

Robot Reliability Through Fuzzy Markov Models

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Key Words: Fault Trees, Markov Modeling, Robotics, Interval Arithmetic, Fuzzy Sets.

SUMMARY & CONCLUSIONS

In the past few years, new applications of robots have increased the importance of robotic reliability and fault tolerance. Standard approaches of reliability engineering rely on the probability model, which is often inappropriate for this task due to a lack of sufficient probabilistic information during the design and prototyping phases. Fuzzy logic offers an alternative to the probability paradigm, possibility, that is much more appropriate to reliability in the robotic context.

Fuzzy Markov modeling, the technique developed in this paper, is a technique for analyzing fault tolerant designs under considerable uncertainty, such as is seen in compilations of component failure rates. It is sufficiently detailed to provide useful information while maintaining the fuzziness (uncertainty) inherent in the situation. It works well in conjunction with fuzzy fault trees, a well-established fuzzy reliability tool. Perhaps most importantly, it builds directly on existing reliability techniques, making it easy to add to our reliability toolbox.

1. INTRODUCTION & BACKGROUND

The increasing desire to produce more reliable robots has created interest in several tools used in fault-tolerant design. The extra components needed for fault-tolerant robot designs obviously add extra costs and extra possibilities of failure. Reliability analysis tools such as fault trees and Markov models give hard numbers showing that the benefits of the fault tolerant design are tangible and worth the effort. Unfortunately, the component failure rates used in these calculations are often very dependent on configuration and environment, and thus known only approximately during the design phase [12]. Some way of considering the full range of failure rates is needed to give a good idea of what is and isn't known.

The standard approaches of reliability engineering rely on the probability model, which is often inappropriate for this task [1, 12]. Probability based analyses usually require more information about the system than is known, such as mean failure rates, or failure rate distributions.

Commonly, this results in dubious assumptions about the original data. Thus, any single value or distribution applied to the failure characteristics is likely to give a result that is misleading.

Fuzzy logic offers an alternative to the probability paradigm, *possibility*, that is much more appropriate to reliability in the robotic context [1, 12]. Possibility mathematics allows for quantitative reliability calculations that preserve the uncertainty present in the original data. The possibility model deals with uncertainty in a way that avoids making unwarranted assumptions, and makes the consequences of the required assumptions clear.

Of the common reliability tools, only fault tree techniques have been *fuzzified* to any great extent. However, while these are very useful, they are somewhat limited in their applications. Partial failures, coverage, repairable systems, and other important reliability issues are not covered well by fault trees, although recent developments in fault tree analysis are expanding their range of application [4, 5]. Markov modeling is a valuable tool for dealing with the above situations. Unfortunately, previous fuzzy Markov models have used a fuzzy integral method, which will be shown here to be inappropriate for reliability analysis.

2. CONSTRUCTION OF A FUZZY MARKOV MODEL

The Markov model is a method of determining system behavior by using information about certain probabilities of events within the system. However, in reliability, it is often necessary to estimate these probabilities. A common approach is to estimate a single crisp probability and assume that it is sufficient. A more sophisticated approach would be to assign a probability distribution to each of these probabilities, resulting in probabilities of probabilities. As discussed previously, these assumptions are often inappropriate.

A classical reliability Markov model breaks the possible configurations of the system into a number of states. Each of these states is connected to all the other states by a crisp *transition rate*. The probability of being in each state (or *population* of that state) evolves over time according to

these rates. For the *fuzzy* Markov models introduced in this paper, both the populations and the transition rates will be fuzzy.

Our approach is to estimate the conservative and optimistic bounds of the probabilities in question, and use them to define a trapezoidal membership function. This estimate is reasonably easy to perform for most systems, and has the benefit of being clear cut and easy to understand and modify. We will use the conservative bounds for the base, and the optimistic bounds for the top, as seen in figure 1. The resulting output for our fuzzy Markov model is three dimensional, with axes of probability, degree of membership (possibility), and time. However, this can be reduced to two dimensions if we only plot the corners, or *breakpoints*, of the possibility distribution (points A-D in figure 1).

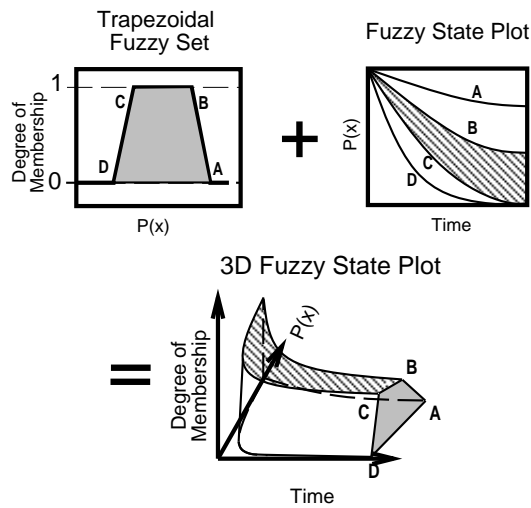


Figure 1: Output Format for a Fuzzy Markov Model.

