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Dynamic Optimization of Knowledge innovation capability based on PSO

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Abstract: Knowledge innovation capability is considered as the major one of organizational innovation capabilities and it, therefore, plays a more vital role in developing a sustainable competitive advantage for organizations, especially in a dynamic environment. Since, knowledge and its values have now become a major source of competitive advantage for organizations, only by possessing knowledge innovation capability, can organizations maintain a dynamic and sustainable competitive advantage. Although enormous studies have focused on the issue of knowledge innovation, those studies did not investigate how to optimize knowledge innovation capability of organizations. In this study, the process of knowledge innovation capability optimization based on Particle Swarm Optimization (PSO) is proposed in order to optimize knowledge innovation capability and realize a global optimal knowledge innovation for organizations. Moreover, a simulation study is pulled into to illustrate the feasibility and availability of PSO from the empirical perspective. This study is expected to be helpful for organizations to develop and optimize their knowledge innovation capability from an evolutionary perspective.

Key words: Knowledge innovation capability, particle swarm optimization, dynamic optimization, evolutionary perspective, competitive advantage

INTRODUCTION

In the new economy, knowledge plays a key role in society and knowledge workers are the single greatest asset in organizations (Drucker, 1993). Since, knowledge and its management are the only sources of sustainable competitive advantage (Sherif and Xing, 2006), to survive in a competitive commercial environment, organizations have to concentrate on a series of knowledge management processes, including acquiring, sharing, transferring, diffusing, creating and applying knowledge, to maintain a competitive advantage. Accordingly, knowledge innovation capability is considered as one of the main sources of the competitive advantage of organizations (Almeida *et al.*, 2002; Zollo and Winter, 2002). At present, there are intensive studies on knowledge creation, however, the concentration is more on the process of knowledge creation (Nonaka and Toyama, 2003; Esterhuizen *et al.*, 2012). There has been little consideration for knowledge innovation capability using deduction. Obviously, it is crucial for both scholars and practitioners to realize the concrete essences of knowledge innovation capability. Knowledge innovation capability of organizations is a set which consists of all the innovation capabilities of knowledge workers. How to realize a global optimum of knowledge innovation capability of organizations is a vital issue. The ways of optimization including Genetic Algorithm (GA) (Hoglund, 2013; Angelova *et al.*, 2012), Particle Swarm Optimization (PSO) (Cai and Pan, 2012; Epitropakis *et al.*, 2012) and Ant Colony Optimization (ACO) (Zhang and Feng, 2012; Kabir *et al.*, 2012) can be employed to realize knowledge innovation capability optimization. However, PSO without the mechanisms of crossover and mutation is much simpler than GA while ACO is a probability algorithm of finding optimal path. PSO with its many advantages including easy implementation, high precision and fast convergence has caused the attention of the academia. Therefore, in this study PSO is used to fully optimize knowledge innovation capability of organizations. The purpose of this study is to develop an evolutionary perspective to explain the essences and optimization of knowledge innovation capability. Traditionally, organization theory regards organization as a machine. However, any organization is composed of its employees and those employees are organic (Huang, 2009) that means all of the organizational behaviors, including knowledge innovation, should be considered as an organic process. In this study, a new perspective is proposed to enlighten novel issues about knowledge innovation capability. Undoubtedly, the development of knowledge innovation capability is a self-organizing process and thus evolutionary perspective can hold this characteristic. Therefore, the contribution of this study is

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to propose a mathematical model to simulate knowledge innovation capability optimization based on the use of PSO from an evolutionary perspective.

BASIC CONCEPTS AND PRINCIPLES OF PSO

Recently, the concepts of evolution have been widely employed in many domains, such as organizational theory (Molleman *et al*., 2013; Pradhan *et al*., 2012; Ellwardt *et al*., 2012) and computational science (Perreault *et al*., 2012; Huber, 2009; Turner and Sederberg, 2012). PSO is an evolutionary computation technique. It comes of the research on bird flock preying behaviour. Meanwhile, PSO stems from Complex Adaptive System (CAS), to be specific, a member of CAS is called the body. Such as in the research of bird flock system, each bird in this system is called the body. A body has an adaptability, it can communicate with the environment and other bodies. In addition, a body can learn and accumulate experiences in accordance with the process of exchange and then change their structures and behaviours. The body of CAS has four basic characteristics (these characteristics are the bases of the development and changes for PSO) which can be described as follows: (1) First, the body is active, (2) The body is interrelated with the environment and other bodies, they affect each other and have an interaction and this effect is the mainspring of the development and changes of the system, (3) Environmental effects are macroscopical while the effects among the bodies are microscopic, macroscopic and microscopic effects need to be combined organically and (4) Finally, the entire system may also be affected by some random factors.

