# EcoSimNet: A Multi-Agent System for Ecological Simulation and Optimization

António Pereira[1], Luís Paulo Reis[1], and Pedro Duarte[2]

[1] NIAD&R-LIACC / DEI-FEUP – Faculty of Engineering, University of Porto
Rua Dr. Roberto Frias s/n, 4200-465 Porto, Portugal
Tel.: +351 22 508 14 00
[2] CIAGEG-UFP – University Fernando Pessoa
Praça 9 de Abril, 349, 4249-004 Porto, Portugal
Tel.: +351 22 507 13 00
{amcp,lpreis}@fe.up.pt, pduarte@ufp.edu.pt

**Abstract.** Ecological models may be very complex due to the large number of physical, chemical, biological processes and variables and their interactions, leading to long simulation times. These models may be used to analyse different management scenarios providing support to decision-makers. Thus, the simultaneous simulation of different scenarios can make the process of analysis and decision quicker, provided that there are mechanisms to accelerate the generation of new scenarios and optimization of the choices between the results presented. This paper presents a new simulation platform – EcoSimNet – specially designed for environmental simulations, which allows the inclusion of intelligent agents and the introduction of parallel simulators to speed up and optimize the decision-making processes. Experiments were performed using EcoSimNet computational platform with an agent controlling several simulators and implementing a parallel version of the simulated annealing algorithm for optimizing aquaculture production. These experiments showed the capabilities of the framework, enabling a fast optimization process and making this work a step forward towards an agent based decision support system to optimize complex environmental problems.

**Keywords:** Ecological Simulations, Agent-Based Applications, Multi-Agent Simulation and Modelling, Optimization, Parallel Simulated Annealing.

## 1 Introduction

The simulation of aquatic ecosystems is an emerging area of research allowing an interdisciplinary approach necessary to understand the complexity of these environments. The need of environmental impact studies when planning interventions in estuaries, lagoons or other coastal areas, has increased the interest in this type of simulations, especially when these ecosystems are used for aquaculture and other economic activities (recreation or tourism) that contribute to the local economy and the dynamics of employment in the region.

In most cases, ecological models are used to test and/or validate hypothetical scenarios of operation or configuration of specific regions or environments. Often, the

L. Seabra Lopes et al. (Eds.): EPIA 2009, LNAI 5816, pp. 473–484, 2009.

goal is optimizing the management of a natural resource capable of producing goods and services of interest to humans. As models try to reflect reality, they tend to incorporate more processes, increasing their complexity and making simulations, necessarily, slower.

The case of coastal environments is paradigmatic because these ecosystems always played an important role in the life of human beings, are very complex from a biological, a chemical and a physical point of view and are very sensitive to environmental and management decisions. They allow an enormous amount of possible activities (such as fishing, aquaculture, harbour activities, tourism, etc.), and guarantee several basic services to humanity, but they are also the final destination of many pollutants generated by agriculture and other human activities [1]. In the last century, human population migrated intensively from inland to coastal boundaries and, nowadays, the World Bank estimates that 50% of the world's population lives within 60km from the sea [2]. These numbers are more relevant in Portugal where almost 89% of the population lives within 50km from the sea in about 39% of the territory [3]. Usually, there are many conflicting human interests on these ecosystems and, unfortunately, there are examples of some recent environmental disasters in coastal areas that could have been minimized, or even avoided, if proper management options had been followed at appropriate times with the commitment of the authorities and the stakeholders.

When coastal ecosystems are exploited for shellfish aquaculture one of the issues that always arises is how far the holders can increase the production in their assets without exceeding ecosystem carrying capacity [4]. Usually, the balance is maintained by legislation, which limits the areas of exploitation and thus the number of licenses in each area. Stakeholder's experience, usually acquired by trial and error, successes and failures, leads them to have an empirical perception of what is the optimal exploitation density of each species per unit area, without much consideration for potential environmental impacts, except those that may hinder their production and profit.

The results of the development of an intelligent bivalve farmer agent to find out the best combination of bivalve seeding areas, within an allowed area of exploitation, without exceeding the carrying capacity of the system, were reported by Cruz et al. [5] and showed promising guidelines. One of the constraints pointed out in the conclusions of that study was the time consumed by the large number of simulations necessary to find the best combinations mentioned above. Therefore, the usage of a network of simulators to speed up the decision process was the natural follow up of that study.

