Self-organizing Approach for Emergent Multi-agent Structures

M. Bakhouya and J. Gaber

Laboratoire Systemes et Transports

Universite de Technologie de Belfort-Montbeliard (UTBM)

90010 Belfort, France

Tel:+33(0) 3 84 58 32 52

{bakhouya, gaber}@utbm.fr

ABSTRACT

Self-organization of a collection of agents is a crucial issue in multi-agent systems that operate in open and dynamic environments. Most self-organizing mechanisms proposed in the literature tackle with organization structure issues at design time. However, in open environments, agents must be able to adapt towards the most appropriate organizations according to the environment conditions and their unpredictable changes. In this paper, a Propitient Multiagent System (PMAS) is presented. The self-organization approach is inspired by the immune system principles that meet the requirements of both scalability and adaptability in dynamic environments. In this approach, the environment conditions and modifications are considered as antigens and the multi-agent system reacts like the immune system against pathogen attacks; it detects the infection, recognizes and adapts its structure in order to deliver an appropriate response to eliminate it.

Categories and Subject Descriptors

I.2.11 [Artificial Intelligence]: Distributed Artificial Intelligence– *Multi-agent systems, Intelligent agents, Languages and structures, Coherence and coordination.*

General Terms

Algorithms, Theory.

Keywords: Multi-agent systems (MAS), Propitient multi-agent systems (PMAS), Propitience, Self-organizing systems, Immune system, affinity networks.

1. INTRODUCTION

Self-organizing multi-agent systems (MAS) can be defined as systems that involve autonomous agents that have to interact in open and dynamic environments. Therefore, suitable interaction mechanisms are required and need to be highly flexible and scalable with self-organizing capabilities in order to cope with dynamically changing environments. In other words, a self-organizing multi-agent system denote a system that is present throughout its environment together with its agent relationships and reacts to changes by emergent responses. For example, the immune system is a self-organizing multi-agent system that is present throughout the body and defends it against harmful diseases and infections. It is capable of recognizing pathogen attacks to eliminate them from the body. It is worth noting that a response of the immune system emerges through interactions between its cells.

According to [2], several organizational structures for modeling multi-agent systems have been proposed. The first organizational structure is a hierarchical organization that comes from the decomposition of a system into a number of different subtasks. However, using a hierarchy can also lead to an overly rigid or fragile organization, prone to single-point failures with potentially global consequences.

The second organizational structure is the holonic organization called also holarchies. The term holon was originally proposed by Arthur Koestler [1] to model self-organization in biological systems. It is based on the Greek word "holos" for "whole" and the suffix "-on" that denotes "part". This term reflects the tendencies of holons to act as autonomous entities, and yet as cooperative parts that form an apparently self-organizing system. As biological examples, the human being consists of organs which in turn consist of tissues that can be further decomposed into cells. Also, the human being is part of a family and a society [6], [8], [9], [10].

The concept of holonic agent or holon was primarily introduced in MAS to model capabilities that result from the composition of several agents' activities. More precisely, a holon may have a functionality that none of its body agents could perform for alone. In addition, body agents may be holonic agents themselves. Hence, holonic multiagent systems provide terminology that transfer modularity and recursion to agent paradigm [8], [9]. Primarily, this concept has been exploited in manufacturing and transportation domains to define and build structures called holarchies or holonic organizations [4], [7]. In these domains, goals can be recursively decomposed into subtasks that can be assigned to individual holons in the holarchy [10]. However, hierarchical organizational structure using super-holon cannot meet the requirements of both

GECCO'06, July 8–12, 2006, Seattle, WA, USA.

scalability and adaptability in open environment due to the risk of bottlenecks and the presence of a single point of failure. In addition, each arriving and leaving agent need to be actively notified to the super-holons in the hierarchy, which incur additional overheads to maintain the whole holarchie.

The third organizational structure is the coalition-based organization. Within a coalition, the organizational structure is typically flat, although there may be a distinguished “leading agent” which acts as a representative and intermediary for the group as a whole [2]. Once formed, coalitions may be treated as a single, atomic entity. The formation of this structure assumes procedures of splitting and merging agents that lead to the creation of new ones [3]. However, coalition-based organizations operating in dynamic environments will be harder to maintain compared to static ones.

