Design of Micro-agents based on the Artificial Economics

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Abstract

This paper describes the results of a simulation to demonstrate the principles and emergent intelligence associated with artificial life. Economic theory can be applied to artificial life in order to analyze and model adaptive or intelligent behaviors. This research is concerned with the principles whereby an animats competent for its resources, and so demonstrates intelligent behavior. 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 behavior (the microeconomic level), physiological and goal oriented behavior are investigated. Agent behaviors can be analyzed using many different metrics; for example, metabolic activity, competition and social interaction with respect to environment and microeconomics.

1. Introduction

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 (Selfridge; 1959). This model attempts to explain mind as a collection of agent type tiny demons. The pioneers such as Selfridge[22], McCarthy[16], Allen Newell and Herbert Simon[19]], Minsky[17][18], Fodor [11], Baars [3], Brustoloni [4], Anderson[2], Franklin[12][13][14], Sloman[24], Davis [7][8] and Singh[25] were viewed 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 [12] [13] [14]. Agent behaviours can be analysed using many different metrics. The major metrics are metabolic activity, competition and social interaction with respect to environment and microeconomics. Application of economics on artificial life to watch 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 [20].

2. Agent Classifications

An agent senses and acts in its environment. The researchers involved in agent research have offered a variety of formal and informal definitions for an agent. Russell [26] defines an agent as “anything that can be viewed as perceiving its environment through sensors and acting through the environment through effectors” Brustoloni [4] says that “autonomous agents are systems capable of autonomous, purposeful action in the real world”. Intelligent agents continuously perform three functions: (1) perceptions, (2) action to effect a change in conditions and (3) reasoning to interpret perceptions, solve problems, draw inferences and determine actions. Some of the relevant agent classifications are explained below.

3. Brustoloni Agent Types

Brustoloni [2] classified three types of autonomous agents: (1) regulation agents, (2) planning agents and (3) adaptive agents. Regulation agents follow a set of predefined rules and regulate things, similar to the way a thermostat controls temperature. There are four types of regulation agents: (1) problem-solving agents (2) case-based agents, (3) operational research agents and (4) randomizing agents. Problem solving agents may search for planned solutions, and some agents can provide satisfactory solutions. The agents can store or remember their moves, plans, and actions. A case-based agent uses the search and analogy method. Case-based agents can store plans, and test their application in specific circumstances. To solve a problem, a case-based agent finds the most suitable plan. Operational research agents use a mathematical model, such as a queuing theory, to provide an optimal control. Randomizing agents simply work by trial-and-error methods. Planning agents follow regulation agents with a planned sequence of actions. The adaptive agents learn by chunking and other methods involving learning and modification [2].

4. Sloman Agent Types

Sloman (2001) defines an agent as a "behaving system with something like motives". Agents can sense and act on the environment. Sloman classifies agent groups based on motivations such as thirst, hunger, sex, communication, preference, society norms, etc. According to Sloman agents can compare and visualize plans, sense and memorize, to various extents based on their degree of mind. According to Sloman, to make a complete functioning human agent needs the design of a human-like flexible architecture. This architecture may be biological or synthetic or take the form of a robot agent. This architecture needs integral diverse capabilities. The agent's architecture requires a wide range of cognitive science components such as vision, speech understanding, concept formation, rule learning, planning, motor control, etc [23][24].

Reactive sub system	Follows external sensors and internal monitoring, acts like more primitive parts of the simple brains. Example like insects.
Deliberative system	Follows the reactive system and works with triggering responses like non human minds.
Metamanagement system	Monitoring and controlling the deliberative models.Metamanagement activities like self monitoring and self modification capabilities.