This paper presents an outline of a multi-agent simulation system of ecological models capable of integrating the human interests, accelerating the generation of results taking advantage from parallel simulation of various scenarios of operation and their analysis in real time.

The architecture presented (EcoSimNet) exploits the concept of computing clusters and parallel computation, creating simulation islands where an agent monitors a set of simulators, simultaneously simulating independent scenarios. One of the agents took the lead role, taking the initiative to encourage other agents to obtain the desired results as quickly as possible.

Coordination is ensured by the existence of points of synchronization during the course of the experiments, allowing the exchange of results between the various agents and the adoption of the best result as a starting point for a new round of independent

simulations until the next point of synchronization. The stop order is given by the coordinator agent when a maximum number of rounds of simulation or a time limit are exceeded or when a criterion of optimization is reached.

This approach was tested with farmer agents trying to get the best combination of areas for cultivation of shellfish in a wider area, maximizing the production without exceeding the permitted area of cultivation.

The remaining of this paper is structured as follows: (i) The next section describes the problem in analysis, followed by the presentation of the architecture for ecological simulations (EcoSimNet) and the solution adopted to do this study; (ii) Section 3 presents the experimental approach pursued and the results obtained; (iii) The paper ends with an analysis of the results, the conclusions and a description of future work to be done.

## 2 Problem in Analysis

The study and experiences were done with one validated ecosystem model for Sungo Bay, People's Republic of China [4], already implemented in the EcoDynamo simulator [6]. The lagoon is modelled with a two-dimensional vertically integrated, coupled hydrodynamic-biogeochemical model, based on a finite difference bathymetric staggered grid with 1120 cells (32 columns x 35 lines) and a spatial resolution of 500m – Figure 1. The model has a land and an ocean boundary and the time step used was 30 seconds.

A previous bivalve farmer agent was developed by Cruz et al. [5] with the objective of maximize bivalve production, finding the best combinations of locations to seed and harvest bivalve species within a delimited area of exploitation, using the previous model. In that work, the farmer agent had to choose the best five cells (corresponding each one to a 500m x 500m area) within an area of 88 admissible cells to explore oysters – corresponding to more than 39 millions of possible combinations. One realistic simulation for the complete bivalve culture cycle should cover approximately 1.5 years, equivalent to more than 1,576,800 simulation steps; in a computer with an Intel® Core™ 2 CPU 6300 @ 1.86GHz and 2.00GB of RAM, the time to run the complete simulation is 10 hours. The long time and the heavy processor power required for one complete simulation, limited the previous experiments to use only 1000 simulation steps in each cycle, extrapolating the results for the complete growth cycle – the computer used ran 1000 steps in about 22 seconds and one experimental round (341 simulations) was completed in approximately two hours.

The usage of a computer network allows decreasing the time needed to generate results and performing longer simulations to obtain more realistic results. The approach idealized was:

- Confirm the results achieved by the experiments made by Cruz et al. [5] using one and four simulators, and more powerful computers;
- Extend the number of simulation steps and compare the results obtained in terms of temporal savings and quality of the final solutions achieved – e.g. confirm if the extrapolation assumed by previous experiments remains valid;
- Repeat the experiments with more cells to further explore, and analyse the results.

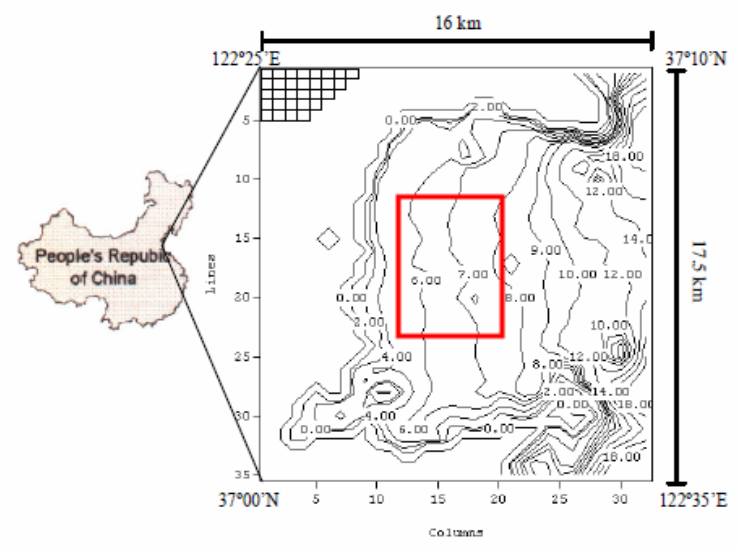


**Fig. 1.** Location of Sungo Bay, including model domain and bathymetry [4] with delimited area of exploitation marked

The experiments used the base algorithms implemented by Cruz et al. [5], controlled by a simulated annealing algorithm [7] modified to support parallelisation and with more flexibility to control the number of simulations in each experimental round.

