A MOLECULAR QUASI-RANDOM MODEL OF COMPUTATIONS APPLIED TO EVALUATE COLLECTIVE INTELLIGENCE

Tadeusz SZUBA
Dept. of Math. and Comp. Science, Kuwait University, E-mail: szuba@mcs.sci.kuniv.edu.kw

ABSTRACT
The paper presents how the Random PROLOG Processor (RPP), a bio-inspired model of computations, can be used for formalization and analysis of a phenomenon - the Collective Intelligence (*CI*) of social structures. The RPP originates from the question of why inference processes are quasi-chaotic in real life. In the RPP, *clause_molecules (CMs)* move quasi-randomly around in abstract *Computational_PROLOG_Space (CS)*. *CMs* can carry clauses of facts, rules, and goals, or *CMs* can even be moving sets of facts, rules, and goals enclosed by membranes. When *CMs* rendezvous, an inference process can occur iff the prerequisite logical conditions are fulfilled. The RPP can be considered an implementation proposal of the NonDeterministic Turing Machine. With the RPP, *CI* can be evaluated as follows: 1) the mapping is done of a given social structure into the structured computational space of the RPP; 2) beings and their behavior are translated into PROLOG expressions, carried by *CMs*; 3) the global or temporary goal(s) of the social structure (of ants, humans, etc.) are translated into an N-step inference (NSI); 4) on this basis, the efficiency of the NSI will be evaluated and given as the Intelligence Quotient of a Social Structure (IQS) projected onto NSI. The concept of IQS can be mathematically developed or used for practical evaluation of a given social structure.

1. INTRODUCTION

We observe that real beings make parallel, quasi-chaotic inferences rather than the ordered ones of CPUs. Why do ordered inferences demand discipline & training, while parallel, quasi-chaotic inferences come easily to us? Certainly, this is an alternative solution like a propeller is an alternative to wings. Perhaps there are undiscovered systems and algorithms more powerful for solving some of these difficult problems. Significant progress has been recently made in the area of nondeterministic bio-inspired computations:

- In 1994 Adleman [2] demonstrated a model of a DNA computer, which should be able to solve NP-complete problems in polynomial time [12]. In this computer, DNA agents react quasi-randomly because the rendezvous in the solution are random; however, the matching (sticky ends) of DNA is deterministic.
- Genetic Algorithms [11] [14] are making significant research progress.
- Cooperating colonies of simple beings like ants are attracting research attention [1] [9] because it can be demonstrated that as a computational system, they are even more efficient than Genetic Algorithms [5].

The problem is that the concept of deterministic computations is doing so well that no computer company will suddenly change policy and invest billions to build a DNA computer. Almost four years have passed [2], and there is still no available successor of Adleman's computer. All bio-inspired computational systems share a common concept: there are agents of any nature which, in parallel and quasi-randomly, move, are born/expire, and infer according to imposed logical diagrams. To advocate this model of computations we either have to build such a computer *and* to prove that it can be better than the existing processors, *or* to find an application where this model is the only one we can use. We want to demonstrate that the evaluation of the *CI* of closed social structures, based on a molecular model of computations with mathematical logic can be proposed as such an application. It can be of great value because all closed social structures such as companies, cities, nations are fighting for better performance. On the basis of estimated *CI*, the necessary measures can be taken to improve their IQS value. The RPP is a bio-inspired concept of parallelism, which can be used as a vital application for *CI* measure where existing computers can be used.

