ISSN: 2393-8528

Contents lists available at www.ijicse.in

International Journal of Innovative Computer Science & Engineering

Volume 6 Issue 1; January-February 2019; Page No. 01-10

Swarm Intelligence Techniques in Artificial Economics for Energy Conservation in Enriched Cognitive Architecture

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ABSTRACT

Energy conservation is the challenging issue in cognitive architecture. Swarm intelligence techniques are an optimized method adopted in artificial economics. Enriched Cognitive architecture for conservation of energy (ECACE) is proposed and design is demonstrated. The ECACE implemented with quantum partial swarm optimization techniques in cognitive architecture simulated Testbed. The result of performance ore and crystal evaluation, The Life Expectancy of Cognition versus BDI Agents and Swarm agents and Consumption rate of Fungus and Ore Collection and life expectancy are discussed. The results obtained from ECACE are compared with Society of mind Approach for distributed cognitive architecture (SMCA) agent's and shows that swarm agent's performance is better than SMCA performance in energy conservation.

Keywords: Energy Conservation, Artificial Economics, cognitive architecture, swarm Intelligence, Partial Optimization algorithm, Continues quantum partial optimization algorithm, BOIDS algorithm

INTRODUCTION

Cognitive architecture provides intellectual properties of human such as Reflex action, Reflexive Layer, Reactive Layer, Deliberative or BDI (Belief-Desire-Intention) agents. Artificial Economics is the process of optimization of resources in the intellectual properties of cognitive architecture. Among one of the optimization techniques of artificial economics in cognitive architecture, this paper identify energy conservation.

Swarm intelligence that involves the collective cooperation of multiple agents that operate in a decentralized, self-organized, and distributed form is adopted for energy conservation. Particle swarm optimization (PSO), that was motivated by the social connection behavior of wild birds and first proposed by Kennedy and Eberhart in 1995 [1] -[2], is a population-based algorithm that is stochastic. Swarm is a group of homogeneous agents which can be specific communicate one of them and with the environment.

Swarm intelligence approaches, such as ant colony optimization, particle swarm optimization, artificial bee colony, bat algorithm, firefly optimization, have successfully been used to solve various this paper adopted continues swarm optimization techniques for energy conservation.

The paper starts with Introduction of need of swarm intelligent in energy conservation for artificial economics in cognitive agent is

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discussed in section 1, followed by identified related works on swarm agent with energy conservation in section II, proposed ECACE architecture in section III, Mathematical model, primitive BOID of swarm algorithm and proposed novel swarm agent layer algorithm for ECACE in section IV, Experimental design, setup are discussed in section V, detail implementation Result discussion with graphs are shown in section VI , comparison of SMCA with ECACE swarm agent performance are show in section VII and followed by conclusion and further enhancement were discussed.

II. RELATED WORK

SMCA (Vijay Kumar, 2008) cognitive architecture employed for a certain task, provided with the duty specific knowledge is known as a model that is intellectual. In line with the Neumann, any architecture that fulfills intellectual the following 3 layers:1. Reflexive Layer: Reflex action is actually produced from animal and human biological neuromuscular action. The reflexes are built in mechanisms where action may appear quickly, before thinking.2. Reactive Layer: Reactive agents are experiencing more control mechanism that is versatile. Here agents tend to be more goals oriented. Therefore, agents in this layer behavior across actions which are incorporated.3. Deliberative Layer: Deliberative or BDI (Belief-Desire-Intention) agents developed in the behaviors utilized in the reflexive and agents being reactive. The deliberative actions are planned and coordinated with regards to the representative, its suggest that is interior motivations as well as its perception of resources in the environment.

Boids was developed by Craig Reynolds(1987: 25-34). Boids is an artificial life program which simulates the flocking behavior of birds. The name “boid” means “bird-oid” object which refers to “bird-like” object. Boids are similar to particle systems but have orientation and geometrical in shape which is used for rendering.

III. ENRICHED COGNITIVE ARCHITECTURE FOR CONSERVATION OF ENERGY

The ECACA (Enriched Cognitive architecture for conservation of energy) that is cognitive was created by taking into consideration the SMCA (Vijay Kumar, 2008) as a base. The ECACA is 6 tier and 3 column architecture as shown in the figure 1. This allows the explanations being basic. The SMCA is a group of individual agents performing different actions which can be individually. Nevertheless the ECACA is really a band of individual agents performs actions being same model is 4 tier and 5 column models as shown within the figure 1 utilized to implement the various cognitive issues like planning, reasoning, thinking, Problem resolving, decision, etc. At every layer you will find agents with behaviors, which react to the nagging issues of the layer. The agents mix of many simple behaviors at each layer. The ECACE model includes reflexive-reactive, deliberative, swarm, meta-learning agents.