Table 1. Sloman Agent Types

Sloman argues that a part of human-like agent should have a diverse collection of tasks, both externally and internally. Internal actions include generating the motives, verifying the motives, selecting the motivations, creating plans, judging inferences, creating, monitoring, and identifying new possibilities. External tasks involve actions such as finding and eating food, avoiding enemies, building houses, making tools and finding friends). Sloman argues that there is no particular or unique design for human intelligence. There is no fixed architecture for an intelligent agent. This also includes many kinds of human learning, such as learning to drive a car, learning to read and write text, learning to play a piece of music, learning to write software, and learning many sports skills. Sloman classified the agents based on the three layers, as shown in Table 1.

5. Minsky's Agent Types

Minsky states that a complete cognitive agent needs four separate and highly interrelated layers (Minsky, 1985). This necessitates the consideration of ongoing arguments in agent research. Each mental agent can, by it self, do some simple things, and when these agents are joined in a special way, the result may lead to true intelligence. Most of the "agents" grow in the mind, from learned experience. According to Minsky, each agent looks simple and smaller (micro) like a toy, and does only small cognitive tasks. Combining all these micro agents in a meaningful way, almost anything can be built [17].

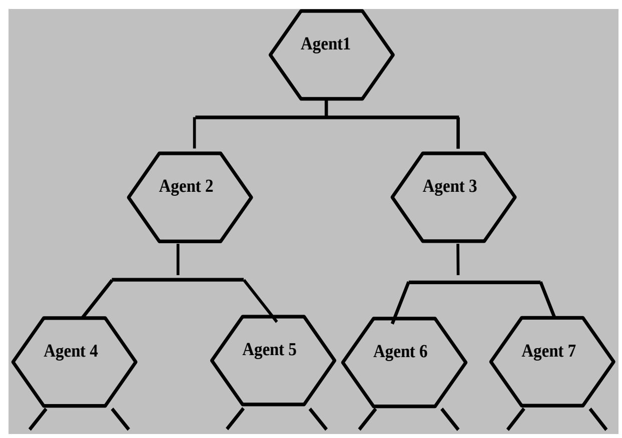


Figure 1. Society of Agents

Minsky considers the following properties: (1) how the agents work, (2) origin and heredity, (3) learning and authority, (4) communication, (5) self awareness or consciousness, (6) feelings and emotions (7) ambition, jealousy, and humour. Minsky argues that creating machines that do the entire range of things people do is very far in the future, if it occurs at all. According to Minsky [17], intelligence is a combination of relatively simple things. Imagine a child playing with building blocks, and how the child likes to watch a tower grow as each new block is added. Minsky says that the mind is like a tower, except that it is composed of processes instead of blocks.

Society of Agents (Figure 1), agents can be designed in a way similar to a child playing with building blocks. Any cognitive architecture contains a large collection of micro agents. Each agent may used in a different way to represent knowledge and reason with it. Each agent is specialized for some type of knowledge or cognitive process [25]. Building an optimal agent cannot be done with a single and simple agent, as it needs to interact with or take help from other agents. Hence, developing a cognitive architecture can be viewed from the perspective of Minsky [17], which leads to the development of many different types of simple agents with different behaviours. Figure 5.1 depicts a tree (graph) like structure, similar to tree concept in graph theory. This contains nodes and branches. Each node represents an individual micro agent. Each branch represents a link between nodes. This illustrates Minsky's K-line theorem. The K-lines are data and control lines (buses) in the design of computer architecture. Assume if there are two different cognitive tasks T1 and T2 to perform in a society of agents. Agents 2, 4 and 5 can perform T1 and, agents 3, 6 and 7 can perform T2 cognitive task. Afterwards T1 and T2 performing agents can be combined as T1 agency. Similarly, any number of agents and agencies can be combined to form as "Society of Mind". Society of Mind can be framed from any smaller degree to any large extent. For example, human mind as a "Society of Mind" is larger, and rat mind as a "Society of Mind" is smaller in degree, with a smaller set of agents and agencies.