PSO is used to solve optimization problems from the inspiration of the behaviours of these biological populations. In PSO, each potential solution of optimization problems can be imagined as a point of d-dimensional search space, we call this point as a particle, each particle has an fitness value which is determined by an objective function, each particle has a rate which determines their directions and distances of flying and then particles search in the solution space following the current best particle. PSO algorithm simulates a process that a flock of birds look for food, each bird is a particle in PSO, i.e., the possible solutions that we need to solve the problem. These birds constantly change their positions and speeds in the air when they are in the process of looking for food.

We can summarize the above concepts and principles to describe the procedure of particle swarm optimization, as shown in Fig. 1. First, the fitness index of each particle can be obtained after initializing the particle swarm and then particles evolve through updates which will make them more adaptable to the environment by the adjustments of the positions and speeds in the particle swarm. Thus, particles can continuously evolve and adapt to the environment.

PROCESS OF KNOWLEDGE INNOVATION CAPABILITY OPTIMIZATION

Knowledge innovation can be conceptualized as a dialectical process, in which various contradictions are synthesized through dynamic interactions among individuals, the organization and the environment (Nonaka and Toyama, 2003). PSO algorithm simulates a

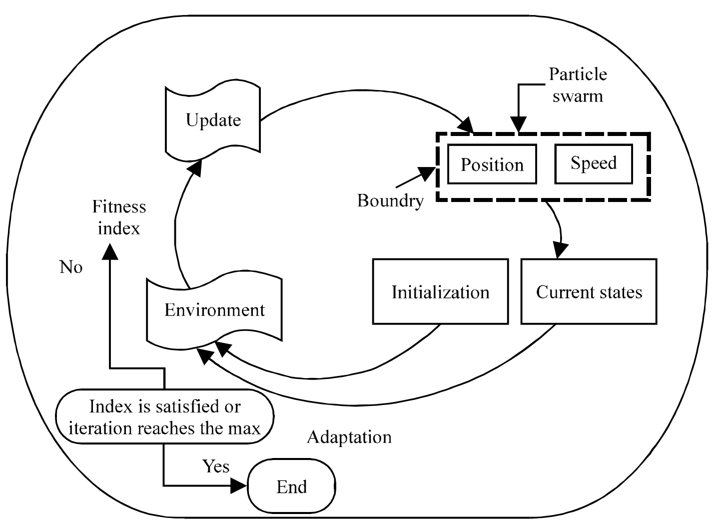

Fig. 1: Concepts and principles of PSO

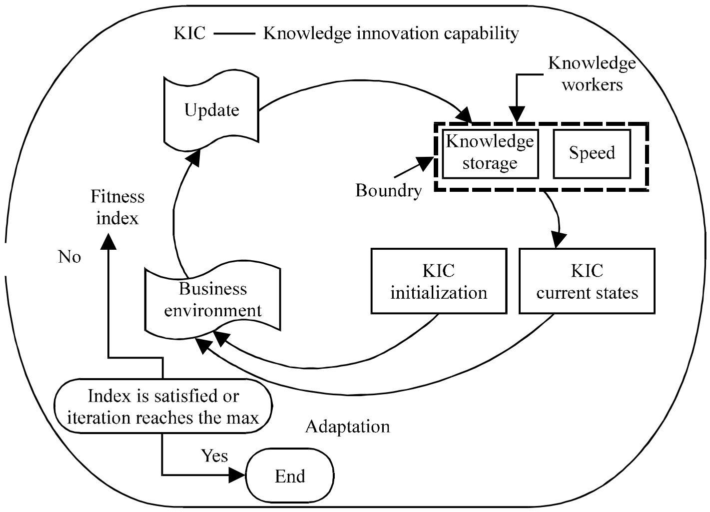

Fig. 2: Process of knowledge innovation capability optimization based on PSO

process that a flock of birds look for food, in this process each bird adjusts its positions and speeds based on the fitness index in order to adapt to the dynamic environment. Likewise, in the process of knowledge innovation capability optimization, each knowledge worker adjusts his knowledge storage and speeds by learning from current best worker in order to obtain a global optimal of knowledge innovation capability for organizations. From the analysis above, it can be seen that knowledge innovation capability optimization is similar to the phenomenon that birds look for food.

We should highlight that PSO evolution is used for analogizing knowledge innovation capability optimization of organizations. A particle swarm is composed of all its individuals; similarly, knowledge workers are the major part of organizations and play a crucial role in knowledge innovation of organizations. In the process of knowledge innovation, each knowledge worker needs to adjust his knowledge storage and speeds according to updating formula in order to reach a global optimum. If the termination condition is satisfied, the iteration will stop, otherwise, the fitness value will be calculated. From the above analyses, the process of knowledge innovation capability optimization based on PSO can be modeled as shown in Fig. 2.

