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An intelligent system for forest fire risk prediction and fire fighting management in Galicia

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Abstract

Over the last two decades in southern Europe, more than 10 million hectares of forest have been damaged by fire. Due to the costs and complications of fire-fighting a number of technical developments in the field have been appeared in recent years. This paper describes a system developed for the region of Galicia in NW Spain, one of the regions of Europe most affected by fires. This system fulfills three main aims: it acts as a preventive tool by predicting forest fire risks, it backs up the forest fire monitoring and extinction phase, and it assists in planning the recuperation of the burned areas. The forest fire prediction model is based on a neural network whose output is classified into four symbolic risk categories, obtaining an accuracy of 0.789. The other two main tasks are carried out by a knowledge-based system developed following the CommonKADS methodology. Currently we are working on the trail of the system in a controlled real environment. This will provide results on real behaviour that can be used to fine-tune the system to the point where it is considered suitable for installation in a real application environment.

Keywords: Neural Networks; Knowledge intensive systems; CommonKads; Forest fires; Fire risk prediction; Resources management

1. Introduction

Over the last two decades in southern Europe, more than 10 million hectares of forest have been damaged by fire. Each annual fire-fighting season incurs significant costs, measurable principally in terms of loss of human life, investment in fire-fighting resources, damage to the environment and the cost of recuperating the affected areas. However, the costs and complications of fire-fighting make it impractical to simultaneously maintain active fire-fighting units in various parts of a country. Recent years, therefore, have seen a number of technical developments in the field, aimed at improving communications networks, detection systems and fire prediction systems design. However, due to differing conditioning factors (vegetation type, climate, soil composition, orography, etc), it is not feasible to adopt general solutions or to adapt solutions developed for specific regions or countries.

This paper describes a system developed for the region of Galicia in NW Spain (Fig. 1), one of the regions of Europe most affected by fires. During the 1990s, for example, although it represents a mere 5.8% of the surface area of Spain, Galicia alone accounted for around 50% of all forest fires in that country. Moreover, in the same period the number of forest fires continued to grow despite an increase in the human and financial resources allocated to fire-fighting (Merida, 2002).

The system developed in this work fulfills three main aims, as follows:

1. It predicts forest fire risks and therefore acts as a crucial preventive tool by permitting fire-fighting units to focus on areas with the highest fire risk.

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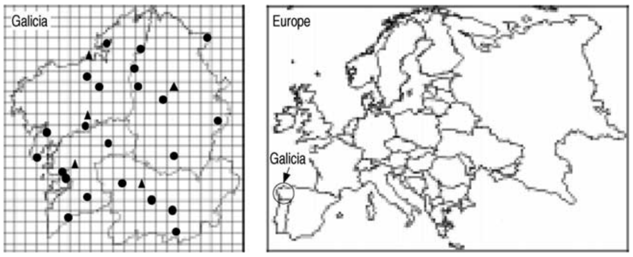

Fig. 1. Location of automatic (●) and non-automatic (▲) meteorological stations in Galicia.

2. It backs up the forest fire monitoring and extinction phase.
3. It assists in planning the recuperation of the burned areas.

The above aims are achieved, from a technical point of view, using artificial neural networks and expert systems.

Our article is organised as follows: Section 2 provides a brief background analysis; Sections 3 and 4 describe, respectively, the fire prediction module and the subsystem for fire management and recuperation of the affected areas; Section 5 describes the overall architecture and additional features of the system; finally, Sections 6 and 7 discuss, respectively, the results obtained and our conclusions.

2. Background

Developed countries currently avail of well structured organisations, programmes and protocols for fighting forest fires, a fact that undoubtedly facilitates the application of new technologies in the domain.

The forest fire domain is an ideal one in which to apply intelligent systems. A large part of the domain knowledge is to be found in procedural models and written material; the remaining knowledge resides in practical accumulated experience that can be captured using knowledge engineering techniques. Nonetheless, in the fire fighting field, intelligent systems are still in the research or prototype phase and are just beginning to be tested in real environments.

A variety of computerised systems have already been developed for the tasks described above, i.e. fire prediction, fire management and recuperation of affected areas. We will discuss these in turn below.

Regarding the *fire risk prediction* task, the FOMFIS (Forest Fire Management and Fire Prevention System) system (Caballero et al., 1999) is an international project partly funded by the European Union. On the basis of weather conditions it provides a measure of probable fire risk for a given area, together with a list of the possible causes of a fire. Another system currently being developed by the Joint Research Centre of the European Commission under its Natural Hazards Project (San-Miguel-Ayanz, Barbosa, Schmuck, Schulte, & Barisisch, 2001) is a fire risk evaluation system based on linear regression models to predict fire hazard for an entire province (Sebastian Lopez et al., 2001). Although other forest fire hazard indices have been developed and applied (Chandler, Cheney, Thomas, Trabaud, & Williams, 1983), their capacity for prevention is greatly reduced outside the area for which they have been designed, as demonstrated in Espinosa, Galinanes, Paz-Andrade, Legido, & Melikhova (1998).

