Knowledge Management: An Application to Wildfire Prevention Planning

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Abstract

Residential encroachment into wildland areas places an additional burden on fire management activities. Prevention programs, fuel management efforts, and suppression strategies, previously employed in wildland areas, require modification for protection of increased values at risk in this interface area. Knowledge-based computer systems are being investigated as knowledge management tools for the organization, synthesis, and application of information pertinent to fire science utilization. Many such systems contain expertise which has been captured from human experts and symbolically encoded for automatic manipulation by computer. Two systems, fire characteristics prediction and initial-attack force dispatch, have been developed elsewhere using this approach. This paper describes a third project, which is currently being developed for wildfire prevention planning. Initial efforts in elicitation of knowledge from experts have produced several benefits prior to system implementation. Results to date in fire management are encouraging, and provide support for the future potential of these methods for the management of knowledge gained from fire research.

Introduction

Expansion of the wildland/urban interface brings human activities and values at risk into closer interaction with areas containing high fire hazard. As urbanization expands the interface, the introduction of urban lifestyles in wildlands creates a significantly higher probability for ignitions than occurred with infrequent leisure-time use.[1] In addition

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Key words: knowledge-based systems; expert systems; knowledge elicitation; intelligent tutoring systems; Delphi.

to this increased risk,* potential damage, no longer limited to natural resources, includes property and personal losses. Wildland fire prevention programs must target these activity patterns, aligning prevention activities more with the increased hazard of the wildland environment.[2] Fuels management tactics in the interface must be designed according to risks and values at risk.[3] Suppression activities need to respond to the increased demand for protection and services which, because of human proximity to danger, cannot be denied.[4] The demographic tendency to populate wildland areas has created a special interest group cohered by similar characteristics, interests, and concerns; fire prevention programs, fuels management efforts, and fire suppression strategies must adapt as fire management needs change at this human-environment interface.[1]

To maintain the necessary flexibility for these problems, the most current management methods and technologies available from fire research must be employed. Basic research in biology, ecology, and physical sciences provides the necessary framework. Ongoing research projects in these areas provide essential information related to fire science utilization, but *application* of the information produced from research efforts receives significantly less emphasis than its production.[5] Managing our scientific knowledge, that is, aggregation, synthesis, and organization of information into a cohesive knowledge structure, creates a more useful mechanism for application-oriented (decision-making) purposes.[6] Van Lohuizen and Kochen have proposed[7] that the definition of research should be extended from information production to structuring, storage, retrieval, dissemination, and utilization of scientific knowledge. Implementation of this approach to fire research would permit managers to react intelligently to new or unusual problems, to make rapid adjustments as situations evolve, and to incorporate new technologies as they become available. Accessible information in a readily-usable form should enable the manager to perform as a more effective decision maker.

To effect the organization and utilization of knowledge, several researchers in fire management have employed a knowledge-based system approach. Two systems are briefly outlined below and the author's work on a tutoring system suggests a variant on knowledge systems that may serve as a teaching and application tool. The initial stage of system development, knowledge acquisition, illustrates the current stage of the author's work and proffers some preliminary benefits.

Knowledge-Based Systems

Knowledge-based systems are being employed to structure information for decision-making purposes. These are computer programs distin-

* In wildfire prevention, the term "risk" is used in a different sense than most readers may be accustomed to. Here, "risk" denotes an activity or activities that have the potential to cause ignitions.

guished by their emphasis on knowledge organization and manipulation. *Knowledge* is defined here as structured information. This structure may be as simple as a tabular organization of research results, or more sophisticated, such as a decision support system. Algorithms, which manipulate this knowledge, are separate and generally applicable to a wide variety of problems. These systems have evolved from the application of artificial intelligence (AI, a branch of computer science concerned with making computers more humanlike and natural to use) techniques to the solution of specific, real-world problems; often the term "expert systems" is used to refer to the subclass of applied AI systems in which knowledge is elicited from a human expert. In contrast, knowledge-based systems may or may not contain expertise. Non-expert knowledge-based systems may perform tasks that do not require capturing human expertise directly,[8] but may involve the application of some complex process—a system to guide the use of a complex simulation program would be an example, or the collection and organization of some body of knowledge from the literature—e.g., an encyclopedia of flora fire effects.[9] By contrast, data bases contain information that is updated and queried through the use of a management system; this information tends to be very narrow in focus, with few connections to other related items of information and little structure to aid the user in applying the stored