The new experiments were performed in computers with processors Intel® Core™ 2 Quad CPU Q9300 @ 2.50GHz, with 8.00 GB of RAM. In these computers, the complete bivalve culture cycle is simulated in about six hours and three quarters.

## 3 Implementation

### 3.1 System Architecture

The system architecture was designed to perform complex simulations of aquatic ecosystems, to integrate easily new applications in the system, like plug-and-play hardware in computers, and enabling communications between different applications.

The Ecological Simulation Network (EcoSimNet) follows the general architectures for intelligent agents [8] and multi-agent systems [9] where all the applications communicate via TCP/IP with messages formatted according to the specification of the ECOLANG language [10]. The framework can support several EcoDynamo simulators [6], to allow parallel or concurrent simulations, and different agents representing the human interests over the simulated ecosystem (Figure 2).

The ECOLANG language specification forces messages to be simple, expansible, independent from any computational platform or operating system, and readable by the humans, allowing easy traceability.

This architecture permits the exploitation of machine learning algorithms with the inclusion of agents in the network [11][12][13].

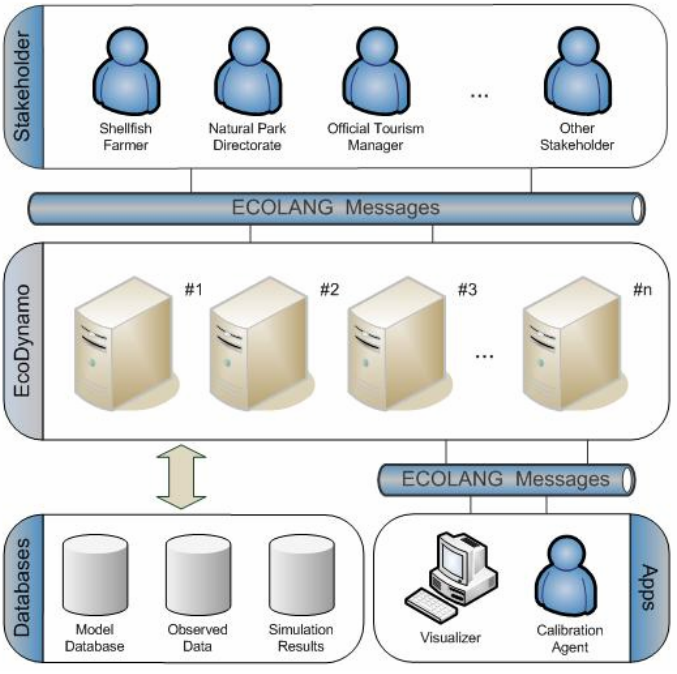


**Fig. 2.** EcoSimNet architecture

The simulator has a simple graphical user interface where users can interact with most of the ecological model properties: select the model to use, the processes to simulate, the period of time simulated, the variables for output, and the output formats. Definitions such as system morphology, geometric representation, dimensions and number of model grid cells, and initial values of variables and parameters are fixed when the model is created. One script file is provided to each simulator for the start up, indicating its identification in the network and the model to run.

Only the simulators have direct access to the models' databases. The agents acquire information about the model through the ECOLANG messages exchanged with the simulators. This approach ensures true independence between the simulator and the agents.

### 3.2 Farmer Agent Implemented Algorithms

The original agent developed a system of customizable tactics [5] to implement the sense of intelligence which may, in some sense, simulate the reasoning of the human farmer. The base algorithm developed for this agent was a simple hill-climbing optimization algorithm, based on simulated annealing with Monte Carlo probability [7] [14] – the agent seeks iteratively a new solution and saves the one with higher quality as the best. Several configurable optimizations can be activated to influence the selection logic of the new solutions [5]. The generation of the new solutions was facilitated and improved by the inclusion of known algorithms, like tabu search [15], genetic

algorithms [16] and reinforcement learning [17], that can be triggered at any stage of the optimization process. The novelty of this approach is centred in the system of customizable tactics that enables the activation (automatic or configurable) of any one of the implemented algorithms during the experiment, and the possibility of having, simultaneously, the various algorithms involved in choosing the best solution.

