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Multi-agent system to monitor oceanic environments

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Abstract. The exchange of CO_2 between the atmosphere and the ocean surface is a problem that has become increasingly important due to its impact on climatic behavior. Given the large quantity of sources of information available for studying the CO_2 problem, it is necessary to provide innovative solutions that facilitate the automation of certain tasks and incorporate decision support systems to obtain a better understanding of this phenomenon. This paper presents a multiagent architecture aimed at providing solutions for monitoring the interaction between the atmosphere and the ocean. The ocean surface and the atmosphere exchange carbon dioxide. This process is can be modeled by a multiagent system with advanced learning and adaption capabilities. The proposed multiagent architecture incorporates CBR-agents that integrate novel strategies that both monitor the parameters that affect the interaction, and facilitate the creation of models. The system was tested and this paper presents the results obtained.

Keywords: Multiagent system, case-based reasoning, Air-Sea Monitoring, CO_2 exchange

1. *Introduction*

One of the factors of greatest concern in climactic behaviour is the quantity of carbon dioxide present in the atmosphere. Carbon dioxide is one of the greenhouse gases that helps to make the earth's temperature habitable, so long as it is maintained at a certain level [47]. The main system regulating carbon dioxide in the atmosphere has traditionally been thought to be the photosynthesis and respiration of plants. However, teledetection techniques have been able to show that the ocean plays a highly important role in the regulation of carbon quantities, although the full significance of this still needs to be determined [18,47]. Current technology allows us to obtain data and make calculations that were unthinkable some time ago. This data provides an insight into the original source of carbon dioxide, the decrease in carbon dioxide, and the causes for both [31], which allows us to make predictions about the behaviour of carbon dioxide in the future.

The need to quantify the carbon dioxide valence and the exchange rate between the oceanic water surface and the atmosphere, motivated us to develop the distributed system, presented here, that incorporates CBR-agents capable of estimating the valence and exchange rate values using accumulated knowledge and updated information. The CBR-agents receive data from satellites, oceanographic databases, oceanic and commercial vessels. Agents and multiagent systems are appropriate for developing applications in dynamic, flexible environments [11,21,33,38,43]. Agents can be characterized through their capacities in areas such as autonomy, communication, learning, goal orientation, mobility, persistence, etc. Autonomy, learning and reasoning are especially important aspects for an agent. These capabilities can be modelled in different ways and with different tools [51]. One of the possibilities is the use of Case Based Reasoning (CBR) systems [25,48,51]. This paper presents a CBR based deliberative agent that incorporates neural networks to implement the retrieve, reuse, revise and retain stages of the CBR system. The CBR-BDI agent [13] is the core of a distributed system

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whose mission is to monitor the interaction between the ocean surface and the atmosphere, and to learn from the available data. The system was initially used to evaluate and predict the quantity of CO_2 exchanged in the North Atlantic Ocean by mining the data that was coming from satellite observations.

The aim of the present study is to obtain an architecture that makes it possible to construct dynamic systems capable of growing in dimension and adapting their knowledge to environmental changes. Multiagent systems seem to be a more than appropriated option to achieve this objective, given their capacities to resolve distributed and dynamic problems.The mission of the multiagent system is to globally monitor the interaction between the ocean surface and the atmosphere, facilitating the work of oceanographers. The system is being used in order to evaluate and predict the amount of carbon dioxide (CO_2) absorbed or expelled by the ocean in the North Atlantic [14]. Several architectures have been proposed for building deliberative agents, most of them based on the BDI model. In the BDI model the internal structure of an agent, and therefore its ability to choose a course of action, is based on mental attitudes. The advantage of using mental attitudes in the design and realization of agents and multi-agent systems is the natural (human-like) modeling and the high abstraction level. The BDI (Beliefs, Desires, Intentions) model uses Beliefs as information attitudes, Desires as motivational attitudes, and Intentions as deliberative attitudes for each agent. A BDI agent can incorporate a CBR engine to improve its autonomy, learning and reasoning capacities [8]. The CBR-BDI agents presented in the framework of this research incorporate innovative techniques in each of the stages of the CBR cycle. The retrieve phase incorporates a novel strategy based on growing cell structure neural network that provides a set of cases grouped in meshes according to similarity criteria. The reuse phase is composed of a multilayer perceptron neural network [1] and a Jacobean sensitive matrix. The revise phase is carried out by means of a pondered weight technique. Finally, the retain stage updates the growing cell structure neural network.

The next section reviews the environmental problem that motivates the majority of this research. Section three describes the multiagent architecture specifically developed to monitor the air-sea interaction. Section four presents the CBR-BDI agent based system developed. Finally the conclusions and some preliminary results are presented.

2. Air sea interaction problem

In recent years a great interest has emerged in climactic behaviour and the impact that mankind has had on the climate. One of the most worrying factors is the quantity of CO_2 present in the atmosphere. Until only a few years ago, the photosynthesis and breathing processes in plants were considered to be the regulatory system that controls the presence of CO_2 in the atmosphere. However, the role of the ocean in the regulation of carbon volume is very significant and so far remains indefinite [45]. Current technology makes it possible to obtain data and estimates that were beyond expectations only a few years ago. The goal of this project is to construct a model that calculates the global air-sea flux of CO_2 exchanged between the atmosphere and the surface waters of the ocean. In order to create a new model for the CO_2 exchange between the atmosphere and the oceanic surface a number of important parameters must be taken into consideration: sea surface temperature, air temperature, sea surface salinity, atmospheric and hydrostatic pressures, the presence of nutrients and the wind speed vector (module and direction) [47].

These parameters can be obtained from oceanographic ships as well as from satellite images. Satellites provide a great amount of daily information and there is a growing need for the ability to automatically process and learn from this source of knowledge. These parameters allow us to calculate the variables that define our models, such as the velocity of gas transfer, solubility, or the differentiation between partial pressures on the atmosphere and sea surface (a case structure is shown in Table 1).

As shown in Table 1, the most influential parameters obtained from the satellite images within our models are: temperature of the water and air, salinity of the water, wind strength, wind direction and biological parameters such as chlorophyll. These parameters allow us to calculate the variables that define our models, such as the velocity of gas transfer, solubility, or the differentiation between partial pressures on the atmosphere and sea surface. The majority of CO_2 either dissolves in the sea water because of phytoplankton, or accumulates at the bottom of the ocean in the form of organic material. The phytoplankton present in deep areas of the ocean rises to the surface by surges or surface appearances that are simply large upward movements of cold water that bring nutrients to the sea surface. The principal cause of the surges is the winds. The most effective way to detect them through satellites is to study the images captured with sensors that are sensitive to longitudes

Table 1
Case attributes

Case field	Measurement
DATE	Date (dd/mm/yyyy)
LAT	Latitude (decimal degrees)
LONG	Longitude (decimal degrees)
SST	Temperature (°C)
S	Salinity (unitless)
WS	Wind strength (m/s)
WD	Wind direction (unitless)
Fluo_calibrated	fluorescence calibrated with chlorophyll
SW pCO_2	surface partial pressure of CO_2 (micro Atmospheres)
Air pCO_2	air partial pressure of CO_2 (micro Atmospheres)
Flux of CO_2	CO_2 exchange flux (Moles/m^2)

of thermal infrared waves (capable of detecting the sea surface temperature SST) and to identify the cold waters. Another possible way to detect them is to monitor the activity of the chlorophyll through sensors within the spectrum range found between blue and green, which are associated with the presence of phytoplankton. In order to obtain the satellite images that contain information about these parameters it is necessary to use different sensors. The earth observation satellites that have been used to obtain images in the Northern Atlantic are NOAA, Orbview-2 and primarily, the ENVISAT satellite of the European Space Agency. Below we shall briefly describe the sensor used in each one of these and the software for the digital processing of the images [40].