There are several important requirements that our fuzzy Markov model must fulfill. The most obvious of these is that it must be better in some way than the crisp (standard) Markov model. This requirement is met by the fuzzy nature of the model, as long as our fuzzy reliability models preserve the uncertainty accurately and reliably throughout the calculation. This requirement will be referred to as the *uncertainty criterion*.

Another important factor to consider is complexity. The fuzzy Markov model is likely to be more complex than a crisp Markov model, as the former uses a fuzzy possibility distribution where the latter has single crisp values. Ideally, the graphic simplification shown in figure 1 will also apply to the mathematics, but this is not guaranteed when multiple distributions interact. The desire to keep the model simple will be referred to as the *complexity criterion*.

The final criterion that any new fuzzy Markov Model will be judged on is 'niceness'. A model that gives illogical, unintuitive, or overly complex output is not likely to be a good model. Although it can be hard to precisely de-

fine 'niceness', it is usually not hard to achieve consensus that certain models are not 'nice'. Additionally, several mathematical 'niceness' criteria are obvious, resulting in tests that exclude a model from being nice. The first of these, *fuzzy niceness*, tests to see if the fuzzy output of the model is a 'nice' fuzzy set. For our purposes, any valid continuous function bounded on the $[0, 1]$ interval is 'nice' [6]. The other criterion is *probabilistic niceness*. The requirement here is that we do not ever have any possibility greater than zero of probabilities outside of the $[0, 1]$ interval. Thus both the domain and range are effectively bounded. However, we will relax the probabilistic axiom 'the sum of all probabilities equals one', as for our fuzzy numbers this can only be true in a fuzzy sense.

One possible fuzzification of the Markov model would use methods similar to those used for fuzzy fault trees, where it can be sufficient to propagate the extremal values through the fault tree as if it were crisp, and take the resulting extremal points as the output possibility distribution [6, 11, 12]. Unfortunately, this method is not sufficient for a good fuzzy Markov model, as it is valid only for trivial Markov systems. It is easy to set up a Markov model where propagation on extremal values results in the problem seen in figure 2.

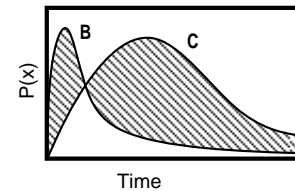


Figure 2: Extreme Values Fail to Produce a Valid Fuzzy Markov Model.

At the point that the two curves cross, the model says that there is no uncertainty in the population of the state. It can be shown that this is not true if one considers the continuum of the possibility distribution, so this method violates the uncertainty criterion described above.

The generalization of a crisp binary operation to a fuzzy operation can be accomplished via the *extension principle*, as presented in [8, 11]. It is natural to try to use the extension principle to fuzzify crisp Markov models. The model is simply solved as if it were crisp, using symbolic constants for the failure probabilities. The resulting equations are then fuzzified by substituting fuzzy possibilities for the probability constants and fuzzy operations for crisp ones.

Although theoretically promising, it was quickly determined that this approach violated the probabilistic niceness criterion - i.e. it resulted in nonzero possibilities for impossible probabilities. A typical result of this approach is seen in figure 3.

This is a property of the discretization of the fuzzy math itself. This impossible situation is generated because the fuzzy arithmetic uses the most extreme *possible* proba-

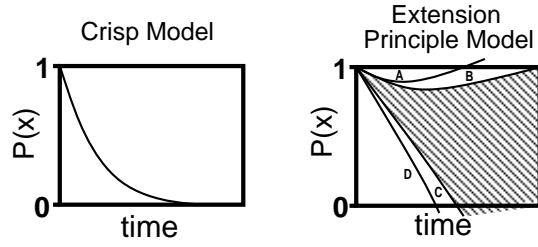


Figure 3: Extension Principle-Based Fuzzy Markov Model.

bility in each stage of the calculation, not caring if different probabilities are used for the same value or if the probabilities in question do not add up to one. It was difficult to modify fuzzy mathematics to force compliance with the additivity property. All of the attempts made to do so resulted in logical self-contradiction, total loss of fuzziness, or unacceptable loss of information.