The updating equation of knowledge storage and speeds of knowledge workers are shown as follows:

$$\begin{aligned} v_{id}^{t+1} &= v_{id}^{t} + c_1 r_1 \left(p_{id}^{t} - x_{id}^{t}\right) + c_2 r_2 \left(g_{id}^{t} - x_{id}^{t}\right) \\ x_{id}^{t+1} &= x_{id}^{t} + v_{id}^{t+1} \end{aligned} \quad (1)$$

where, the speed of d-dimensional component at time t for the ith particle can be denoted as v^t_{id} and knowledge storage of d-dimensional component at time t for the ith particle can be denoted as x^t_{id}. The weight coefficient of tracking historical optimal value of knowledge worker oneself can be denoted as c_1 and the weight coefficient of tracking group optimal value can be denoted as c_2. Note that r_1 and r_2 can be denoted as the random numbers which are uniformly distributed in [0, 1].

From the updating formulas, it is clear that the update of knowledge workers is divided into three parts: historical status, self-knowledge and social collaborations. In the optimization process, knowledge workers constantly sum up self-experience and learn from the best individual of the organization in the current time and then move closer up to the optimal knowledge worker gradually.

SIMULATION STUDY AND DISCUSSION

It is supposed that Enterprise H is a knowledge-intensive enterprise. There are 30 knowledge workers in Enterprise H. The most preferred index that can fully reflect knowledge innovation capability of organizations is the number of patents registered (Lee *et al*., 2013). Therefore, the number of patents registered is used to represent knowledge innovation capability of Enterprise H. The optimal of knowledge innovation capability of Enterprise H can be obtained based on PSO. It is assumed that the relation between knowledge innovation capability and the number of patents registered can be denoted as the following function:

$$y = 1-\cos(2\times x)\times \exp(-x) \quad (2)$$

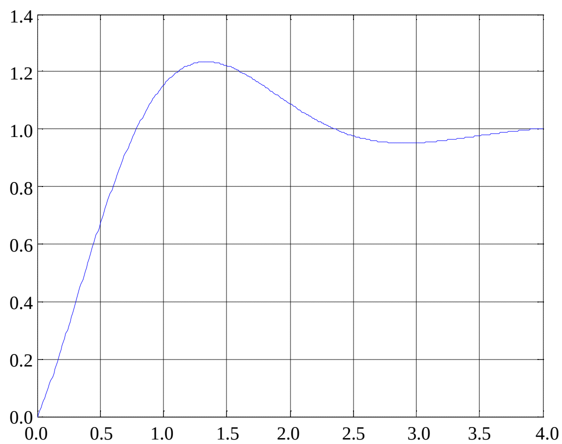

Fig. 3: Figure description of function 2

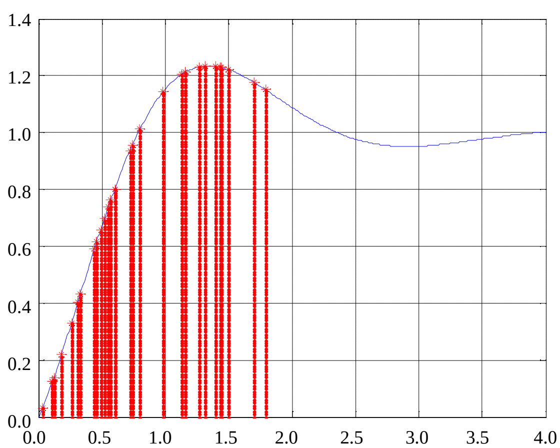

Fig. 4: Description of final results

where, x denotes the number of patents registered of per knowledge worker and y denotes knowledge innovation capability. The figure of the function 2 can be described as shown in Fig. 3. The task is to search the max of y when x is in [0, 4]. According to updating equation, the optimal of knowledge innovation capability can be obtained by using MATLAB software, as shown in Fig. 4. On the basis of Fig. 4, it is clear that the value of knowledge innovation capability reaches the max of $y = 1.2344$ when the number of patents registered is 1.34 and knowledge innovation capability of Enterprise H realizes a global optimum.