2. THE MOLECULAR PROLOG MODEL OF COMPUTATIONS

Observing social structures of humans, it is striking that the inferences are parallel, chaotic, and at the same time different schemes of inference are applied. It is difficult to separate messages from message-processing agents. The same agent can be the processor, the message carrier, and the message, from the point of view of different parallel-running processes. The inferring process can be observed as global, but the role of specific elements can not be easily identified and interpreted. Thus, a symbolic representation is necessary for analysis, separated from interpretation. We have to rely only on approximations of the inference process we observe, and we must be able to easily improve a given approximation; thus declarative, loosely coupled inference systems are necessary. PROLOG seems to fulfill the requirements after modifications:

1. PROLOG is declarative, i.e. facts, rules, and goals can easily be real-time added/retracted in the inference system. Different independent variants of facts and procedures are allowed. This is basic for chaotic systems;
2. Symbols and interpretation of clauses are independent because PROLOG is based on 1st order predicate calculus. Thus, clauses can describe observable aspects of behavior (e.g. of ants) without understanding them;
3. Without changing the PROLOG dialect, it is easy to adopt a molecular model of computations, as has been done in the RPP .

2.1 CLAUSES AND COMPUTATIONAL_PROLOG_SPACE IN THE MOLECULAR RPP

The 1st level *CS* with inside quasi-random traveling *CMs* of facts, rules, and goals c_i is denoted as the multiset $CS^1 = \{c_1, \ldots, c_n\}$. Thus, clauses of facts, rules, and goals are themselves 0-level *CS*. For a given *CS*, we define a membrane similar to the Chemical Abstract Machine [3] denoted by $|\cdot|$ which encloses inherent facts, rules, and goals. It is obvious that $CS^1 = \{c_1, \ldots, c_n\} \equiv \{|c_1, \ldots, c_n|\}$. For a certain kind of membrane $|\cdot|$ its type p_i is given, which will be denoted $|\cdot|_{p_i}$ to define which *CMs* can pass through it. Such an act is considered as Input/Output for the given *CS* with given $|\cdot|$ It is also allowable in the RPP to define degenerated membranes marked with $\cdot|$ or $|\cdot$ i.e. the collision-free (with membrane) path can be found going from exterior to interior of an area enclosed by such a membrane, for all types of *CMs*. The simplest possible application of degenerated membranes in the *CS* simulating a given social structure is to make, e.g. streets or other boundaries. If the *CS* contains clauses as well as other *CSs*, then it is considered a higher order one, depending on the level of internal *CS*. Such internal *CS* will be also labeled with $\hat{v}_j$ e.g.

$$CS^2 = \left\{\left| c_1, \ldots CS^1_{\hat{v}_j}, \ldots c_n \right|\right\} \ iff \ CS^1_{\hat{v}_j} \equiv \left\{\left| b_1, \ldots, b_n \right|\right\} \ where\ b_i \quad i = 1 \ldots m;\ c_j \quad j = 1 \ldots n \ are \ clauses$$

Every c_i can be labeled with $\hat{v}_j$ to denote characteristics of its individual quasi-random displacements. The general practice will be that higher level *CSs* will take fixed positions, i.e. will create structures, and lower level *CSs* will perform displacements. For a given *CS* there is a defined position function *pos*:

$$pos\colon\ O_i \rightarrow \langle position\ description \rangle \cup undefined \quad where \quad O_i \in CS$$