6. Minsky's Meta-model or (Minsky's A,B and C-Brain

Minsky [17] addressed the possible inner mechanisms, and higher level thinking of the mind. Minsky initially postulated an A-Brain and B-Brain mechanisms (Fig. 2). A-Brain is connected to outer world through sensors and effectors. A-Brian collects information form the outer world or environment. A-Brain will control the cognitive tasks or mental processes in the architecture. The mental processes include perception, memory, imagery, language, problem solving, reasoning and decision making activities. B-Brain act like a supervisor for A-Brian.

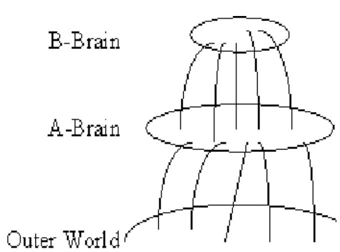


Figure 2. Minsky A B and C-Brain

A-Brain stops or struck or in confusion state to react, then B-Brain makes self reflection of A-Brain. B-Brain can supervise an A-Brain without understanding A-Brain working mechanisms. Minsky suggested that, A & B-Brains can have C-Brain. This can control, watch, and influence the B-Brain. B-Brain and C-Brain works as similar to the A and B-Brains. In addition to this, Minsky suggested "closed loop" concept. The closed loop concept follows transitive mechanism. For example, B is a supervisor of A, C is a supervisor of B and, C is also a supervisor of A. According to Kennedy [6], A and B-Brain's can not mutually monitor and can modify each other. This is called as closed system, but not reflective.

7. Design of SMCA using Metacontrol and Metacognition rules

SMCA [28] is a distributed model of mind, which is an extended architecture of CAMAL [4] with an extra processing layer. SMCA demonstrates planning, reasoning, decision making, self-reflection, problem solving and learning capabilities, predicting, repairing, reviewing, comparing, generalizing and simplifying and many other ways of thinking. SMCA is a six layered architecture with reflexive, reactive, deliberative, learning, metacontrol and metacognition levels (Figure 3). This uses Fungus eater test bed to simulate simple to complex level intelligent agents [28].

Fungus eater Test bed: An agent in fungus eater environment has different biochemical parameters such as metabolism and performance. Metabolism is the rate of energy consumption of an agent to demonstrate simple behaviours and the performance is how optimally an agent can collect the resources in the environment to increase the reward by maintaining its energy levels. The fungus eater environment has various parameters: metabolic parameters which include medicine. The medicine is consumed by the agent to maintain low metabolic rate so that it can survive for longer in the environment. The energy resource parameters are standard fungus (green squares), bad fungus (black squares) and small fungus (small green square). The goal based parameters are Ore (red stars), Golden-Ore (yellow stars) and Crystals (white stars).This environment is populated with many synthetic artificial agents who perform better by maintaining their energy levels under the guidance and control mechanisms of higher layers in SMCA[11]. SMCA has many simple agents which work together to exhibit intelligent behaviour. It has many simple reflexive agents to highly intelligent metacognitive agents which can learn and adapt to the dynamic environments. This architecture simulated six reflexive, seven reactive, fifteen deliberative, nineteen perceptual, fifteen learning, fifteen metacontrol and seventy seven metacognition behaviours.

Reflexive layer: The agents in this lowest level layer can exhibit simple reflexive behaviours, where their actions fully depend on the state of environment given. The reflexive agents can sense the edges of the environment and centre of the environment. These agents can move in all four directions, if the space is free. It moves to the edges of the environment, if the space is not available or when it is idle. The agents can exhibit two kinds of reflexes (the actions which happen before thinking): simple reflexes which do not require any learning and combined reflexes. The reflexive behaviours are implemented through Finite State Machine (FSM). The FSM is a mathematical model works on finite number of inputs and outputs. This means the agents responds to only a finite set of stimuli. The output of FSM is directly mapped on to the agent’s actions.