A second set of applications is geared specifically to optimising the fight against forest fires and the management of the resources used for fire extinction. Worthy of particular note in this area are the CHARADE, CARICA, PIROMACOS and FOMFIS systems. The CHARADE project, originated as a software platform, is designed to supervise environmental emergencies using case-based reasoning. A demonstrator has been developed which, by analysing past cases, constructs preliminary intervention plans adapted to each situation (Avesani, Perini, & Ricci, 1993; Ricci, Mam, Marti, Normand, & Olmo, 1994), subsequently evaluated in terms of a fire simulation, resources and geographic information. Experimentation with this project has led to the development of the CARICA system, which includes additional features such as a database of genuine emergency cases and a forestry agent training model (CARICA, 2000). Finally, the PIROMACOS (PIROMACOS, 2002) project optimises fire-fighting using a variety of geographical databases as well as controlling the overall extinction process. It combines information on the fire's advance with information on resources, and indicates any changes necessary in fire-fighting strategies. The optimal strategy is obtained using Bayesian global optimisation methods, updated for changes in the fire profile and in the fire extinction process. All this information is contained in a Geographical Information System (GIS), which manages the databases and the outputs of a program that simulates the progression of the fire. More recently, tailor-made systems have been developed for specific regions of Europe, such as the above-mentioned FOMFIS, a prototype of which has been tested in three areas of southern Europe, namely, Galicia, Aquitaine (France) and Evia Island (Greece). It estimates the most cost effective strategy for both fire prevention and fire-fighting. Operating offline, it provides information on the likely outcome in terms of fire-fighting costs and environmental damage.

The final set of applications concerns *recuperation of burned areas*. The impact of fire on the environment can be reduced through the acquisition of knowledge on the area (in terms of meteorology, topography and vegetation), an evaluation of the consequences of fire and the application of recuperation measures. An example of a system that automates these tasks is the PROMETEUS (U.F. Service, 2002) project, a knowledge-based system that uses a GIS as interface. It acts as a Decision Support System (DSS) that responds to the expected consequences of a fire on the environment. As part of its development, experiments were carried out in Greece and Italy on the impact of fires on soil, vegetation and forest ecosystems.

A common characteristic of all these systems is that they are designed to resolve specific problems within the fire management domain. None of them, however, monitors each and every one of the organisational tasks corresponding to this domain, for the simple reason that they have all been designed as research projects that resolve concrete problems by abstracting the particular details of a specific fire-fighting organisation. Our particular project is designed to tackle all the basic tasks carried out from the outbreak of a forest fire to its extinction, and including the recuperation of the burned area.

3. The forest fire risk prediction subsystem

The aim of this sub-system (Alonso-Betanzos et al., 2002) is to calculate a numeric daily forest fire risk index for each of the 360 $10 \times 10\ \mathrm{km}^2$ squares into which the map of Galicia is divided by the Zone 29 of the UTM (Universal Transverse Mercator). Before this index is presented to the user, however, it will need to be classified in terms of one of four symbolic risk categories: *low*, *medium*, *high* and *extreme*.

The basis for this subsystem is historical information on fires that have occurred between 1988 and 2001 in the areas represented by each of the squares. However, although we know the UTM coordinates of the square in which each fire occurred the fire's precise location is an unknown. Also, meteorological data is normally included as a variable in forest fire prediction since the occurrence of a fire and its subsequent progression will depend largely on meteorological factors (Reifsnyder & Albers, 1994). Historical meteorological data obtained from five non-automatic weather stations (Fig. 1) was thus extrapolated to calculate meteorological data for all the map squares. From this set of data and for each square, six variables were selected as inputs to the fire prediction model based on the following information:

1. Temperature (°C) for the day in question and previous days
2. Daily humidity
3. Daily rainfall
4. Fire history

Although the prediction model was developed on the basis of real data, the system once operational will not be able to avail of real data, and so weather forecast data for the day in question will be used.

3.1. Development of the model

For this research, a neural network model was used for the forest fire prediction system. Neural networks are a method for dealing with highly complex classification problems (Bishop, 1995; Haykin, 1994). Furthermore, they have been demonstrated to be tolerant of input noise, a particularly important criterion for this research, where real, predicted and extrapolated data will be used as inputs; moreover, data precision will vary depending on the year in which they were recorded.

For this research, the system was trained using the Levenberg-Marquardt algorithm (Hagan & Menhaj, 1994) one of the most efficient methods for training moderate-sized neural networks—and, as cost function, the mean squared error (MSE). For the development of the training, validation and test sets, the available data were first analysed. Only about 5% of the samples were positive cases representing the occurrence of a fire. In order to ensure a balanced set all positive cases were included in the training/validation sets along with an equal number of negative examples uniformly selected from among all the squares and randomly selected from each square. Finally, 125,156 and 13,906 examples were included in the training and validation sets, respectively. In addition, 29,842 examples for the years 2000 and 2001 and equally distributed between positive and negative cases were reserved as a test set in order to be able to assess the performance of the system on data not used in its development (Bishop, 1995).

