An Integrated Prescription-Based Health Management System (PBHMS) for CBM will be developed. Automated reasoning systems are used daily in the medical arena for generating prescriptions based on patient symptoms, diagnosis, and prognosis [add ref]. It is well known how to automatically generate prescriptions as well as how to use Decision Trees to provide decision support to doctors for generating prescriptions. The military CBM problem is more complex than the medical problem since it also requires taking account of limited maintenance units, mission requirements, battle unit integrity, and opportunity/convenience of maintenance. Various techniques have been used to confront the military CBM/PHM problem by several groups [ref Impact Technologies, etc.].

We propose the multi-component PBHMS shown in the Figure that takes as inputs Diagnostic and Prognostic/RUL information from various sources [ref ICAS, Impact Technol., Skormin, ]; Priority Information including costs, risk, mission requirements; and Maintenance Resource Capacity and availability information. PBHMS generates optimized maintenance tasks, and a maintenance plan with prioritized work orders.

PBHMS consists of (1) a Prescription Library and Decision Support System, (2) a Maintenance Priority Generator, (3) a Maintenance Requirements Planning System, and (4) a Resource Assignment and Dispatching System.

The subsystems in Fig. 1 are separated from each other due to the fact that different authorities preside over each one. Priorities and mission due dates are decided on a higher level than are required maintenance prescriptions. MRP integrates these two. Finally, dispatching depends on knowledge of available maintenance units such as is held by warrant officers and chiefs in the field.

**Prescription Library (PL) and Decision Support System.** Prescriptions to confront diagnosed fault or failure conditions are based on experience and urgency. The urgency is conveyed by prognostic information, RUL, and priority measures. The experience to make correct decisions can be collected into a case-based reasoning system we call a Prescription Library. Experts’ opinions can be collected in the form of rules such as appear in Fig. 2. Proper construction of the PL allows the addition of rules and knowledge to adaptively integrate new information through learning. Many techniques have been used for reasoning system, as listed in the Figure. A fuzzy logic system has many of the best features of expert systems and other techniques. It is based on expert rules and so is easy to put together. FL systems will be explored since they can include many of the other techniques listed in the Figure.

A rigorous mathematical framework for FL systems in system theory was given in [Lewis]. A FL system is described mathematically as
 where we are using product inferencing and centroid defuzzification. The control representative values are $z'$ and the 1-D membership functions are $\mu_j(.)$. The $x_j$ are the components of the $n$-vector input $x$. Traditional membership functions can be triangular, gaussian, etc. Fig. 3 illustrates Gaussian MFs for the 2-D case. Here, each hump represents a different prescription depending on different values of the two fault symptoms.

**Bayesian, Dempster-Shafer, and Statistical Decision-Making in FL Systems.** A FL system assigns a confidence level to each rule and combines rules to obtain an optimal decision based on several pieces of evidence. It can be shown that, with the correct selection of the membership functions and control representative values, a FL system can implement either Bayesian Inference or Dempster-Shafer evidential decision-making. In fact, Bayes rule yields

$$P(\pi_i / \delta) = \frac{P(\delta / \pi_i)P(\pi_i)}{\sum_i P(\delta / \pi_i)P(\pi_i)} \tag{2}$$

where $\pi_i$ is prescription $i$ and $\delta$ is a vector containing the diagnostic and prognostic information. Dempster-Shafer rules of evidence give the belief for prescription $i$ as

$$Bel(\pi_i) = \frac{\sum_j \prod_{i=1}^{n} m_j(S_j)}{1 - \sum_j \prod_{i=1}^{n} m_j(S_j)} \tag{3}$$

where $S_j$ is the evidence. Function $m(s)$ is akin to the likelihood function $P(\delta / \pi_i)$. The similarity of these formulas to the FL system (1) is striking. In this work we will use FL systems to implement both Bayesian and DS reasoning about prescriptions.

It has been shown in Wang [] that FL systems can also include information obtained through statistical techniques. In fact (1) can generate the conditional pdf of the prescriptions given the observed symptoms. A confidence interval can be generated using bootstrap techniques.

**Adaptive Updating of Fuzzy/Neural Systems.** It was shown in [] that a fuzzy logic system is a special case of structured neural network. Therefore, all the techniques for tuning and learning in NN can be used to adapt the membership function centers and spreads in FL systems. We will explore this to tune the PL to learn new prescription information through interaction with a human user. Updating of the PL can also be done by a human user adding new rules.

**Decision Trees for Prescription/Side Effect Decision Support.** Often there is more than one suitable prescription, and one must consider *side effects* in making an appropriate choice. Again, there may not be enough information to make a prescription, and additional information may be needed to allow a decision. For example, maintenance options might include repair or replacement of a faulty motor. If a motor is unavailable it might be taken from
another system. Decisions depend on additional information such as mission requirements of the two involved systems, times of repair and replacement, and availability of technicians skilled enough to repair a unit which might easily be replaced by less skilled technicians. Side effects would include downtime of the two systems, tying down maintenance technicians, etc.

