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Frame- and rule-based knowledge representation in an expert system for integrated management of bark beetles

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TIIVISTELMÄ: KEHYS- JA SÄÄNTÖPOHJAINEN TIETÄMYKSEN ESITYS KAARNAKUORIAISTUHOJEN INTEGROIDUN HALLINNAN ASIANTUNTIJAJÄRJESTELMÄSSÄ

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Decision making in forest protection involves diagnosing the pest, making predictions of the effects of the pest on forest, knowing the possible control tactics, and cost/benefit integration. To cope with all that, a generalist forest manager needs a tool like an expert system to support decisions.

This paper presents an expert system that approaches the goals of integrated pest management. With the system, the user can make diagnosis and prediction of 12 North European bark beetles. Written in Common LISP and Flavors, the expert system has a combined frame- and rule-based knowledge representation. Frames are used to represent the hierarchy of insect taxonomy in diagnosis. Prediction is made with qualitative reasoning with rules. The inference engine applies both forward and backward chaining. The system has a graphical user interface that supports exploring the sensitivity of advice on input.

It is concluded that expert systems and artificial intelligence have high applicability everywhere in forestry where complicated decisions have to be made. Especially, an integrated pest management system in forestry is largely equivalent to a computerized decision making aid.

Metsänsuojelun päätöksenteko edellyttää tuholaisen tunnistamista, ennusteiden laatimista tuholaisen vaikutuksesta metsään, torjuntamahdollisuuksien tuntemista ja hyötyjen ja kustannusten vertailua. Jotta metsäammattilainen, joka ei ole metsätuhojen asiantuntija selviäisi näistä tehtävistä, hänellä täytyy olla käytettävissään jonkinlainen väline päätöksenteon tukemiseen, esim. asiantuntijajärjestelmä.

Tutkimuksessa esitellään asiantuntijajärjestelmä, joka on rakennettu integroidun metsätuhojen hallinnan periaatteiden mukaisesti. Sen avulla voidaan tunnistaa ja laatia ennusteet 12 Suomessa esiintyvälle kaarnakuoriaiselle. Ohjelmisto on kirjoitettu Common LISPillä ja sen Flavors-laajennuksella ja siinä yhdistyvät kehys- ja sääntöpohjainen tietämyksen esitys. Kehysten hierarkiaa käytetään hyönteisten taksonomian esittämiseen. Ennuste laaditaan sääntöpohjaisella eteen- ja taaksepäin ketjuttavalla laadullisella päättelyllä. Ohjelmalla on graafinen käyttöliittymä, jonka avulla voidaan tutkia johtopäätösten riippuvuutta syöttötiedoista.

Asiantuntijajärjestelmät todetaan soveltamiskelpoisiksi metsätalouden monimutkaisten päätösten tukemisessa. Erityisesti metsätuholaisten integroidun hallinnan järjestelmät ovat täysin riippuvaisia päätösten tukemisesta tietokoneiden avulla.

Keywords: expert systems, frame-based knowledge representation, integrated pest management, modeling, Scolytidae.
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1. Introduction

When dealing with bark beetles that potentially can damage forest, the forest manager must be able to diagnose the situation and have some idea how it will develop before decisions about control can be made (Waters and Stark 1980). Diagnosing the situation includes determining the pest species, that can be many, and making forecasts about their population dynamics and their effects on the stand. Generally, forest managers that are not pest control experts can recognize a risky situation, but are uncertain about the specific insects unless they are dealing with major pests such as the North American *Dendroctonus* species. In making forecasts, even the experts are often uncertain because predictive models do not exist but for a handful of pests. Decision making under such uncertainties can lead to costly mistakes and is stressing for the individuals involved.

These stresses can be relieved if there is a decison aid that brings the knowledge of the experts into the hands of forest managers (Coulson and Saunders 1986, Kaila and Saarenmaa 1990). Expert systems seem to offer this possibility. Expert systems are based on the paradigms of artificial intelligence, which means that for the first time there are computer programs that are geared to mimic the reasoning of human experts. In every expert system there is an inference engine that executes the contents of a knowledge base which contains a description of the knowledge of the domain. A human-like flexible line of thought and explanation of the underlying mechanisms is achieved by creating the actual control program in run-time from the user input and the contents of the knowledge base. This is reasonable only with such artificial intelligence languages as LISP and Prolog where programs and data are the same (e.g. Winston and Horn 1984, Clocksin and Mellish 1984).