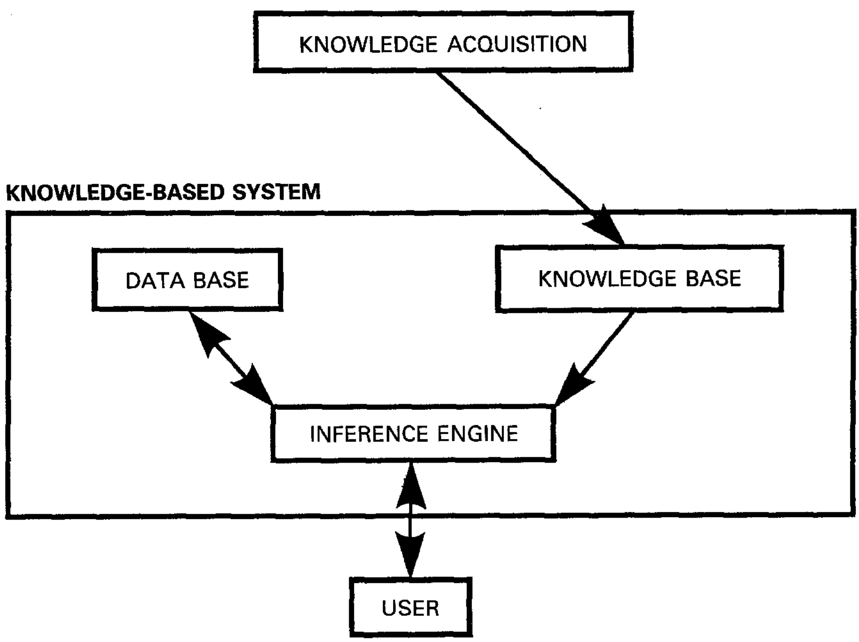

Figure 1. The components of a knowledge-based system include consultation (user) and knowledge acquisition functions; data flow is depicted by arrows.

information. A thorough discussion of knowledge systems has appeared elsewhere; a brief summary is included here.[6,10–12]

The graphic in Figure 1 depicts three main components of a knowledge-based system. These include: a knowledge base, which contains application-specific information represented in a form that permits inferences to be made; a data base, which serves as a working memory of information pertinent to the current problem being investigated; and an inference engine, which draws conclusions about the current problem instance from the information in the data base and the conditional associations of the knowledge base. A user interacts with the system for solutions to specific problems. During the construction of such a system, knowledge must be acquired and deposited in the knowledge base by reviewing the literature, interviewing human experts, or working extensively with management models or methods. Often, the knowledge base consists of if-then rules representing links between conditions (antecedents) in the data base and actions or hypotheses (conclusions) to be achieved. The modularity of this approach makes it easier to modify the knowledge and tailor the system for particular problem areas; domain-specific knowledge is not imbedded in program code where it becomes enigmatic and incomprehensible.

By March 1987, more than 30 knowledge-system prototypes were under development in the areas of agriculture and natural resources.[13] From contacts with other researchers since that time, the current estimate might be more accurately placed at three or four times the previous figure. Interest and activity in this technology seems to be expanding at a phenomenal rate.

Two Examples

Two recent projects have initiated knowledge systems work in fire science research. An expert system has been developed by the Canadian Forestry Service for the dispatch of initial-attack suppression forces.[14] In Australia, knowledge of brushfire behavior is being used to predict ecological effects of brushfires that occur on a large portion of the Kakadu National Park.[15] Potential diversity of knowledge systems applications becomes evident by these two examples—a biophysical (fire behavior) problem and a real-time, resource-allocation situation. In the interest of introducing the use of this technology in fire protection, it seems appropriate to briefly summarize these two research efforts.

Prediction of brushfire effects on the Kakadu National Park influences management of the park's plant and animal communities. Knowledge of two characteristics (flame height and scorch height) of wildfire behavior can translate into understanding potential effects on vegetation. Fuel load, grass type, and burning index combine within more than 100 if-then decision rules to provide an estimate of flame height.