The use of various sorts of decision trees for assisting human users in decision-making is by now standard. Included are quadtrees, upper semi-lattices, programming language type flow charts, etc. It is difficult to integrate support trees with a standard logical or fuzzy logic reasoning system. We will explore the use of repetitive inquiries to a FL system as a decision support mechanism. At each iteration, the FL system will provide multiple prescription options. The user selects several options and provides additional information. Another query is made to the FL system, which further narrows the prescriptions, etc. We have a theory of contraction mappings developed for neural network control systems that could apply here to prove convergence to a consistent prescription.

**Maintenance Tasks as Prescriptions.** In the existing USN 3-M Preventive Maintenance System, each task is described by a PMS card that lists the steps needed to effect the maintenance action. This knowledge is standard, and will be stored in a database. Then, the PL system will output a prescription in the form of a PMS card to be delivered to the maintenance tech when and as detailed by the remainder of the PBHMS system to be described below.

**Maintenance Priority Generator.** To suitably schedule the prescriptions coming from the PL, one requires priority dispatching information. Standard decision-making techniques including linear programming, dynamic programming, reinforcement learning, etc. use performance measures with definite structures such as linear or quadratic. In CBM decision-making one must include many factors such as those listed in Fig. 1. It is not clear how to form the multi-modal cost functions needed to apply standard decision tools. Some priority factors, such as Estimated Time of Failure and Mission Due Date requirements, are hard limits that cannot be exceeded. Some, such as safety, risk, cost, can be combined into mathematical functions that can be minimized through correct decisions. Others, such as numbers of maintenance units, opportunity/convenience must be taken into account in the resource assignment phase of PHM.

In communications networks there are many techniques to guarantee Quality of Service, including due date satisfaction, minimum packet loss, and fast transmission times [1]. We have begun to look at such techniques for the CBM problem. Mixed hard constraints and soft constraints make this a so-called hybrid decision-making problem. We have used hybrid systems in manufacturing scheduling control systems [2]. We believe that similar techniques will allow us to combine the multiple priority objectives of CBM into a tractable algorithm for assigning priorities to maintenance prescriptions with guaranteed mission due date satisfaction.

**Mission Criticality and Progressive Escalation of Required Maintenance.** In a rather interesting situation, mission criticality and estimated time to failure ETF can interact. Fig. 4 shows a situation where a fault becomes worse, progressively escalating the required maintenance prescribed. In the 4% fault state, ETF means time till the fault goes to the 10% state. Thus, suppose one prescribes a maintenance task for the 4% state. Then, if the ETF is exceeded one must go back with a new diagnosis to the PL and get a revised prescription. Mission criticality considerations may prevent the system from being taken out of service in time to service the 4% fault, so that increased maintenance is needed after the mission is complete. Such situations need to be handled in the priority generator subsystem.
Maintenance Requirements Planning. Given the prescriptions and their due date and cost priorities, it is necessary to generate work orders and a Maintenance Plan with Priority Rankings that have guaranteed QoS. Advanced planning and scheduling techniques are by now in standard use in manufacturing. Manufacturing Resource Planning (MRP) algorithms allow one to schedule component and subsystem assembly activities in such a manner that the overall product due dates and required delivery numbers are satisfied. We have shown how to combine MRP with high-level computer science machine planners, including hierarchical task network (HTN) planners, to allow automatic generation of start and due dates based on priority information including customer required due dates, available units in inventory, limited resource units, etc.

These techniques can be applied for Maintenance Requirements Planning. Military maintenance MRP differs from manufacturing MRP in that there are several hard time constraints, not just a product due date. Fig. 5 Shows that the faulty part must be taken out of service before the ETF and repaired prior to the mission due date. Based on our prior work it will be fairly straightforward to modify manufacturing MRP to account for multiple time constraints.

Resource Assignment and Dispatching. Given a Maintenance Plan and work orders with Priority Rankings, it is necessary to assign maintenance units to perform the tasks. This is very closely related to the shared resource assignment problems in manufacturing and communication networks. Since some resources are shared, it is necessary to assign them based on priority orderings. Care must be taken to avoid deadlock and blocking phenomena, where units are held up waiting for other units or resources. We have a US patent in priority dispatching of multiple shared resources in manufacturing workcells. We have designed a discrete event supervisory controller that assigns resources in real-time given the actual status of the system, including jobs that are scheduled, resources available, and due dates. Deadlock and blocking are guaranteed to be avoided. We have implemented this DE supervisor very simply in LabVIEW on a PC computer.

We will combine our resource dispatching supervisory techniques with priority dispatching algorithms such as earliest due date, least maintenance slack, etc. to assign maintenance resources in real-time based on mission requirements and maintenance unit readiness.

Computer Implementation of Networked PBHMS. We have implemented several subsystems like those appearing in Fig. 1 very simply using PCs, and have experience in distributed control and remote site monitoring over the internet. We envision that the overall PBHMS will be composed of several subsystems possibly at different locations. One must confront issues of integrated CBM/PHM using subsystems that need to be coordinated over the internet. User interfaces can be provided for integrated decision support and human user decision augmentation.