Reactive Layer: The agents in this layer exhibits a well planned and coordinated actions to satisfy the goal specified for that agent. The reactive agents are controlled by deliberative BDI agents which sets the goal for reactive agents. The BDI agents decide which reactive agents and how many are required to be activated to satisfy the goal set for the entire architecture. There are seven reactive agents: Reactive-ore, reactive-golden-ore, reactive-crystal, reactive-resource, reactive-unit, reactive-medicine and reactive-fungus. Reactive-ore agent always moves towards the nearest ore and collect it. Similarly other agent moves towards the intended resources and collect them. Reactive agents understand the affecting parameters of their behaviour such as distance to the resource and the type of resource. The agent always moves in the direction in which the nearest resource is available. If there are no resources available in their perceptual range they move to the edges of the environment.

Deliberative layer: The third layer of the architecture is deliberative layer which is populated with many BDI (Belief Desire and Intension) agents. These deliberative BDI agents use required number of reactive agents and reflexive agents to meet the goal specified by the entire architecture. There are five BDI agents: BDI-Ore which selects and controls reactive-ore, reactive-ore-crystal, reactive-fungus and reactive medicine. Similarly it has BDI-Ore-Crystal, BDI-Crystal, BDI-Adaptive, and BDI-Reflexive.

Learning layer: This helps the agents in decision making based on its previous experience or handling the problems at lower level layers. This layer works in control of metacontrol layer. The agent’s learning is based on reinforcement learning algorithm such as Q-learning. This algorithm always finds a maximum reward for an action. The algorithm is given in figure 3. There are four basic terms to be understood in Q-learning algorithm: policy, reward function, value function and model. Q-learning algorithms work by estimating the values of state-action pairs. The value Q(s, a) is defined as the expected discounted sum of future payoffs. This can be obtained by taking an action ‘a’ from state‘s’. Given the delta value from the current state s, selecting an action a, will cause receipt of an immediate goal unit and arrival at the next move. The rules can be symbolic, fuzzy, neural or other, depending on the direction taken in devising the metacontrol and metacognition part of the architecture. The metacontrol mechanisms can be viewed in terms of which the agents use existing controllers, learn behaviours (i.e. existing Q(s, a) values) or learn new behaviours by training the agents.

Q-Learning Algorithm:-

Let Q(s,a) be the expected discount of reinforcement of taking action an in state s, then continuing 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 $a \in A$) and execute it.
3. Observe the immediate reward r,Reward defined using some agent relation, for example distance to desired object. Observe the new state s', achieved by action a on state s, where $a \in A$ and $s \in S$.
4. Update the table entry for Q value using an appropriate rule, for example New(s, a) = Old(s, a) + (r(s) - r(s'))/ r(s).The Q values are nearly converged to their optimal values
5. Update the state: $s \rightarrow s'$.
6. Repeat from 2 until learning finished.

Figure 3. Q-Learning algorithm

The Policy is a simple function that maps the perception state from the environment to the stimulus-response action of an agent in the given environment. The reward function defines the goal for the reinforcement learning, which maps a state and action pair on to a single reward. This determines good or bad events for an agent. The reward function determines the immediate and intrinsic desirability of an agent. The value functions define the future payoffs for achieving a reward, being in state‘s’ and taking an action ‘a’. It may be sequence of actions taken by an agent to achieve the optimal reward starting from state s over its lifetime. The model is used for planning, which helps the agent to decide on an action in a particular state of a given environment. An agent applies a policy in each move by looking at the value function to maximize the reward. The delta value is calculated from agent’s distance and new distance values: Delta is 1 / (Distance + 1); and Delta is Old + ((Distance - New distance)/Distance).

Metacontrol layer: The metacontrol layer is the fifth layer of SMCA.