In order to improve the performance of the learning process, the desired output was normalised in the interval [0.05, 0.95] (Haykin, 1994). Several topologies were trained using the network growing strategy (Haykin, 1994), which begins with a very simple network to which new elements, hidden neurons and layers are successively added to the point where performance improves no further. The results described in (Gori & Scarselli, 1998; Hecht-Neilson, 1990; Kurková, 1991) were employed; these state the minimum ($H_{\min}$) and maximum ($H_{\max}$) number of hidden units needed in the network as $H_{\min} > n$ and $H_{\max} \leq 2n + 1$, where n is the number of inputs. Therefore, topologies with 7–13 hidden units were trained several times using a different set of initial weights in order to increase the probability of obtaining an optimal solution. The training process terminated once error was stable.

3.2. Results for the fire prediction model

Once the candidate topologies were trained, their ROC (Receiver Operating Characteristic) curves (Adlassnig & Scheithauer, 1989) were calculated in order to select the best curve. These curves were constructed by varying the detection threshold–i.e. a network output value above which a fire is predicted–between 0.05 and 0.95. On comparing the curves obtained over the validation set, the 6-9-1 network topology (6 inputs, 9 hidden neurons and 1 output neuron) was selected.

In order to determine whether or not the network output indicates the prediction of a fire, a detection threshold

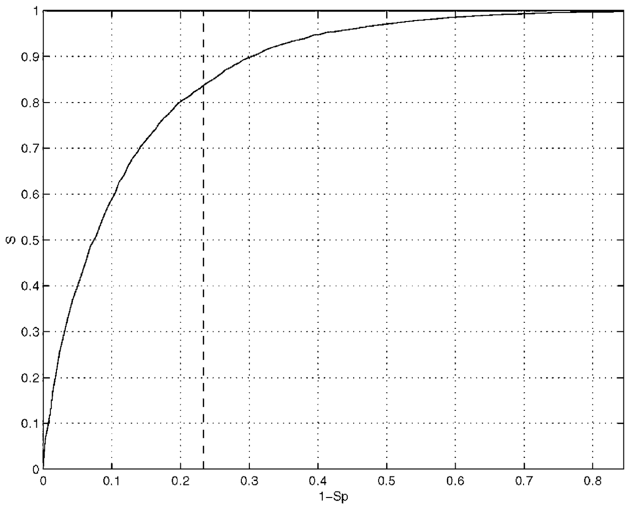

Fig. 2. ROC curve for the 6-9-1 network using the validation data.

splitting the output interval into two sub-intervals was fixed. Using the ROC curve built using the validation set and following the recommendations of experts in the field regarding the maximum false positive rate allowed (around 23.3%; represented by a broken line in Fig. 2), the final detection threshold was fixed at 0.5. Afterwards, the performance of this network was assessed using measures based on the number of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN). These measures were (Weiss & Kulikowski, 1990):

- Accuracy (A) = (TP + TN)/(TP + FN + FP + TN)
- Sensitivity (S) = TP/(TP + FN)
- Specificity (Sp) = TN/(FP + TN)
- Positive Predicted Value (PPV) = TP/(TP + FP)
- Negative Predicted Value (NPV) = TN/(FN + TN)

Table 1 shows the contingency matrix obtained for the training and validation data, and Table 2 shows the performance measurements for the same sets.

A study was also carried out on a year-by-year basis for the 6-9-1 network in order to check the variability of the performance of the system for years 1988–1999. Fig. 3 shows the ROC curves for each of these years, using all the available data and not only cases in the training and validation sets. As can be observed, sensitivity for the fixed threshold (vertical line) ranges from 0.757 (years 1989 and 1992) to 0.915 (years 1996 and 1997).

Once the best network was selected and its parameters and thresholds fixed using the training and validation sets, the network was applied to the test data in order to assess the generalisation capacities of the model. The right column in Table 1 shows the results for the contingency matrix and the performance measurement values are shown in Table 2. The ROC curves for all the days of 2000 and 2001 are depicted in Fig. 3.

As previously mentioned, for the benefit of the user the predictions will be categorised in terms of four symbolic risk levels (low, medium, high and extreme). The risk classification low was assigned to the negative cases, i.e. cases falling in the interval [0.05, 0.5]. The range indicating prediction of a fire, i.e. the interval [0.5, 0.95], was further uniformly divided into three sub-intervals associated with the risk classifications *medium*, *high* and *extreme*. On the basis of these thresholds, the set of cases predicted by the system for the test set in Table 1 was broken down as in Table 3. Finally, in the form of a bar diagram, Fig. 4 shows the proportion of real fires in each of the risk categories predicted by the network for each day of the years 2000 and 2001. Fig. 4a shows this information by predicted category, while Fig. 4b shows the same information in terms of the occurrence or non-occurrence of a real fire.

4. The fire management subsystem

The development of a software platform for fire management and recuperation of the burned areas requires a methodical structuring of the knowledge specific to the fire-fighting organisation for which the system is being developed. The system described here, which manages fires from beginning to end, includes a series of features that will assist decision making in terms of the organisation of the resources to be mobilised.