If there are any two internal *CS* objects O_i, O_j in the given *CS*, then there is a defined distance function $D\left(pos(O_i), pos(O_j)\right) \rightarrow \Re$ and rendezvous distance. We say that during the computational process, at any time t or time period Δt, two objects O_i, O_j come to rendezvous iff $D\left(pos(O_i), pos(O_j)\right) \leq d$. The rendezvous act will be denoted by the rendezvous relation ®, e.g. O_i ® O_j which is reflexive and symmetric, but not transitive. For another definition of rendezvous as the λ-operator, see [7]. The computational PROLOG process for the given *CS* is defined as the sequence of frames *F* labeled by t or Δt, interpreted as the time (given in standard time units or simulation cycles) with a well-defined *start* and *end* e.g. $F_{t_0}, \ldots, F_{t_e}$. For every frame its multiset $F_j \equiv \left(\left| c_1, \ldots, c_m \right|\right)$ is explicitly given, with all related specifications: *pos(.)*, membrane types *p*, and movement specifications *v* if available. The simplest case of *CS* for the RPP used in our simulations is the 3-D cube with randomly traveling clauses of facts, rules, and goals inside. The RPP is initialized to start the inference process after the set of clauses, facts, rules, and goals (defined by the programmer) is injected into this *CS*. More advanced examples of the *CS* for the RPP include a single main CS^2 with a set of internal CS^1 which take fixed positions inside CS^2, and a number of CS^0 who are either local for a given CS^1_i (because the membrane is not transparent for them) or global for any subset of $CS^1_j \in CS^2$. When modeling the *CI* of certain closed social structures, interpretations in the structure will be given for all CS^m_n, i.e. "this *CS* is a message"; "this is a single human"; "this is a village, a city", etc. The importance of properly defining $\hat{v}_j$ for very CS^i_j should be emphasized. As has been mentioned, the higher level CS^i_j will take a fixed position to model substructures like villages or cities. If we model a single human as CS^1_j, then $\hat{v}_j$ will reflect displacement of the human. Characteristics of the given $\hat{v}_j$ can be purely Brownian or can be quasi-random, e.g. in lattice, but it is profitable to subject it to the present form of CS^i_j. When $\hat{v}_j$ has the proper characteristics, there are the following essential tools:

- The goal clause, when it reaches the final form can migrate toward the defined *Output* location. This can be a membrane of the main *CS* or even a specific, local *CS*. Thus the appearance of a solution of a problem in the *CS* can be observable;
- Temporarily, the density of some *CMs* can be increased in the given area of *CS* in such a way that after the given low-level CS^i_j reaches the necessary form, it migrates to specific area(s) to increase the speed of selected inferences in some areas.

The dialect of the RPP is elementary, but some redefinition of rule and goal clauses is necessary. The right side of the rule and goal clause in the RPP any set *S(...)* of unit clauses, contrary to standard PROLOG, where there is an ordered list of unit clauses. Such a set can even be considered a local, invariable *CS* of rules, containing unit clauses. This approach is compatible with the general philosophy of the RPP and allows us to define clusters, e.g. to construct sets of facts enclosed by membranes traveling through *CS*. For some simulated problems it would be necessary to introduce the *configuration*, to order in any way (even spatially) the unit clauses in the set *S(...)*.

2.2. THE INFERENCE MODEL IN THE MOLECULAR RPP

The pattern of inference in Random PROLOG generalized for any CS has the form:
<u>Definition 1. Generalized inference in CS^n</u>

Assuming that $CS = \{...CS_j^i...CS_l^k...\}$, on this basis we can define:

CS_j^i ® CS_l^k and $U(CS_j^i$, $CS_l^k)$ and C(one or more CS_n^m of conclusions) $\Rightarrow$
one or more CS_n^m of conclusions, $R(CS_j^i$ or $CS_l^k)$ ∎

The above description should be interpreted as follows:
CS_j^i ® CS_l^k denotes rendezvous relation
$U(CS_j^i$, $CS_l^k)$ denotes that unification of necessary type can be successfully applied;
C(*one or more* CS_n^m *of conclusions*) denotes that CS_n^m are satisfiable;
Observe, that the reaction $\rightarrow$ in *cham* semantics is equivalent to $\Rightarrow$ inference here.
$R(CS_j^i$ or $CS_l^k)$ denotes that any parent *CMs* is retracted if necessary.