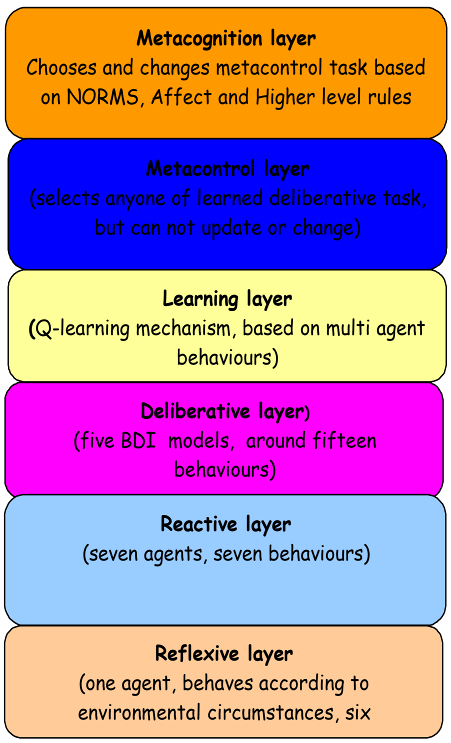


Figure 4. Layers of SMCA

The agents in this layer decide which deliberative agents are to be learned. These agents have different levels of skills such as, reflexive, reactive, deliberative and learning capabilities and can be viewed as learned BDI agents which can learn and train themselves to achieve maximum rewards. The metacontrol agents implemented are: learned-BDI-Ore, Learned-BDI-Ore-crystal, Learned–BDI-adaptive, learned-BDI-crystal and learned-BDI-reflexive.

Metacognition layer: The last layer of the architecture has highly intelligent agents. These agents’ uses metacomponents such as norms affect mechanism and higher level rules to choose the set of learned BDI agents to meet the goal set for the entire architecture. It can learn optimal steps taken by an agent using m-norms and affect mechanism by using Q-learning algorithm. This layer details are given in section 5.

8. Designing of Metacontrol and Metacognition Rules.

Metacontrol agent decides which deliberative agents are to be learned and ready to perform in different conditions. The deliberative actions are called control actions. A Meta controller determines the relevant control actions. The metacontrol agent learns actions upon the environment. The agent calculates all the combinations of deliberative agent’s states (inputs) and actions. Metacontrol agents have different levels of skills, such as reflexive, reactive, deliberative, or learning capabilities. The metacontrol agent can select and controls any of one of the decision models such as :(1) learned-BDI-ore, (2) learn-BDI-crystal, (3) learned-BDI-ore and crystal, (4) learned-BDI-adaptive and (5) learned-BDI-reflexives. BDI agents should learn themselves by trained method. Hence by adding learning methodology makes more effective. Reward is a goal of the metacontrol agent. This defines the good and bad events for the selected BDI agent. Metacontrol agent’s main objective is to maximize the total reward of the running BDI agent. The metacontrol level may be a neural or some Neuro-symbolic hybrid, and that allows learning. These rules can be used by the metacontrol part of the SMCA architecture. The rules can be symbolic, fuzzy, neural or other depending on the direction taken in devising the metacontrol part of the architecture.

9. Norms and Affect

The affect mechanism defined will make the agent to ensure that its metabolism is maintained low, which means it makes the agent check frequently to see if its metabolism has gone below the defined threshold. In this case it will change its desire to collect medicine. The affect of an agent is calculated by the given rule:
Performance (BDI-Ore) = Ore + Golden-Ore + age
Affect (BDI-Ore) = Norm (BDI-Ore)/Performance (BDI-Ore) Similarly,
Performance (Crystal BDI) = Crystal + Age
Affect (Crystal) = Norm (Crystal)/ Performance (Crystal)
Performance (OreCrystalBDI) = Ore + Golden_ore + Crystal + Age
Affect (OreCrystalBDI) = Norm (OreCrystalBDI) / Performance (OreCrystalBDI).