Attributes of different geographical regions within the park, which are pertinent to flame height estimation, are maintained in a geographic data base. Eventually, when all the necessary knowledge relating fire behavior and fire effects has been incorporated into the system, managers at the park will have access to this expertise when making management prescriptions. This project seems significant for two reasons: the authors have incorporated a geographic data base with a knowledge system; and a predictive, rather than the familiar classification, type of problem has been explored.

The Canadian expert system developed for initial-attack force dispatch by the Petewawa National Forestry Institute may be the first real-time application in forestry. That is, a decision is made in a matter of minutes as the necessary information is gathered. Classification of the wildfire situation and resource dispatch are the two subtasks included in the initial-attack problem. A two-stage fire classification begins with an initial classification based on information from the fire report; this may be later revised, in the second stage, on the basis of other anticipated fires and the current time of day. A recommended force level, corresponding to the classification, is easily assigned. Actual allocation of forces requires locating resources and setting priorities for fires that exact these specific resources. This project is a significant contribution to the application of knowledge systems technology because it has undergone testing and implementation. Also, it has incorporated a large amount of decision-support software, which is already in use by the Canadian Forestry Service. Knowledge-based systems possess the capability of merging existing computational tools and human expertise for the solution of difficult problems.

Intelligent Tutoring Systems

Computer-aided instruction began in the 1950s with behavioral psychology's "linear program" view of instruction.[16] Here, direction toward some desired behavior is intimated, and reinforcing stimuli results from a successful response. Since this time, many other approaches have been used; most recently, knowledge-based systems have been utilized.

In addition to being effective for problem solving, knowledge systems possess some desirable properties for instructional uses. Expert reasoning and intuition can be represented in the system, and conveyed to the student through tutored examples (example-driven problem solving) or declarative explanation (line of reasoning). The student is able to work many examples at varying complexity levels and at a comfortable pace without the instructor's exhaustion. MYCIN, a diagnostic expert system for infectious diseases,[17] has been transformed into a tutor for medical students.[18] Other tutors have been created for teaching: computer

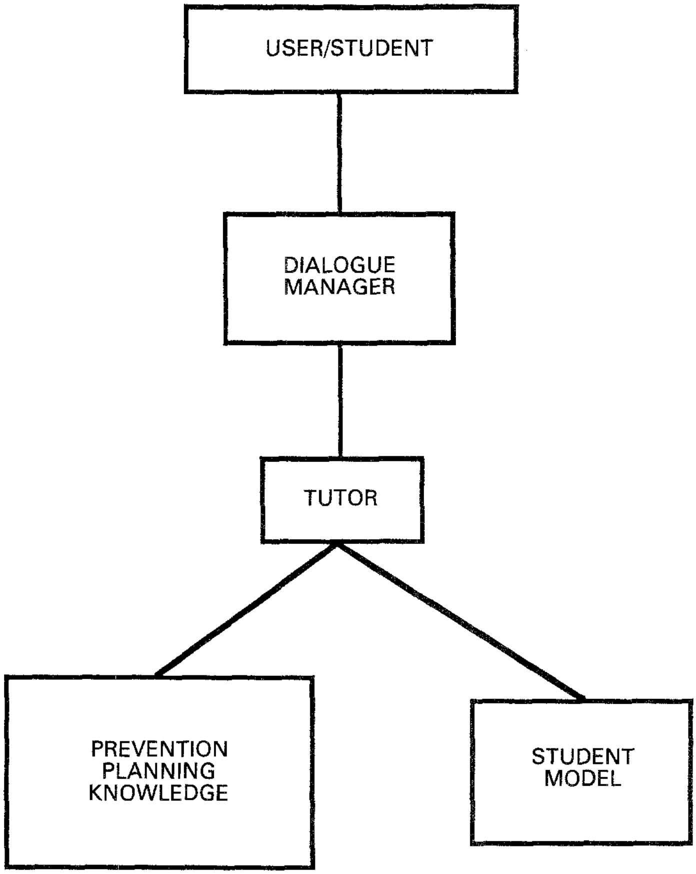

Figure 2. An intelligent tutoring system for prevention planning contains the essential components listed here. The detail and complexity within each component has been omitted.

programming,[19,20] natural language,[21] geometry,[22] physics,[23] and a pulp-and-paper process.[24] Merging computer-aided instruction and knowledge-based systems has resulted in intelligent tutoring systems (ITSs).