The standard PROLOG inferences are simple cases of the above definition. Later on, when discussing N-step inference, we will be only interested in "constructive" inferences, i.e. a full chain of inferences exists. Thus the above diagram will be abbreviated as $CS_j^i ; CS_l^k \xrightarrow{RPP} \sum_n CS_n^m$ without mentioning the retracted *CMs* given by $R(CS_j^i$ or $CS_l^k)$. In general, successful rendezvous can result in the "birth" of one or more child *CMs*. All of them must then fulfill a *C(...)* condition; otherwise, they are aborted. Because our proposed RPP is designed to evaluate the inference power of closed social structures, simplifying assumptions based on real life observation can be made. It is difficult to find cases of direct rendezvous and inference between two CS_i^m *and* CS_j^n *if* $m,n \geq 1$ without an intermediary involved $CS_k^0 \quad k = 1,2...$ (messages, pheromones, observation of behavior, e.g. the bee's dance, etc.). Even in Genetic Algorithms, the crossover of genes can be considered the inference of the two genomes, CS_i^0 *and* CS_j^0. Only if we consider CS^n on the level of whole nations, where mutual exchange (migration) of humans takes place, can such a case be considered an approximation to such higher level rendezvous and inferences. This is, however, just approximation, because finally this exchange is implemented at the level of personal contact of humans, which are just rendezvous and inferences of two CS_i^0 *and* CS_j^0 with the help of $CS_k^0 \quad k = 1,2...$. Thus, rendezvous and direct inference between two

CS_j^i *if* $i \geq 1$ will be left for further research. In this paper, we only make use of single CS_{main}^n *for* $n > 1$ as the main *CS*. Single beings like humans or ants can be represented as $CS_{individual}^1$. Such beings are performing internal inferences (in their brains), independently of higher level, cooperative inferences inside CS_{main} and exchange of messages of the type CS^0. It will be allowable to have internal CS^k inside the main *CS*, but only as static ones (taking fixed positions) to define sub-structures such as streets, companies, villages, cities, etc. For simplicity, however, we will try to approximate beings as CS^0; otherwise, even statistical analysis would be too complicated. It is also important to assume that the results of inference are not allowed to infer between themselves after they are created. Products of inference must immediately disperse; however, later, inferences between them are allowed (in [8] it is called *refraction*).

2.3. Properties of the inference model of the Molecular RPP

The standard PROLOG execution model is restricted to backward inference, starting from a goal [10]. The nature of the RPP is quasi-random, with parallel rendezvous of *CMs* carrying multiple occurrences of clauses, so it is obvious that it is possible to implement more inferring diagrams. We can have backward, forward, and aggregated inferences, i.e. rule with rule at the same time. In addition, standard PROLOG assumes a linear form of clauses of goals and rules. The check for unification is done in a linear structure from left to right. In the RPP we have sets, i.e. the premises of rules are no longer lists, but sets of clauses. Moreover, we can impose any type of ordering on this set, e.g. 3-D structuring which allows more possibilities of inference diagrams. Additional inferring diagrams not available in standard PROLOG have been implemented for the purpose of IQS calculation in the present version of the RPP [15]. As can be seen during simulations, multiple overlapping inference processes speed-up inferences compensating low probability of favorable inferences and randomness of rendezvous. This was also observed in [2] [12]. For chaotic systems, stabilizing measures are necessary 1) to reduce the extensive number of copies of the same *CMs* 2) to sort and retract *CMs* of certain types, if a priori there are known necessary heuristic functions to do this. The basic solution is for the *CS* to have set restriction clauses of the form: *retract*(*CMs pattern*).

3. The Collective Intelligence of Social Structures

The phenomenon of the *CI* of humans and animals is easily observable, and is appreciated because of potential applications, but the difficulty is in formally defining and measuring it. The theory of group dynamics of humans provides results of experiments and analyses [13] related to the problem of *CI*:

- people try to join groups;
- small groups produce more and better solutions to a problem than do individuals;
- with divisible problems, for maximizing, optimizing tasks, groups are better;
- group judgements reduce error of judgement and groups take more risky decisions;
- heterogeneity in the group increases logical performance;
- centralized networks are more efficient when the task is simple; decentralized groups are more efficient when the task is complex;

- distance between members in a structured group affects the exchange of information and their problem-solving ability .