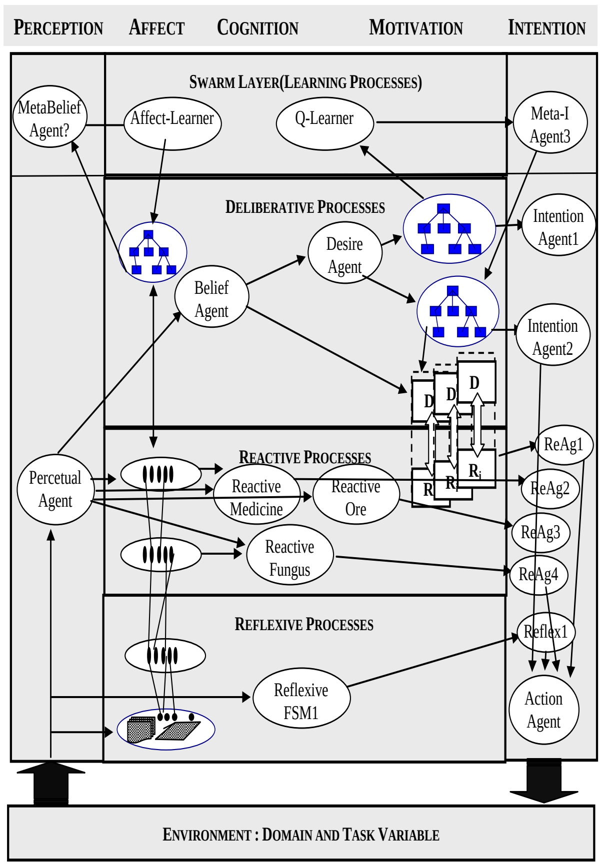

Figure 1: ECACE architecture using SMCA (Dr.Vijayakumar, 2008)

The ECACE architecture describes the behavior that is collective of and smart agents.

IV. THE MATHEMATICAL MODEL FOR SWARM INTELLIGENCE LAYER

A. Mathematical model to select the swarm agents using continuous quantum particle swarm optimization (CQPSO)

Into the original PSO 3,5, the particle that is ith includes a place Xi and a velocity V The position and velocity guidelines which can be updating the following

$$v_i^j \leftarrow v_i^j + C_1 r_1^j (pbest_i^j - x_i^j) + C_2 r_2^j (gbest_i^j - x_i^j)$$

.........(1)

Where pbesti and gbesti would be the particle that is ith local and global optimal solution, correspondingly. C1 and c2 are parameters to consider the significance of solution discovered by its swarm and very own. r/ and r/ are random figures

$$x_i^j \leftarrow x_i^j + v_i^j \text{.. (2)}$$

Quantum Computing Principles to agent Movement The information and product knowledge that is littlest in electronic computer systems is certainly one bit being either within the state "1" or "0" [6]. Much like bits being traditional, a little are in "1 "state or "O"state, but in addition, additionally in just about any superposition of both states. Hawaii of the bit can be explained as

$$\|\Psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \text{.. (3)}$$

Where lα| l2 and l β |l2 are the probability of a quantum bit to collapse to state "0" and "1", respectively Description of the CQPSO: CQPSO is a swarm search method. A quantum individual i at generation t contains a quantum bit string Si (t) with m quantum bits.

$$S_i(t) = S_i^1(t) S_i^2(t) \dots S_i^m(t) = \begin{bmatrix} \alpha_i^1 & \alpha_1^2 \dots & \alpha_i^m \\ \beta_i^1 & \beta_i^2 \dots & \beta_i^m \end{bmatrix}$$

.... (4)

The quantum rotation gate U can be defined as

$$U = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \text{................................ (5)}$$

$$\begin{bmatrix} \alpha_i^j(t+1) \\ \beta_i^j(t+1) \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_i^j(t) \\ \beta_i^j(t) \end{bmatrix} \text{.....................(6)}$$

$$Q = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \text{..(7)}$$

Where the constant q B is a rotation angle [7]. Quantum non-gate Q is adopted to make quantum bits mutated C. Position Update in CQPSO (7)

