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Development Of Cognitive Architecture For Implementing Micro And Macro Economic Concepts

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This paper describes the results of a simulation using metrics associated with the principles of artificial economics in animal cognition. The main purpose of this research paper is to understand the principles of natural minds and adopt these principles in a simulation environment. This approach necessasarily requires the design and test of a range of simple and complex computational agents. The developed micro-agents in a fungus world testbed are designed to investigate artificial minds for animals and synthetic agents, drawing on qualities found in the natural minds. Qualities such as level of decision making, its cost function and utility behaviour (the microeconomic level), physiological and goal oriented behaviour are investigated.

1. Introduction

The AI era started with John McCarthy, who named "Artificial Intelligence" as the new topic for the 1956 Dartmouth conference. At the same conference, Alan Newell, J.C Shaw, and Herbert Simon demonstrated the first AI programme (Logic Theorist) that could construct logical proofs from a given set of premises. This event has been interpreted as the first example of a machine performing a cognitive task. A cognitive task is considered to be an element of the mind. The mind is a core concept for the field of cognitive science. cognitive architecture as an embodiment of the scientific hypothesis of human and nonhuman cognition. Cognitive architectures are designed to be capable of performing certain behaviours and functions based on our understanding of human and nonhuman minds [5] [6] [11] [20].

Agent behaviours can be analyzed using many different metrics; for example, metabolic activity, competition and social interaction with respect to environment and microeconomics, and the application of economics on artificial life to analyse adaptive behaviours. This follows the microeconomic regularities such as cost and utility. Testbeds and benchmarks are mainly using for simulating, comparing architectures and outcomes in the field of robotics or cognitive architectures. Pfeiffer describes the fungus eater concept as a testbed for simulating models in emotion psychology. The fungus world environment allows the principles and behaviours of a robot or simulated animal or any artificial mind simulation to be monitored, measured and compared [13].

2. Artificial Minds

Minsky [10] defines mind as the functioning of the brain. Franklin [6] defines mind as a mechanism of the brain. Minsky says “minds are just what brains do”. Franklin [6] [7] argues that the foundation of exploring a mechanism of mind can be done through the possibility of artificial minds. The implemented artificial minds are man made systems that exhibit behavioural and characteristics of natural minds.

Artificial mind can be viewed as a control structure for an autonomous software agent. Any cognitive or computational architecture can be viewed as either a single agent or a large collection of agents. There is a long history of representing mind as collection of agents, dating back to Selfridges’s Pandemonium model [14]. This model attempts to explain mind as a collection of agent type tiny demons. The pioneers such as Selfridge [14], McCarthy, Brustoloni, Allen Newell and Herbert Simon [12], Minsky [10], Baars [2], Anderson [1] Franklin [6], Sloman [16], Davis [5] and Singh [15] were viewed and tested computational theories of mind, from artificial agents.

Different skills and cognitive tasks may be represented as individual micro agents. These individual micro agents will demonstrate simple, complex or intelligent behaviour, and serve to fulfil the capabilities expected of an intelligent agent, such as planning, decision making, problem solving, and learning. The purpose of this research is to understand the theory of natural minds and adopt these principles into simulations of artificial minds. The theory of mind includes abstract and broad sketches of architectures to support the functioning associated with mind. The design and implementation of a specific architecture follows hypotheses about human and nonhuman minds. This broad approach necessarily requires designing different computational simple and complex level agents. Agents are verified by seeing how they coordinate their goals by planned solutions and the general process of cognition to improve performance [6] [7].

2.1 Reasons for Studying Artificial minds

Why do we need to study artificial minds? What is the need for studying nonhuman minds such as animals or robots? In "Artificial Minds", Franklin [6] gave three important reasons for studying artificial minds.

- Questions related to the nature of intelligence in human and nonhuman minds are inherently fascinating. The research on artificial minds may well throw a light on these questions.
- To better understand upcoming man machine mechanisms.
- To build better robots or intelligent machines and to work with them more effectively.

Stillings [17] also gives some important reasons for simulating human and nonhuman minds in the form of artificial minds.

- Cognitive science theories are complicated and sometimes impossible to understand without simulating and observing in software.
- Comparing people with different capabilities and their cognitive processes via simulation. These different cognitive capabilities are applied on arts and science to give rise to diverse practical applications.

2.2 Conversion of Natural to Artificial Mind

The conversion from a life to artificial system can be done in three stages

- Understanding fundamental properties of the living systems.
- Simulating a basic organism and their entire life cycle, and
- Finally, designing the rules and symbols for governing behaviour by interacting with an environment.