As seen in [9], some work has been done in the field of fuzzy Markov modeling using the concept of the fuzzy integral. It would be useful if this work could be adapted to reliability. Unfortunately, this is not the case. The problem lies in the fuzzy integral. Although a fuzzy integral takes the fuzzy possibility of a fuzzy event, the result of such an integral is crisp [9]! Although this may be a logical approach in some instances, it is not appropriate for the problem considered here. The uncertainty criterion is clearly not satisfied for the fuzzy integral, where the arguments are uncertain but the results are not. The uncertainty in the situation has been lost.

Previously, we considered the approach where we solved for the extremal values of the trapezoidal membership function. It is natural to consider what would happen if we considered all of the values in between as well. This approach attacks the problem from first principles, following the general definition of interval extension in [10]. If the failure rate is within a certain interval, we can determine the possible behavior of the system by examining the behavior of the models resulting from every possible value on this interval.

Of course, this approach has its own problems. Since an interval contains an infinite number of points, one needs an infinite number of Markov models to solve the problem. This is clearly impossible, but if one assumes some smoothness, one can reduce this to a close sampling of these values instead of a continuum. Areas on the population graph that are between different plots can be assumed to be covered by some probability value between the values that resulted in those plots. Complexity for this approach is still high, but a solution to the problem is now possible, as seen in figure 4, where six crisp Markov models are used to determine one fuzzy model.

Despite its brute force nature, this approach meets all of our requirements listed for the fuzzy Markov model except for one - complexity. Close sampling requires that many crisp Markov models be solved to solve a single fuzzy

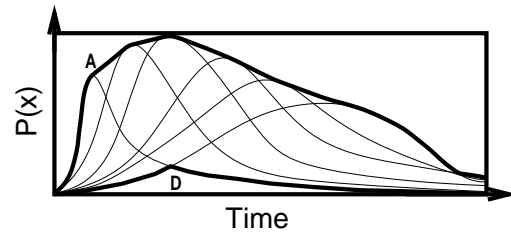


Figure 4: Fuzzy Markov Modeling Through Close Sampling Method.

Markov model. If one is taking N samples on the interval, and there are M fuzzy failure rates, N^M crisp Markov models must be solved. As N is typically on the order of 5-20, this can quickly grow to an unreasonable number of calculations.

This close sampling approach is the method used here to calculate fuzzy Markov models. Despite the complexity issue, it is the only method found that has neither lost the important information nor resulted in impossible or useless output. Thus, the original problem of finding a fuzzy Markov model has become the problem of simplifying and implementing the close sampling fuzzy Markov model.

In systems with many similar components in similar roles, this can be accomplished by grouping the failures of these components together in the Markov model. Instead of having a state representing 'pressure sensor 23 has failed', for example, we have 'a pressure sensor has failed'. Provided the failure of any single sensor has a similar effect on the system, this is a valid simplification. This often also allows us to use a single possibility distribution for all of the similar components, cutting down the number of crisp Markov models that need to be solved considerably.

A complex system with many different parts will probably have many fuzzy failure rates to deal with, more than enough to make a fuzzy Markov model impractical. However, when examining the failure characteristics of any complex system, we are quite likely to organize it into subsystems. This increases our understanding of the system. For example, if we were examining the failure characteristics of a robot arm, we might want to consider joint failures in our primary analysis. Once we knew those characteristics, we could then sharpen our focus to a model of the individual joints, considering motor, sensor, and mechanical failures, and so forth. This type of simplification comes naturally and is helpful in promoting greater understanding of the system.

We can use the natural scheme of organization above to simplify our fuzzy Markov models. All we need to do is find a way to group the failure rates of the individual components into a single component failure rate. Fuzzy fault trees are ideal for this purpose. They are easy to implement, fuzzy mathematically sound, and specifically

designed to determine failure rates for collections of components. Fuzzy Markov modeling using fuzzy fault trees for simplification shows promise as a reliability tool, as seen in the next section.

3. AN EXAMPLE: THE MLDUA ROBOT SYSTEM

The Modified Light Duty Utility Arm, (MLDUA), is a robot arm designed to assist in the removal of hazardous radioactive waste from large underground storage tanks at Oak Ridge National Laboratory [2, 7]. The MLDUA is inserted through a narrow central access riser, and used to manipulate a ‘hose management system’ for waste extraction, as seen in figure 5.

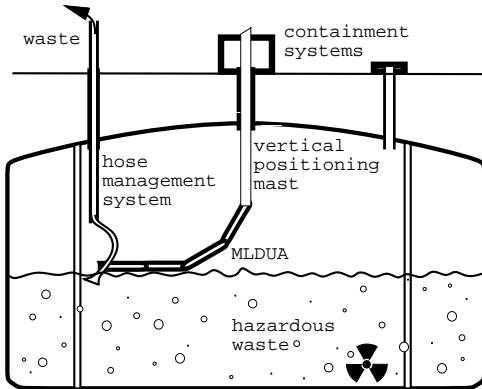


Figure 5: MLDUA Manipulator in Waste Tank.