The main feature of a Metacontrol agent is learning the meaningful behaviours. Q-learning is reinforcement learning method, which is adapted by an agent for learning. Metacomponents affects on the agent behaviour from a sense of what is important instead of what to do. Metacognition agents follow well aligned norms, perceptual range, metarules, and learning and affect values. A well driven agent will maximize its performance as a consequence of learning to maximize its own reward. The metacognition agents can change the framework of BDI agents with reasoning. This level works to control and monitor the deliberative models. Two ways metacognition technique can be applied on humans: controlling and monitoring cognitions; and self reflection of individuals their own mental process. The deliberative models can be switched off or on based on the norms.

The term “norm” is an interdisciplinary term, and can be used to refer to a standard principle or a model used for a right action. The executive processes that controls the other cognitive components are responsible for “figuring out how to do a particular task or set of tasks, and then making sure that the task or set of tasks are done correctly”. In a given state an agent before taking an action the agent will compute the norm value. For example if the collected ore is 0, norm of ore is set to 0.75 and if it is greater than 0, the norm of ore is computed as total ore perceived divided by total ore collected. Once the norms are computed for each resource, the agent now compares the norm value and adapts the norm with the highest norm value. The norm1 is given below (Figure. 5).

Norm 1

Collected (Ore) = 0,

Norm (OreBDI) = 0.75.

Collected (Ore) > 0,

Norm (OreBDI) = Perceived (Ore)/Collected (Ore).

Collected ore is Ore1 + Golden ore1, Collected (Crystal) = 0,

⇒ Norm (Crystal) = 0.75.

Collected (Crystal) > 0,

Norm (Crystal) = Perceived (Crystal)/Collected (Crystal).

(Collected (Ore) + Collected (Crystal) = 0,

Norm (Ore_CrystalBDI) = 1.

(Collected (Ore) + Collected (Crystal)) > 0,

Norm (OreCystalBDI) = Perceived (Cystal+Ore)/Collected (Cystal+Ore).

Figure 5. Norm1 used in Metacognition agent

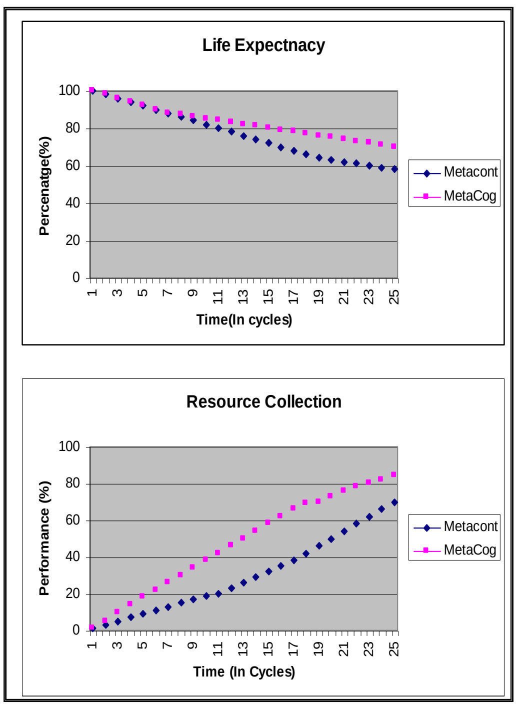
The metacognition agent checks the affect value of the norm before being adapting. The affect value of each resource is set according to the agents dynamic requirements, for example if the metabolism rate is high, the affect value of medicine will be high compare to any other resource. Now the metacognition agent switch the BDI model to deliberative-Medicine and collects the near by medicine. Similarly if the energy level is below the decision-boundary, the affect value of the fungus is set high than any other resource and agent will automatically move towards the nearest fungus, even when its norm is to collect ore or any other resource. This ensures that the agent survives for longer in the environment. The affect mechanisms are used by norms to improve the agent’s performance by switching between BDI models as and when required, depending on the agent’s dynamic requirements. The algorithm given below shows how a metacognitive agent works.