QPSO was introduced by Sun in 2004 [8]. According to the uncertainty principle, a particle, instead of having Position and velocity, has a wave function If/{r, t). And the governing equation of quantum mechanics is given by

$$jq\frac{\partial}{\partial t}\Psi(r,t) = \hat{H}(r)\Psi(r,t) \text{...........................(8)}$$

Where H is a time-independent Hamiltonian operator. Then distribution function is given as follows:

$$D_f(y) = \int_{-\infty}^{y} Q(y)dy = e^{-2|y|/L} \text{....................(9)}$$

Where,

$Q(y) = e^{-2|y|L}/L\,, L = 2\beta|J - x|$, and L is the distance between particles' current position and point J .The particle's local attractor point J is defined as:

$$J_d(t) = \alpha_1 P_{gd}(t) + \alpha_2 P_{id}(t) \text{......................(10)}$$

Where, $\alpha_1 = 2a/[3(a+b)]$ and $\alpha_2 = 2b/[3(a+b)]$ and aand b are two uniformly distributed random numbers. mbest is the best position, and can be defined as

$$mbest(t) = \frac{1}{R}\sum_{i=1}^{R} P_i(t) = \frac{1}{R}\sum_{i=1}^{R} P_{i1}(t), \dots\dots, \frac{1}{R}\sum_{i=1}^{R} P_{iD}(t) \text{................(11)}$$

Where pi is the best position of each particle, S is the size of the population and D is the number of dimensions.

B: Swarm Agents Strategies Using BOIDS to Have Self-Awareness In Their Internal States Such As Belief, Desire And Intentions (BDI).

The boids used a set of simple to determine how they would move. These rules developed by the Reynolds are the basis for the modern flocking simulation. There are three rules as shown below (Craig W Reynolds, 2007): SEPARATION: To maintain a reasonable amount of distance each bird has to attempt itself and nearby birds to prevent overcrowding. ALIGNMENT: Each bird tries to change their positions so that they correspond with the alignment of other birds nearby. COHESION: Each bird will attempt to move towards the average position of other nearby birds.

Algorithm 1: Boids algorithm

The boid is the bird representation in the simulation model. Each boid should have three attributes: location (current position of the boid x and y coordinates), course (angle of the current course of the boid), velocity (speed at which the boid travels)

```
Input: A boid
goal= (0,0);
neighbours = getNeighbours(boid);
        for each nBoid in neighbours do
        goal = goal + positionOf(nBoids);
        end
goal = goal/ neighbours.size();
steerTowards(goal, boid); (Craig W Reynolds, 2007)
```

STEP2: Swarm agents have self-awareness in their internal states such as belief, desire and intentions (BDI).This rule makes other boids to follow each other's course and speed.
getNeighbours(Boid) method is used to get the neighbors of the given boid. The neighbourhood decides for a next move, what other boids a boid should take into account. (Carig W Reynolds, Boids, Background and Update, 2001)
$\tau ij\ (t)=\rho\tau ij\ (t-1)+\Delta\tau ij\ \Delta\tau ij=\sum k=1\ m\ \Delta\tau k\ ij\ \Delta\tau k\ ij=\{QL\ k$ if ant k uses arc (i j) in its tour0otherwise (2)

Algorithm 2: Cohesion rule

Cohesion is the rule that keeps the boids together. The algorithm finds the average position of the neighbor boids and tries to move the boids towards it. All the boids are initialized at a starting position and initialization is done at random locations. All the boids will fly towards the middle of the screen when simulation starts. One frame of animation is drawn with all boids being in their current positions. Moving all boids to new position involves simple vector operations on boids positions.

```
Input: A boid
 goal= (0,0);
  neighbours = getNeighbours(boid);
   for each nBoid in neighbours do
           goal = goal + positionOf(boids) - positionOf(nBoids);
    end
           goal = goal/ neighbours.size();
           steerTowards(goal, boid); (Craig W Reynolds, 2007)
```

