environment.

8. NETWORKING STRATEGIES

A node can establish knowledge flows with other nodes by adopting the following strategies.

(1) *Random*: each node forwards the query to a randomly selected node.
(2) *Greedy*: each node sends the query to a node with the highest energy.
(3) *Generous*: each node forwards the query to a node with the lowest energy.
(4) *Selfish*: a node sends the query to the node with higher energy. If the node has the top energy, it randomly selects a node with the same energy.

To know the impact of different knowledge networking strategies on the effectiveness of a knowledge flow, we conduct the following simulation.

A peer-to-peer knowledge flow network with 1000 autonomous agents is constructed where agents can query each other and knowledge flows with answers. The initial knowledge energies of the agents are randomly distributed. 200 agents are selected randomly and each of them generates a query per time slot. The maximum number of queries that can be accepted by a node per time slot is

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supposed to be five. The results of interactions would react on the knowledge energies of relative nodes. The simulation experiment lasts for 10 time slots. Four groups of experiments are compared according to the performance of individual nodes and the whole groups. The evaluation metrics are as follows.

(1) *The number of successful interactions*, which represents the number of queries that have been handled successfully by the node.
(2) *The load of nodes*, which means that how many queries the nodes have received.
(3) *The total successful, failure, and lost interactions of the whole groups*. (Whether a knowledge flow interaction is successful relies on the nodes' knowledge energy difference and the risk factor. Any answer delayed over the maximum time slot will be treated as lost.)

Figure 12(a) gives the results of the groups with random strategy, (b) gives the results of using the greedy strategy (nodes are allowed to randomly select one of the top five nodes with the highest energy), (c) gives the results of using the generous strategy (nodes are allowed to randomly select one of top five nodes with the lowest energy), and (d) gives the results of using selfish strategy. The performance of the four groups is compared in Figure 13. Figure 13(a) compares the proportion of successful, failure, and lost interactions, and Figure 13(b) compares the amount of total successful interactions.

The results of these experiments are as follows.

(1) The selfish strategy results in the highest success rate compared with the other three strategies, and the query loads are shared by most nodes. Pushing queries to the nodes with a higher rank leads to both the high possibility of success and the sharing of load.
(2) Under the random strategy, the query loads are also balanced. The success rate is not very high because the randomly selected nodes may have a low energy leading to a failure.
(3) The greedy strategy is dissatisfying, despite the queries being sent to the nodes with the highest energy that potentially have the highest success rate. However, because the capabilities of nodes are limited, many of queries are lost and the overloads of a few nodes decrease the performance of the greedy strategy. This is in agreement with the social experience that when too many students consult an expert, even if the expert is willing and able to answer, the result is ineffective.
(4) The generous strategy performs the worst, both with regards to the success rate and the load of nodes. Focusing all queries on several lowest energy nodes leads to most of the queries either being lost or failing.

So a knowledge flow network should avoid not only inefficient flows but also the overloaded nodes in a knowledge flow network.

9. CONCLUSION

Knowledge flow networks are a means of reflecting, monitoring, managing, and ordering knowledge exchange processes in knowledge-intensive teams. This paper proposes a knowledge energy model and certain principles, and describes a system based on that model, as an important step in realizing knowledge flow network modeling, optimization, and use. The advantages of using energy in designing knowledge flow networks are as follows: (1) reflecting reputation, creativity, and learning ability in a cooperative environment; (2) supporting efficient knowledge flow management, orderly organization,