Many of these ITSs have some common components; the arrangement of these components for fire prevention planning is illustrated in Figure 2. Knowledge of the actual domain (subject area) being taught must be represented, sometimes in multiple forms at various levels of understanding; this resides in the Prevention Planning Knowledge component.[23] In some tutor designs, this knowledge is referred to as the "ideal student" model.[16] Strategies (tutor component) for tutoring the student in the particular domain must also be defined. These may include immediate or delayed error feedback, maintaining an actual student history model (student model), and specifying the intensity of tutor and student interaction (dialogue manager). To provide a comprehensive learning environment, the student must have access to large amounts of explanation, both for correcting erroneous behavior and promoting desired behavior. Specific implementation of these features will depend on the teaching task and the types of students anticipated.

Prevention Planning Tutor

Wildfire prevention programs in the U.S. Forest Service are subject to an efficiency criterion; program costs and resource losses must be minimized. Consequently, ignitions that have the greatest potential to become large and/or damaging fires become targeted for prevention budget investment.[2] Numbers of ignitions are no longer the primary concern.

To determine whether prevention dollars reduce wildfire losses, program outputs must be balanced against planning goals. These goals are set through analysis of fire problems within an entire planning area. A prevention program contains prescriptions on how an organization will attempt to reduce the number and severity of wildfires and their losses. The San Bernardino National Forest in southern California contains more than 250,000 hectares and is managed by the USDA Forest Service. A systematic prevention planning process recently developed on the San Bernardino National Forest incorporates a detailed inventory of fire problems. Prevention program prescriptions address specific fire problem conditions, and subsequent prevention program evaluation compares fire occurrence and prescription accomplishment. This detailed approach provides accountability in both program selection and follow-up assessment of success/failure.

This process still contains a large subjective aspect. Several district (sub-units of the entire forest) plans have been developed through the use of this process, but no comprehensive manual details the necessary steps and inherent rationale. New users experience difficulty in beginning a fire problem analysis (the first, and essential, component of the process). The apparent learning curve associated with this process illustrates a limitation for more widespread adoption. The current research effort proposes that a knowledge-based tutor could facilitate learning about the planning process, and could supply guidelines for development of specific prevention programs. At the same time, tutoring systems can be examined as one potential aide in managing knowledge in fire science.

Process Components

The planning process consists of the sequence of steps depicted in Figure 3. Systematic analysis of ignition problems constitutes the