Algorithm to implement Metacognition agent:

1. Map Internals states onto Belief Set from the perceptual range or perceptual level increases the agent’s belief set for sensing in an environment. Example level 5 returns Sense List = [5-spacefree, 4-agent, 3-spacefree, 2-fungus, and 1-spacefree].Updates Belief Set with Perceptions and perceptual range.
2. Use Affect mechanism (metacomponent), to find a need of the Metabolism and need of a food.
3. Use a Metacomponets such as Norms or M-Norms (Such as Norm1, Norm2, Norm3, ETC are standard rules) to decide which BDI model to choose in right time by using right decision (optimal decision)by comparing resources available and balance the resources in a testbed.
4. Metacomphrension or Remedial action: Select Appropriate Belief-Desire-Intention Combination (BDI-Ore, BDI-Crystal, BDI-Ore Crystal, ETC), by comparing the architectural results.
5. Metamanagement: Uses M-Norms to Switch the BDI Models (Such as BDI-Ore, BDI-Crystal, BDI-Ore Crystal, ETC),
6. Schema training: Use a Q-Learning (given below) for optimal steps taken from agent by using M-Norms and Affect Mechanism (mtacognition level).
7. Repeats the steps (Step1 to Step6) until Simulation ends.

10. Simulation Results

Experiments were conducted separately for each type of agent. In order to compare results in the experiment, the same statistics were collected. Different types of agents in different level of architecture were employed for these experiments. The metacontrol and metacognition agents began the experiment with the same percentage (100%) of life expectancy, and resources (refer Graph 1). The metacognition agent manages an energy level of 72%, compared to 58% from the metacontrol agent. The metacognition agent collected 82% of resources, and the metacontrol agent collected 68% of resources. The metacognition mechanism agent performs better than the metacontrol agents. This explains through result graphs, how the concept of metacognition improves the performance through unification.



Graph1. Metacontrol v/s Metacognition Agent

11. Conclusion

This research paper illustrated how to design and adopt a metacontrol and Metacognition mechanisms for cognitive architectures in the broad area of Artificial Intelligence. This paper also given how to frame rules for Metacontrol and Metacognition Mechanisms using Norms and Affect models. The result concludes that BDI with Metacognition agents are better than other agents. A Metacognition agent collects more resource and manages the higher life expectancy than all other agents.This result proves a concept of metacognition is a powerful catalyst for control, unification and self-reflection. Metacognition used on BDI models with respect to planning, reasoning, decision making, self reflection, problem solving, learning and the general process of cognition improved the performance. This research paper explained how mind research can benefit from the use of metacontrol and metacognition. Finally, this research gives a clear roadmap for researches, to develop a metacognition and metacognition concepts on cognitive modeling.

12. References

[1] Adkins.J, Metacognition, university of Saskatchewan, Canada.

[2] Anderson J R, 1993, *Problem solving and learning*, American Psychologist, 48, 35-44.

[3] Baars B J, 1998, In The Theatre of Consciousness: Global workspace theory, a rigorous scientific theory of consciousness, Journal of Consciousness Studies, 4, 292-309 Oxford: Oxford University Press.

[4] Brustoloni J C, 1991, *Autonomous Agents: Characterization and Requirements*, Carnegie Mellon Technical Report CMU-CS-91-204, Pittsburgh: Carnegie Mellon University.

[5] Cox M T, Metacognition, problem solving and aging, Cognitive Science Tech. Rep. *Atlanta, Georgia Institute of Technology*, 1994, College of Computing No. 15.

[6] Cox M T, *Metacognition* in Computation: A selected research review, *Artificial Intelligence*. *169*(2), 2005, 104-141.

[7] Davis D N, 2002, Computational Architectures for Intelligence and Motivation, *17th IEEE International Symposium on Intelligent Control*, Vancouver, Canada.

[8] Davis D N, 2007, *Linking Perception and Action through Perception, Experimental & Theoretical Artificial Intelligence*, and JETAI is available online at: http://www.tandf.co.uk/journals/tf/0952813X.html.