Satellite information is vital for the construction of oceanographic models. In this case, the use of artificial intelligence models produces estimates of air-sea fluxes of CO_2 with much higher spatial and temporal resolution that what can be achieved realistically by direct in situ sampling of upper ocean CO_2. In order to handle all the potentially useful data to create daily models in reasonable time and at a reasonable cost, it is necessary to use automated distributed systems capable of incorporating new knowledge. Our proposal is presented in the following section.

3. Multiagent architecture for monitoring the air-sea interaction

Our final aim is to model the Air-Sea interaction with data obtained from the open ocean, working under the assumption that by assimilating Earth Observation (EO) data into artificial intelligence models the problem of predicting the CO_2 exchange may be solved. Earth observation data (both for assimilation and for validation) are vital for the successful development of reliable models that can describe the complex physical and biogeochemical interactions involved in marine carbon cycling. Satellite information is vital for constructing oceanographic models. In this case, artificial intelligence models can produce estimates of air-sea fluxes of carbon dioxide with a much higher spatial and temporal resolution than what can be achieved by direct in situ sampling of upper ocean carbon dioxide. A model is an abstract conceptualization of the CO_2 exchange between the ocean surface and the atmosphere. The parameters which have most influence within our models are: temperature of the water and air, salinity of the water, wind strength, wind direction and biological parameters such as chlorophyll. These parameters allow us to calculate the variables that define our models, such as the velocity of gas transfer, solubility, or the differentiation between partial pressures on the atmosphere and sea surface. To handle all the potentially useful data to create daily models in a reasonable time and with a reasonable cost, it is necessary to use automated distributed systems capable of incorporating new knowledge. Our proposal consists of a multiagent system whose main characteristic is the use of CBR-BDI agents.

Figure 1 illustrates a multiagent system in which the types of agents are defined taking into account a social criteria. The agents play the roles of the human users involved in the ocean monitoring process. In Fig. 1 is it possible to observe how a Modelling agent with a CBR-BDI architecture is responsible for the creation and evaluation of models in terms of the data received from the Store, Vessel and User agents. This model makes it possible to monitor and predict the carbon dioxide exchange between the ocean surface and the atmosphere. The Store agent processes the images from the satellite and transforms them for use by the system. Each Vessel agent is installed in a ship and collects information in-situ that makes it possible to evaluate the models created by the Modelling agent. The User agent can interact with any of the other agents [50]

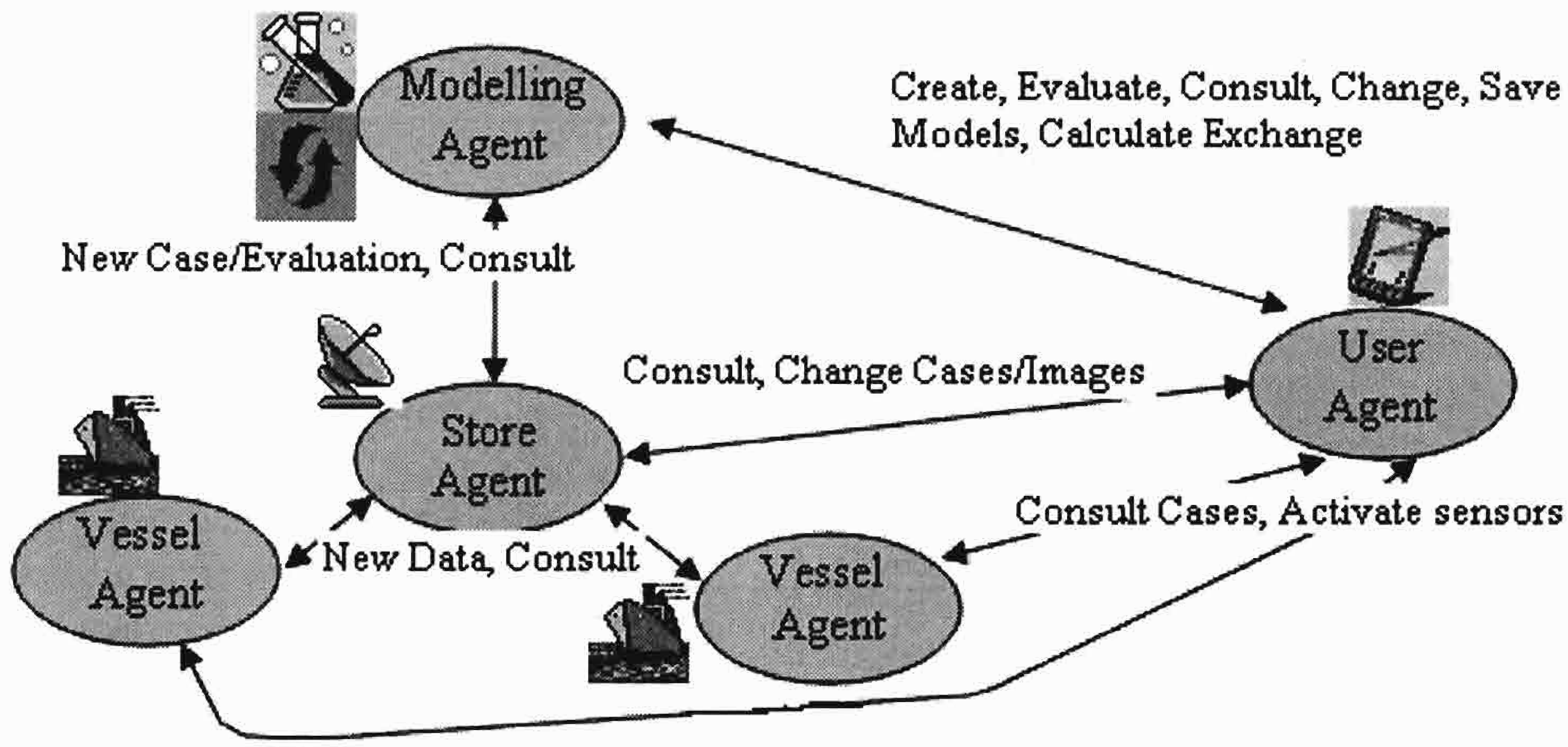

Fig. 1. Diagram of the architecture of our MAS.

and allows the oceanographers to access and evaluate the models. Figure 1 shows how the agents interact with each other and with their surroundings [1,10]. In order to resolve the problem from an oceanographic perspective, the ocean was divided into a series of zones in each of which there is a Modelling Agent, a Store Agent, and various Vessel Agents.