It can be seen that knowledge innovation capability can reach a max value with the increase of the number of patents registered in the interval [0, 4]. Afterwards, knowledge innovation capability presents a declining trend. It is noted that knowledge innovation capability will not go on to grow with the increase of the number of patents registered. This meaning of Fig. 4 is to present a phenomenon that knowledge innovation capability will not grow unboundedly in spite of the number of patents registered is increasing. It means that knowledge innovation capability of Enterprise H is not necessarily higher when each knowledge workers has more number of patents registered. It is possible that, to some extent, engaging in producing more patents is not good for knowledge innovation capability optimum. Therefore, knowledge innovation capability of Enterprise H can realize a global optimum when the number of patents registered is 1.34.

CONCLUSION

Knowledge innovation capability optimization is a vital issue for organizations. This study describes the process of knowledge innovation capability optimization based on the perspective of evolution. Since, knowledge innovation capability optimization is similar to the characteristics of birds. In this study, the process of knowledge innovation capability optimization is modeled as the process that birds look for food. The issue of knowledge innovation capability optimization is reconsidered using PSO. Furthermore, this study takes Enterprise H as a simulation example to illustrate the feasibility and availability of PSO. The simulated results indicate that the number of patents registered does not necessarily ensure increasing knowledge innovation capability. Only when the number of patents registered is suitable, knowledge innovation capability of Enterprise H can reach a global optimum. In order to fully optimize knowledge innovation capability, improved PSO algorithm should be considered in the future. In addition, the specific process of knowledge innovation capability needs to be studied in depth in future research.

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REFERENCES

Almeida, P., J. Song and R.M. Grant, 2002. Are firms superior to alliances and markets? An empirical test of cross-border knowledge building. Org. Sci., 13: 147-161.

Angelova, M., K. Atanassov and T. Pencheva, 2012. Purposeful model parameters genesis in simple genetic algorithms. Comput. Math. Appl., 64: 221-228.

Cai, J. and W.D. Pan, 2012. On fast and accurate block-based motion estimation algorithms using particle swarm optimization. Inform. Sci., 197: 53-64.

Drucker, P.F., 1993. Post-Capitalist Society. Butterworth-Heinemann, Oxford, UK..

Ellwardt, L., C. Steglich and R. Wittek, 2012. The co-evolution of gossip and friendship in workplace social networks. Soc. Networks, 34: 623-633.

Epitropakis, M.G., V.P. Plagianakos and M.N. Vrahatis, 2012. Evolving cognitive and social experience in particle swarm optimization through differential evolution: A hybrid approach. Inform. Sci., 216: 50-92.

Esterhuizen, D., C.S.L. Schutte and A.S.A. du Toit, 2012. Knowledge creation processes as critical enablers for innovation. Int. J. Inform. Manage., 32: 354-364.

Hoglund, H., 2013. Estimating discretionary accruals using a grouping genetic algorithm. Expert Syst. Appl., 40: 2366-2372.

Huang, J.J., 2009. The evolutionary perspective of knowledge creation-A mathematical representation. Knowledge-Based Syst., 22: 430-438.

Huber, A., 2009. On non-linear evolution equations of higher order-the introduction and application of a novel computational approach. Applied Math. Comput., 215: 2337-2348.

Kabir, M.M., M. Shahjahan and K. Murase, 2012. A new hybrid ant colony optimization algorithm for feature selection. Expert Syst. Appl., 39: 3747-3763.

Lee, I.H., E. Hong and L.X. Sun, 2013. Regional knowledge production and entrepreneurial firm creation: Spatial dynamic analyses. J. Bus. Res., 66: 2106-2115.

Molleman, L., A.E. Quinones and F.J. Weissing, 2013. Cultural evolution of cooperation: The interplay between forms of social learning and group selection. Evol. Hum. Behav., 34: 342-349.

Nonaka, I. and R. Toyama, 2003. The knowledge-creating theory revisited: knowledge creation as a synthesizing process. Knowl. Manage. Res. Pract., 1: 2-10.

Perreault, C., C. Moya and R. Boyd, 2012. A Bayesian approach to the evolution of social learning. Evol. Hum. Behav., 33: 449-459.

Pradhan, G.R., C. Tennie and C.P. van Schaik, 2012. Social organization and the evolution of cumulative technology in apes and hominins. J. Hum. Evol., 63: 180-190.

Sherif, K. and B. Xing, 2006. Adaptive processes for knowledge creation in complex systems: The case of a global IT consulting firm. Inform. Manage., 43: 530-540.

Turner, B.M. and P.B. Sederberg, 2012. Approximate bayesian computation with differential evolution. J. Math. Psychol., 56: 375-385.

Zhang, Z.J. and Z. Feng, 2012. Two-stage updating pheromone for invariant ant colony optimization algorithm. Expert Syst. Appl., 39: 706-712.

Zollo, M. and S.G. Winter, 2002. Deliberate learning and the evolution of dynamic capabilities. Org. Sci., 13: 339-351.