Results such as those mentioned above, immediately pointed out that:

- the groups considered by [13] were small (several members only);
- the structure of the groups was simple, with fixed location of members ;
- all members had the same knowledge about the problem, and the same goal;
- experiments were changing the natural behavior of group members;

whereas from the point of view of CI:

- the social structure must be big to display statistical properties of behavior;
- knowledge and abilities (as resources) must be distributed around the group. For a real life social structure we can almost never define who/where/what possesses the necessary resources/abilities. Often it is conscious "game-playing";
- *CI* must be observed and analyzed as a natural process, without interacting.

Studies on the efficiency of path-finding [5], [6], [4] resulting from the collective behavior of ants, in fact head toward a definition of *Collective Intelligence*.

3.1 A Formal Definition of Collective Intelligence Measure (IQS)

The basic question is to find a proper IQS test for social structures of beings. Global intelligent behavior of groups is different that of individuals; thus IQ tests oriented for static testing of individual are useless. Moreover, group behavior is more nondeterministic than individual, and different beings express their intelligence through different actions. Let's, however, assume that we have managed to map a social structure's activities into a set of logic expressions; a good example of such a mapping is given for ants [5]. As mentioned before, using a declarative PROLOG description of a social structure, we can have logic formulas without interpretation relating to real life, and we can easily change the applied approximation at any time. Another problem is that the number of logic inferences per given period is not sufficient as an IQS test for *CI*. There are examples of high frequency of inferences, but the desired conclusion is not reached at all. The benchmark we propose for *CI* is the N-step inference (*NSI*).

<u>Definition 2: N-step inference in CS^n</u>

There is a given *CS* of any level $CS^n = \left\{CS_1^{a_1}, \ldots, CS_m^{a_m}\right\}$ with these subdefinitions:

- $D\left(pos\left(CS_i^j\right), pos\left(CS_k^l\right)\right) \to \Re$ for every *CS* , and rendezvous distance *d*;
- $\hat{v}_j \;\; j = 1 \ldots n$ i.e. characteristics of random displacements;
- an ordered subset of *CMs* of the form $\left(CS_0^{b_0}, CS_1^{b_1} \ldots CS_{n-1}^{b_{n-1}}\right)$ can be generated such that either $CS_s^t \in CS^n$ or it can be derived from an intermediate state of CS^n by the inferences of the form $CS_j^i ; CS_l^k \xrightarrow{RPP} \sum_n CS_n^m$ ∎

<u>Definition 3: Collective Intelligence Quotient IQS</u>

The IQS is measured by the probability *P* that after *m* frames *F,* the conclusion $CM_{conclusion}$ will be reached, from the starting *state of* CS^n as the result of the assumed N-step inference. This is denoted $IQS = P_{n-step}^{F_0 \mapsto F_m}$. If we use experimental evaluation, then the average number of frames $\overline{m}$ is given (or cycles of recalculation of a situation), after which $CM_{conclusion}$ is reached. ∎

This benchmark is proposed for the following reasons:

1. N-step inference can be interpreted as: *a)* any problem-solving process in a social structure or inside a single being, where N inferences are necessary to get a result, or *b)* any production process, where N-technologies/elements have to be found and unified into one final technology or product;
2. Simulating N-step inference in the RPP, we can easily model the distribution of inference resources between individuals, dissipation in space or time, movements (or temporary concentration) in the *CS*. This reflects well the dissipated, moving, or concentrated resources in the village, city, etc. of humans or swarms of any type;
3. With this benchmark, cases can be simulated very easily, where some elements of the inference chain are temporarily not available, e.g. the chain of inference can be temporarily broken, but at a certain time *t*, another inference running in the background or parallel will produce the missing component. Such situations are well known in human social structures, e.g. when a given research or technological discovery is blocked until missing theorems or sub-technology is discovered.
4. Human social systems infer in all directions, i.e. forward (e.g. improvements of technology), backward (e.g. searching for tool/product coming from need), and through generalization, e.g. some technologies are combined into one general technology or algorithm. *NSI* simulated in the RPP reflects all these cases very well.