Algorithm 3: Separation rule

This rule attempts the boid to move away from the collision. The distance at which the boids avoid each other should be less than the distance at which the boids attract each other.

```
Input: A boid
      dCourse = 0;
      dVelocity =0;
      neighbours = getNeighbours(boid);
      for each nBoid in neighbours do
          dCourse  =dCourse + getCourse(nBoid)  - getCourse(boid);
          dVelocity = dVelocity + getVelocity(nBoid)  - getVelocity(boid);
      end
      dCourse  =dCourse / neighbours.size();
      dVelocity = dVelocity / neighbours.size();
      boid.addCourse(dCourse);
      boid.addVelocity(dVelocity); (Craig W Reynolds, 2007)
```

Algorithm 4: Alignment rule

Particle swarm optimization algorithm consists of "n" particles. This survey has the three principles, based on the optimist positions the particles change its condition. The principles are:

1. Swarms optimist position, it changes the condition
2. Based on the swarm's most optimist position, it changes the condition
3. To maintain its inertia

Initialization of values: Initialize the A_{ij} and n_{ij} values.

a. Construction of BOID

1. For each BOID k in state i do:
2. loop
1. Choose the state j to move to (with prob.)
2. Add the chosen move to $tabu_k$
3. Until the BIRD k has completed its solution

b. Update

c. For each ant move (i j) do:

1. Compute ΔT (i j)
2. Update the trial matrix

d. exit

e. If not exited of test, Goto the step 2

C: Algorithm to Swarm Layer in ECACE Architecture

STEP1: Select the Swarm agents with Swarm agents strategies (BDI set)
STEP2: Swarm agents have self-awareness in their internal states such as belief, desire and intentions (BDI).
STEP3: The Swarm agents dynamically change their attention switching in swarm agents.
STEP4: The deliberative agents converted to swarm agents adopting the learning method to memorize the experience
(1)Metabolism > Low,
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)
The agent desire to move towards to fungus to avoid the hunger condition or their death (Physiological oriented) uses the Reactive Fungus, Finds 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)
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.
STEP5: Switches to belief desire intention agents for agent's performance
STEP6: The deliberative agents broken down the reflexive and the reactive behaviors
STEP7: Reach the goal
STEP 8: If energy level is below threshold and no-food parameters in the perceptual range then move to explore food
STEP 9: If energy level is 0 the agent dies

VI. DESIGN AND EXPERIMENTAL SETUP:

A: ECACE Architecture work flow

First the agents which are swarming created. Then the intelligence is defined for each agent that are swarming. The parameters are defined for the agents after the creation of swarm agents. Then agents will go towards the parameters to gather them.

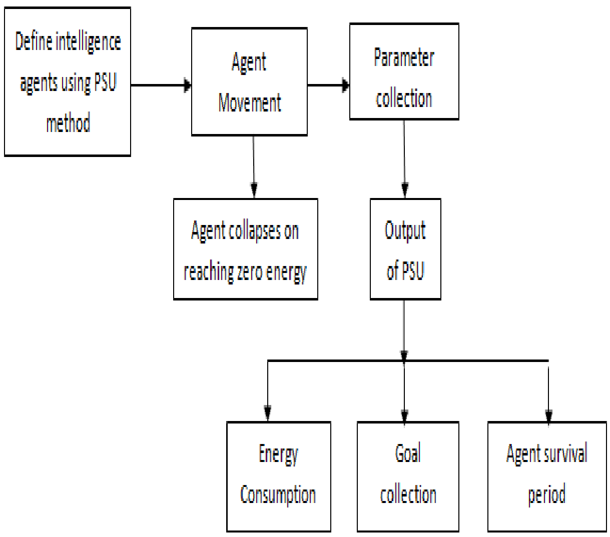

Figure 2: schematic diagram of ECACE Architecture experiment

Production of swarm agents is determined in line with the power usage, goal gathered and the success regarding the representation. In the agent's energy reaching to zero the agent shall die.

B: 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.