With a view to developing a system that can be easily maintained, the CommonKADS methodology (Schreiber et al., 2000) was applied to the preparation and management of the project. A standard for the analysis and construction of knowledge-based systems, this methodology covers all development process stages. To construct the system, CommonKADS develops a set of models that take different perspectives on the situation being analysed and for which it

Table 1
Contingency matrix for the training, validation and test sets

		Real classification					
		Training		Validation		Test	
		Fire	¬ Fire	Fire	¬ Fire	Fire	¬ Fire
System classification	Fire	53685	15059	5903	1736	13494	4864
	¬ Fire	8914	47498	1029	5238	1427	10057

Table 2
Performance measures obtained for the training, validation and test sets

	A	S	Sp	PPV	NPV
Training	0.809	0.858	0.759	0.781	0.842
Validation	0.801	0.852	0.751	0.773	0.836
Test	0.789	0.904	0.674	0.735	0.876

is intended to construct the knowledge-based system. Below we describe the main modeling phases.

4.1. Contextual modeling

This phase represents the initial approximation to the problem covered by CommonKADS in its Organisation, Task and Agent models. These models allow us to understand the organisational context in which the system is to be developed, to identify knowledge-intensive tasks, knowledge assets and the agents possessing these assets, and finally, to estimate the feasibility of the project, among other tasks. After analysing the fire-fighting processes (Paz López, 2002), a set of knowledge-intensive tasks that delimit the range of the system was identified. These tasks, depicted in Fig. 5, are as follows:

- *Study of fire propagation* to predict how the fire develops.
- *Study of the difficulty of controlling the fire*.
- *Classification of the fire* according to a scale established by the organisation.
- *Selection of general recommendations* within the standard procedures of the organisation, so as to mobilise the necessary resources in function of the level of fire risk and the characteristics of both the fire and the environment.
- *Planning of the initial action* so as to determine the human and material resources required for extinction.

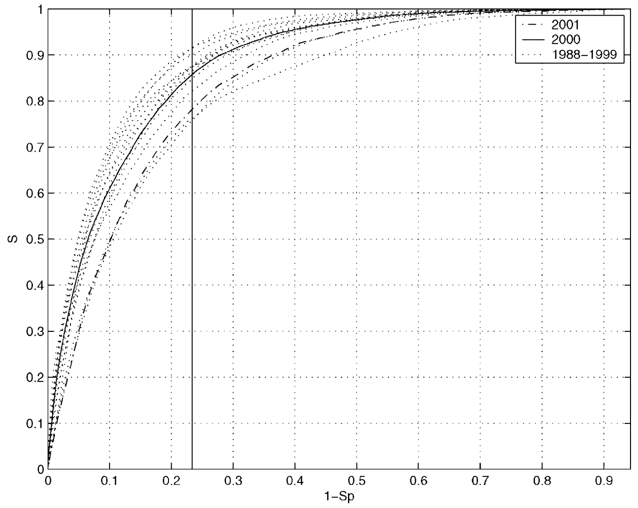

Fig. 3. ROC curves for 1988–2001. Dotted lines refer to the years 1988–1999, while the other lines correspond to test data for the years 2000–2001.

Table 3
Contingency matrix for test data (years 2000–2001) showing the four fire risk levels

		Real classification	
		Fire	¬ Fire
System classification	Extreme	7023	1071
	High	4744	2028
	Medium	1727	1765
	Low	1427	10057

- *Planning of extended action* so as to manage the forest fire on an ongoing basis and bring in new resources if required.
- *Analysis of the impact of the fire* in terms of damage to the environment and future levels of degradation.
- *Evaluation of the set of measures necessary* for the recuperation of the environment.
- *Prioritisation of the recuperation of the area* to determine the degree of urgency of recuperation.

It is important to mention that the fire analysis tasks are carried out on an ongoing basis in order to monitor the fire's characteristics, development and progression. This information will be vital in designing any approach to controlling and extinguish a fire.

In this phase also, the required fire fighting equipment and computational and other resources were identified, including historical databases, information on the geographic locations for available fire-fighting resources, the location of natural parks, daily meteorological data, fire reports, etc. Also, frequently manipulated by the organisation are digital maps that include edapholgical, geological, hydrographical and vegetation information, etc. Finally,

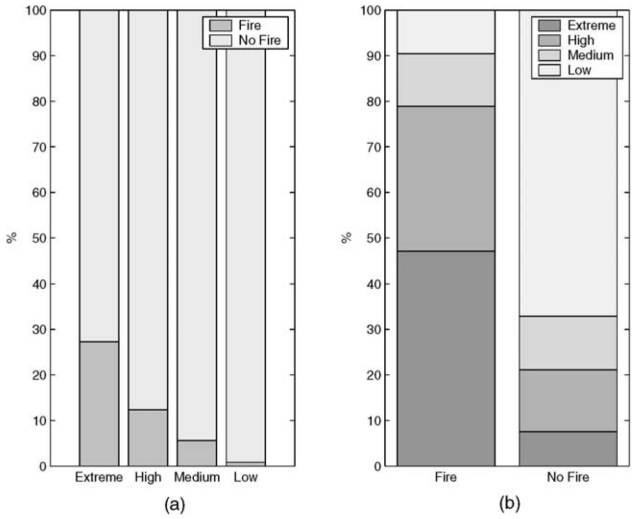

Fig. 4. Bar diagrams calculated for the years 2000 and 2001 that compare the real classification of cases and predicted risk: (a) percentage of real categories for each predicted category, (b) percentage of predicted categories for each real category.