The models generated by the Modelling agent provide accurate predictions about the CO_2 exchange between the ocean surface and the atmosphere. To create a new model it is necessary to have information available about the description of the problem that will be modeled. The problem description is obtained from the data extracted from satellite images. Store agent is the one responsible for processing the satellite images and extracting the information that will be used by the system. Figure 2 shows a screenshot of the Store agent, in which it is possible to observe the data obtained by means of satellite images filtered over an a specific period of time, for the given intervals of latitudes and longitudes. The data obtained from the satellite images are mainly chlorophile, salinity and temperature. To process the satellite images, some specific algorithms are used by the Store agent [16,30]. Figure 2 shows some processed data obtained for specific zones of the North Atlantic Ocean. The processed data are sent to the Modelling agent which creates a new model. The model is then evaluated in order to revise its efficiency. To do this, it is necessary to use the information provided by the Vessel agents, which are installed in vessels and obtain in-situ data that can use the models generated by the Modelling agent to evaluate the results provided.

The User agent can interact with each of the agents in the system and can be executed in mobile devices such as PDAs in addition to laptops, which notably facilitates the work of the oceanographers, providing ubiquitous access regardless of the physical location. There is a User agent for each of the oceanographers that acts as a personal interface to access the multiagent system.

A user can access the system rapidly and efficiently using their personal agent. This agent is able to sit within a "light" device and can communicate through wireless technology with the other system agents. This allows oceanographers work independently and unhindered by location. Figure 3 shows the interface of a User agent accessed via a personal digital assistant. It is possible to see how the user can access the Modelling, Store or Vessel agent. The appropriate Store or Vessel can be selected through a simple interface that only presents the necessary information and avoids showing too many elements on the screen. The oceanographers themselves can decide the amount of elements that they wish to see. Figure 3b) presents the options that can be executed by the Modelling agent: request the creation of a new model, for which it will be necessary to enter the appropriate parameters; predict the level of exchange in a particular zone of the ocean; make an inquiry about the models stored; evaluate a model by entering real data or saving the corresponding data to the models that are being currently used. The User agent offers similar menus that allow the user to interact with the Vessel and Store agents. Figure 3c) shows the parameters that an oceanographer needs to enter when wishing to inquire about the cases stored by the Store agent for the zone of the Atlantic Ocean situated

Fig. 2. Store agent. Cases obtained from satellite images.

between 10° and 100° latitude and 10° and 100° longitude on the 11/03/2006. After the inquiry is made, the cases are shown to the user in a table, as shown in Fig. 3d). The user can select each one of these cases and modify the parameters.

The multiagent system has been implemented using the JADE platform [9] and the Jadex tool [40], an add-on for Jade that incorporates a BDI architecture to the Jade agents.

4. CBR-BDI modelling agent

The agents are equipped with capabilities, such as mobility, pro-activity or social abilities, as well as the possibility of solving problems in a distributed way. These characteristics make the agents perfectly suited for constructing intelligent distributed environments. There are many architectures for constructing deliberative agents, many of which are based on the Beliefs Desires Intentions (BDI) model [8]. In this model, the internal structure of an agent and its ability to choose is based on mental aptitudes: agent behaviour is composed of beliefs, desires, and intentions. The beliefs represent the agent's information state, what the agent knows about itself and its environment. The desires are its motivation state, what the agent is trying to achieve. The intentions represent the agent's deliberative states. Intentions are sequences of actions that can be identified as plans.

Case-based Reasoning (CBR) is a type of reasoning based on the use of past experiences [21]. The purpose of case-based reasoning systems is to solve new problems by adapting solutions that have been used to solve similar problems in the past. The fundamental concept when working with case-based reasoning is the concept of case. A case can be defined as a past experience, and is composed of three elements: A problem description which describes the initial problem, a solution which provides the sequence of actions carried out in order to solve the problem, and the final state which describes the state achieved once the solution was applied. A case-based reasoning system manages cases (past experiences) to solve new problems. The way in which cases are managed is known as the case-based reasoning cycle, which is composed of four sequential stages: retrieve, reuse, revise and retain [21].

The deliberative agents proposed in the framework of this investigation use this concept to gain autonomy and improve their problem-solving capabilities. The method proposed in [13] facilitates the incorporation of case-based reasoning systems as a deliberative mech-