The environment in these tanks is extremely hostile, and the waste involved is too hazardous to allow leakage. Thus the MLDUA system has to meet many stringent safety requirements [2]. The environment inside the tank is so hostile that the MLDUA itself is endangered. Extremely high radiation levels combine with explosive and corrosive chemicals to make eventual damage to the MLDUA a virtual certainty. However, the overall effect cannot be predicted accurately before deployment. Stringent reliability requirements and uncertain failure characteristics thus combine to make the MLDUA system an ideal real world test case for fuzzy reliability analysis.

Considerable reliability work has already been done for the MLDUA. The design itself is very reliability conscious. Each joint is monitored by two redundant sensors. There are seven joints, allowing the MLDUA to continue working after a single joint failure (kinematic redundancy). Five of these joints are powered by hydraulic motors connected to a ‘limping system’, which will allow the robot to be straightened out and removed from the tank without power. This is an important consideration, as the robot arm is inserted through a narrow riser and must be ‘limp’ (straight) to remove from the tank. However, due to the hazardousness of the tank’s contents, only severely limited options are available for in-tank repair if the system fails [6].

A fault tree analysis of the MLDUA system has been done by our group [2]. This analysis considers the overall

Component	Failure Rate
Bearing	0.00291
Electric Motor	0.0092
Electronic Timer	0.0012
Hydraulic Motor	0.540
Hydraulic Pump	0.0470
Hydraulic Valve	0.00882
Mechanical Brake	0.1386
Optical Encoder	0.0155
Power Supply	0.0137
Rotary Joint	0.0075
Sensor, General	0.00361
Sensor, Level, Liquid	0.0026
Sensor, Pressure	0.00923
Sensor, Temperature	0.00182
Strainer (filter)	0.00019

Table 1: MLDUA Component Failure Rates Per 1000 hours.

failure of the MLDUA system as well as tracking numerous lesser failures as subsidiary events. The events of interest are component failures that lead to failure of the MLDUA while operating in the tank. Power system failure, joint failure, braking system failure, servo control failure, and limping system failure are all considered as separate events modeled by trees, as found in [2].

Table 1 gives typical mean failure rates in failures per thousand hours of operation found in [3] for the components of these fault trees. These are fuzzified as appropriate [6, 12] before use in the fault tree. (This is based on a simple proportional operation, so these values are not shown). Also, the frequencies of several events, such as pressure errors in the hydraulic system were not known at all. For these, a fuzzy representation of ‘unknown’ is used.

Fuzzy Markov modeling of the MLDUA system is of interest to us due to the importance of the order of occurrence of some of the system failures. Two cases are considered. In the first, the operator runs the MLDUA for up to ten hours at a time, stopping only in case of total system failure. The second case considers a conservative operator who removes the MLDUA shortly after any joint failure, despite the kinematic redundancy, in order to avoid a subsequent failure combined with a limping failure resulting in a trapped robot. Between uses, the strict maintenance schedule of the robot is expected to return it to an undamaged condition. The failure rates for both situations are calculated using fuzzy fault trees [6] (not shown). Figure 6 shows the Markov model used for both of these cases. The results of these two models, are seen in figure 7. (Note that the lower bounds of some of the log plots are off the bottom of the scale.)

The first thing one notices is the high possibility that the MLDUA will not survive through a ten hour working day without a work halting failure (state F). This is not