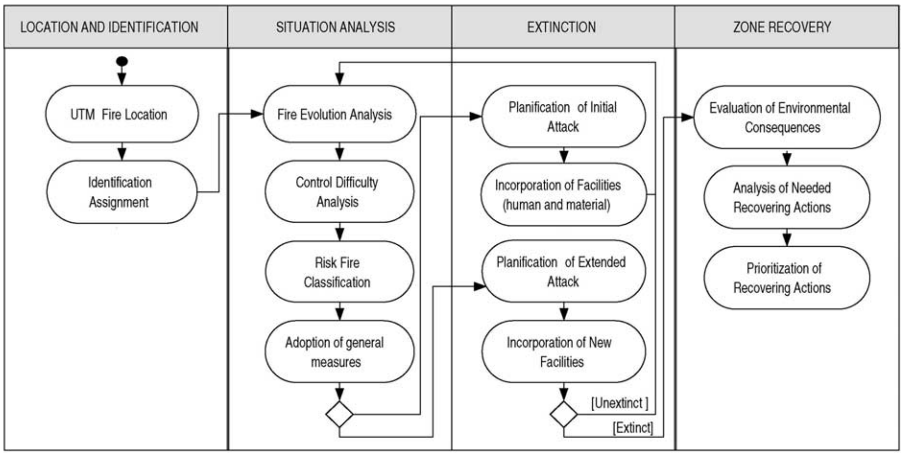

Fig. 5. Activity diagram of the breakdown of the process into tasks for the fire management subsystem.

certain meteorological parameters were also obtained from a network of observation points distributed throughout the region.

4.2. Conceptual modeling

Conceptual analysis enables the descriptive or procedural knowledge used in the implementation of activities to be identified and described and, in conjunction with the above model, the requirements of the system to be established. This analysis, the results of which are summarised below, was performed for each of the tasks identified in Section 4.1.

4.2.1. Study of fire propagation

The aim of this task is to analyse active fires with a view to predicting the way in which they propagate. This information is used for a variety of purposes: to evaluate the risk of a fire endangering a populated area or a zone of natural beauty or to evaluate the movement or optimal location of fire extinction resources. To predict the speed and direction of the fire, we use a model developed specifically for Galicia by the Lourizán Forestry Research Centre on the basis of controlled fire studies. The model is based on meteorological variables such as humidity and wind patterns and on characteristics of the terrain, obtained automatically or provided and/or modified by the user.

4.2.2. Study of degree of fire control difficulty

The level of difficulty experienced in terms of bringing the fire under control is one of the variables that influences the prioritisation awarded to the different fires active at a given moment. The objective here is to provide a rapid idea of the difficulty of bringing the fire under control at any given moment in its development, bearing in mind variables such as type of fire (subsoil, soil or treetop fire), the speed of propagation of the fire, characteristics of the affected area (accessibility, proximity to water sources, etc.) and meteorological variables. Again, these variables can be obtained automatically and can be further refined by the user. Moreover, the module for this task is equipped to work with incomplete information. Finally, the output of this task is a symbolic classification of the difficulty of bringing the fire under control as *low*, *medium* or *high*, which may be accompanied by an explanation if the user so requires.

4.2.3. Classification of the fire and selection of general recommendations

The module concerned with these tasks provides a classification of the gravity of the fire according to a scale used by Galician fire-fighting organisations, as per Fig. 6.

Along with a description of the characteristics of the fire and the established level of seriousness, a series of measures of a general nature for practical application are recommended. These measures range from alerts to the local population to information on the need to bring in additional fire extinction resources from outside Galicia.

4.2.4. Planning of initial and extended action

After the analysis of the situation carried out in the above tasks is complete, a new task concerned with extinguishing the fire is implemented, with a view to developing programmes and protocols for fighting the fires. The system is capable of establishing and managing the general plans and protocols defined by the fire-fighting organisation. On the basis of characteristics of the fire such as seriousness or

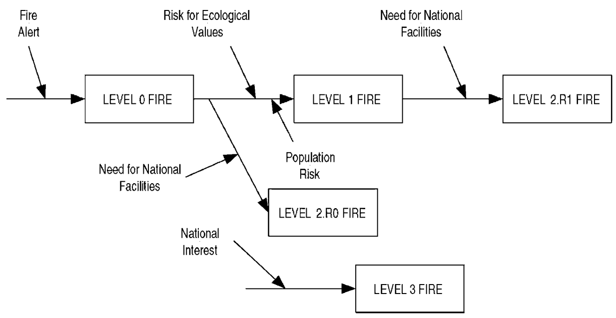

Fig. 6. Classification of forest fires in levels of seriousness.

the difficulty of bringing it under control have been assessed, the initial action is taken and is subsequently refined by means of successive planning of extended actions, depending on how the fire progresses (Fig. 5).