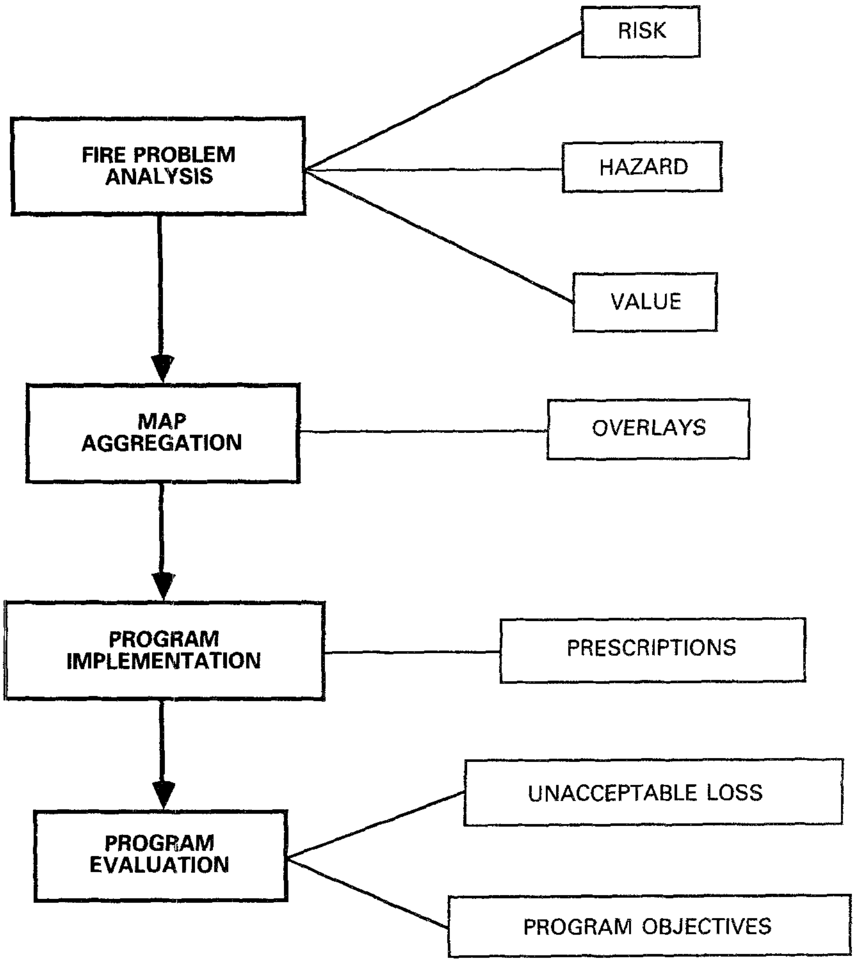

Figure 3. The prevention planning process contains an ordered sequence of steps (bold) and secondary steps.

primary advantage of this planning approach. Subsequent steps rely on the inventories and maps produced in the analysis phase.

Analysis of wildfire ignition problems involves the examination of three independent aspects of the wildfire situation. Risk analysis consists of the inventory, ranking, and mapping of human activities that have the potential to cause ignitions. Hazard analysis incorporates fuel conditions (a function of fuel type and climatic conditions) and slope classes for estimating resistance to control should an ignition occur; ratings of resistance to control for contiguous areas are identified on a separate map. Value analysis consists of inventory, rating, and mapping based upon perceived value changes resulting from fire. As each analysis is performed, there is no consideration given to the effects of the other two aspects of analysis. For example, the potential for ignition has no effect on fire behavior given an ignition. Because each analysis is independent of the others, no particular order must be followed, although each must be included in a comprehensive analysis.

After all analyses have been completed, the three maps are combined into one comprehensive map of the entire planning area. Fire prevention management compartments (map areas) are delineated based upon risk analysis because ignition potential is the major concern of prevention. Each compartment receives a rating score for risk, hazard, and value; a final inventory summarizes the specific human activities, fuels, and values contained in each compartment. This aggregate map forms the data base for subsequent implementation—via program prescriptions and follow-up evaluation.

From the combined inventory and aggregate map, specific action items are identified for each management unit. Prescriptions are written for each action item; they cover the duties to be performed and their priority under the average range (90th percentile) of fire conditions. Contingency prescriptions may also be detailed for fire conditions that exceed the 90th percentile. Ninetieth-percentile conditions are those fuel and weather factors that are prevalent during most fire season situations. Four categories of prevention programs are covered by these prescriptions: mandatory, targeted, maintenance, and indirect. Eventual evaluation of program effectiveness will entail examination of these prescriptions in relation to the extent and location of actual fire losses.

Because the goal of prevention is the encouragement of non-events (no fires), successful prevention efforts can only be assessed in terms of numbers and severity of events that do occur; i.e., unacceptable losses. When unacceptable fire losses have not occurred, then, assuming average fire conditions, it may be possible to conclude that prevention efforts have been successful. However, faced with significant losses, a careful examination of those specific, damaging fire problems should identify the most prominent causes. Prevention personnel may refer to the document detailing prescriptions for verifying completion of all prescribed tasks. Failure to achieve specified tasks indicates a performance problem; whereas successful achievement under normal fire conditions implies that specific prescriptions must be modified or added to eliminate the specific fire losses experienced. In the course of rewriting prescriptions, it will be necessary to re-analyze the risk, hazard, or value assessments associated with particular loss areas.

Knowledge Elicitation

Our ITS approach differs from ITSs described above by a desire to create a non-singular use system; i.e., a system that aids both learning and problem solving. Most ITSs contain a method of simulating or hypothesizing learning situations (examples). The prevention planning tutor will operate with examples provided by the user, which, presumably, will reflect actual planning needs. In this way we will create a knowledge-based system which solves actual ignition management problems and, at the same time, tutors fire prevention personnel in the techniques of the planning process.

The first step in development of the tutor involves creating a representation of knowledge about the planning process; i.e., the domain knowledge. Several prevention personnel assigned to the San Bernardino National Forest are familiar with the process and have their own personal insights into the subtleties of fire problem analysis and implementation. In addition, no individual within this group was previously involved in all aspects of the process. Therefore, it became necessary to combine the knowledge of several experts, and at the same time obtain consensus on the structure and operation of the planning process.