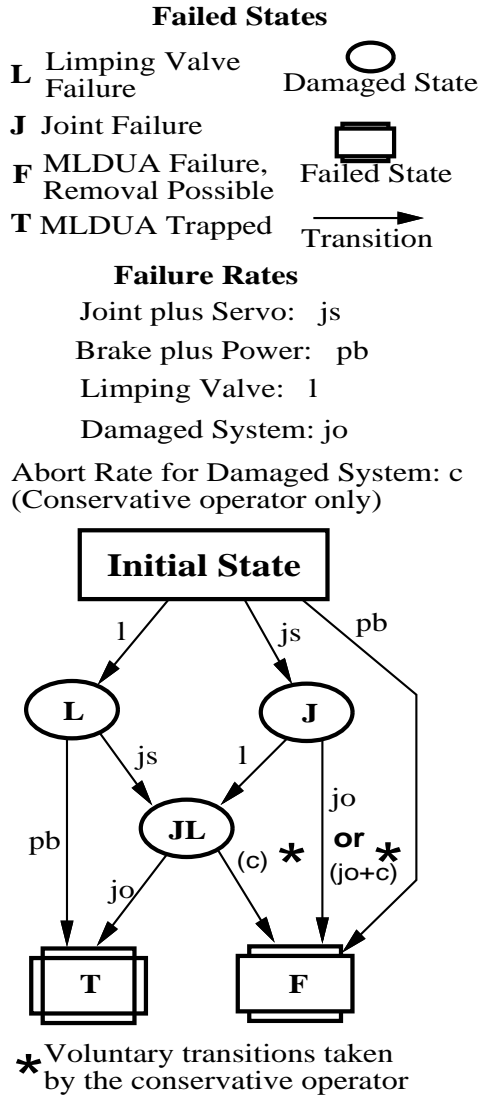


Figure 6: MLDUA Manipulator Markov Model.

good news, but it is not surprising, considering the complex nature of the system and hostile environment. Careful daily maintenance should help with this problem.

One can also note that the possible probabilities for the ‘trapped’ state (state T) are fairly low for both Markov models, with worst-case values on the order of one in ten thousand. This may or may not be an acceptable risk level, depending on expected frequency of use and on the effectiveness of contingency plans for dealing with this failure.

It is also interesting to consider the fact that while a conservative operator decreases the chance of being trapped (state T) considerably (nearly half an order of magnitude), this event still happens. This is due to the possibility of instant failures such as power or brake failure, which do not give the operator time to remove the robot arm. Note also that the nonconservative operator gets more working time in the tank, as the other operator voluntarily enters state F if anything goes wrong.

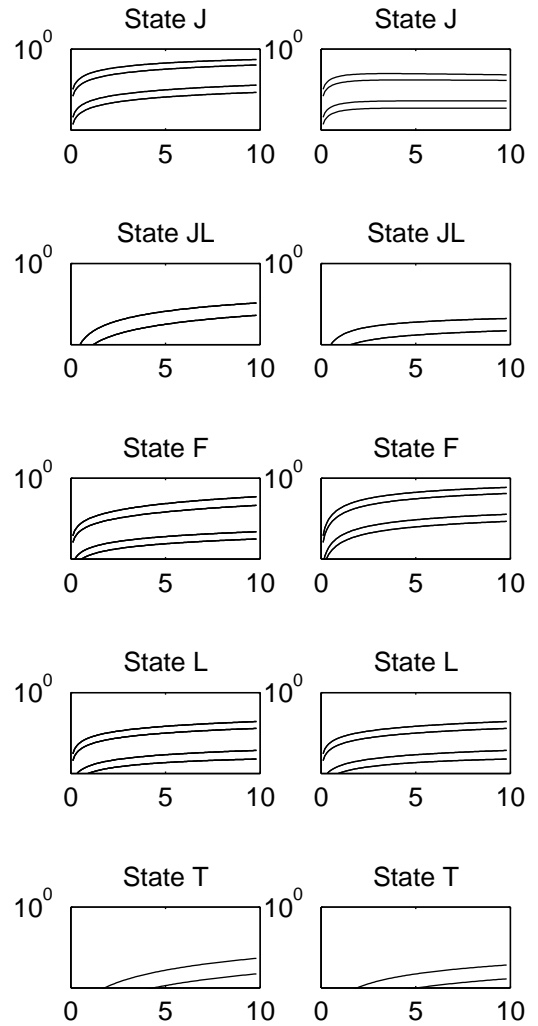


Figure 7: Log Plots of State Populations for Nonconservative (Left) and Conservative (Right) Operators. Vertical scale is 10^{-5} to 10^0 , horizontal scale is 0 to 10 hours.

4. PROBLEMS AND PROSPECTS

The main drawback of the fuzzy Markov modeling method presented in this paper is its computational complexity. The complexity of the model increases exponentially with the number of fuzzy possibility distributions being considered. Currently, only simple or simplified models are solvable in a reasonable amount of time.

Future work in the area of fuzzy Markov modeling is likely to focus on four areas. The first and most obvious of these is reduction of the computational complexity of the model. Similarly, further methods of simplification of the model should be considered. Additionally, Markov modeling is a very broad area, and expanding this technique to some of the modified Markov models shows promise. Finally, application of this technique to other systems is an interesting research issue.

This work was supported in part by the National Science Foundation under grants IRI-9526363 and CMS 9532081, NASA grant NAG 9-845, the Office of Naval Research under contract N00014-06-C-0320, and by DOE Sandia National Laboratory Contract #AL3017.

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