The mind can be considered to demonstrate the principles and emergent intelligence associated with artificial life. Economic theory can be applied to artificial life in order to analyse and model adaptive or intelligent behaviours. The money or energy spent in such a way is the utility to be maximized. This follows the economic concepts such as price (cost) and utility [3]. The behaviours of a life can be analyzed using many different metrics. The major metrics are metabolic activity, competition and social interaction [3].

3. Principles of Natural Minds

Animal cognition is defined as the mental process, or activity, or mental capabilities of an animal. This has been developed from different disciplines like ethnology, behavioural ecology, and evolutionary psychology. Animal psychology includes experiments on the intelligence of animals. This is one of the simplest ways of exploring the complex behaviour of human beings. Most cognitive scientists are interested in comparing human cognition with machine cognitions, only few are interested in animal cognition [9].

The common biological origin of animal and human cognition suggests that there is a great resemblance in animal and human cognition, rather than the resemblance between machine and human cognition. Animal cognition is similar to human cognition, and follows, more or less, human cognitive psychology. Animals are both like and unlike humans. Children sometimes behave like animals, through their reflexive behaviours way. Examples include feeding and training children, and so on.

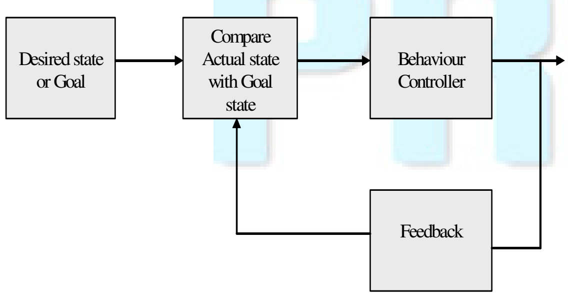
The behaviors of an animal have consequences which depend on situation, energy use and other physiological commodities such as water, weather etc. The important consequence of behaviour is energy expenditure. Such expenditure must be taken into account, because it influences the animal state. According to Thorndike [18], the behaviour of animals is predictable and follows the uniformity of nature. He says that "any mind will produce the same effect, when it is in the same situation." Similarly, an animal produces the same response, and if the same response is produced on two occasions, then the animal behaviour for that response must changes. The law of instinct or original behaviour is that an animal in any situation, apart from learning, responds by its inherited nature. An animal behavior is not simply a matter of cognition; rather it is product of the behavioural capacity and the environmental circumstances [9]. Charles Darwin argued that animals possess some power of reasoning. This research is concerned with the principles whereby an animal is competent for its resources, and so demonstrates intelligent behaviour [4] [9].

3.1Optimal Behaviours in Artificial Minds

Animal behaviour is a trade off between the native courses of action, i.e. physiological, and goal oriented behaviour. An animal is engaged with activities to optimize its pattern of behaviour with respect to the use of energy and time. If the conditions are relevant to two or more activities simultaneously, it chooses the optimal action among them in terms of its innate and learnt decision boundaries. The mechanisms of designing a machine are different from the animal's kingdom, but the principles remain the same [9].

3.2 Goal directed Behaviour in artificial minds

As shown in Figure 1, goal directed behaviour in artificial minds (a human, animal or machine) involves representation of the goal to be achieved. This means that behaviour can be actively controlled by internally represented states. Goal directed behaviour aims to minimize the difference between the "desired" state of affairs and the actual state of affairs. This difference can be viewed as error in behaviour, and this can be corrected using different factors. The design of an animal is genetically based and product of natural selection. But the robot is based on human engineering principles. However, the principles of their function and goal achievement can be similar [9].



"Figure 1. Goal directed Behaviour".

3.3 Cost of Behaviour

The decision making level in animals can be defined in terms of cost function and utility behaviours - the microeconomic level. Cost functions and utility behaviour in animals operate in such a way that a utility (for example, energy) is maximized or minimized. Let us consider an example as brick laying robot. Initially the robot has stored some sort of energy. The building of bricks is an energy consuming process. The robot monitors its energy level and recharges its energy level when low. This principle relies on some boundary condition and the same is true for animals. The boundary or hunger condition can be varied and sometimes the variable must be nearer the risk of death. It is dangerous to allow hunger condition level if the food supply is not guaranteed. There are three aspects for calculating a cost.

- Cost of being in a particular state,
- Cost to performing an activity;
- Cost of changing the activity.