An expert system can be constructed in many ways, but the most popular form, rule-based expert system (Buchanan and Shortliffe 1984, Hayes-Roth 1985), uses rules of the form: IF antecedents THEN conclusions. Making of such an expert system is essentially creating a rule base for the domain where the knowledge pertinent to problem solving is stored. By giving some initial facts and then matching them against the rule base and chaining these inferences, solutions to problems can be found. When needed, the system asks for more facts. Explanation of the reasoning can be printed out while the inferences are made.

Another form of expert systems utilizes frames to represent prototypical knowledge for situations (Aikins 1983, Fikes and Kehler 1985). This is like having a description of a typical situation where the inferences of matching or mismatching of facts against the details in that frame are made in parallel. Much of the problem solving of experts in determining insects is like using frame-based knowledge: "The specimen belongs to species x, because it looks like x". An expert's mind can be understood as a collection of frames: only being able to cover an entire field by frames a person becomes an expert. And by using heuristics the expert can fill the possible gaps between the frames. Frames can store any kind of knowledge in their slots, e.g. rules for diagnosis verification (in the case that the specimen does not look like anything), or lists of actions after the situation in a frame has been verified, and so on. A common use of frames is to organize large rule-bases into smaller units. Normally frames form a hierarchy. Specialized low-level taxa inherit features from the levels above.

Now it should be apparent how expert systems for bark beetle related forest management can be done. However, previous attempts to computerize pest management systems have not been very successful (Coulson and Saunders 1986, Coulson et al. 1989). Before making an expensive commitment to still another system, we must understand why the technology transfer has not taken place earlier. These systems have been stand-alone simulation models that predict pest population dynamics and their effects in forests. A decision support system for southern pine beetle management is the only of its kind in forestry (Saunders et al. 1986), but has not gained wide acceptance among potential users. Loh et al. (in prep.) and Coulson et al. (1989) concluded that the reasons for this unacceptance have to do with 1) interpretation difficulties with the numeric predictions, 2) unergonomic user interface, 3) subtle confidence estimates, 4) lack of sensitivity estimates, 5) lack of explanation of the underlying mechanisms, and 6) lack of computer access and skills. While time takes care of the last one, expert systems can address all the rest of the problems.

The purpose of this study is to study the design of an expert system that helps the non-expert forest manager to make decisions about bark beetle management. The system should be able to diagnose the pest(s) and predict the course of their dynamics and effects on the forest. Exploring the control tactics and costs /benefits is left for another context. The system should address the problems of the previous computer-based systems by better explanation and to create understanding of the underlying mechanisms in the user.

2. General structure of the system

21. Concepts of integrated pest management in the context of expert systems

The theory of integrated pest management (IPM) provides the concepts along which modern pest management systems have been built during the last two decades. Its general outline in forests has been described by Rabb and Guthrie (1970), Waters and Stark (1980), Wood (1980), Payne and Saarenmaa (1988). Normally an IPM system has components for 1) pest population dynamics, 2) forest dynamics, 3) pest /forest impacts, 4) control tactics, and 5) cost/benefit integration. While this outline provides a good start for this project, it must be redefined for expert systems development (Stone et al. 1987, Stone and Saarenmaa 1988, Coulson et al. 1989). The necessary extensions can be seen in Fig. 1.

First, a monitoring component has to be made explicit. Monitoring results are stored in a geographic information system that holds data on all forest resources. These important components are not not dealt with in the present study. However, monitoring may alert the diagnosis module, which also needs to be added to the classical IPM scheme. An explicit module for diagnostics is necessary, because generalist forest managers seldom are experts when diagnosing but major pests. In most cases also multiple pest species are involved. Hence, cases should rather be diagnosed than insects.

For each of the pest species, separate predictions of population dynamics need to be made. With the predictions, however, we usually have to suffice with qualitative estimates, since for most pests there are no quantitative models available that could be used for exact predictions. Bearing in mind this major gap in our knowledge, exact reasoning further from this point is meaningless: in pest/forest interactions, control tactics and cost/benefit integration, only emergent trends must be recognized and reasoned about. This also indicates why IPM systems have not actually been implemented in forests yet: the large uncertainties have made decision making more opinion- and experience-based art than exact science. IPM is complicated and largely equivalent to a computerized decision making tool, but only expert systems provide the kind of qualitative reasoning and explanation which is needed.