4.2.5. Analysis of the impact of the fire, evaluation of the measures for recuperation of the area, and prioritisation of recuperation

This final part includes three tasks, namely *analysis of the impact of the fire* on the environment ,*evaluation of the set of measures necessary for recuperation* of the environment and *prioritisation of recuperation*. The impact of the fire on the natural environment is evaluated on the basis of the fire's intensity, duration and depth of penetration in the soil, the loss of organic material on the surface and the danger of erosion. Once the consequences for the environment have been evaluated, measures for suitable recuperation of the environment are studied. These measures are structured in terms of general recommendations with different implementation phases and activities, such as replanting and the replacement of microorganisms, etc. When various areas need action the first of the tasks is to establish priorities within the restrictions imposed by financial, material, personal and time resources. Taken into account are input factors such as soil degradation, the kind of vegetation to replace, the size of the affected area and the time of year.

4.3. Design model

Once the requirements of the knowledge-based management system in the models described above have been established, the design model describes the structure of the system software that is required. This process commences with a specification of the software architecture in terms of subsystems and modules, and applies a structure-preserving approach. In this way the content and structure of the information in previous models are maintained, thus guaranteeing the quality of the application and facilitating maintenance, updating and code reuse. Also identified at this point is the hardware and software required for the implementation platform; in our case the system has been designed for use on personal computers. For this knowledge-based system an approach based on rules that employ CLIPS (Riley, 2002) as the development language was used. DELPHI was used for the implementation of the skeleton of the application, i.e. the user interface; control and access functions for the historical and meteorological databases were implemented in Paradox format.

The features of the system have been successively validated by experts, with a view to ensuring correct results and the suitability of the system to the organisational environment in which it will be implemented. Following the modeling phases a fully operative prototype adapted to the Galician fire-fighting organisation's requirements was tested, which provides many possibilities for extension and fine-tuning of the proposed solution.

5. System architecture

The tasks described form part of a more ambitious project that includes the components depicted in Fig. 7; these are:

- *Extern Data Access*
    - *Online acquisition of meteorological data*: an independent module designed to obtain data, via the Internet, from the automatic meteorological stations in Galicia (marked in Fig. 1). These data are used both by the prediction system and the fire management system.
    - *Databases*: these store information on previous fire control actions, the environment, records of meteorological variables, characteristics of the terrain, resources, etc.
    - *Geographical Information System*: this provides geographical data, such as on accessibility or the orography of an area, to be used by the resource management system.
- *Intelligent System*
    - *Fire risk prediction*: as already discussed in Section 3 this system predicts the risk of forest fires. To graphically illustrate prediction results, the four risk categories (low, medium, high, extreme) are represented on a map of Galicia using the colours green, yellow, orange and red, respectively (Fig. 8).
    - *Fire management*: this module plans fire extinction actions and recuperation of the affected areas, as described in Section 4.

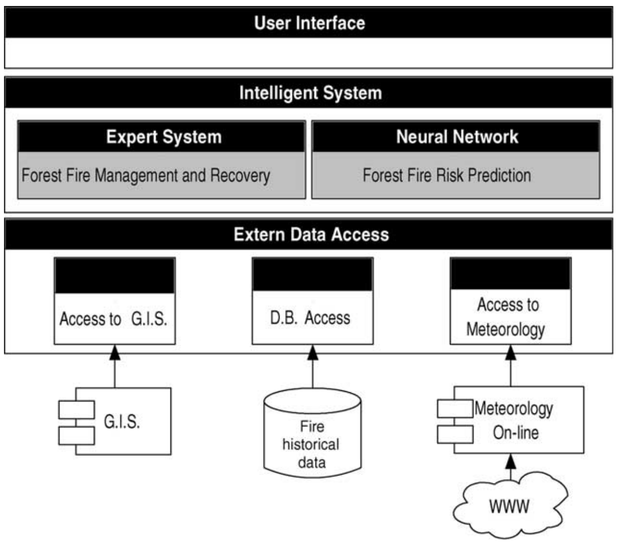

Fig. 7. Overall architecture of the system.

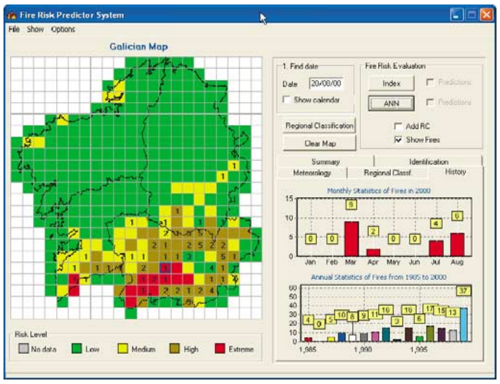

Fig. 8. View of the user interface of the fire prediction system.