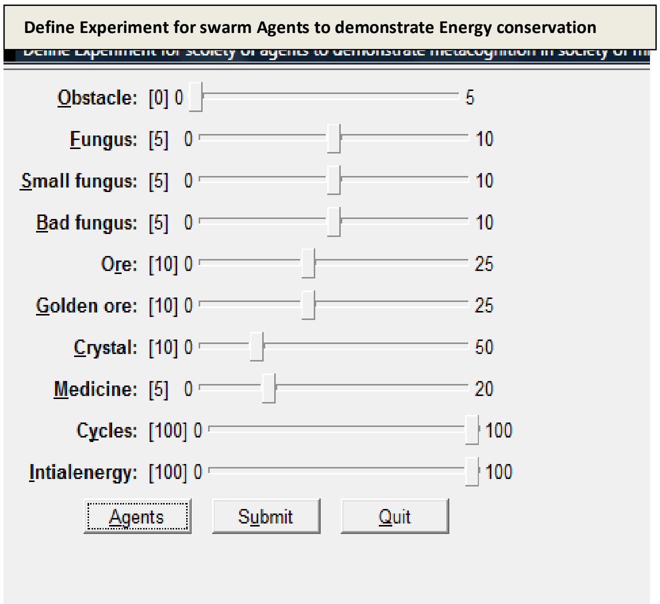

Figure 3 Parameters Selection Menu

The same analytical parameters were recorded in each study: energy left after their maximum cycles, ore collected, fungus consumption, and life expectancy of agents. Figure 3 and 4 gives brief explanations of experimental setup parameters used, including their types, values, and effects on the experiment.

Table 1.1 gives the details of actors present in the fungus world environment, including their type (numeric or atom), their assigned range of values (0 to n), and their default effects on the environment. For example, numeric value for "Number of Agents" is (0 to 50: 20). The range is 0 to 50, and default value is 20. All the parameters are similarly defined.

Table 1.1: Parameter for fungus world environment.

Parameter	Type	Value	Default Effect
Number of Agents	Numeric	0 to 50 : 20	Amount of Agents in testbed
Agent Type	Categorical: atom	type1 etc	Defines type of agent in environment
Obstacles	Categorical: atom	None, Static, random	Obstacles present or not
Number of Ore	Numeric	0 to 150: 20	Amount of Ore in Testbed
Number of Golden Ore	Numeric	0 to 150: 10	Amount of Golden Ore in Testbed
Number of Crystal	Numeric	0 to 150: 10	Amount of Crystal in Testbed
Number of Fungus	Numeric	0 to 150 : 20	Amount of Fungus in Testbed
Number of Small Fungus	Numeric	0 to 150 : 20	Amount of Small Fungus in Testbed
Number of Bad Fungus	Numeric	0 to 150 : 20	Amount of Bad Fungus in Testbed

C: Swarm Agent's to demonstrate Energy conservation Setup in the Experiment.

The Swarm Agent's approach to Energy conservation of artificial economics in a cognitive architecture is divided into four tiers: reflexive, reactive, deliberative and swarm level. Agents are distributed across different layers of architecture, to cover all processing and functioning associated with the adopted Swarm Intelligence. The following cognition: reflexive (six behaviours), reactive (eight behaviours), and Swarm Intelligence: deliberative (fifteen behaviours), learning (learning all given behaviours) and swarm agents (complex) are set up in the experiment.

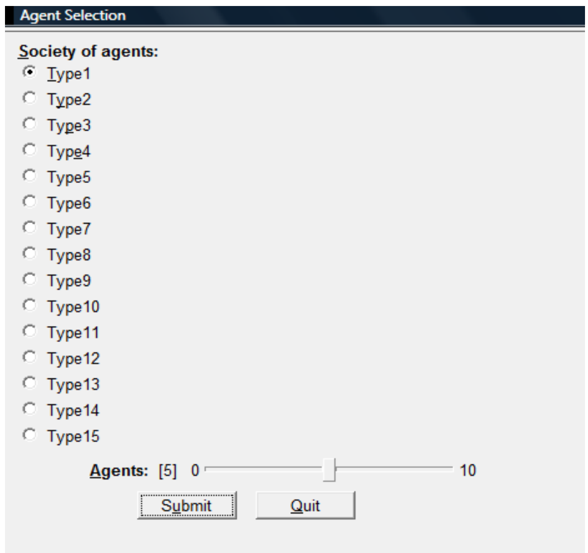

Figure 4: Swarm Agents for Energy conservation Selection Menu

D: TESTBED SETUP

The ambient testbed is implemented using SWI-Prolog 6.6.4.The Ambient testbed experiments include cognitive and psychological aspects on the architecture. The testbed is created to have dynamic parameters as shown in the figure 5. There are four buttons created. Definition button is used to select all the parameters and agents, configure the agent's initial energy and number of cycles to perform.Exp button is used to start the experiment where an agent starts the assigned task in the environment. Movement is a continuous process. Cycle button is used to see agents every move only on click. Each time the cycle button has to be clicked for agent to move. Quit button is used to exit from the graphical user interface (GUI).