The present system that is called I-IPM (Intelligent IPM) was designed along these concepts (Saarenmaa 1988). At the top level there is an IPM control program that calls the subtasks. There are separate modules for diagnosis and prediction, which must be called in this order. Each pest species has its own knowledge base for prediction. Modules

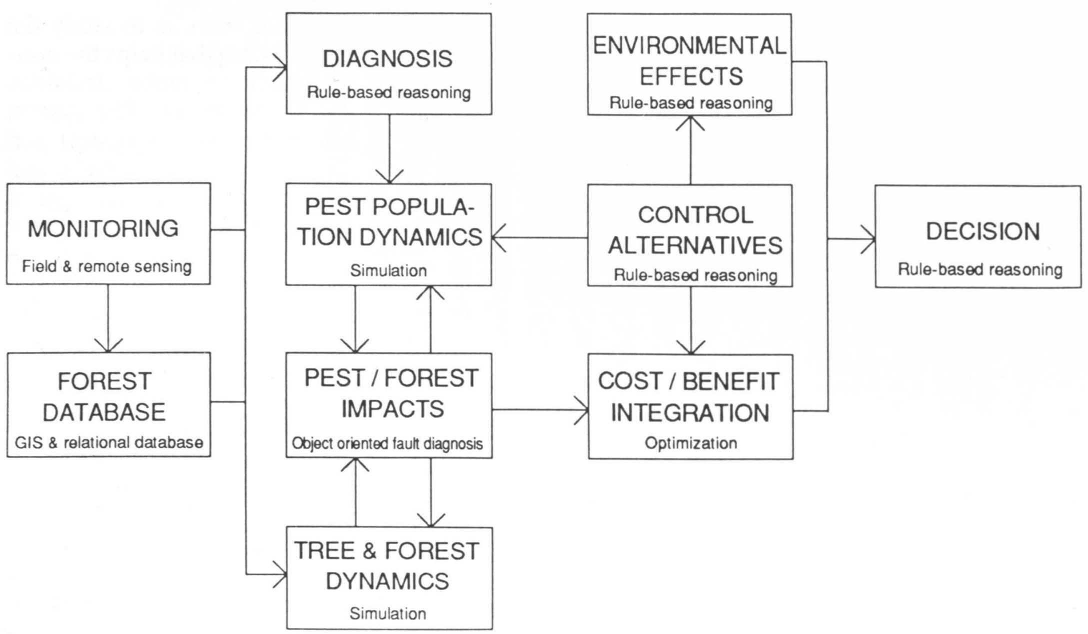

Fig 1. Components of an information system for integrated pest management.

for control, impacts, and decision-making can be added later.

22. Implementation and user interface

The program I-IPM is written in Common LISP and the object-oriented programming package Flavors on a Symbolics 3620 workstation. Object-oriented programming makes constructing of complex systems relatively easy and the incremental development on a LISP-machine greatly accelerates the pace of prototype creation.

When running on a computer, such a complicated system as IPM must have a clear interface. The windowing system of Symbolics is used for this purpose. The screen is divided into three panes. At the top of the screen there is a permanent top-level IPM window that controls the other windows (Fig. 2). Large boxes represent the separate modules. These are represented by frames holding task lists in the program. By clicking a box with the mouse, the user can execute a module, provided that its initial data from other modules has already been retrieved. The control can also be passed over to the program by executing all the modules in default order.

The lowermost pane is also permanent. It is used for explanation of queries and reasoning. The middle pane changes with the program under execution. Normally it shows graphically the dependency networks of the knowledge that is currently being used.

3. Diagnosis

31. Knowledge representation

Medical diagnosis is the first area where rule-based expert systems proved to be successful (Buchanan and Shortliffe 1984). Diagnostic expert systems have after that spawned over an array of fields. Identification of insects has also been shown to work well (Stone et al.