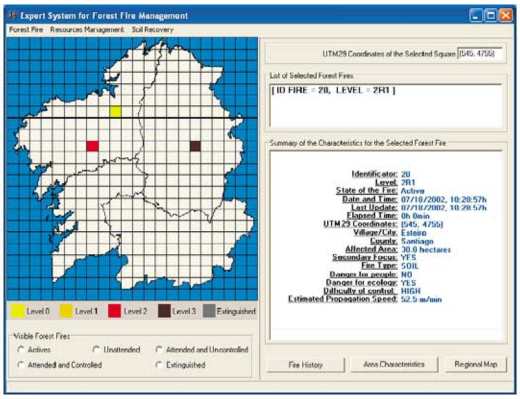

Fig. 9. View of the user interface of the system developed for managing fire-fighting resources.

- Additional features:
  - Maintenance, update and viewing of information on each forest fire tackled by the fire-fighting organisation. This includes both information on the characteristics of the fire and its progression over time, as well as geographical and meteorological data on the affected area.
  - Search for and selection of fires on the basis of parameters such as level of risk, status or location.
  - Viewing of raster maps and provision of a range of data for specific areas of Galicia.

Figs. 8–10 show examples of the user interface of the system prototype. Fig. 8 shows fire prediction for a specific day. Each square of the map is coloured according to the level risk forecasted; also recorded are the number of fires that actually occurred. This interface can be used to view both future prediction data and historical prediction data. The system also shows monthly and annual fire statistics for any square selected by the user.

Fig. 9 shows the resource management system. Views are obtained of the list of fires in any selected square according to the status of each fire: active, unattended fires (no resources have been dispatched), attended fires under control, attended fires out of control, and extinguished fires. Selecting a square also calls up a list of fires declared, as well as detailed information on each. The system also has a set of functions so that the user can consult additional

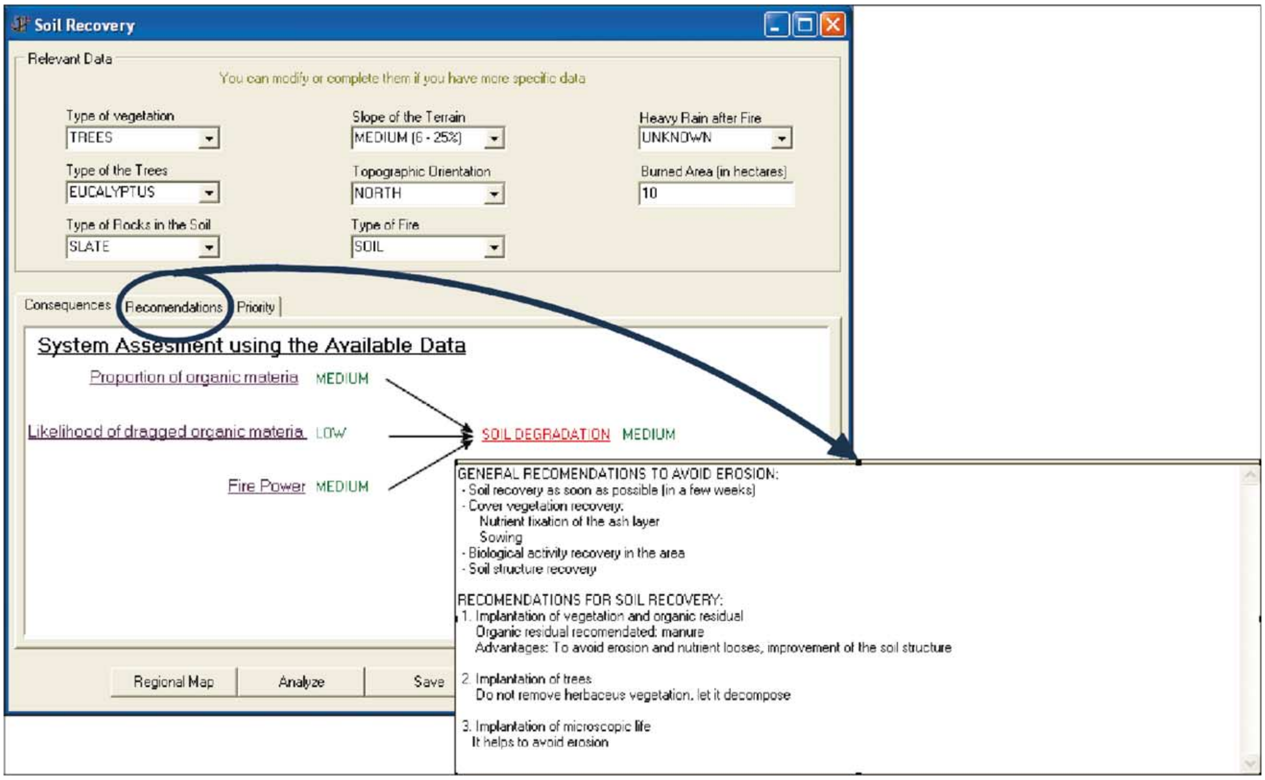

Fig. 10. View of the user interface of the system developed for recuperation of the burned areas.

information on the geography and meteorology of the area or raster maps of the square in question.