3.2. Analysis of Selected *CI* Phenomena with IQS

The *CI* measure demonstrates that some of the social behavior can be explained as "social necessity" from the point of view of IQS optimization. We base this on simulation results because formal proofs in quasi-chaotic systems are difficult. We are conscious of how rough the approximations given below are since many crucial social factors are left out of the simulation.

1. Social structures with a city significantly improve the *CI*

It is obvious that the hordes of early humans were more efficient for hunting/defense than individuals, but at a certain stage of development, cities emerged. This probably happened when the ability to produce/store food and to use language improved. The percentage of the population which is living in cities all around the world is still growing. Let's analyze the simulation of *CS*, (Table 1.) which can be interpreted as any small nation with one capital city in the central area. It is visible that the speed of inference with a city increases by more than a factor of 10. The definition of the *NSI* does not strictly impose how it is interpreted; thus it can be interpreted as any real life N-step technical assembly process, or as a purely mental N-step inference process in this structure. This means that the mental ability of a social structure as well as its production ability grows by a factor of ten! This confirms observations of real life – life in the city is easier in most aspects.

Rendezvous distance $d = 0.025$; Size of main CS^2: $1 \times 1 \times 1$; size of city CS^1: $sphere\ at\ (0,0,0)\ R = 0.2$; Brownian movements: Gaussian distribution with variance $\nu = 0.124$, $\mu = 0$; NSI = 10-step inference;		
	CS without City	with City (50 cycles inside)
Conclusion reached after cycles	17643	1436
Final number of *IMs* in CS^2	69	74

Table 1. Influence of City on Collective Intelligence.

2. Communication/travel and information-access abilities affects the *CI*

Humans are continually developing communication abilities, developing language, and abilities to change location in a short time using tools like wheels, sails, etc. Remote information transfer through books, telephones, television, Internet, etc. provides virtual travel for information. With IQS measure, it is possible to analyze the communication/travel factor from the point of view of *CI* because any form of passing information can be formalized as displacement of CS^0, and any form of personal travel can be formalized as CS^1 displacement in the RPP.

Rendezvous distance $d = 0.025$; Size of CS: $1 \times 1 \times 1$; no City Brownian movements: Gaussian distribution with $\mu = 0$; NSI = 10-step inference;			
variance	$\langle v \rangle = 0.124$	$\langle v \rangle = 0.062$	$\langle v \rangle = 0.031$
Conclusion reached after cycles	17643	28265	45029
Final number of *information_molecules* in CS	69	44	97

Table 2. Influence of average speed $\langle v \rangle$ to speed of NSI.

For a given social structure we can average available technical travel and communication facilities to get one common, averaged *v* displacement per time period with the given variance. Notice in Table 2. how the value *v* computed in such a way affects the *CI* of the social structure. An increase of travel/communication abilities allows us to have significantly more inferences per given period, which results in almost linear increases of IQS. An interesting problem emerges here; "How have the Internet search engines increased the value of *v* coefficient?"

3. "group judgements reduce error of judgement" [13]

Group judgement is better because individuals can make false conclusions based on incorrect use of inferring rules or because of incomplete databases, and nobody will correct them. However, this is a complex problem because bad leadership can force to *Output* incorrect evaluations. Let's assume that in *CS*, there is no leadership, i.e. inferences are not prioritized and are context free. Let's assume the source of logical incorrectness is that in the *CS* the same time rules of the pattern: $a \to b$; $a \to \neg b$ are allowed. It is also a well-known fact that committees have problems reaching agreement because the same doubts are raised repeatedly by the same members. This case can be simulated by introduction of infinite loops of inference. Some members of a committee are able to infer only one step at a time, others can jump ahead with inferences. Our experiment has a 10-step inference with one starting fact, a set of ten rules of the form $a \to b$, and the goal.