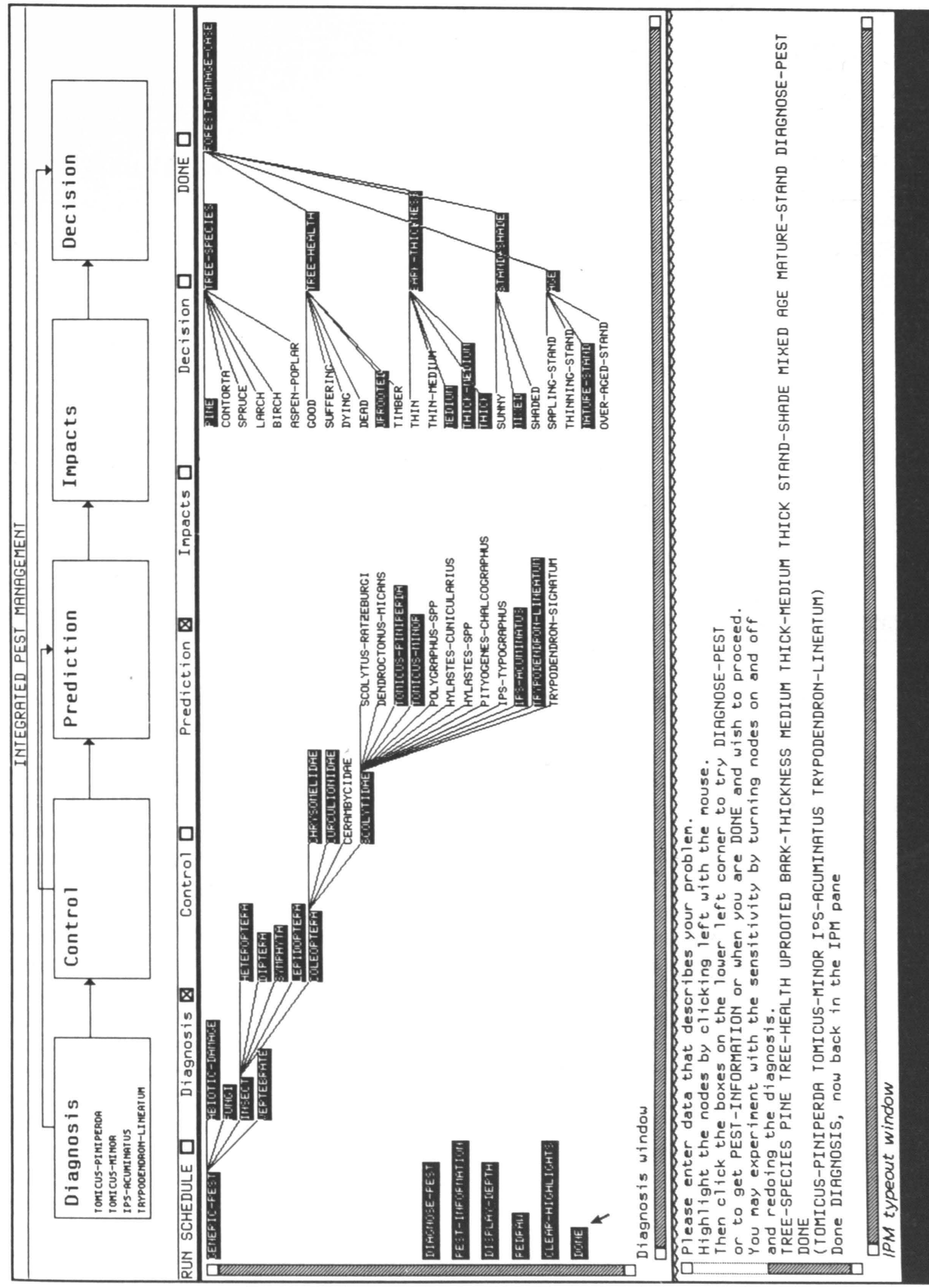

Fig 2. Screen of the Symbolics workstation showing the diagnosis phase of a consultation.