Similar to coalitions, congregation organization are groups of individual agents who have been bounded together in order to derive additional benefits. Congregations are formed among agents with similar or complementary characteristics to facilitate the process of finding suitable collaborators [2]. Like coalition formation, congregation formation involves creating and selecting operations for an appropriate congregation to join, and suffers from similar complexity problems as the agent population grows.

The main issue in these proposed multiagent system is the specification of an organizational structure for the collection of agents at design-time [8]. However, in dynamic setting, the challenge is to define a scalable self-organizing mechanism that determine the most appropriate organizational structure for the system at run-time that are adaptable according to environment changes.

In this paper, to address scalability and adaptability issues in dynamic environments, a self-organizing approach based on a the creation of affinity networks between autonomous agents, and inspired by the natural immune system, is proposed. The natural immune system provides a good example of self organization and highly distributed system with the ability to adapt to constantly changing and hostile environment.

A multi-agent system that has self-organizing principles and that can exhibit emergent behaviors presents what we can call a propitience functionality. The word propitience comes from the Latin terms "propitius" with the suffix "-ence" from the term emergence. In other words, a propitient system is a system with the ability to self-organize in order to adapt towards the most appropriate agent organization structures according to unpredictable changes in the environment. An emergent behavior is delivered as result of agents-to-agents and agent-to-environment interactions that adapt until the system hits a most suitable affinity network.

The rest of the paper is organized as follows. Section 2 presents an overview of the immune system. Section 3 presents the proposed self-organizing approach to build propitient multi-agent systems. Conclusion is given in section 4.

2. IMMUNE SYSTEM: AN OVERVIEW

Biological principles have been exploited in a variety of computationally based learning systems such as artificial neural networks and genetic algorithms [11]. Also, the emergence of complex collective behavior from the local interactions of simple agents is illustrated by many natural systems, like Ant colony [12] and Bee colony [13], that exhibit capabilities of complex distributed solving. The artificial immune system receives similar attention like other biological-inspired approaches. They are a great source of inspiration in many different areas including network security [14], [15], [16], parallel processing [17], robotic [19] and many others applications [18], [21].

A major role of the immune system is to defends the body against harmful diseases and infections. It is capable of recognizing most pathogens and eliminating them from the body. Jerne proposed the concept of the idiotypic network (i.e., affinity network), which states that B-cells are not just isolated, but they are communicating to each other through stimulation/suppression chains that form a large-scaled network [23]. More precisely, B-cells work as a self and non-self recognizer that have receptors on their surface, which can recognize antigens invading a human body, such as virus, and produces antibodies specific to the recognized antigen [19]. The key portion of the antigen recognized by the antibody is called an epitope (i.e. antigen determinant). The key portion of the corresponding antibody that recognizes the antigen determinant is called a paratope such as depicted in figure 1. Each type of antibody has its own antigenic determinant, called idiotope. In fact, an antibody is recognized as an antigen by other antibodies.

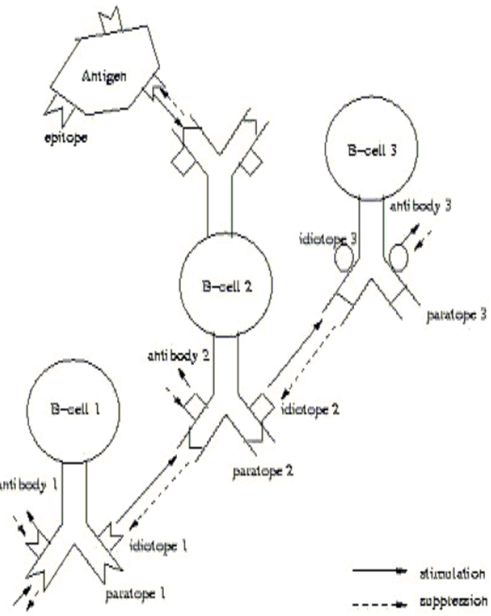

Figure 1. The Jerne’s idiotypic network [19], [22]

In this way, the immune system response to eliminate foreign antigens is offered by the entire system in collective manner. This phenomenon is called *emergent* as it results from the interaction between these entities that show particular behavior that the individual entities cannot achieve on their own. In other words, the immune system is distributed throughout the body and function continually using its own network lymphatic vessels with no central organ to control it. The entities of immune system are self-organizing and function continually to learn and remember from past and adapt to environment changes.