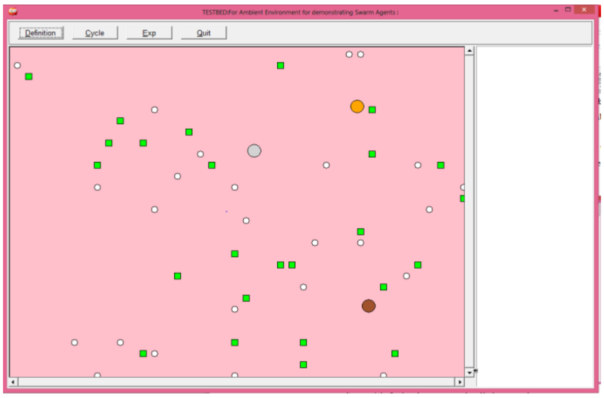

Figure 5: ECACE Simulation Test Bed

The experiment outcomes show the performance of these agents which is swarming ambient environment. The results will show that communication alone is not sufficient for individual performance in a mixed group, but perhaps the behavior of a person plays the role motivation. The outcomes of these experiments provide the cornerstone solution or a solution that is partially the problems stated in this paper ECACE architecture is made to always check exactly how individual agents will act in friends, how agents' behavior will have an affect the team performance. Agent behavior is analyzed utilizing various metrics like competition, life expectancy together with a connection that is social respect for the environment and its parameter. The simulation shows the interaction that is complex different variety of agents, agents' behavior with respect to make use of of power and time for you to make decisions. The ECACE email address details are simulated for:

1. Performance of swarm agents with respects to quantity of diamonds collected.

2. The life expectancy of swarm agents with regards to number of rounds lived.

3. The energy distribution of swarm agents: at each and every cycle how agent's power is getting reduced as well as for use of meals how energy of on agents is getting increased.

4. Comparison of performance of agents and thus concluding the extremely motivated agent much less representative that is inspired.

The cycle is fixed for the agents. Here to test the number of rounds considered is 500 and energy that is initial each representative is 100 units. Wide range of meals considered is 25 pieces and diamonds 25 pieces. Each representative is experimented for the period that is same exact same initial energy, same resources like metals and diamonds. The input value of every parameter defines the configuration file. The output file provides the details of each agent. Based on the information being statistically for every agent, the experiments are carried out. The following statistics had been gathered: life expectancy, diamonds gathered to compare a result of each agent. The agent's performance that is totally calculated predicated on range diamonds gathered and centered on endurance. The experiments conducted many amount of times, by taking into consideration the input that is same. The results which can be final are considered by firmly taking top data out of the test carried out. The data is going to be plotted regarding the sheet that excels. Then graphs are created.

VI RESULTS DISCUSSION

VI A: Performance of Swarm-Ore and crystal versus BDI Ore versus Reactive Ore Agent

The results of this experiment (Graph 1.1) show that Swarm-ore maintain a higher level of life expectancy than BDI-ore agents and reactive agents. Swarm agents manage the energy level of 85%, BDI agents manage 80%and reactive agents manage 0%. The reactive agent dies in 18 cycles out of the 25 maximum cycles assigned. The swarm-ore agent's collects 85% of ore as compared to BDI-ore (BDI with goal towards ore) agents collect 83% of ore (resource) and 42% of ore collected by the reactive agent.

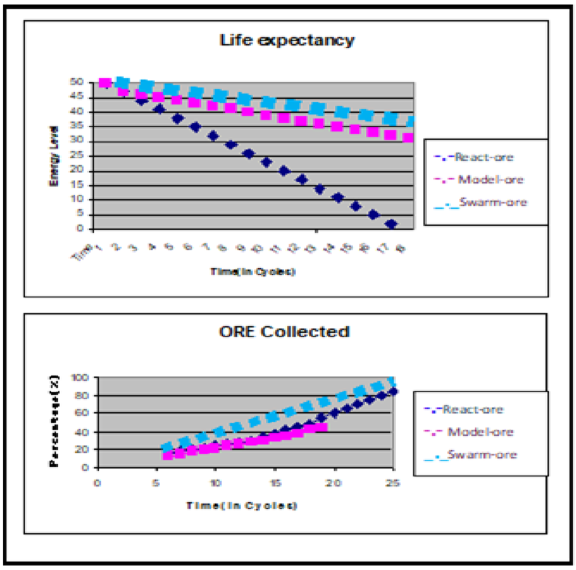

Figure 1.1: Reactive verse BDI verse swarm Agents ore and crystal collection

Similarly swarm agents manage the energy level of 89%, BDI-crystal agents manage 84% and reactive agents manage 0%. The reactive agent dies in 18 cycles out of the 25 maximum cycles assigned. The swarm-crystal agent's collects 89% of crystal as compared to