Size of CS: $1 \times 1 \times 1$; rendezvous distance $d = 0.025$; Brownian movements: Gaussian distribution with μ=0; $\langle v \rangle = 0.124$ NSI=10-step inconsistent inference; no City	
Conclusion reached after cycles	25436
Final number of *IMs* in CS	108

Table 3. Inconsistent inferences.

We have one-step inferences as well as ones which jump ahead over elementary inferences, but also inferences which go back to conclusions already proven. Simple stabilizing measures have been used, such that when rendezvous occur with opposite *CMs* like b ® ¬b, the result will be retraction of both. Compared to Table 1, the period necessary to reach the conclusion is similar to the speed of the 10-step inference in a non-City environment where there are no inconsistent rules, jumps or loops. The above simulation confirms the hypothesis that a group is more resistant to incorrect judgement than any single member.

4. CONCLUSION

This paper presents the molecular quasi-random model of computations applied to evaluate an Intelligence Quotient (IQS) for any nature of Social Structures. The present stage of research indicates that it can be applied to a human social structure or an animal one (e.g. ants). The IQS is of a statistical nature because it is expressed by probability and is based on the result of behavior of beings in a social structure. The simulation system has been built in parallel C, with 3-D graphics to observe the chaotic parallel inferring. This was necessary since the complexity of computations. Now the research is directed at Kuwait University (KU) in the following way:

- A social structure has been selected with the cooperation of the KU Psychology Dept., the proper IQS test is now under construction;
- The *CI* of foraging ants is analyzed in cooperation with the KU Zoology Dept.;
- It is expected that for cases like the “City”, a formal proof of necessity can be done in cooperation with the KU Statistics Dept.;

5. LITERATURE

[1] --- ANT COLONY OPTIMIZATION. Homepage managed by Marco Dorigo, at location http://iridia.ulb.ac.be/dorigo/ACO/ACO.html#Bib

[2] Adleman L. M.: Molecular computations of solutions to combinatorial problems. Science Nov. 11. 1994.

[3] Berry G., Boudol G.: The chemical abstract machine. Theoretical Computer Science. 1992. p. 217-248.

[4] Deneuborg J.L. et al: The Dynamics of Collective Sorting, Robot-like Ants, Ants-like Robots. *From Animals to Animats,* MIT Press, 1991.

[5] Dorigo M., Maniezzo V., Colorni A.: The Ant System: Optimization by a Colony of Cooperating Agents. IEEE Trans. on SMB-Part B, (1996), 26, 1, 29-41

[6] Dorigo M., Gambardella L.M.: Ant Colonies... BioSystems, 1997.

[7] Fontana W., Buss L. W.: The arrival of the fittest. Bull. Math. Biol. 56, 1994

[8] Giarratano J., Riley G.: Expert Systems. PWS Pub. II ed. 1994.

[9] --- Multi-Agent Simulation of Honey Bee Colonies. Homepage: http://www.ma.umist.ac.uk/dsumpter/beesim/Simulation/overview.html

[10] Kogge P. M. : The architectures of symbolic computers. McGraw Hill. 1991.

[11] Michalewicz Z.: GA + data structures = evolution programs. Springer 1992.

[12] Reif J. H.: Parallel molecular computation - models and simulations. http://www/cs.duke.edu/~reif/paper/paper.html

[13] Shaw M. E.: Group Dynamics. IV ed. McGraw-Hill 1971.

[14] Szuba T., Stras R.: Parallel evolutionary computing with the Random PROLOG Processor. J. on Parallel and Distributed Computing. (early 1998).

[15] Szuba T.: Evaluation measures for the collective intelligence of closed social structures. ISAS’97 Gaithersburg/Washington D.C. 22-25 Sept. 1997.