According to the Jerne model, the immune system is a self-organized system, the structure of immune system is not fixed, but varies continuously according to dynamic changes of the environment [23]. This function, called the metadynamics function [19], is mainly realized by incorporating newly generated cells or activated cells that proliferates and removing useless one. It turns out that this function works to maintain an appropriate repertoire (i.e. memory) of cells that cope with changes in the environment. More precisely, the immune memory greatly speeds up the response to pathogens that have been previously encountered. When new pathogens are encountered, the immune system mounts a primary response during which affinity maturation is used to learn the structure of the pathogens; the *primary response* can take some time to clear the infection. If the body is re-infected with a previously encountered pathogen, it will have an adapted subpopulation of B-cells to provide a very specific and rapid *secondary response*. This secondary response is usually so fast and efficient, that we are not aware we have been re-infected.

3. SELF-ORGANIZING APPROACH

The relation between agents and the environment can be modeled as a relation of stimulation/reaction such as depicted in the figure 2. Agents sense the environment and react in order to adapt to it. The adaptation is an adjustment process using the positive/negative feedback that permit to system to adapt its organizational structure to environment. More precisely, a positive (resp. negative) feedback is a process that reinforce (resp. weakens) a most suitable (resp. inappropriate) structure of the system.

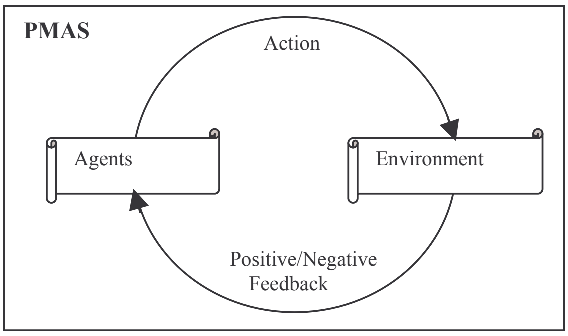

Figure 2. Adjustment process in a Propitient Multiagent System (PMAS)

Changing dynamically the structure of system situated in dynamic environments is non-trivial issue in absence of central controller. The solution that use central controller cannot meet the requirements of both scalability and adaptability due to the risk of bottlenecks and the presence of a single point of failure. To address scalability, agents can establish relationships between them based on their affinity. To address adaptability issue, affinity relationships between agents are dynamic; the affinity values can be adjusted at run-time to cope with changes in the environment. In such a changing environment, agents can disappear, be created or they can be spawned. In fact, the organizational structure of agents can change and an operational behavior can emerge.

The proposed self-organization approach assumes that individual agents are autonomous agents while multi-agent organizations are emerged structures that are not represented explicitly, but they exist through the affinity relationships between agents. In other words, agents cooperate equally rather than being assigned subordinate and supervisory relationships. It is worth noting that this multi-organizations based on dynamic affinities supported by relationships provides a highly decentralized system while remaining adaptive in dynamic and open environments. More precisely, this decentralized organizational structure offers a high degree of resilience against agent leaving the organization. For example, when an agent leaves an organization, all the peer affinity relationships with other agents are removed without additional messages since it does not rely on any overlay control structure.

3.1 Building of affinity networks

To build multi-agent organizations, individual agents establish affinity relationships between them. Such as depicted in the figure 3, the paratope describes the condition (i.e., capabilities) under which an agent is stimulated and the idiotope describes the reference to stimulating agents in its environment and the degree of stimulus (i.e. affinity value). Affinity corresponds to the adequacy with which two agents could bind. In other words, affinity corresponds to the adequacy with which two agents could cooperate to resolve collectively a problem (i.e., to point out a similar or complementary functionalities). For example, adequacy could be implemented based on keywords or objects in common describing a capabilities provided by agents. Hence, an agent will co-operate only with selected and suitable co-agents. Also, an individual agent can be a member in parallel of several affinity networks.

Precondition under which this agent is stimulated	Identifier, Type, location, etc…	Links to stimulating co-agents and their affinity relationships
Paratope	**Agent specification**	**Idiotope**

Figure 3. The structure of an agent that is similar to the B-cell structure [22], [24].

It should be noted that the changes of the organizational structure of multi-agent influences the emerged behavior (example, the immune system response, objectives, etc) of the system but also the future organization structure. These organizational structures emerge through interaction between agents according to the stimulation/reaction relationships such as depicted in Figure 4. Consequently, several organizations (i.e., affinity networks) emerge through dynamically adding and removing agents. In other words, new organizations may be created or other may be modified according to dynamically changing environment.