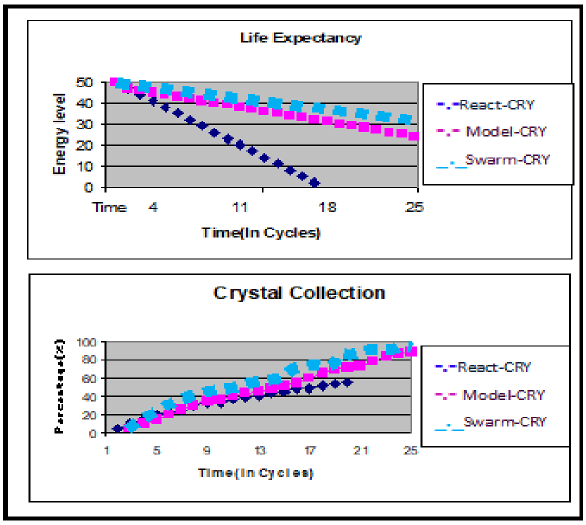

Figure 1.2: Reactive verse BDI verse swarm Agents ore and crystal collection

BDI-crystal (BDI with goal towards ore) agents collect 84% of ore (resource) and 55% of ore collected by the reactive agent.

VI B: Study Two (Experimentation on BDI models)

As shown in graph 1.4, Swarm agent manages to live up to 480 life cycles as compared to BDI agent manages to live up to 438 life cycles. The swarm agent shows a complete control mechanism in managing an energy level of 50 (assigned threshold or decision variable) compared to BDI agent (CAMAL)as 40 energy level, 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.

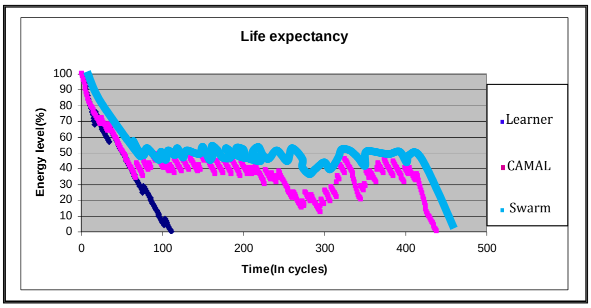

Figure 1.4: The Life Expectancy of Cognition versus BDI Agents

VI C: BDI and Reflexive-learner

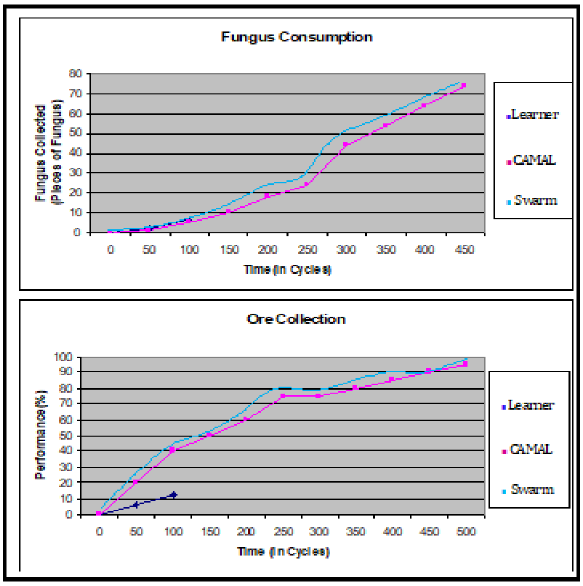

Figure 1.3: Fungus and Ore Collection

The resource (ore, golden ore and crystal) collection of the simple cognition, BDI agents and Swarm agents is as follows: cognition agents managed to collect 12 pieces of ore, BDI agents managed to collect 95 pieces of ore and Swarm agents manages to collect 98 pieces of ore. figure 1.4 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.