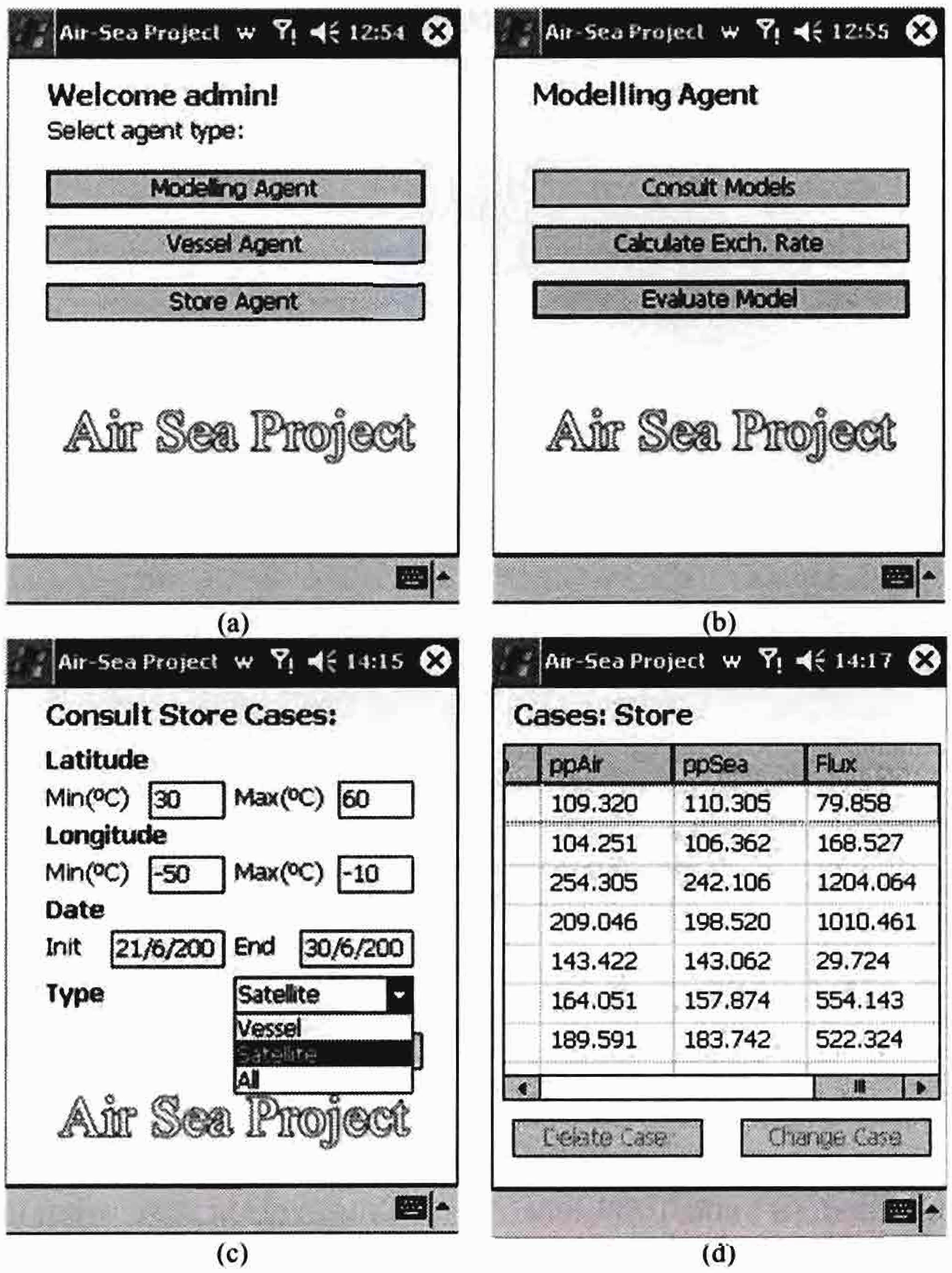

Fig. 3. User agent. Interaction model for the system through PDAs.

anism within BDI agents, allowing them to learn and adapt themselves, lending them a greater level of autonomy than pure BDI architectures [8]. Accordingly, CBR-agents implemented using case-based reasoning systems can reason autonomously and therefore adapt themselves to environmental changes. The case-based reasoning system is completely integrated within the agents' architecture.

The relationship between case-based reasoning systems and BDI agents can be established by implementing cases as beliefs, intentions and desires which lead to the resolution of a problem. As described in [13], each state in a CBR-BDI agent is considered as a belief; the objective to be reached may also be a belief. The intentions are plans of actions that the agent has to carry out in order to achieve its objectives, which makes every intention is an ordered set of actions; and each change from state to state is made after carrying out an action (the agent remembers the action carried out in the past, when it was in a specified state, and the subsequent result). A desire will be any of the final states reached in the past (if the agent has to deal with a situation, which is similar to a past one, it will try to achieve a similar result to that previously obtained).

Figure 4 presents the class diagram for the Modelling agent, a CBR-BDI agent that has two principal functions. The first function is to generate models that are capable of predicting the atmospheric/oceanic interaction in a particular area of the ocean in advance. The second is to permit the use of such models. The reasoning cycle of a CBR system is included among the activities, and is comprised of the retrieval, reuse, revise and retain stages. An additional stage is used to introduce an expert's knowledge. This reasoning cycle must correspond to the sequential execution of some of the agent roles. The Modelling agent carries out roles to generate models such as Jacobean Sensitivity Matrix (JSM), Pondered Weigh Technique (PWT), Revision Simulated Equation (RSE), and other roles that allow it to operate with the calculating models, like Forecast Exchange Rate, Evaluate Model or Consult model. The roles used to carry out the stages of the CBR cycle are described as follows.

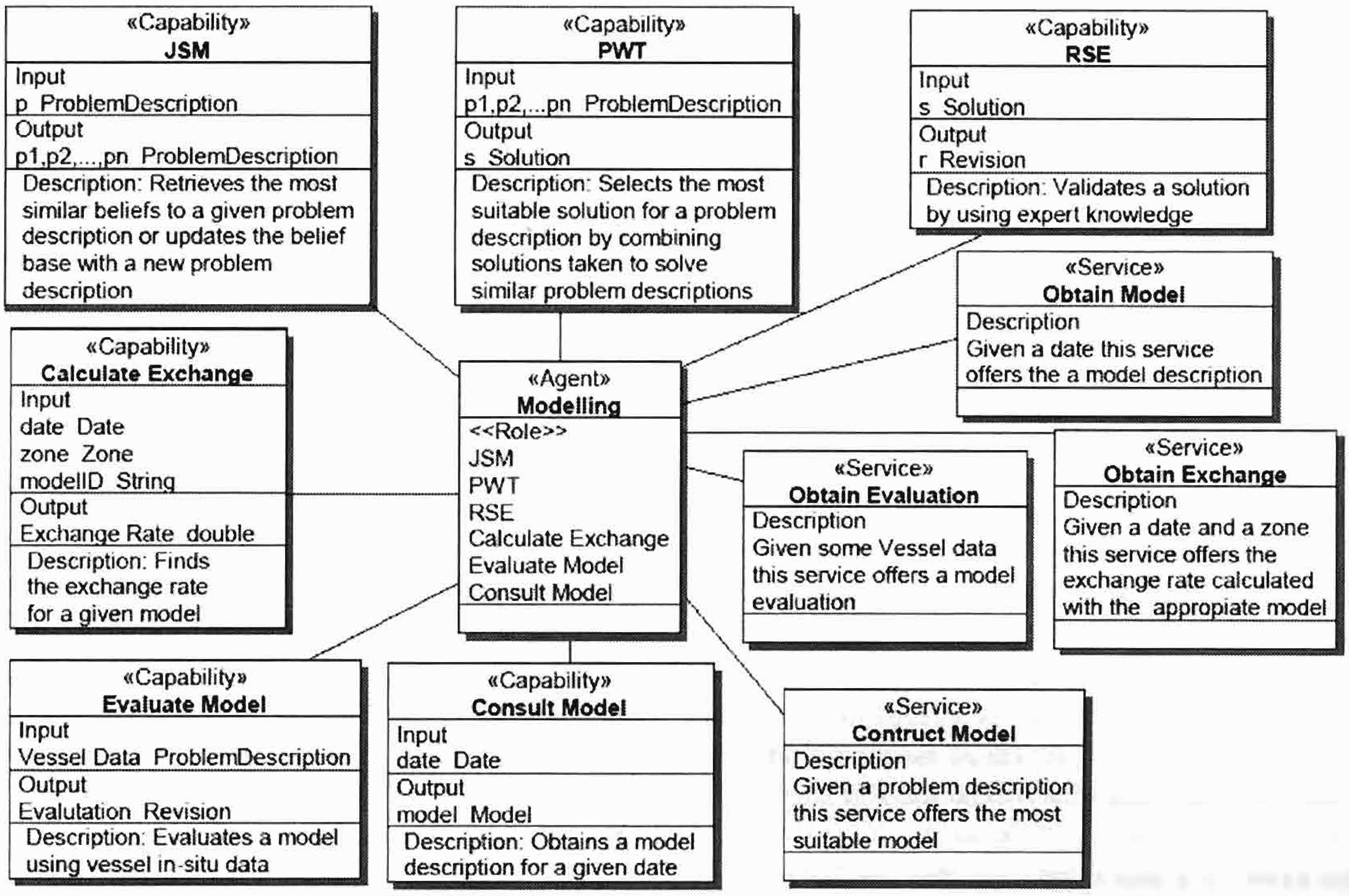

Fig. 4. Class diagram for the modelling agent.