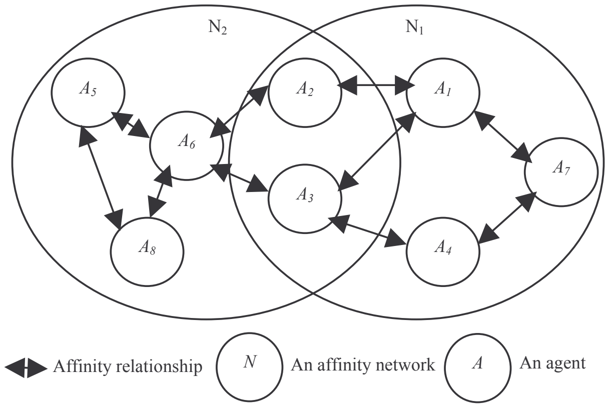

Figure 4. Each Agent contains affinity relationships to other agents. Agents together with their affinity relationships as a whole form a propitient multi-agent system represented by affinity networks.

3.2 Behavior emergence

For a collective behavior to emerge, agents must co-operate with each other through established affinity relationships in one hand and with their environment on the other hand. In fact, the behavior will be emerged through interactions between agents in the organizations. Like immune system, agents work as a self and non-self recognizer. Thought, established relationships, the idiotope of an agent is recognized by another agent as an antigen (i.e., pathogen). In fact, an agent is considered to be both a resource provider and a resource requestor. Agents interact with each other through stimulation/reaction chain until the emergence of an appropriate behavior (ex., immune response or problem resolution). Let consider that an individual agent A_i has an affinity relationship with an agent A_j and m_{ij} denotes the affinity between them. This value corresponds to the degree of stimulation between agent A_i and agent A_j. More precisely, the affinity m_{ij} could be a parameter that represents a utility U_{ij} of the relationships between A_i and A_j. It helps to distinguish between agents that can satisfy certain conditions (e.g., capacity to respond to environment requirements). Let consider also that the antigen represent the current environment conditions C. In order to respond to environment conditions, the organizational structures can re-arrange themselves at run-time by changing affinity values based on the previous experiences. This mechanism allows the agents to learn from results in order to cooperate in the most efficient way. Generally, the affinity value m_{ij} between an agent A_i and an agent A_j at step $t+1$ is as follows:

$$m_{ij}(t+1)=m_{ij}(t)+\Delta m_{ij}(t+1)$$

where,

$$\Delta m_{ij}(t+1)=f(m_{ij}(t),C(t+1),U_{ij}(t+1))$$

Where C represents the environment condition and U_{ij} represents the utility of the affinity relationship. More precisely, the relationship between A_i and A_j is desirable if it leads to increase utility U_{ij} based on condition C. For example, the utility of an affinity relationship can be evaluated *locally* based on partially interaction success or result in the situation C and *globally* to evaluate how well are globally interaction success is achieved in an organizational structure.

This reinforcement learning mechanism constitutes an organizational memory that permit to system to adapt to the environment changes, similar to adaptive memory in immune system. More precisely, each relationship is characterized by a weight, the affinity value, that summarize history on how a relationship performed in the past and is adjusted according to the utility U to respond to the environment condition C. Thus, agents will use affinity values to distinguish which of relationships to other agents are more likely to be useful for satisfying actual environment condition.

Behavior emergence refers to dynamic changes in the multi-agent organization structure. Agents may acquire new or drop current agents through establishing or deleting affinity relationship. More precisely, three operations can be distinguished to achieve this:

- *joining or merging operation*: permits for an gent to find "appropriate" agents to interact with. For example, a agent may select an other agent that it has most recently interacted with.
- *leaving or splitting operation*: permits for an agent to leave autonomously an organization and enter to other.
- Learning operation: permits to agents to adapt to dynamic environment conditions through the emergent behavior and affinity relationship to other agents.

These operations represent an essential and challenging issues in self-organizing multi-agent systems that operate in dynamic and open environments.

There are various methods that permit to agents to join, leave an affinity network (i.e., community) and learn their affinity relationships [5], [18], [20], [25]. A community is a collection of individual agents that form an organizational structure wherein each of these agents offers a capabilities to the other agents of the community. An agent A_i enters to the community if it has an affinity with one or several members of this community.