The Delphi technique was selected because it forms a general framework for arriving at agreement among individuals within a group on some non-trivial problem. However, a number of serious drawbacks to this technique have been suggested previously,[25] e.g., reliability of results, definition of consensus, and stability of group responses. These limitations are further complicated by the situation at hand, which requires the development of an extensive body of knowledge, rather than the construction of some scale or the estimation of some value. The author proposes a modified Delphi procedure that avoids these drawbacks, and yet seems able, from current experience, to support the construction of a complex description of a planning process.

Modified Delphi Technique

Standard implementation of the Delphi technique incorporates questionnaires to which each member of the group anonymously responds. These questionnaires are repeatedly administered to the group, intermixed with feedback of questionnaire summaries, until some consensus has been reached.

The following discussion of a modified Delphi centers on the concept of a cumulative knowledge packet used in the place of multiple copies of a questionnaire. Figure 4 illustrates the interaction of experts and knowledge packets in this cumulative Delphi technique. Each E_i and KP_i

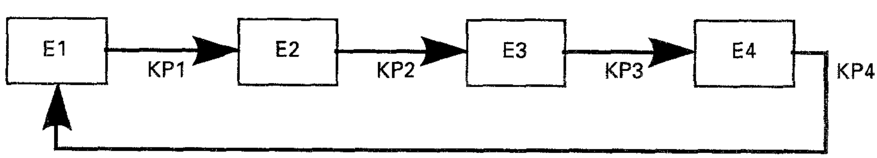

Figure 4. Cumulative knowledge packets (KP_1, ...) are routed between experts (E_1, ...) in the modified Delphi technique.

refers to particular experts and knowledge packets, respectively. Preliminary, general discussions were held with the experts, in which the most experienced in the planning process were identified; these individuals were given positions E_1 and E_2. This means that for each round of the cumulative Delphi the most knowledgeable experts are interviewed first.

For each component of the planning process identified in Figure 3, a round of the cumulative Delphi is completed. An interview with E_1 produces KP_1, which contains: the concepts describing the particular component, definitions of these concepts, relationships between concepts, and the types of concept relationships. Subsequently, KP_1 is given to E_2, and E_2 is asked to make any modifications to the knowledge packet that seem appropriate; these modifications are made and recorded in an interview setting. The revised knowledge packet is then presented to E_3 as KP_2. The routing of knowledge packets continues in this manner. When KP_4 from E_4 is presented to E_1, E_1 is asked to review the changes to KP_1 contained in KP_4. If the changes are acceptable, then KP_4 is installed as the initial representation of this component of the planning process.

The case has not yet arisen in which KP_4 is unacceptable. In the event of such a conflict, two solutions are possible. Another routing of knowledge packets through the experts (beginning with KP_4) may mitigate most significant differences, leaving only minor discrepancies whose importance will generally be small in terms of an initial representation. Alternatively, a nonconfrontational arbitration may be used to smooth divergent views, in which case the author may mediate some mutual agreement. When the domain being represented has the property of consistent expertise (a property considered essential to effective development of an expert system[10]), then large deviations from consensus should not be problematic or should be easily resolved by the above procedures.

The question of reliability of Delphi results relies more on the form of the domain than on the cumulative Delphi technique itself. In a planning process description, unlike consensus value assignment, a second group of experts might arrive at a different representation, but it would be functionally similar to the previous one, provided the two groups were describing the same process. Routing of a common document forces acceptance of major points, which should be identical between two Delphi groups, and facilitates non-confrontational discussions of smaller discrepancies. Consensus is specifically defined as acceptance of the final knowledge packet by the first expert; this definition may be extended to include acceptance by all experts if it seems necessary. The commonalty attribute of the knowledge packet encourages stability toward a rapid consensus. Because direct group interaction has been avoided, some potentially valuable dialogue may have been sacrificed in the process. However, this form of detached cooperation between group members is less engaging and more efficient.