Finally, Fig. 10 shows the output provided by the system for the tasks involving *analysis of the impact of the fire* and *evaluation of the measures* necessary for the recuperation of the affected area.

6. Discussion and future work

The system described in this article integrates three tasks that are crucial to the fight against forest fires: prediction of fires, management of fire extinction resources and recuperation of the affected areas.

Regarding to the *Prediction System*, comparing the performance measures provided in Table 2, it can be observed that the generalisation capacities of the network are maintained when evaluated over a set of cases not used in its development. This fact can also be observed in the ROC curves in Fig. 3, were the curves for the years 2000 and 2001, i.e. the test sets, are similar to the others. This indicates that the training and validation data sets were adequately designed to optimise the generalisation capacities of the neural network.

As far as test results are concerned, the highest performance indices for the neural network were the sensitivity and the NPV measurements, both of which were above 0.87. Consequently, (a) the system's fire prediction capacity have been proven to be quite satisfactory (see fire category in Fig. 4b), and (b) almost no fires were recorded (Fig. 4a) when a negative classification was predicted (i.e. *low* risk category). On the other hand, the PPV and particularly the specificity values indicate that the false positive rate is high (Table 1). This can be partly explained by the following:

- The detection threshold was fixed on the basis of expert criteria so as to minimise the risk of failing to predict a real fire; the cost of this error would obviously be higher than that of a falsely predicted fire.
- The system was designed to evaluate meteorological conditions that might indicate a possible outbreak of fire. However, the fact that meteorological conditions are favourable does not imply that a fire is necessarily produced.
- A low PPV is, to a some extent, intrinsic to any prediction system when preventative actions are carried out in order to avoid the occurrence of the fact it is trying to predict, i.e. fire outbreaks in our case.

As can be seen in Fig. 4, the relationship between the risk level represented by each category (low, medium, high and extreme) and the number of true positives and true negatives classified in that category is particularly worthy of note. A positive correlation exists between the predicted risk level and the number of real fires in each category.

Furthermore, several additional experiments were carried out: (a) to verify whether meaningful differences existed between real and extrapolated data, the network was trained using only real meteorological data; (b) to check if there were significant differences between regions, a network for each of the five non-automatic meteorological stations was trained; and (c) to observe whether there was any relevant seasonality information that was not reflected in the variables already included, an input variable indicating the day of the year was included.

In none of the cases did the results obtained significantly improve our initial proposed solution.

In order to improve the specificity of the network we are currently considering new input variables for the prediction model, such as socio-economic and terrain factors (i.e. existence of a road, type of vegetation, etc.). These new variables are better handled using symbolic techniques, and an expert system is currently being developed to take this additional knowledge into account that will eventually be integrated with the neural network described above.

Finally, the thresholds used to discriminate between fire risk categories have been assigned so as to uniformly divide the interval [0.5,0.95] for true positive cases. However, the fixing of these thresholds is a subjective matter that needs to be assessed by experts, and consequently, we are currently in consultation with a group of field experts for this purpose.

As for the evaluation of the subsystems for *resource management*, *fire extinction* and *recuperation* of the burned areas, these have been built applying a spiral development software methodology. Thus, the different phases have been reviewed on a number of occasions throughout the software development process. For example, the modeling phase results were presented to experts so as to detect knowledge engineer interpretation errors. The features of the knowledge-intensive tasks have been reviewed by experts so as to detect possible improvements in the way these tasks are resolved. Moreover, several prototypes have been developed, thus providing users with the opportunity of participating more actively in the development of the software, as follows:

- Several user interface prototypes were developed and tested by the client throughout the development of the system.
- The method for presenting results to the user was reviewed, resulting in a shift from text format to graphic and schematic format.

Lines of investigation for the near future include extension of the planning tasks for fire-fighting actions to include *dynamic* reallocation of resources on the basis of the progress of a fire, and the validation of the system in a controlled real environment.

7. Conclusions

This paper describes an intelligent system for management and control of fire-fighting actions from beginning to end to be applied in Galicia. A rule-based system supports decision-making in the organization of fire-fighting actions and the recuperation of the affected area. It is based largely on meteorological and geographical data, and the decisions are guided by a need to minimise costs in terms of human life and the loss of natural resources. The CommonKADS methodology was used to develop the system, which required significant work on the structuring of domain knowledge. It will also facilitate future extensions and improvements.

The system also includes a forest fire prediction model based on a neural network and using meteorological data as the basis for assessing fire risk. The prediction obtained acceptable results using real data, bearing in mind that an intrinsic level of error that cannot be reduced occurs as a consequence of the significant number of fires that are deliberately provoked in this area.

Currently we are working on the trail of the system in a controlled real environment. This will provide results on real behaviour that can be used to fine-tune the system to the point where it is considered suitable for installation in a real application environment.

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