In particular, an example that illustrates the use of a propitient system PMAS to set up a ubiquitous and pervasive application is presented in [20]. More precisely, if a PMAS represents a service that emerge in a pervasive environment through interactions in an adhoc network, capabilities of agents should be expressively described by a web service description language[20]. A semantically rich description and its query language will permit to obtain effective matches between agents capabilities offered and requested to determine their affinity relationships, especially when agents negotiate without external help.

Let consider that the potential (i.e., capabilities) offered by the individual agent A_i that want to become a member of a community, composed of others individual agents $A_{j,}\ldots,A_m$, is described par a given function $D(A_i)$. Let us consider also a function $affinity(D(A_i),D(A_j))$ that returns an affinity measure m_{ij} which indicates if the description capabilities of A_i match with the capabilities of A_j. For example, an individual agent A_i that want to join a community M composed of a collection of agents A_j determines its affinity value m_{ij} with agents A_j, for all j in M. If this affinity value is above a certain threshold σ , agent A_i creates an affinity relationship with the agent A_j denoted $A_i \xrightarrow{m_{ij}} A_j$ and A_j creates an affinity relationship $A_j \xrightarrow{m_{ji}} A_i$ with A_i. Initially, m_{ij} and m_{ji} could be set to an equivalent value. Moreover, an affinity relationship $A_i \xrightarrow{m_{ij}} A_j$ between A_i and A_j can be considered *valid* if $m_{ij} \geq \sigma$. Otherwise, if $m_{ij} \leq \sigma$ the affinity relationship is considered not valid or discarded and could be removed from the affinity relationship set of agent A_i. Also, when an agent leaves a community, all its peer relationships with other agents should be removed. It's worth noting that the affinity value of each relationship changes dynamically according to a reinforcement learning mechanism.

In a learning of affinity relationships, there are various methods to determine $\Delta m_{ij}(t+1)$. An example is as follows:

$$\Delta m_{ij}(t+1) = \tau(u_i^{\ell}.u_j^{\ell} - f(m_{ij}(t))) \quad (1)$$

$m_{ij}(t)$ is the value of the affinity relationship between the A_i and the agent A_j. u_i^{ℓ} (resp. u_j^{ℓ}) is the *local satisfaction* value of the agent A_i according to its potential cooperation with the agent (resp. A_j). The satisfaction value is set to 1 if agents are satisfied and 0 otherwise. Consequently, the agent adjusts the affinity of relationships using equation (1), where τ is a positive value between 0 and 1. The value of affinity is mapped to a value between 0 and 1 by using the logistic equation:

$$f(m_{ij}) = \frac{1}{1+e^{-m_{ij}}} \quad (2)$$

With this equation (2), the affinity value m_{ij} increases quickly when it is near 0 and satisfaction is equal to 1. Also, the affinity value m_{ij} decreases quickly when the satisfaction is equal to 0.

The affinity value can be adjusted also using the *global satisfaction* of an agent in the community as follows:

$$\Delta m_{ij}(t) = \tau(u^g - f(m_{ij}(t)))$$

u^g is the global satisfaction value of the agent regarding its objective in the community [18], [20], [25].

4. CONCLUSION

Self-organization is a crucial issue in multi-agent systems that operate in an open and dynamic environment. In this paper, a propitient multi-agent system with a self-organizing mechanism is presented. In this approach, agents are organized into affinity networks. The affinity relationships between agents are adjusted by a reinforcement learning mechanism according to environment changes.

Current research direction address the application of this approach and the development of conceptual formal models that enable the specification of propitient multi-agent system.

5. REFERENCES

[1] Koestler, A. *The ghost in the machine*, hutchinson, 1967.

[2] Horling, B., and Lesser, V. A survey of multi-Agent organizational paradigms, *Knowledge Engineering Review. 2005*. Available at http://dis.cs.umass.edu/~bhorling/

[3] Gerber, C., Siekmann, J., and Vierke, G. *Holonic multi-agent systems*, Technical Report R-99-0*3*, DFKI GmbH, ISSN 094-008X, 1999.

[4] Bûrckert, H. J., Fischer K., Vierke, G., Holonic transport scheduling with TeleTruck, *Journal of Applied Artificial Intelligence*, 14:697-725, Taylor & Francis 2000.