Discussion

On the basis of preliminary work with knowledge elicitation in this study, a number of interesting observations have been made. Due to the previously unrecorded nature of this planning process knowledge, our efforts to date have identified and scrutinized what is known, and have contributed significantly to its understanding and specification. Specific planning process tasks and fire prevention concepts have been isolated and their meanings solidified. Areas of subjective knowledge used by the experts at various steps in planning have been identified; this judgmental component will be further elucidated in subsequent stages of this study. Although using multiple experts makes the knowledge elicitation impediment of expert system development more pronounced, each expert has some personal intuition and perspective which has proven valuable to the overall knowledge collected. On several occasions, an expert has discussed particular details which would not have been proffered in a group situation. Individuality seems to have been preserved while realizing group consensus. It appears that the knowledge packet approach provides sufficient interaction of ideas without disruptive confrontation or dominant role playing. The visual-aid quality of the knowledge packet also helps application-oriented people (experts) make the transition from experience to abstract concepts describing the planning process.

Knowledge-based systems examples cited and this current work in ITS are applications of a new and widely-applicable technology derived

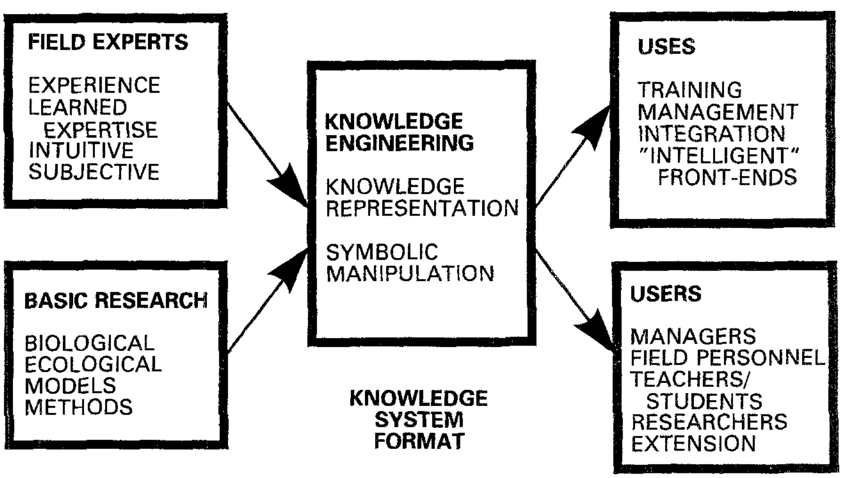

Figure 5. Knowledge-based systems in fire science can be utilized for the transfer of fire research technology and expertise to various users and for different uses.

from artificial intelligence research. Preliminary work completed in the area of fire sciences indicates that the eventual impact on fire research and management can be extremely beneficial. From the work under way on the prevention planning process, it seems that even systems that never reach field implementation may be valuable from the viewpoint of effort expended during intense scrutiny of the problem area.

Figure 5 illustrates how these systems may be useful for the management of scientific knowledge; i.e., organization, storage, and utilization. Expert systems, which rely on the expertise or training of a few valuable individuals, provide scarce, largely intuitive and subjective knowledge to a wider audience of users. In circumstances where expertise is rare or valuable, these systems fill a void by offering multiple copies of the human expert, and provide for storage of experience that would otherwise be lost through retirement or transfer. Knowledge-based systems permit more effective use of current tools and research results. Many management and simulation tools are difficult to use—input may be complicated to organize, or output may be complex to interpret. To this purpose, knowledge application systems may be useful as pseudo-"intelligent" user interfaces to complex mathematical models and analytical methods (e.g., statistical packages). The potential exists for representing and manipulating both private (human) knowledge and public (literature and methods) knowledge.

Most of the biological and ecological research results are published in textual form such as journals, books, newsletters, proceedings, etc.; availability of these materials to managers may be limited by awareness of their existence or interest in their subject matter. These results are often presented in an informational format and not in a structured, decision-making style. Flat, two-dimensional information structures display little depth of knowledge and, consequently, do not often lend themselves to easy application for specific, real-world problems. Although such information is recorded and valuable, all pertinent factors to be considered in specific problem instances are not integrated and synthesized in any one location; application knowledge is scattered and unorganized. To be most useful, our knowledge of real-world objects must be multidimensional; that is, able to link with other objects and ideas in many possible ways. In the areas of expertise transfer, translation of research results, and application of current management tools, knowledge-based systems (including expert systems) have exhibited potential as mechanisms for processing information into a more structured and more useful decision-making format.

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