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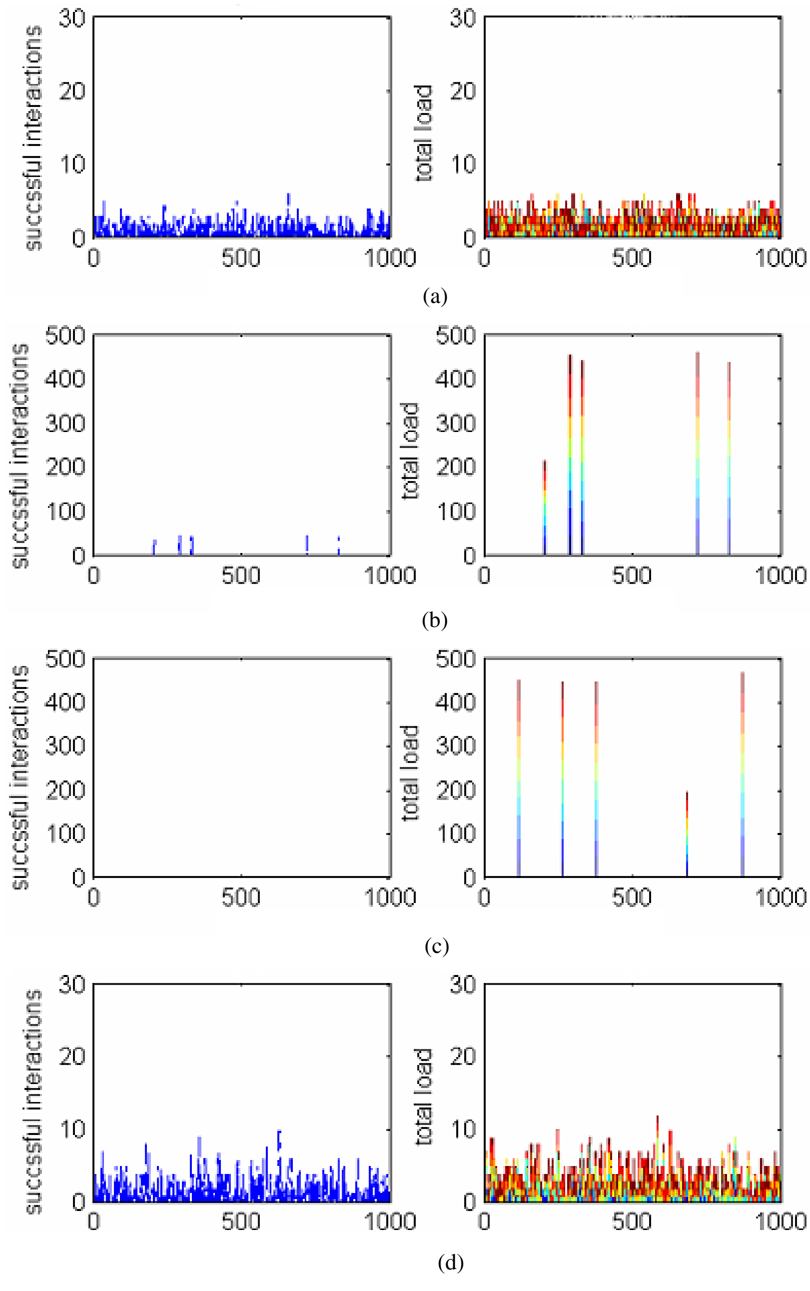
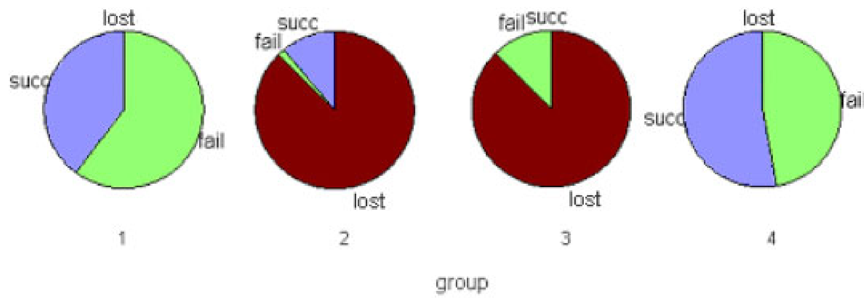
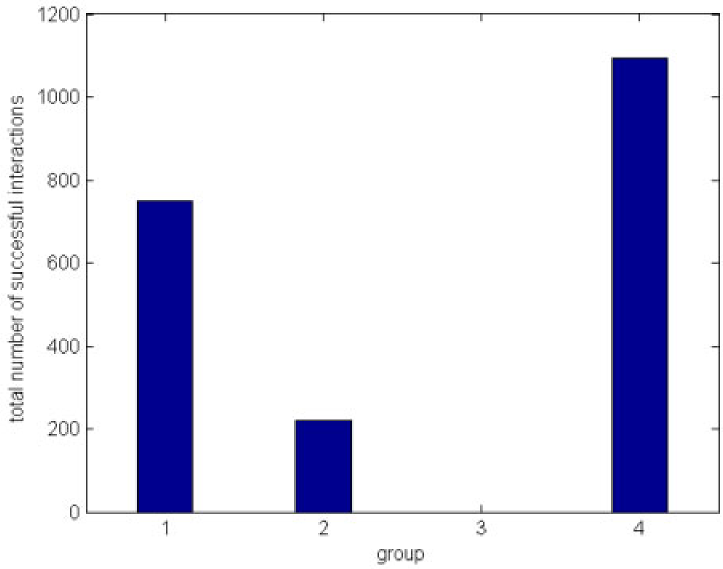


Figure 12. The number of successful interactions and the loads of nodes.



(a)



(b)

Figure 13. Experiments for performance comparison: (a) proportion of successful, failure, and lost interactions of four groups; (b) total numbers of successful interactions of four groups.

and adaptation of networks and control of the direction of flows to avoid redundancy and inefficiency; (3) ensuring the effectiveness of flows, and thus the provision of a basis for properly controlling the knowledge processes of a team; and (4) adopting an appropriate strategy to ensure an effective knowledge flow network.

A knowledge flow network support system is the higher overlay of the Knowledge Grid—an ideal intelligent interconnection environment [16,23]. Achievements in the study of social network, Web, Semantic Web, Grid, Semantic Grid, and Peer-to-Peer [21,24,25] help establish a high-performance

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Knowledge Grid for supporting efficient distributed teamwork. Our continuing work addresses the diversity and dynamics of team membership, trust impact, psychological issues, and knowledge flow networks in hierarchical organizations [8,26,27].

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