The combination of physiological and perceptual state of the animal can be represented as a motivational state. This includes the animal's activities and the animal's present behaviour. The motivation of an animal depends on the physiological state (ecological properties) and perception of the external world, as well as the consequence of its current behaviour. Cost can be measured by considering the fitness of an animal over a period of time (life expectancy), where fitness is defined in terms of future expected reproductive success after this period. The cost function deals with real risks, real costs and the benefits. The utility function is the inverse function of the goal function in ethology. Animal behaviour is rational and behaves optimally with respect to this utility [9] [18] [20].

3.4 Decision Variables

A decision-making of a person, animal or robot can be described as an activity whereby decision variables are compared to decision boundaries. From the economic point of view, the decision-making unit is the cost or performance. Decision-making with respect to use of a cost and utility function depends on given thresholds, decision variables and decision boundaries. Cognitive modeling designs implementation mainly based on the analogies between animals and products. The product may be food, benefit (goal) and physiological aspect. We can also analyse life cycle of the product and life cycle of the animal. A decision of a robot, a person or animal is simply the process by which the decision variables are changed [9] [18] [20].

3.5 Learning in Animals

Learning is a part of development. It is a result of adaptation to accidental or uncertain circumstance. When an animal learns

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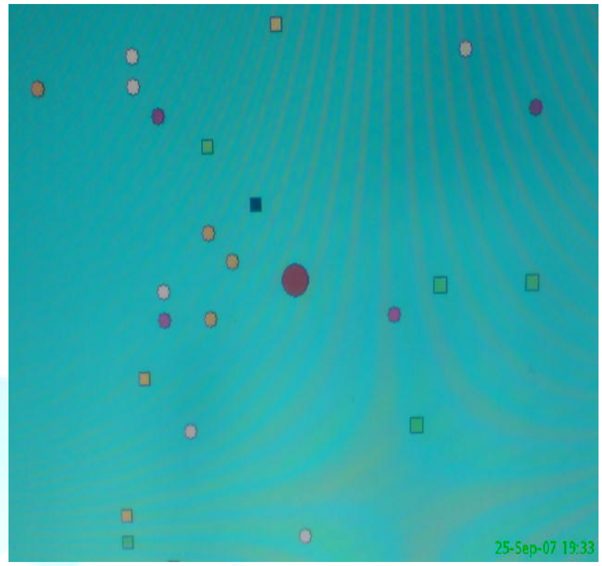
environmental situations, it undergoes permanent change. We expect that learning should, in general, bring beneficial results. Animal learning is similar to reinforcement learning in machine learning or robotics [9] [18].

4. Experimental Testbed Setup

The fungus world testbed is implemented using Prolog (SWI-Prolog, 2003). The fungus world testbed experiments include cognitive and engineering perspectives. The fungus world environment has been created to have both dynamic and static (Figure 2). The static blocks are more flexible, to create a particular location of the environment. There are different parameters in the environment for an agent's (big circle shape) biochemical engine and performance (refer Table1).

Resource parameters in the environment are created through the checkbox consisting of: (1) standard fungus; (2) small fungus; (3) bad fungus; (4) ore; (5) golden ore; (6) crystal and (7) medicine. The agents are created in the environment by using Prolog graphics (Figure 2). Fungus is a nutrient for the agents. Each standard fungus gives an agent 10 energy units. Initially, each agent has predetermined energy units. For each cycle, the agent consumes a fixed number of energy units. If the energy level (nutrients) reaches 0, the agent will die. The small fungus gives an agent 5 energy units. If the agent consumes a small fungus, 5 energy units (default) are added to the energy storage. The bad fungus has 0 energy units. If the agent consumes bad fungus, it gets null energy. Moreover, bad fungus increases the metabolism rate, and changes the metabolism affect.The medicine affects the metabolism of the agent in the testbed. The collection of medicine decreases the metabolism. The metabolic effect is exactly opposite that of collection of bad fungus.



"Figure 2.Fungus world Testbed".

The collecting of ore is the ultimate goal of each agent. Each agent group tries to collect as much ore as possible in the environment. At the same time, an agent has to maintain the energy level necessary to live in the environment. Initially, collection is 0, and one value is added after collecting each piece of ore. Collection of golden ore increases the performance of an agent. One piece of golden ore is equal to five standard ore units. Collection of crystal increases the performance of agent by a factor that is double that of ore.

4.1 Experimental Setup

This environment supports the running of the various types of agents, where each agent uses a different type of rules and mechanisms. In these experiments, a maximum of 50 agents were defined..The experiments were conducted for the same number of agents, the same type, the same number of fungi (including standard, small, and bad), ore (including standard and golden ore) and the same objects (including obstacles). The time scale and maximum cycles were kept constant by adding the same type of agent in each experiment.