Graph 1.3 shows the fungus consumption rate of cognition, BDI agents and Swarm agent in their lifetimes. The cognition(reflexive-learner) agent managed to collect 6 pieces of fungus , BDI agent are managed to collect 74 pieces of fungus and the swarm agents managed to collect 84 pieces of fungus. As graph 1.3 illustrates, in the initial stages, the (reflexive-learner) cognition agent and the BDI agent was found to collect more fungus than the Swarm agent. The Swarm agent was not concerned about fungus in this stage. Agents in the initial stage born energy with medium metabolism. The Swarm agent collects the medicine to decrease metabolism. Agents, once they achieved low metabolism by collecting required medicine, then it does not concerned about medicine.

VII COMPARSION OF REFLEXIVE, REACTIVE AND DELIBERATIVE (CQPSO) OF AGENTS:

The outcomes state that initially, the agents had the total amount that is the exact same of 100 devices. The deliberative representative has done for 366 rounds away from 500 rounds so when gathered 21 diamonds away from 25 diamonds shortly after operating the test. The reactive representative has done for 66 rounds and built-up 9 diamonds. The representative that is reflexive performed for 111 rounds and collected one diamond. Because the representative that is deliberative collected a higher portion of diamonds and done for much longer cycle than reactive and reflexive, the deliberative representative is extremely determined agent than reactive and reflexive. The reactive representative has done for 66 rounds and has now gathered 9 diamonds than reflexive, reactive representative is inspired than reflexive. When compared to all three kinds of agents, Deliberative agents are highly inspired, Reactive representative is moderately motivated and Reflexive representative is less/0 inspired. This outcome suggests that the representative that is deliberately explained about their modification of aims, since their state and attain their objectives. This concludes that deliberative representative has complex behavior that is smart. Deliberative agents have controls that are completely handled meals and objective, make an effort to balance motivations. Deliberative agents collect more objectives and handle greater life expediency than many other agents. This outcome shows agent that is deliberative, more control and self- expression catalyst. Therefore, saying that deliberative representative this very determined than many other agents and increases the performance as shown in graph 1.9

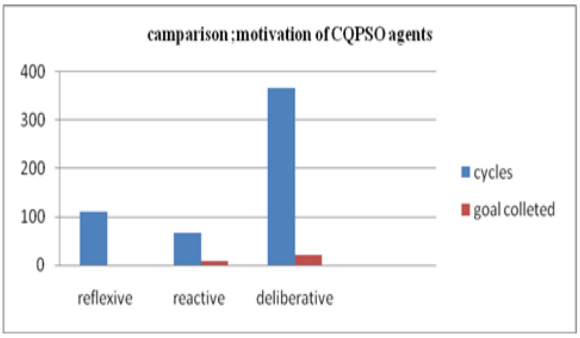

Figure 1.9 Comparison of reflexive, reactive and deliberative (CQPSO) Agent

Agents, Deliberative agents are highly inspired, Reactive representative is moderately motivated and Reflexive representative is less/0 inspired. This outcome suggests that the representative that is deliberately explained about their modification of aims, since their state and attain their objectives. This concludes that deliberative representative has complex behavior that is smart. Deliberative agents have controls that are completely handled meals and objective, make an effort to balance motivations. Deliberative agents collect more objectives and handle greater life expediency than many other agents. This outcome shows agent that is deliberative, more control and self- expression catalyst. Therefore, saying that deliberative representative this very determined than many other agents and increases the performance.

CONCLUSION

Energy conservation through artificial economic in cognitive architecture challenges are achieve through soft computing techniques named swarm intelligence. The swarm intelligence agents adopt quantum partial optimization method with BOIDS algorithm for agent interaction, cooperation and coordination in ECACE architecture. The ECACE architecture is derived through SMCA architecture as an enhancement of methods used to demonstrate cognitive process. Design and implementation of ECACE using SWI-Prolog 6.6.4 to setup experiment, parameter, and workflow of experiment. Performance evolution of ore and crystal collection, life expectancy and fungus collection by reflexive, BDI and swarm agent were discussed. The comparison of reflexive reactive and CQPSO agents is discussed. Further ECACE can be develop through conscious and commonsense to improve ore and crystal collection, life expectancy and fungus collection on energy conservation as artificial economic in cognitive architecture observation, which helps in proper utilization of cognitive architecture.

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