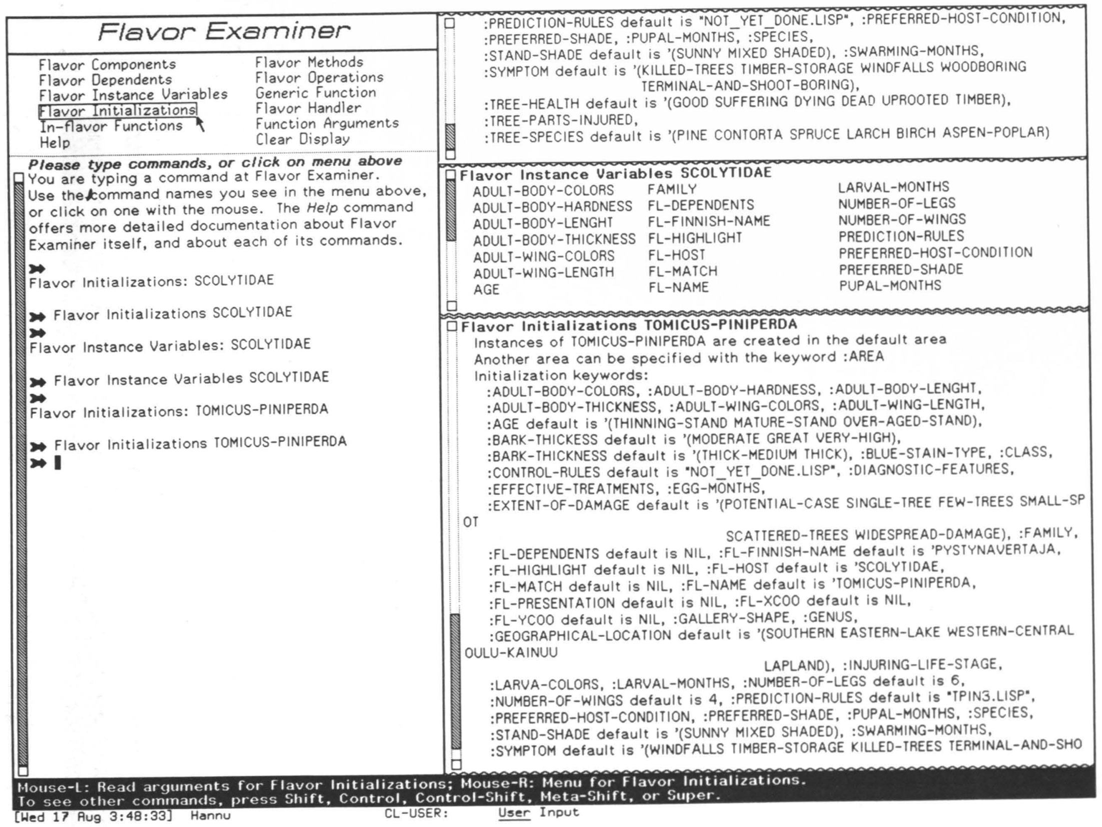

Fig 3. SCOLYTIDAE and TOMICUS-PINIPERDA flavors in the Symbolics' flavor examiner.

1986a, 1987). Most of the diagnostic expert systems have been rule-based, but especially in industrial fault diagnosis where the system under study is closed and well-defined, frame- and model-based systems have also been created (IntelliCorp 1986).

Frame-based representation offers several advantages in entomological diagnosis. The most formidable one is that the natural system of taxonomy can be used as a model. The inheritance among frames representing the individual pest taxa can be modeled after it. E.g. the bark beetle frame has slots that contain attributes found in all bark beetles such as egg gallery type, preferred bark thickness, and aggressiveness. These attributes are inherited from the family level to the individual species. Any special data at the species level overrides the family data where needed. The pest hierarchy is shown in the middle window of Fig. 2 and the SCOLYTIDAE and TOMICUS-PINIPERDA flavors in Fig. 3. The frames were implemented by the outlines given by Aikins (1983).

In the present system, frame-based representation is used also to store data about the forest. However, representing the forest for this or for any purpose where tree health is considered is more complicated than just asking for inital data. In its simplest form, the slots in pest frames determine the data from the forest that is needed for diagnosis. These are also presented as frames, and shown in the right hand side of the middle window of Fig. 2. However, in the present model these have no bearing to the functioning of forest at all and hence are typical "surface knowledge". In the present work we accept this representation, but in further work a deeper model-based representation of forest will be sought for.

32. Reasoning and sensitivity

The user gives the initial data by clicking on the nodes in the tree representing the forest. The nodes will be highlighted (see Fig. 2). When the user is satisfied with the desciption, s/he clicks on 'DIAGNOSE-PEST' and the highlighted forest-nodes will be matched against the values of the instance variables in the pest nodes. The matching pest nodes are then highlighted. This shows another advantage of frame-based representation: determining bark beetles in the forest is determining a situation. The bark beetles that are possible pests in a forest can be inferred from the stand and infestation characteristics rather than from scrutinizing the actual insects. Multiple pests are usually found for a case.