"Table 1.Parameter for fungus world environment".

Parameter	Type	Value	Default Effect
Fungus	Object : Numeric	10	Increases the energy level by 10 energy units, to live in the environment
Small Fungus	Object : Numeric	5	Increases the energy level by 5 energy units, to live in the environment
Bad Fungus	Object: Numeric	0	Increases the energy level by 0 energy units, to live in the environment Decreases the performance by Increasing metabolism
Ore	Numeric	1	Increases the Performance by 1.
Golden Ore	Numeric	5	Golden Ore increases the agent performance 5 times More than an ore.
Crystal	Numeric	2	Crystal Increases the agent Performance 2 Times more than a Ore.
Medicine	Object: Numeric	0	Increases the performance by Decreasing metabolism
ENP (Energy storage)	Object: Numeric	N/A	Stores the energy based on consumption of Fungus, Small Fungus, and Bad Fungus.
Cycle	Object: categorical	1 or 2 or 5 Energy units	Agent consumes the Energy

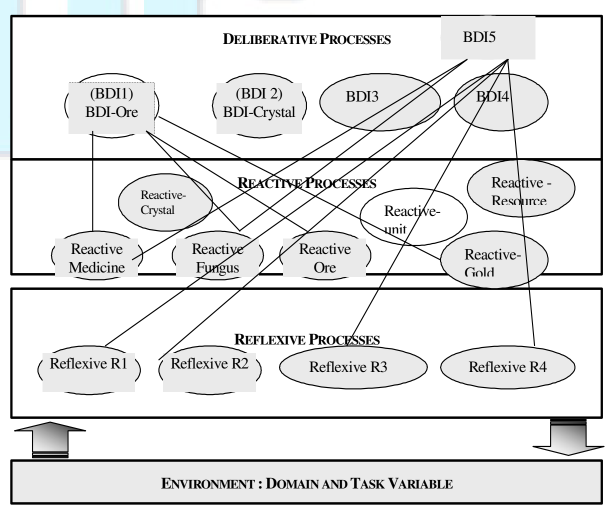
To compare the results for each agent, the following statistics were collected: life expectancy, fungus consumption (including standard fungus, small fungus and bad fungus), ore (standard ore and golden ore), crystal collected and metabolism. The life expectancy or age of the agent is noted, along with the agent's death (or age after the end of the maximum cycles or time). The agent's total performance will be calculated by amount of resources (ore, golden ore and crystal) collected, and based on life expectancy.

4.2 Micro-agent Design (BDI agent)

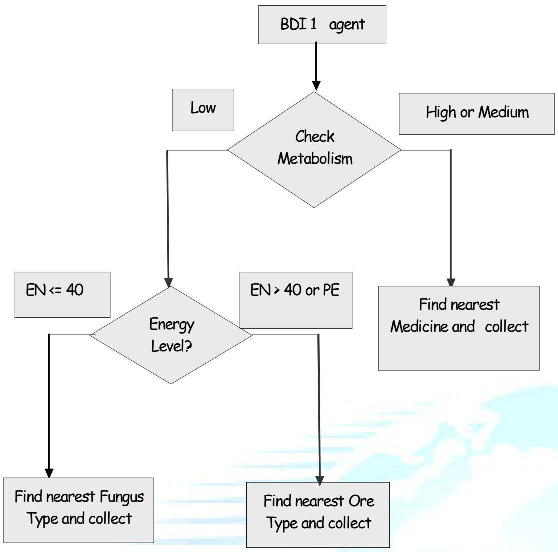
Animal based micro (deliberative) agents in a fungus world testbed are capable of performing different tasks related to principles of artificial economics. Ecah BDI (Belief- Desire-Intention) model has a different group of coordinated capabilities to meet a particular intention. BDI models were designed to mirror the reactive mechanisms necessary for the tasks in the simulation testbed. BDI agent follows the reactive actions in each move based on given rules and decision variables (refer Figure 3). Some BDI models favor specific goals towards: (1) ore; (2) crystal; (3) medicine, or (4) fungus. BDI models work in terms of a fixed threshold and adaptable energy use.