The content of the information stored in the memory of cases for each of the cases is described in Table 1. As can be seen, a case consists of a series of variables that can be represented as a tuple c = (d, l, o, t, s, w, r, f, p, a, M, e, x), where d represents the date, l the latitude, o the longitude, t the temperature, s the salinity, w the wind strength, wd the wind direction, f the fluorescence calibrated, s the surface partial pressure of CO_2, a the air partial pressure of CO_2, M the Multilayer Perceptron (MLP) associated to the case, e the CO_2 Flux, and i the exchange value. The memory of cases is defined as a set of cases and is represented as $C = \{c\}$. When a new problem is studied, the system incorporates a new case c_{n+1} and a new CBR cycle is executed as shown in the next subsections.

4.1. Retrieve phase

The retrieval process identifies those cases in the memory of cases that have the highest level of similarity with the new case c_{n+1}. In order to do so, the memory of cases is structured in such a way so as to group together the most similar cases. There are different techniques that can be used to create clusters, such as the use of distance metrics like the cosine [22], euclidean, etc. or more complex techniques based on algorithms of different types: hierarchical [45], iterative [21], genetic algorithm [2,21,24], or others based on the use of neural networks. Neural networks were chosen for this study since they present certain advantages including the automatic selection of the number of clusters to create, and the ability to adapt themselves to data distributions with irregular surfaces. In order to identify the neural network that better adapts to the characteristics of the problem under consideration, we have evaluated different alternatives [36,44] such as SOM [19,29] (self-organizing map), GNG [19] (Growing neural Gas) resulting from the union of techniques CHL [22,37] (competitive Hebbian Learning) and NG [35] (neural gas), GCS [19] (Growing Cell Structure). Some of the methods, such as self-organized Kohonen maps, set the number of clusters in the initial phase of training when using the algorithm of the k-means learning method. This is the reason that these methods cannot be used for the problem at hand, since in this case the number of clusters is unknown.

However, the number of groups could be varied and the degree of waste compaction checked so that according to this value, the final number of groups could be set. This solution would require too much computing time and it would be difficult to limit the number of groups to include. The self-organized maps include other variants of learning methods that base their behaviour on methods similar to the NG by creating a mesh that is adjusted automatically to a specific area. The greatest disadvantage, however, is that both the number of neurons that are distributed over the surface and the degree of proximity are set beforehand, resulting in the number remaining constant throughout the entire training process, thus complicating, to a certain extent, the adaptation of the mesh. Unlike the self-organizing maps based on meshes, Growing Grid or GCS do not set the number of neurons, or the degree of connectivity. GCS networks adjust the data by means of a series of disconnected meshes that are obtained during the training stage of the neural network. In this sense, the neural network provides a series of distributed meshes that represent the memory of cases. Each of the cases of the memory of cases is assigned to the nearest mesh, so when a new case is studied, the closest mesh is selected along with the cases associated to the mesh. These are the cases that will be used in the reuse phase.

If there exists is a neural network that has been previously trained with the set of retrieved cases, that is, a CBR cycle previously executed with the cases of the selected mesh, then the settings of the neural network are reloaded.

When the training process finishes, the result obtained is a set of cases grouped in meshes that are represented as $G = \{g_i/g_i \subseteq C\}$, where $g_i \cap g_j = \phi \forall i \neq j$.

4.2. Reuse phase

This phase is carried out by means of a multilayer perceptron [38]. The MLP makes only use of the data recovered in the retrieve phase instead of working with all the data stored in the memory of cases. This fact provides a notable reduction in the time required for the training stage of the MLP, and improves the prediction provided by the neural network since the data are more homogeneous. When the group g_i has already executed a Reuse phase and, as a result, it is associated with a previously trained MLP, then it is necessary to calculate the estimate error rate for the cases used by the MLP. If the condition established by Eq. (1) is met, the training stage is not carried out.

$$\frac{\sum_{i=1}^{N} |M_{g_j}(c_i) - x_i|}{N \cdot \bar{x}} < \mu \quad (1)$$

where N represents the set of cases for the group g_j, $M_{g_j}(c_i)$ is the value estimated by the MLP for the case c_i, x_i is the exchange value, and μ is the threshold that identifies the limit considered as valid.

Otherwise, when a MLP does not previously exist, it is necessary to execute the training phase before making predictions. To carry out the training phase of the MLP, it is necessary to readjust the data in such a way that all the data are normalized in the interval [0.2–0.8]. In the input layer of the MLP there is a neuron for each of the parameters shown in Table 1, except the Flux of CO_2, which is the solution for the cases. The number of neurons selected for the hidden layer of the MLP is determined using the expression $2n+1$, where n is the number of neurons in the input layer. This value was defined following the criteria proposed by Kolmogorov [38]. Finally, the output layer of the MLP is composed of a neuron that represents the Flux of CO_2 parameter shown in Table 1. The training stage finishes when the cross validation, which uses 10% of the initial cases, provides an error rate that is lower than μ. Once the MLP has been trained, the Jacobean Sensitivity Matrix (JSM) is calculated.

The Jacobean Sensitivity Matrix method is a novel approach for feature selection. It can be used to visualize and extract information from complex and highly dynamic data. The model is based in the principal component analysis and is used to identify which input variables have more influence in the output of the neural network used to perform the principal component analysis. The neural network identifies the beliefs stored by the agent that can be the most useful to solve a given problem. The mathematical model is outlined as follows.