The sensitivity of the diagnosis can be explored by turning nodes off and on and redoing 'DIAGNOSE-PEST'. The analysis works also inversely like a Prolog program. By marking insects, the user can show the conditions in which they can occur by clicking 'PEST-INFORMATION'. Implementing this is easy when there is a model to be reasoned about.

Sometimes the trees may not fit in the middle window. To overcome this, the window has scroll bars and the trees can also be shown dynamically from the part that is only needed. Should the user know the species already, s/he can directly mark it and click 'DONE' to transmit diagnosis to other modules.

4. Prediction

41. Knowledge representation

There are many ways to predict the course of an infestation. Experts do that by reasoning from the environmental facts and pest-related knowledge. For a handful of pests there are simulation models available that do the same in quantitative measures. In the present domain, such a model exists only for *Tomicus piniperda* (Saarenmaa 1985) and partially for *Ips typographus* (Schlyter 1985, Anderbrandt et al. 1988). In most cases the prediction has to be done in qualitative reasoning using textbook knowledge and expert opinion. This is a typical domain for a rule-based expert system.

In I-IPM after the diagnosis, prediction rules that are stored in a slot of the pest flavor are loaded, and the course of the infestation is inferred. Starting from such facts as tree characteristics, pest density, climate, etc., rough quantitative estimates for pest population dynamics are derived, and their effects on trees evaluated the same way. What comes up from this rule-based qualitative reasoning is a rough estimate of the damage, e.g. "moderate". Some of the rules for prediction in the case of *Tomicus piniperda* are shown in Table 1 and the dependency network of the rule base in the middle window of Fig. 4. Rule bases for other bark beetles are underway.

Before a rule base can be written, a dependency network like the one in Fig. 4 must be first drawn on a paper and then translated into the rule language. In I-IPM these dependencies are shown graphically as a network of entities affecting each other. This knowledge is readily available in publications and, enriched with the heuristics that the expert has acquired during his life, very well can be represented as rules. The "deepness" of the knowledge (Kinnucan 1984, Koton 1985) does not depend on the representation chosen, but on the proximity in which the elements in the knowledge base model the essential causal components of the real system.

These rules as well as functions for simulation models can be stored in the slots of the particular pest frame to be invoked after the diagnosis. This representation is good also because later knowledge about the control tactics and further actions can be stored in other slots for each pest species.