The original agent communicated only with one simulator. To manipulate the information of several simulators, it was necessary to create a different agent, extending the former one and making it able to communicate simultaneously with several simulators, with a decision-making process that should integrate, in real time, the results from the various simulators as they were generated. The choice made was the implementation of a kind of parallel simulated annealing algorithm [18].

### 3.3 Parallel Simulated Annealing Algorithm

Simulated annealing (SA) is considered a good tool for complex nonlinear optimization problems [7] but one of its major drawbacks is its slow convergence. One way to improve its efficiency it's parallelisation (the development of a parallel version of the algorithm).

Many implementations of this algorithm exist but they are, inherently, problem dependent. Ram et al. [18] proposed two distributed algorithms for parallel simulated annealing – the clustering algorithm (CA) and the genetic clustering algorithm (GCA). Both explore the evidence that a good initial solution results in a faster convergence.

The CA technique starts n nodes of the network to run SA algorithm using different n initial solutions. After a fixed number of iterations, the nodes exchange their partial results to get the best one. All the nodes accept that solution and restart new SA round based on that solution. This process is repeated a predefined number of times. There must be a coordinator node to choose the best solution and to determine the time to stop the rounds and finishing the process.

The process implemented in the experimental agent can be viewed as integrating the CA technique described: all the agents can have the function of generating solutions (worker node) and one agent has to perform the functions of coordination (coordinator node); the generation of the new solutions is driven by the tactics chosen in each agent taking advantage of their autonomy. The flexibility of the framework allows each agent to control only a part of the network simulators. It can be seen as a collection of simulation islands or clusters. The basic algorithm for the coordinator node is presented in Figure 3.

The number of synchronization points determines the number of times the worker nodes exchange partial results with the coordinator node, and this is important to speed up the optimization process. With this process, the number of iterations is distributed uniformly by the agents (worker nodes) but not necessarily by the simulators: while the coordinator node waits for agents synchronization to exchange the partial results (Figure 3, line 3.2), each worker node controls the number of iterations with all simulators monitored by it, which means that if there is one very fast simulator and another one very slow, it is expectable that the faster one runs more simulations than the slower.

As simulators run in different computers, each one finalizes its simulation independently and the agent compares the result against all results accumulated so far; there is no need to synchronize the simulators.

**Parallel SA – coordinator node**

**Parameters:**
initialTemperature – initial temperature
temperatureModifier – decrease temperature factor
N – maximum number of iterations
W – number of worker agents
P – number of synchronization points

**Global Variables:**
counterMS – number of missing synchronizations
bestResult – best production value returned by the agents
bestSolution – solution that generates the best result

**Algorithm:**

```
1:   for each agent w
         initSA (initialTemperature, temperatureModifier,
                 N / (W * P), 0, <empty>)
2:   bestResult = 0;
3:   bestSolution = <empty>;
4:   counterMS = P;
3:   while (counterMS > 0)
     {
3.1:     for each agent w
             runSA ( );
3.2:     for each agent w
             results[w] = collectResults (w);
3.3:     choose (results[ ], bestResult, bestSolution);
3.4:     for each agent w
             prepareSA (bestResult, bestSolution);
3.5:     decrement (counterMS);
     }
4:   publish (bestResult, bestSolution);
```

**Fig. 3.** Parallel Simulated Annealing Algorithm – coordinator node

Taking into account the time needed for each simulation and the time required to choose the best solution, often there are benefits if one agent accumulates the coordinator and worker tasks.

## 4 Experiments and Results

The experiments were carried out with only one agent that implements the algorithms previously used by Cruz et al. [5] with the inclusion of the presented parallel SA algorithm and a new user-friendly interface to configure and parameterize the implemented algorithms and tactics. The agent accumulates the coordinator and worker roles.

Two training experiments were conducted to validate the framework and see if the results reported by Cruz et al. were reproducible. The first training experiment runs with one simulator and the second with four simulators; in each experimental round the agent controlled the same number of simulations with 1000 steps (341 iterations, each one simulating eight hours and 20 minutes of real time). The oysters were seeded with a fixed density of 55.15 units per square meter, and each oyster had 0.0005g of shell weight and 0.00002g of meat weight.