If JSM is a matrix NxM where N is the number of input of the neural network and M is the number of output of the neural network. And if the element Ski in the matrix represents the sensitivity (influence) of the output k over the input I, then Eq. (1).

$$S_{ki} = \frac{\partial y_k}{\partial x_i} = \frac{\partial f_k(net_k)}{\partial x_i} = \frac{\partial f_k(net_k)}{\partial net_k} \frac{\partial net_k}{\partial y_j} \frac{\partial y_j}{\partial net_j} \frac{\partial net_j}{\partial x_i} = \frac{\partial f_k(net_k)}{\partial net_k} \left(\sum_{j=1}^{H} w_{kj} \frac{\partial f_j(net_j)}{\partial net_j} \right) \quad (2)$$

Where w_{ij} is the weight of the connection between the input neuron i and the hidden neuron j. w_{kj} is the weight of the connection between the hidden neuron j and the output neuron k. y_k is the output obtained for neuron k of the output layer. Then $y_k = f_k$ (netk). y_j

is the output obtained for neuron j of the hidden layer. Then $y_j = f_j$ (netj). x_i is the input for neuron i and f_h is the activation function in neuron h. Then

$$net_j = \sum_{i=1}^{N} w_{ji}, x_i + \theta_j \quad (3)$$

$$net_k = \sum_{j=1}^{H} w_{kj}, y_j + \theta_k \quad (4)$$

Where H is the number of neurons in the hidden layer, θ_j is the threshold value for neuron j of the hidden layer and θ_k is the threshold value for neuron k of the output layer.

Pondered Weigh Technique (PWT): The reuse is carried out using the cases selected during the retrieval stage. The cases are pondered [17] and the bigger weight is given to the one that most resembles the current problem in the following way:

$$p^* = \frac{1}{\sum_{r=1}^{Z} e^{-|a-r|}} \sum_{r=1}^{Z} e^{-|a-r|} p_r \quad (5)$$

Where p^* is the solution prediction, Z is the number of retained cases from the base of beliefs, a is the measure of minimum similarity between the retained cases from the base of beliefs and the current case, p_r is the retained prediction r-th from the base of beliefs and r is the measure of similarity between the retained cases r-th from the base of beliefs and the current case.

4.3. Revise phase

Revision Simulated Equation (RSE): During the revision stage an equation (F) is used to validate the proposed solution p^*.

$$F = kso(pCO_2SW - pCO_2AIR) \quad (6)$$

Where F is the flux of CO_2, k is the gas transfer velocity Eq. (6), so is the solubility verifying Eq. (7) and pCO_2 is the partial pressure of CO_2 Eq. (8).

$$k = (-5,204Lat + 0,729Long + 2562,765) \\ /3600 \quad (7)$$

$$so = e^{\left(\frac{93.4517}{100tk} - 60,2409 + 23,3585 \log(100tk) \\ + s(0,023517 - 0,023656 \cdot 100tk + 0,0047036 \cdot 1002tk)\right)} \quad (8)$$

$$pCO_2 = A + BLong + CLat + DSST \\ + EYear \quad (9)$$

As can be seen in Eq. (6), k depends on Lat (Latitude), $Long$ (Longitude). As can be seen in Eq. (7) so depends on $tk = 273{,}15 + t$. where t is the temperature and s is the salinity. Finally, in Eq. (8) it is possible to observe that pCO_2 depends on the SST, which is the temperature of the marine surface or air as it corresponds to pCO_2SW or pCO_2AIR. The coefficients of the Eq. (8) depend on the month.

During the revision, the agent compares the obtained F value with the predicted one and if the prediction differs by less than 10% the case is stored on the base of beliefs. As has been shown the CBR-BDI agents use a CBR system, at a low level of implementation, which is the reason for using cases. One case for the CBR consists of a problem (initial situation and a number of goals) and the plans to resolve it. For oceanic/atmospheric interaction, we define the problem in terms of the attributes shown in Table 1.

Table 1 shows the description of a case: DATE, LAT, LONG, SST, S, WS, WD, Fluo_calibrated, SW pCO_2 and Air pCO_2. Flux of CO_2 is the value to be identified.

4.4. Retain phase

This phase begins once the prediction has been compared to the result provided using the mathematical model. If the case is considered valid (if the prediction differs by less than 10%), the case is stored in the memory of cases. When this occurs, it is necessary to train the GCS network in order to include the new case in the structure of the memory of cases. In this way the new experience obtained processing the current case will be taken into consideration for the next prediction.

5. Results

The system described above was tested with data from the North Atlantic Ocean obtained during 2005. Although the system is not fully operational and the aim of the project is to construct a research prototype and not a commercial tool, the initial results have been very successful from a technical and scientific point of view. The construction of the distributed system was relatively simple, using previously developed CBR-BDI libraries [6,7,10,13,14] that facilitates the straight mapping between the agent definition and the CBR construction. The multiagent system automatically incorporated over 50,000 instances during the five months and eliminated 12% of the initial ones.