For example, As in Figure 3 The animal based BDI agents determines which of the reactive or reflexive control mechanisms are active according to the goals attempts to satisfy. These goals are either task related or agent's internal condition related. This determines the number of different types of reflexive and reactive agent required for this specific testbed. As in Figure 3 depicts BDI-Ore (BDI1) selects and controls the combination of reactive-fungus, reactive-ore, and reactive-golden-ore and reactive-medicine behaviours. BDI5 or BDI-Reflexive agent selects and controls the combination set of reactive-fungus, reactive-medicine and reflexive behaviours. The different versions of deliberative models uses in this experiment are: BDI-Ore (BDI1), BDI-Crystal (BDI2), BDI-ore-and-crystal (BDI3), BDI-adaptive (BDI4); and BDI-Reflexive (BDI5).

For example consider a scenario of hungry agent in a fungus world testbed. The agent intends to collect ore. If the agent in a hunger state (energy level is less than threshold or predicted energy value) or high metabolism condition, then agent changes their desire towards fungus or medicine. Based on the agents needs and cost function, different deliberative agents can be framed. The difference between each BDI model in terms of energy level, biochemical and in terms of goals.BDI models are capable of reasoning about their own internal tasks and plans. A smarter BDI model thinks further ahead, so the agent has sufficient energy to collect ore and collect next fungus before running out of energy available. Figure 4 and Figure 5 illustrates as follows: initially agent searches the nearest medicine to collect, and decreases their metabolism to low. Second, the agent compares its energy level with the fixed energy value 40 or predicted energy level. If the energy level is more than predicted or threshold, then it moves towards ore (goal), based on cost and utility function (microeconomic level).



"Figure 3. Animal based BDI and their control".



"Figure 4. Design of BDI-Ore (Micro-agent)".

Similarly, other version of BDI (BDI 5) agent searches the nearest medicine to collect, and decreases their metabolism to low. Second, the agent compares its energy level with the predicted energy level (smarter energy). The energy required to survive and reach their goal. If the energy level is more than predicted energy level, then it moves (different goal) reflexive conditions based on cost and utility function (microeconomics).

BDI 1(First) model

(1)Metabolism > Low,

Then searches the nearest medicine to collect to lower the metabolism by their reactive mechanism. Uses the Reactive Medicine,

Find the nearest Medicine by their distance,

Select the direction towards nearest Medicine,

Move towards Medicine direction | left| right |Up| down.

(2)Energy Level <= 40 (Threshold value) or PE

The agent desire to move towards to fungus to avoid the hunger condition or their death (Physiological oriented) uses the Reactive Fungus, Findes the nearest Fungus by distance formula,

Select the direction towards nearest fungus,

Move towards Fungus type direction | left| right |Up| down.

(3)Energy Level > 40 (Threshold value) or PE

Reactive Ore (Goal based behaviour move towards nearest Ore)

Find the nearest Ore

Select the direction towards Ore.

Move towards Resource direction | left| right |Up| down.

"Figure 5.BDI-Ore Design".

4.3 Micro agents Learning

This experiment uses simple reflexive level learning and animal based micro agent for comparison purpose [9] [18]. Reinforcement learning is learning, planning, and action selection paradigm based on maximizing reward .Update the state: $s' \rightarrow s$. Q-learning algorithms work by estimating the values of state-action pairs. The valueQ(s,a) (refer given below Algorithm) is defined to be the expected discounted sum of future payoffs obtained by taking action a from state s and following an optimal policy (i.e. delta value to find Q values) from the current state s, selecting an action a. This will cause receipt of an immediate goal unit and arrival at a next move.

"Q-Learning Algorithm"

Let $\mathbf{Q}(s, a)$ be the expected discount of reinforcement of taking action a in state s, and then continue by choosing actions optimally.

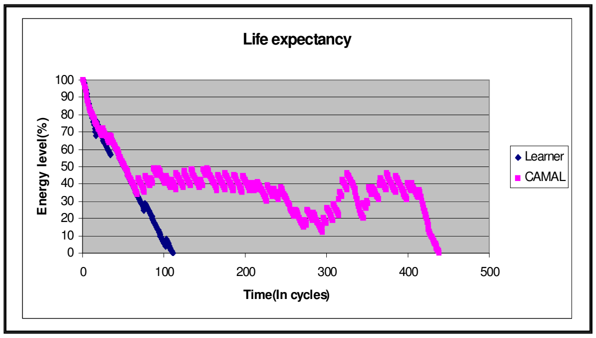
1. Initialize a table **f** with states**S**, actions **A** and the **Q** (utility or reward) value estimates.
2. Select an action a(where $a \in \mathbf{A}$) and execute it.
3. Observe the immediate reward r. Reward is defined using some agent relation, for example distance to desired object. Observe the new state s', achieved by action a on state s, where $a \in \mathbf{A}$ and $s \in \mathbf{S}$.
4. Update the table entry for **Q** value using an appropriate rule, for example,

New $\mathbf{Q}(s, a) = \text{Old } \mathbf{Q}(s, a) + (r(s) - r(s'))/ r(s)$.