In terms of results quality and time savings, it seems that the new approach is working as expected – the results maintain the tendency observed previously by Cruz et al. [5] occupying the northeast side of the region - and the time savings are directly related to the number of simulators in the network – the first training experiment rounds spent about one hour and 27 minutes and the second ones about 23 minutes, a save of 75%, as expected. In these experiments, the difference between the maximum and the minimum production value indicators was irrelevant due to the low simulated time.

Due to the memorization by the agent of all the solutions tested previously, the log of the last experiment revealed that 1598 solutions were tested but only 341 new combinations were explored and simulated, those that the outcome of the simulation was unknown. The randomness of the initial solution guarantees the necessary diversity required for this type of optimization algorithms.

The production value indicator is calculated based on the quantity of shellfish harvested, in tonnes, and its economical weight.

**First Experiment.** To take advantage of the new computing platform, in the first experiment the number of simulation steps was increased to cover one month of real time oysters growth (from 1000 to 86 400 steps) to verify if the extrapolation assumed in the training experiments remains valid. Each experimental set took about 1 day and 6 hours to finish. The difference between the maximum and the minimum production value indicators was now 15.2% of the minimum and partial results are presented in Table 1 and Figure 4.

**Table 1.** Five best results and worse result of the first experimental set

| Rank | Production Value (Indicator) | Seeded Cells |
|---|---|---|
| 1 | 19 922.9 | 31, 45, 47, 70, 78 |
| 2 | 19 908.8 | 37, 38 45, 69, 78 |
| 3 | 19 879.6 | 38, 53, 54, 61, 87 |
| 4 | 19 876.9 | 30, 46, 53, 63, 87 |
| 5 | 19 813.0 | 22, 27, 30, 52, 60 |
| worse | 17 298.4 | 2, 7, 16, 41, 74 |

The results of this experiment show a spread of best solutions that smoothly reveals a trend to seed in the east side of the delimited region, near the open sea. It is important to note that the ecosystem in question is subjected to tides, which influence how organic substances and phytoplankton are transported along the bay. The availability of these two items – the main bivalve food sources – determines oyster growth and production.

It is no surprise that the trends revealed in the initial experiments were only partially confirmed, due to their very short simulation time. The simulated eight hours is insignificant when compared to water residence time in the bay – between one and 19 days [4]. Therefore, eight hours is not enough to simulate properly the mixing processes and the food variability affecting oyster growth. Furthermore, when oyster biomass increases, important feedbacks to available food become apparent where local depletion of food items may limit bivalve growth [19].

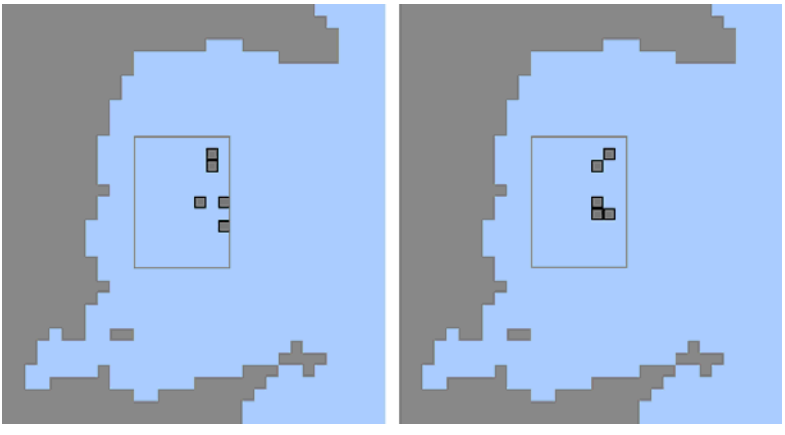

**Fig. 4.** Visualization of the best solutions (set #1)

**Second Experiment.** The second set of experiments extended the first one increasing the number of cells to seed to 30. Even without an obvious tendency in the area occupation, this experimental set was realized to verify if the results were more reliable when the ratio between occupied area vs. exploitation area increases – from 5.7% in the previous experiments to 34.1% in this one (from five to 30 cells to seed within the same area of 88 cells to explore). With no surprise the time required for each experiment is equal to that of previous experience, since it is dependent on the number of simulation steps and not on the number of areas occupied by aquaculture. The results are presented in Table 2 and Figure 5.