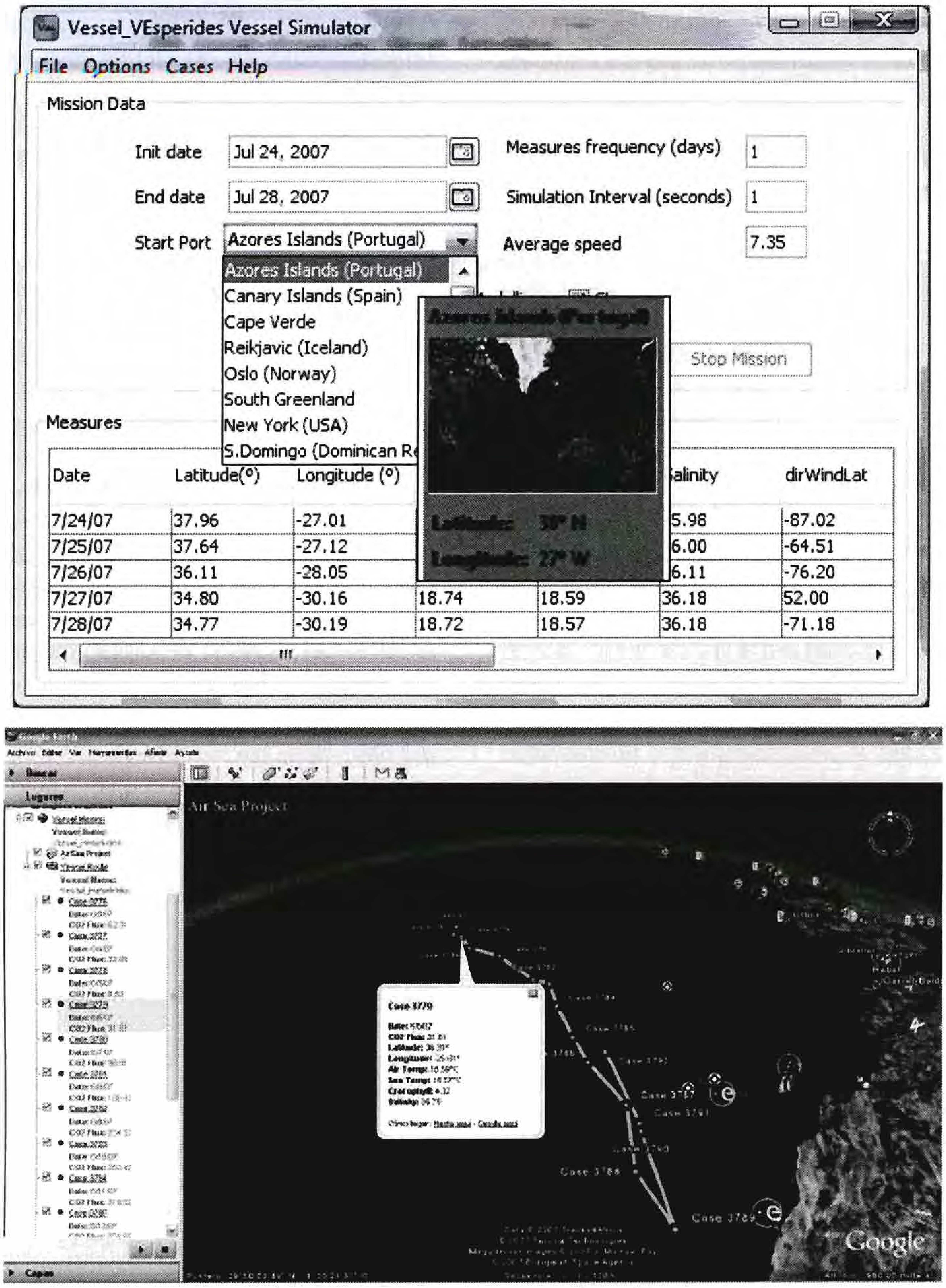

Fig. 5. Vessel agent interface (a) and presentation of the routed followed for a ship by means of the Google Eath tool (b).

Figure 5 shows the appearance of a Vessel agent. The vessel agent periodically sends information about the data obtained from its corresponding ship. Oceanographers can employ the user agent to easily observe the in-situ data obtained as well as the route followed by the ship can be easily observed. For this study vessel simulators that work with real stored data were used. As can be seen in Fig. 5, the interface facilitated to the oceanographers is very simple and intuitive and contains all the information required to evaluate the models. Furthermore, a graphical tool is available to represent the routes followed by the vessels. The agent notably improves the evaluation tasks.

The system was tested with data from the last three months of 2005 and the results were very accurate. Table 2 presents the results obtained with the Multiagent systems and with mathematical Models [31] used by oceanographers to identify the amount of CO_2 ex-

Table 2
Million of tones of $C0_2$ exchanged in the North Atlanthic

	Oct. 05	Nov. 05	Dec. 06	Jan. 06	Feb. 06
Multiagent System	−19	21	33	29	29
Manual models	−20	25	40	37	32

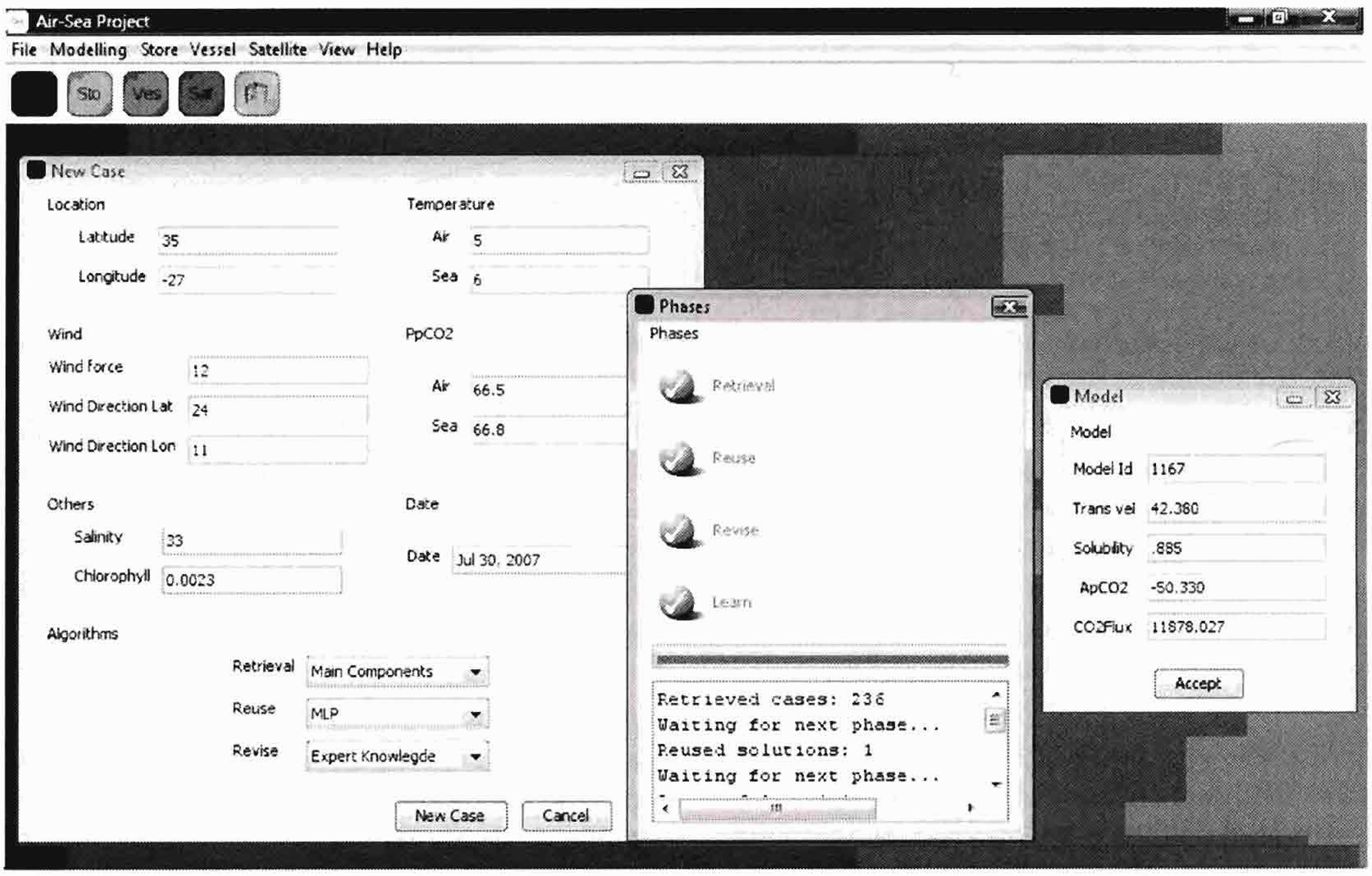

Fig. 6. Screenshot of a Modelling agent during the generation of a model.

changed. The numerical values represent the million of tonnes of carbon dioxide that have been absorbed (negative values) or generated (positive value) by the ocean during each of the three months.

Figure 6 shows the interface of a Modelling agent, and more specifically the interface for generating a model. In Fig. 6 it is possible to observe how an oceanographer can establish the settings for each of the algorithms used in the stages of the CBR cycle. There was continual interaction between programmers and oceanographers during the construction and evaluation of the prototype. The system was tested under simulation conditions and the Store and Vessel agents were specifically implemented to generate synthetic cases from real data obtained in the North Atlantic Ocean (± 37N, 25W). Under these conditions, the models generated by the multiagent system became progressively more accurate. However, when the number of cases grew excessively, the efficiency of the system decreased. Figure 7 shows a comparison of the real data and the predictions provided by the multiagent system working with data from 2003–2004.