[5] Gaber, J., New paradigms for ubiquitous and pervasive computing. *Technical report*, University of Technology of Belfort-Montbeliard (UTBM), pp 1-6, September 2000.

[6] Fischer, K., Schillo, M., and Siekmann, J. Holonic multiagent systems: The foundation for the organization of multiagent systems, *Proceedings of the First International Conference on Applications of Holonic and Multiagent Systems* (HoloMAS'03), LNAI 2744:71-80, Springer-Verlag 2003.

[7] Fischer, K. Agent-based design of holonic manufacturing systems, *Journal of Robotics and Autonomous Systems*, Vol. 27:1-2:3-13, Elsevier Science B.V. 1999.

[8] Schillo, M., and Fischer, K. *Holonic multiagent systems*, KI Zeitschrift, 4:54, arendtap 2003. http://www.virtosphere.de/data/publications/articles/SchilloFischer.HoloMAS.pdf

[9] Schillo, M., Fley, B., Florian, M., Hillebrandt, F., and Hinck, D. Self-organization in multiagent systems: from agent interaction to agent organization, in *Proceedings of the 3rd International Workshop on Modeling Artificial Societies and Hybrid Organizations* (MASHO'02), Workshop at KI2002, the 25th German Conference on Artificial Intelligence Aachen, pp. 47-56.

[10] Ulieru, M., Brennan, R., and Walker, S. The holonic enterprise - A model for Internet-enabled global supply chain and workflow management, *Int. Journal of Integrated Manufacturing Systems,* No 13/8, 2002, ISSN 0957-6061.

[11] Marrow, P. Nature-inspired computing technology and applications. *BT Technol J*, 18(4), October 2000.

[12] Fenet, S., and Hassas, S., A.N.T. a distributed network control framework based on mobile agents. In *Proceeding of the International ICSC Congress on Intelligent Systems And Applications*, CI'2000 (in ISA'2000), 2000.

[13] Minar, N., Gray, M., Roup, O., Krikorian, R., and Maes, P. Hive: Distributed agents for networking things. *First ISASA/MA ,* Palm Springs, CA, USA, 1999

[14] Dasgupta, D. Immunity-based intrusion detection system: A general framework. In *the proceedings of the 22nd National Information Systems Security Conference* (NISSC), 1999.

[15] Hofmeyr, S. A. An immunological model of distributed detection and its application to computer security. *PhD thesis*, University of New Mexico, 1999.

[16] Hofmeyr, S. A., and Forrest, S., Architecture for an artificial immune system. *Evolutionary Computation*, 8(4):443–473, 2000.

[17] King, R. L., Lambert, A. B., Russ H. S., and Reese, D. S. The biological basis of the immune system as a model for intelligent agents. *Second Workshop on Bio-Inspired Solutions to Parallel Processing Problems*, Lecture Notes In Computer Science 1586, pp. 156-164, 1999.

[18] Bakhouya, M., Self-adaptive approach based on mobile agent and inspired by human immune system for service discovery in large scale networks, *PhD Thesis*, Universite de Technologies de Belfort-Montbeliard, 2005.

[19] Watanabe Y., Ishiguro A., Uchkawa Y., Decentralized behavior arbitration mechanism for autonomous mobile robot using immune system. *Books Artificial Immune Systems and Their Applications*, Springer-Verlag, ISBN 3-540-64390-7, 1999.

[20] Gaber, J. and Bakhouya, M., An affinity-driven clustering approach for service discovery and composition for pervasive computing*, IEEE ICPS'06*, 26-29 Juin, France, 2006.

[21] Castro, L. N., and Von Zuben, F. J. Artificial Immune Systems: Part II – A Survey of Applications, *Technical Report – RT DCA 02/00*, p. 65, 2000.

[22] Farmer, J. D, Packard, N. H, and Perelson, A. S.,The immune system, adaptation and machine learning. *Physica 22D*, pp 72-81, 1986.

[23] Jerne, N., Towards a network theory of the immune system. *Ann. Immunol*. (Inst. Pasteur) 125C. 373, 1974.

[24] Suzuki J. and Yamamoto Y., A Decentralized Policy Coordination facility in OpenWebServer, In *Proc. of The SPA'00*, 2000.

[25] Bakhouya M., Gaber J. A reinforcement learning of link affinities and user requests for Self-adaptive graph emergence from an arbitrary graph, *Technical report*, SeT-UTBM, pp 1-12, Juillet 2003.