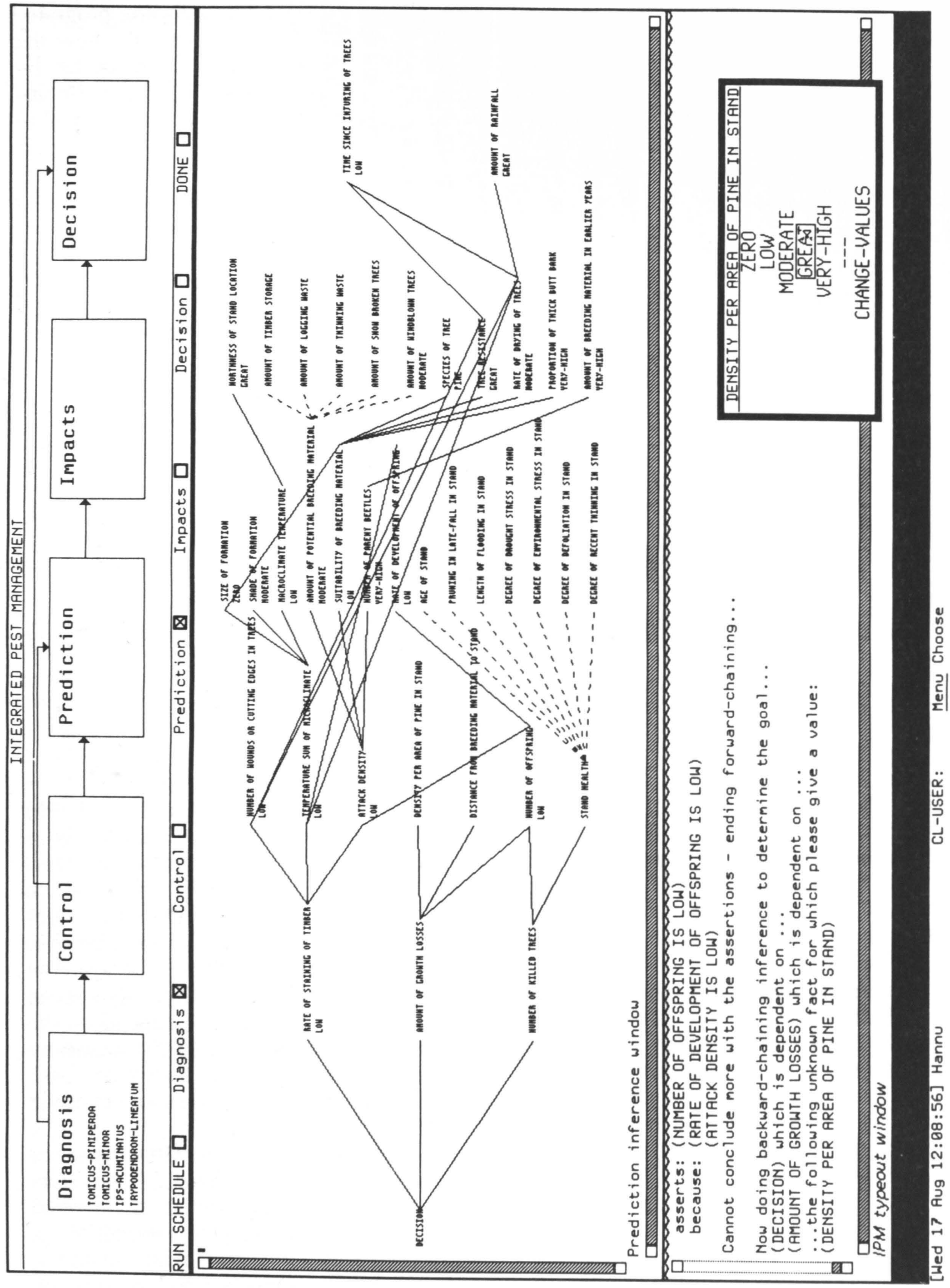

Fig 4. Screen of the Symbolics workstation showing the prediction phase of a consultation.

Table 1. An excerpt of the prediction rule base for *Tomicus piniperda*. The language and notation are declared in Whiston and Horn (1984) with the following additions: <- is negative correlation, << apply funcall to the following list. Cf. the middle window of Fig. 4.

```
setq rules '(

;;; THIS META-RULE FORMS A HIERARCHY OUT OF THE THREE GOALS

(rule decision-meta-rule
      (if (number of killed trees is (> killed))
          (amount of growth losses is (> loss))
          (rate of staining of timber is (> stain)))
      (then (decision is possible-to-do)))

;;; FIRST GOAL

(rule killed_trees
      (if (number of offspring is (> offspring))
          (stand health is (> health)))
      (then (number of killed trees is (<< (mini ((< offspring) (<- health)))) )))

;;; SECOND GOAL

(rule growth_loss
      (if (number of offspring is (> offspring))
          (distance from breeding material to stand is (>dist))
          (density per area of pine in stand is (> dens)))
      (then (amount of growth losses is (<< (mini ((< offspring) (<- dist) (<- dens)))) )))

(rule offspring
      (if (attack density is (> attack))
          (rate of development of offspring is (> devel)))
      (then (number of offspring is (<< (mini ((< attack) (< devel)))) )))

(rule attack_density
      (if (number of parent beetles is (> parents))
          (suitability of breeding material is (> suitab))
          (amount of potential breeding material is (> mater)))
      (then (attack density is (<< (mini ((< parents) (< suitab) (< mater)))) )))

;;; THIRD GOAL

(rule staining
      (if (attack density is (> attack))
          (temperature sum of microclimate is (> dd))
          (number of wounds or cutting edges in trees is (> wounds)))
      (then (rate of staing of timber is (<< (mini ((< attack) (< dd) (< wounds)))) )))

))
```

42. Reasoning and sensitivity

The production system for prediction must be able to reason forward, backward, solve internal conflicts that may rise from parallel rules, and use mathematical functions. In I-IPM, when the forward-chaining part gets stuck, a backward-chaining depth-first search is started. It leads to a meaningful inquiry of further facts from the user. The user is not asked about such things as attack density of bark beetles because he is not supposed to know these. Instead, the search directs questions to such end nodes as type of breeding material, size of formation, temperatures this year, etc., from which the population parameters are concluded. Qualitative or rough quantitative estimates (such as zero, low, moderate, high, very-high) are used for variables. The result is a kind of simulation with rules. The results of the reasoning are shown graphically (Fig. 4).