6. Conclusions

The application of Artificial Intelligence techniques is extremely useful in a field like oceanography, and specifically in the study of the carbon dioxide exchange between the ocean surface and the atmosphere. One of the factors of greatest concern in climactic behaviour is the quantity of carbon dioxide present in the atmosphere. The need to quantify the carbon dioxide valence, and the exchange rate between the oceanic water surface and the atmosphere, has motivated us to develop the distributed system. To handle all the potentially useful data to create daily models in a reasonable time and with a reasonable cost, it is necessary to use automated distributed systems capable of incorporating new knowledge. The use of CBR-BDI agents makes it much easier to deal with a great amount of satellite images. The results obtained demonstrates the appropriateness of multiagent systems and artificial intelligence models to cover climatic problems. Moreover, the approach is easily extensible to problems of similar characteristics.

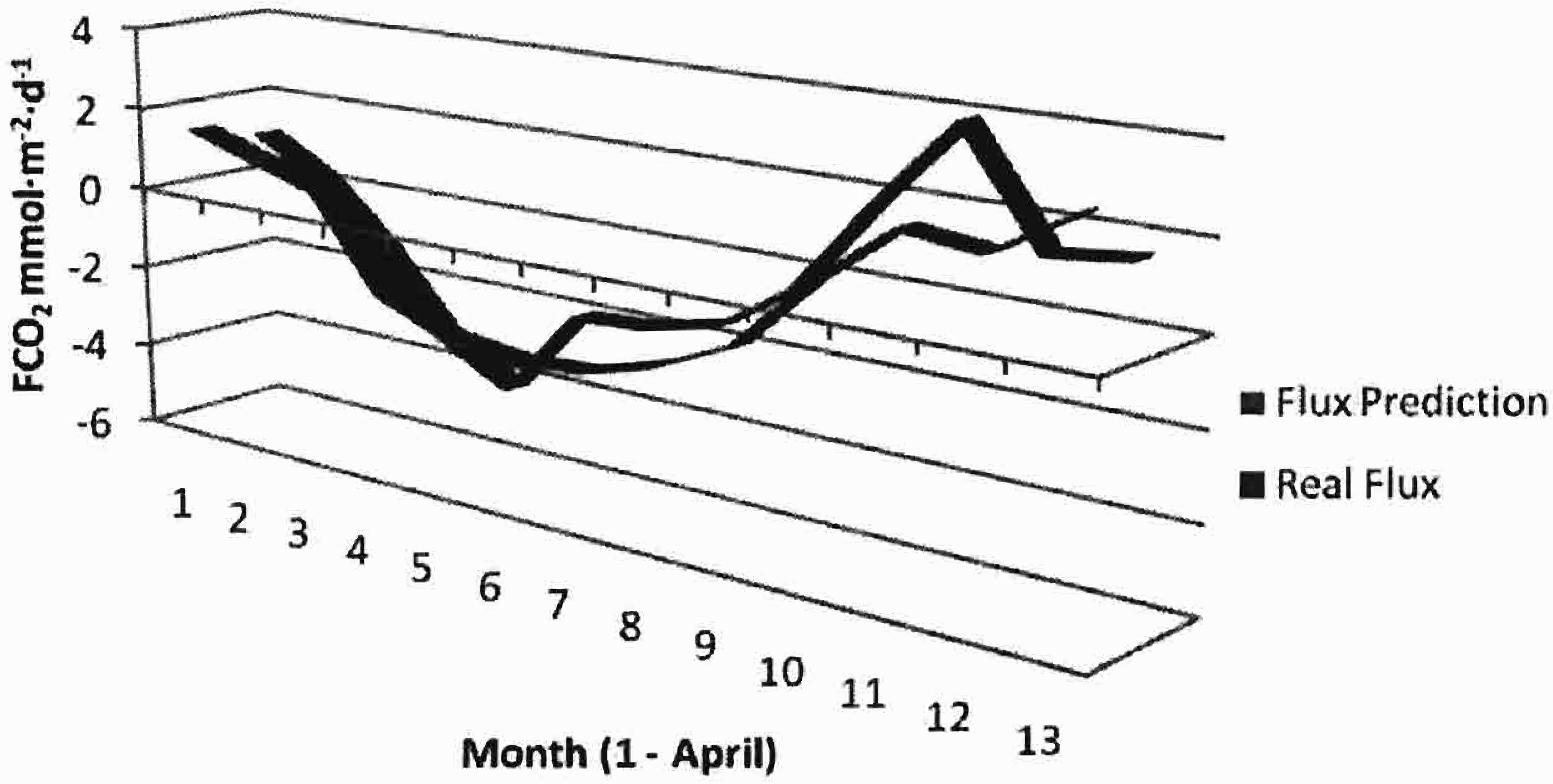

Fig. 7. Real CO_2 flux and flux prediction.

The values proposed by the CBR-BDI agent are quite similar to the ones obtained by the standard technique, with an average rate of similitude of 86,098%. While the CBR-BDI Modelling Agent generates results on a daily basis without any human intervention, the Casix manual modelling techniques require the work of one researcher processing data during at least four working days. Although the system proposed requires further improvements and more work, the initial results are very promising. Compared to the previously developed CBR-BDI models based on Hebbian Learning (CoHel) [5,11,14] or variational calculus techniques (VCBP) [6], the results obtained with the reasoning engine presented in this paper are very similar to those obtained applying hebbian learning, and they give a quicker response than VCBP engines. This research presents the development of new algorithms to improve the CBR engine incorporated in the BDI agent. These algorithms are included in each of the stages of the CBR reasoning cycle.

As shown in Fig. 7 the predictions provided by the multiagent system are accurate (9 of the 12 models were accepted as successful). The multiagent system makes predictions based on previous experiences, taking into account the similitude with past situations. Figure 7 shows how the precision of the prediction improves when the number of cases increases. On the other hand, it is necessary to control the number of cases in the memory of cases in order to avoid an excessive growth of the cases available. To maintain the memory of cases, we used a strategy based on priorities, consisting of a pyramidal structure of efficiencies.

The interaction between the system developers and oceanographers with the multiagent system has been continuous during the construction and pruning period. They have noted that the agents do not represent a mere software that interacts between the user and the technology, but also has the capacity to make decisions and act for themselves in a distributed way, in order to respond and adapt to the changes that are produced within the environment and within its own internal knowledge structure.

The multiagent system facilitates the incorporation of new agents that use different modeling techniques and learning strategies, so our future work will focus on the incorporation of new agents with alternative techniques, on improving the retain stage of the CBR system to also learn by failure and the execution of additional experiments.

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