**Table 2.** Five best results and worse result of the second experimental set

| Rank | Production Value (Indicator) | Seeded Cells |
|---|---|---|
| 1 | 57 756.5 | Different sets of 30 cells |
| 2 | 57 720.9 | |
| 3 | 57 659.5 | |
| 4 | 57 639.2 | |
| 5 | 57 538.1 | |
| worse | 55 026.6 | |

The solutions present different patterns but with a tendency to concentrate oysters in the north and east sides of the exploitation area. The patterns strengthen the tendency to fill the areas near the open sea, where sea water exchanges are more intense and food tends to be more abundant.

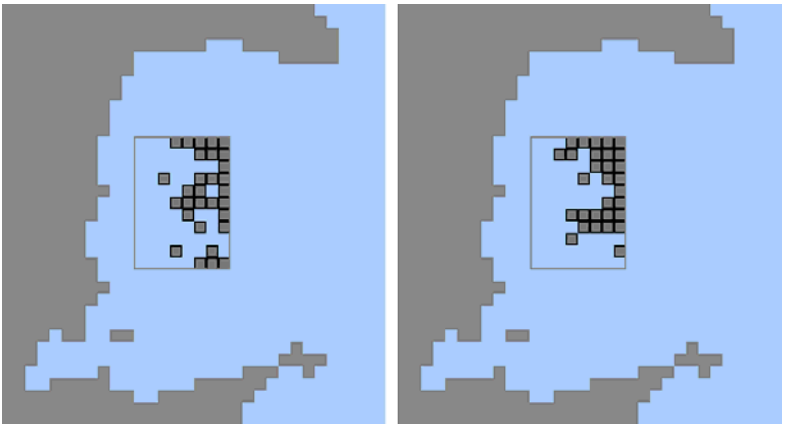

**Fig. 5.** Visualization of the best solutions (set #2)

Another interesting result is the coincidence in the occupied areas – the 2 best solutions share 18 cells out of 30 (60%) and in the five best solutions 12 cells remain selected (40%). The difference between the maximum and the minimum production value indicator decreases to 5.0% of the minimum.

The expected production value indicators (approximately six times larger than those of previous experience) were not confirmed; in fact it is a little bit less than three times more. The most likely explanation is local food depletion leading to slower bivalve growth as cultivated area increases. Experiments with this population density showed that the relationship between bivalve's production and cultivated area is linear if the number of cells to seed is less than 10; for greater values of seeded cells the production per cultivated grid cell decreases. More experiments should be performed with lower densities to find the value at which growth ceases to be linear.

## 5 Conclusions and Future Work

This paper presented a new framework for complex ecological simulations and optimization - EcoSimNet. This framework allows the coexistence of multiple simulators in the network, controlled by different agents, enabling the parallel simulation of different scenarios, increasing the number of simulations and the real time simulated, without compromising the quality of results and ensuring a more complete analysis of scenarios. As the number of parallel simulators on the network increases, the time needed to find a "near" optimal solution decreases proportionally.

The strategy followed in the implementation of the parallel simulated annealing algorithm, separating the roles of the coordinator and the worker nodes, allowed the

independence of each agent tactics for optimization; the experiments showed that the inclusion of the two roles in the same agent didn't compromise the agent's rationality.

In this kind of ecological models the main advantage of using parallel simulations is the computational performance achieved, because issues like conceptual distribution of different aspects of the reality simulated are very difficult to separate in different simulators – the mixing processes and the food variability affecting oyster growth, the feedbacks to available food and the local depletion of food items that limit bivalve growth must be integrated in each simulation step by all entities, and the synchronization effort required for synchronization between the simulators would make the system much slower.

This work is a step forward towards an agent based decision support system to optimize complex environmental problems. At the moment the architecture presented is exploiting the concept of simulation islands or clusters, each one composed by one agent controlling several simulators, simultaneously simulating independent scenarios. One of the agents took the lead role, taking the initiative to encourage other agents to obtain the desired results as quickly as possible.

More experiments need to be done, increasing the number of simulators and agents in the network, in order to have a clear idea of what reasonable limits should be imposed on the size of the EcoSimNet framework.

The next steps in this platform will incorporate automatic decision in the coordinator agent, to decide how many simulators and worker agents will be necessary to consider new scenarios, and to determine degrees of similarity with scenarios already exploited. Furthermore, multi-criteria optimization simulations will be tested, where agents will evaluate different scenarios according to environmental and economical objectives.

The results were encouraging, and the researchers plan to use this approach for testing variations of the optimization criteria: considering a fixed exploitation area and different bivalve densities, considering the joint exploitation of several species of bivalves in the same area, and considering the commercial market value of each bivalve species and optimizing the production ensuring the largest economic return on investment.