The **Q** values converge to their optimal values

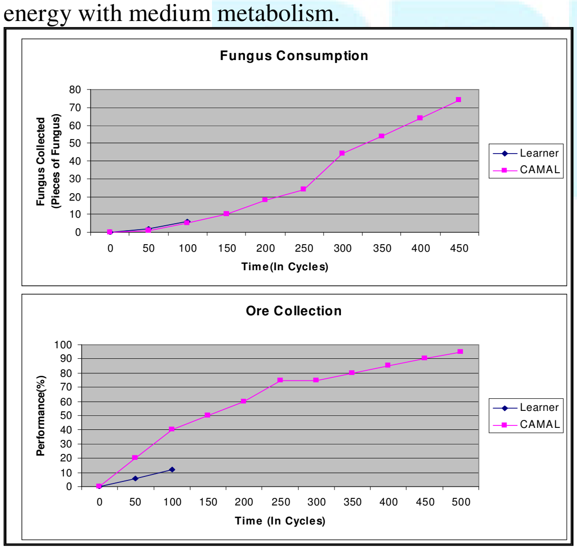
5. Experimental Results

As shown in Figure 6 and Figure 7, the animal based micro agent manages to live up to 438 life cycles. The animal based micro agent (Camal) shows a complete control mechanism in managing an energy level of 40 (assigned threshold or decision variable), and trying to manage the same line for the maximum time of its life cycle. The agents will exhibit optimal decision making capabilities near the decision boundary. The life expectancy of the two types of agents is shown below. The cognition (reflexive-learner) agent manages to live up to 110 life cycles in a fungus world environment.



"Figure 6. Life Expectancy of animal based Micro-agent".

The resource (ore, golden ore and crystal) collection of the simple cognition and animal based micro agents is as follows: cognition agents managed to collect 12 pieces of ore, and animal based BDI micro agents managed to collect 95 pieces of ore. Figure 6 illustrates agent decision making capability at the threshold value. If an agent acquires more than the threshold or predicted energy level, then agent tries to collect ore. If the agent has a lack of energy, then it collects fungus, from their hunger condition. Figure 7 shows the fungus consumption rate of cognition and Animal based micro agents in their lifetimes. The cognition (reflexive-learner) agent managed to collect 6 pieces of fungus and the Animal based micro agent are managed to collect 74 pieces of fungus. As Figure 7 illustrates, the (reflexive-learner) cognition agent initially, found to collect more fungus than the animal based micro agent. The Animal based micro agent was not concerned about fungus in this stage. Agents in the initial stage born energy with medium metabolism.



"Figure 7.Fungus and OreCollection of Micro agents".

6. Conclusions

The experiment was conducted for 500 life cycles, to find out the in-depth potential of the micro agents through their lifespan. Cognition agents lived up to 110th of their life cycle. Cognition agents collected 12 pieces of ore and 6 pieces of fungus in their lifetime. Animal based micro agent life expectancy is 438 life cycles, and

the managed to collect 74 pieces of ore and 95 pieces of fungus in their life cycle. For the animal based micro agent, fungus consumption is considerably less, unless it was found to have less energy storage. As in Figure 7 depicts, in between the 250 and 300th life cycle, the Animal based micro agent's fungus consumption rate is found be very high. In this stage, the Animal based micro agent is in the hunger condition, and needs more fungus. This follows the fitness or life expectancy. Hence it switches towards the collection of fungus. This results proves that Animal based micro agents can reason about their change of aims (deliberations), watch their status (self regulation or self control), and achieve their goals.

Animal based micro agent manifest decision making and intelligent behaviours. Animal based micro agents have a complete control mechanism for managing food and metabolism. These agents' exhibit decision making capabilities near decision variable boundary. Animal based micro agents engaged in activities to utilize their pattern of behaviour with respect to the use of energy and time. The level of decision making when they are hungry (less than the decision making energy level) switch into the fungus consumption for fitness and if they normal, switch towards goal-oriented (i.e. collection of ore), demonstrates physiological and goal-oriented behaviour. Animal based micro agent manages the affect mechanisms, such as energy level, based on a given threshold or predicted energy level to manage the decision boundary (fitness).

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