During and after the reasoning the user can change the values inferred or given by himself if he wants to explore with the sensitivity of the predictions. The changes are reflected in a way similar to a spreadsheet in the graph of the dependency network.

5. Discussion

Validation of an expert system is different when compared with the validation of a conventional simulation model. The modular structure of a rule-base makes validation easy because it can be targeted to the individual rules that contain usually only qualitative estimates, textbook knowledge, and heuristics, all expressed in natural language. On the other hand, formal methods for testing the consistency and completness of a rule set still are few (cf. Buchanan and Shortliffe 1984). From the individual rules it is relatively easy to say when they produce reasonable estimates. It can happen that a set of valid rules does not explain the phenomena consistently and completely. In this case rules have interactions or they do not cover the entire problem domain. Besides sensitivity analysis, statistical methods have been presented that reveal those rules that are invoked most often with incorrect conclusions (Politakis and Weiss 1984).

Dealing with expert systems quickly points out things of problem solving that do not come up otherwise. Researchers seldom analyse their own reasoning, but knowing how the problems can be solved is half of the solution and it guides further research. An expert system is essentially a model of the knowledge in the problem domain (Feigenbaum 1977), and abreast with publications, video, audio, etc., knowledge based systems form a new class of knowledge medium. Trying to bring the applicable knowledge of a domain into usable form also leads to a new definition of fundamental and applied research: knowledge that can not be applied in decision making or execution of those decisions in the field, is basic research regardless of topic, and vice versa.

In the rule base the mechanisms of the particular system must be in clearly encoded form which creates some resemblace with mechanistic simulation models (Shannon et al. 1985). Indeed, *qualitative reasoning* (Kuipers 1989) approaches modeling and simulation from the standpoint of reasoning about the first principles of physical systems. When an exact model is too incomplete, possible behaviors of a system can still be produced from its emergent properties and attractors by reasoning with such possible values as "increasing", "stable", and "decreasing", or with ordered qualitative estimates as in this study. Although quantitative models are advantageous in many ways, chaos reasearch has shown us the limits of such an approach. Furthermore, producing simulation models for all the pest species is an extremely costly way to make research. If simulation models are available, there is no obstacle for incorporating them into the present system to make quantitative estimates. However, rule based simulation has its advantages. The mechanisms how things affect each other are clearly isolated in individual rules and the rule base is like an extremely reduced biophysical model. New knowledge can be easily added and changes can be made because of the modularity. There is no obstacle of using quantitive estimates, either, in which case the functions in the THEN part must be available. If we connect the goal states in the rule net into the input, we can have a simulation loop from generation to generation.

Artificial intelligence is much wider than just expert systems. One particularly important technique for ecological modeling is object-oriented programming which merges programs in the data objects in simulation. This creates a powerful and truly mechanistic simulation where action is not caused by an artificial program loop, but by signals like in real world. Such a model has been made for moose behavior and its effect on natural resources (Saarenmaa et al. 1988). It can be concluded that AI techniques promote scientific method by introducing a mechanistic point of view to the systems under study.

The next step in this project would be the construction of the modules for control tactics. This can be done in two ways: as a strict consultation system or as a planning system. Planning is still very poorly handled in the expert systems world because in that case we are not dealing with deducting knowledge from existing rules or frames, but we must by inductive reasoning expand into an empty area. To generate a plan of actions, we need a set of constaints and lots of heuristics to reduce the search (Stefik 1981). Stone et al. (1987) present a fine example how biological and economical analyses can be integrated in an expert system implementation of IPM.

So far, integrated pest management in forests has been more theory than practice (Waters and Stark 1980). This can been seen to be a consequence of the complicated nature of forest ecosystems which makes decision making very difficult. The forester must be aware of such a number of different facts, rules and regulations that their handling without a computerized decision aid often becomes too unwieldy. I.e., a forest IPM system is largely equivalent to computer based decision making in the field (Saarenmaa 1985, Stone and Saarenmaa 1988). Earlier attempts to create such systems have more or less failed for reasons that could not be seen beforehand. Expert systems along with the new wave of powerful workstations promise to solve most of the problems (Naegele et al. 1986, Stone et al. 1986b, 1987). New problems may rise, though. Among the most apparent ones are a possible rise of "knowledge czars", liablity in the case of wrong decisions, and the tease of giving decision making entirely to the computer.

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