**Acknowledgements.** This work was started during the ABSES project – "Agent-Based Simulation of Ecological Systems" (FCT/POSC/EIA/57671/2004) and António Pereira was supported by the FCT scholarship SFRH/BD/1633/2004 during part of its execution.

## References

1. Duarte, P., Azevedo, B., Ribeiro, C., Pereira, A., Falcão, M., Serpa, D., Bandeira, R., Reia, J.: Management oriented mathematical modelling of Ria Formosa (South Portugal). Transitional Water Monographs 1(1), 13–51 (2007)
2. Watson, R.T., Zinyowera, M.C., Moss, R.H.: Climate Change 1995 - Impacts, adaptations and mitigation of climate change. In: I.-I.P.o.C Change (ed.) Scientific-Technical Analyses, vol. 1. Cambridge University Press, Cambridge (1996)
3. INE, Instituto Nacional de Estataistica. Statistical Yearbook of Portugal 2007. 1st edn., vol. 1. Instituto Nacional de Estatística, IP, Lisboa (2008)

4. Duarte, P., Meneses, R., Hawkins, A.J.S., Zhu, M., Fang, J., Grant, J.: Mathematical modelling to assess the carrying capacity for multi-species culture within coastal waters. Ecological Modelling 168(1-2), 109–143 (2003)
5. Cruz, F., Pereira, A., Valente, P., Duarte, P., Reis, L.P.: Intelligent Farmer Agent for Multi-agent Ecological Simulations Optimization. In: Proceedings of the 13th Portuguese Conference on Artificial Intelligence, Guimaraes, Portugal, pp. 593–604 (2007)
6. Pereira, A., Duarte, P., Norro, A.: Different modelling tools of aquatic ecosystems: A proposal for a unified approach. Ecological Informatics 1(4), 407–421 (2006)
7. Kirkpatrick, S., Gelatt, C.D., Vecchi, M.P.: Optimization by Simulated Annealing. Science 220(4598), 671–680 (1983)
8. Wooldridge, M.: Intelligent Agents. In: Weiss, G. (ed.) Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence, pp. 27–77. The MIT Press, Cambridge (1999)
9. Huhns, M.N., Stephens, L.M.: Multiagent Systems and Societies of Agents. In: Weiss, G. (ed.) Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence, pp. 79–120. The MIT Press, Cambridge (1999)
10. Pereira, A., Duarte, P., Reis, L.P.: ECOLANG - A communication language for simulations of complex ecological systems. In: Proceedings of the 19th European Conference on Modelling and Simulation ECMS 2005, Riga, Latvia, pp. 493–500 (2005)
11. Dzeroski, S.: Applications of symbolic machine learning to ecological modelling. Ecological Modelling 146(1-3), 263–273 (2001)
12. Russel, S.J., Norvig, P.: Artificial Intelligence: A Modern Approach, 2nd edn. Prentice Hall, New Jersey (2002)
13. Pereira, A., Duarte, P., Reis, L.P.: Agent-Based Simulation of Ecological Models. In: Proceedings of the 5th Workshop on Agent-Based Simulation, Lisbon, Portugal, pp. 135–140. SCS Publishing House (2004)
14. Mishra, N., Prakash, M., Tiwari, K., Shankar, R., Chan, F.T.S.: Hybrid tabu-simulated annealing based approach to solve multi-constraint product mix decision problem. Expert systems with applications 29(2), 446–454 (2005)
15. Glover, F.: Future paths for integer programming and links to artificial intelligence. Computers & Operations Research 13(5), 533–549 (1986)
16. Holland, J.H.: Adaptation in natural and artificial systems. The University of Michigan Press, Ann Arbor (1975)
17. Sutton, R.S., Barto, A.G.: Reinforcement Learning: An Introduction, vol. 1. MIT Press, Cambridge (1998)
18. Ram, D.J., Sreenivas, T.H., Subramaniam, K.G.: Parallel Simulated Annealing Algorithms. Journal of Parallel and Distributed Computing 37(2), 207–212 (1996)
19. Duarte, P., Hawkins, A.J.S., Pereira, A.: How does estimation of environmental carrying capacity for bivalve culture depend upon spatial and temporal scales. In: Dame, R.F., Olenin, S. (eds.) Comparative Roles of Suspension-Feeders in Ecosystems, Nida, Lithuania, pp. 121–135 (2005)