[9] Flavell J H, 1979, *Metacognition and cognitive monitoring: A new area of cognitive developmental inquiry*. American Psychologist, *34*, 906-911.

[10] Fodor J A, 1982, "Cognitive Science and the Twin-Earth Problem," Notre Dame Journal of Formal Logic 23 (1982): 98-118.

[11] Fodor J A, 1983, *Modularity* of Mind, Bradford Books.MIT Press, Cambridge, MA.

[12] Franklin S, 1995, Artificial minds, A Bradford book, MIT press.

[13] Franklin S and Graesser, 1997 "Is it an Agent, or just a Program? Taxonomy for Autonomous Agents," Proceedings of the Agent Theories, Architectures, and Languages Workshop, Berlin: Springer Verlag, 193-206.

[14] Franklin S, 1997, *Autonomous Agents as Embodied A,I*, Cybernetics and Systems, 28:6(1997) 499-520 Available at http://www.cs.memphis.edu/~franklin/AAEI.html [Accesses on 16th October 2006]

[15] Kennedy C M, 2003, "Distributed Reflective Architectures for Anomaly Detection and Autonomous Recovery", PhD thesis, University of Birmingham.

[16] McCarthy J, 1959, ``Programs with Common Sense'', in *Proceedings of the Teddington Conference on the Mechanization of Thought Processes*, Her Majesty's Stationery Office, London. Reprinted in [McCarthy, 1990].

[17] Minsky M, The *society of Mind*, (Cofounder of the artificial intelligence, Laboratory, MIT, 1985).

[18] Minsky M, A Response to Four Reviews of the Society of Mind," Artificial Intelligence, Vol. 48, pp. 371-396, April 1991.

[19] Newell A and Simon H, 1972 Human Problem Solving. Englewood Cliffs, NJ: Prentice-Hall.

[20] Pfeifer R, 1988, Artificial Intelligence models of emotion. In V. Hamilton, G. H. Bower & N. H. Frijda (Eds.), *Cognitive perspectives of emotion and motivation* (p. 287-321). Dordrecht: Kluwer.

[21] Raja A, 2003, Meta-Level Control in Multi-Agent Systems, PhD Thesis, University of Massachusetts Amherst, http://www.sis.uncc.edu/~anraja/thesis.pdf, September 2003, [Accessed 15th May 2005].

[22] Selfridge O, 1959, Pandemonium: A paradigm for learning. In Symposium on the mechanization of thought processes.

[23] Sloman A, 2001, *Beyond Shallow Models of Emotion*, University Of Birmingham. Available at http://www.cs.bham.ac.uk/research/cogaff/. [Accessed 22nd July 2005].

[24] Sloman A, 2002, *How To think About Cognitive Systems: Requirements And Design*, Available at http://www.cs.bham.ac.uk/research/cogaff/. [Accessed 21st July 2005].

[25] Singh P, 2005, EM-ONE: Architecture for Reflective Commonsense Thinking PhD Thesis. Available at http://web.media.mit.edu/~pus.

[26] Russell and Norvig, 1995, Artificial intelligence: a modern approach, University of California, Berkeley

[27] Stillings N, Cognitive Science. Second edition. Cambridge, MA: MIT Press, 1995.

[28] Vijayakumar M V, Society of Mind Approach to Cognition and Metacognition in a Cognitive Architecture, PhD Thesis (University of Hull, UK, 2008).

[29] Vijayakumar M V and Davis D.N, July 2008, Principles of Artificial Economics in Animal Minds, AIPR-08, Orlando, FL, USA.

[30] Vijayakumar M V and Davis D N, 2008, Society of Mind Cognitive Architecture, Accepted ICAI'08 - The 2008 International Conference on Artificial Intelligence, Monte Carlo Resort, Las Vegas, Nevada, USA (July 14-17, 2008).

[31] Zalta E N, 2005, *Stanford Encyclopaedia of Philosophy [online]*, available: www.platostanford.edu,