Probabilities of Qualitative Behaviors for Dependability Analysis: Overview*

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Abstract

The quantitative aspects of model specifications are often only partially known. Thus there is a need for ways to analyze models whose quantitative specifications are incomplete. One important goal for model analysis is finding the probabilities of the different qualitatively distinct behaviors a model can exhibit. We show how a model with partial quantitative specifications may be analyzed to bound the probabilities of its behaviors. Some specifications may be characterized by intervals and others by probability distributions, making the technique quite flexible in its ability to use what quantitative information is available.

The technique takes knowledge in the form of a *structural model* with partial quantitative specifications. This model is used to automatically construct *behavioral models* by simulating it. The behavioral models together with the given partial quantitative information are then analyzed probabilistically by a modification of the histogram discretization method, resulting in intervals bounding the probabilities of occurrence for the behaviors.

We use dependability analysis as an example domain. The choice of dependability analysis as a domain was motivated by the fact that most dependability analysis tools face some significant problems that our approach addresses. In our example domain, the technique is applied to a simple dependability model, where the goal is to bound the probability that a modeled system will work dependably for a given period of time.

1 Introduction

We describe a technique for finding probabilities of qualitative behaviors given partial quantitative information about model specifications in the form of intervals and probability distributions, and apply it to a dependability analysis problem. By quantitative model specifications we mean quantitative aspects of the a model such as parameters, inputs, and initial conditions. Our technique for bounding the probabilities of qualitatively meaningful behaviors given partial quantitative model specifications uses a modification of the histogram discretization method [Ingram et al. 68; Colombo and Jaarsma 80].

Critical applications like the Space Shuttle Program have contributed to the computer industry's

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quest for highly dependable computers. Such applications have increased the importance of dependability analysis in computer system development. However, even modern, state of the art dependability analysis tools rely on accurate quantitative model specifications, which in real situations are not available. Such specifications are obtainable only roughly at best, via expert knowledge or limited testing data. Therefore there is a need to do dependability analysis given uncertain quantitative information, thus avoiding unsupported assumptions.

We explain a dependability analysis technique which overcomes some problems facing present dependability analysis tools. This dependability modeling technique uses models whose quantitative specifications may be described with intervals, probability distributions, or numbers. In this application of Q3 [Berleant and Kuipers 91] we find the *probabilities of qualitative behaviors*. In this dependability example, the behaviors are system *crash* by some time point of interest, and system *dependable* until (at least) that time. Dependability is simply the probability of the dependable behavior.

Presently there are four major dependability analysis techniques, three of them analytical. The simplest analytical techniques use combinatorics while the complex analytical evaluation techniques make use of Markov models. Petri net modeling is a popular simulation dependability analysis technique. Another simulation technique for dependability analysis is Monte Carlo simulation. Many dependability analysis tools like HARP [Bavuso 87], ARIES [Makam 82] and SHARPE [Sahner and Trivedi 86] have been developed and are available. All of these tools support one or more of the major dependability analysis techniques. See Johnson [1988] and Mullazini [1986] for a thorough comparison of the available dependability analysis tools.

The state of the art dependability analysis tools face some significant problems. These include:

1. Numerical specifications are assumed correct. Yet accurate numerical inputs are often difficult or impossible to obtain, so tools return incorrect (unrealistic) results.
2. Present evaluation techniques do not easily handle uncertainty in the quantitative model specifications to convert it to uncertainty at the output (that is, the dependability).
3. With the notable exception of SHARPE, tools usually do not support hierarchical modeling.

Our Q3-based [Berleant and Kuipers 91] approach gives us the ability to describe quantitative model specifications as probability distribution functions or intervals (or numbers which are degenerate intervals). This alleviates problem (**??**) by providing more flexibility in describing the quantitative knowledge available, instead of requiring modellers to choose arbitrary "reasonable" numbers. The ability to express quantitative information using pdfs and intervals also alleviates problem (**??**). Given model inputs described as intervals or pdfs, output is an interval bounding the dependability, that is, the probability of system failure.

2 A Dependability Model Example

We model dependability using a simple model for a large system that can tolerate some limited number of failed elements. The elements fail at some rate, are repaired at some rate, and if the total number of failed elements exceeds the tolerance of the system it crashes. The rates and tolerance are to be described using partial quantitative information in the form of intervals or probability distribution functions (pdfs). Figure **??** shows the model.

Suppose we want to specify one of the model inputs, for example the *element failure rate* of figure **??**, with a pdf. Figure **??** shows an iscosceles pdf representing a failure rate such as might be obtained subjectively from an expert.

Triangular and trapezoidal shapes are often assumed, e.g. by work in fuzzy reasoning [Shen and Leitch 91]. Gaussian (bell) curves with clipped

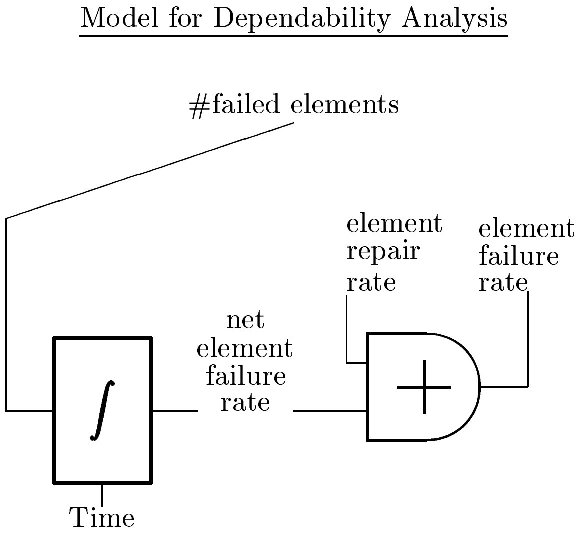

Figure 1: Simple dependability model for a larger system. If elements fail faster than they are repaired, eventually the failed element tolerance is exceeded and the system crashes. If this occurs after some time t of interest, the system is dependable. (This model is compared with a standard Markov dependability model in section **??**.)

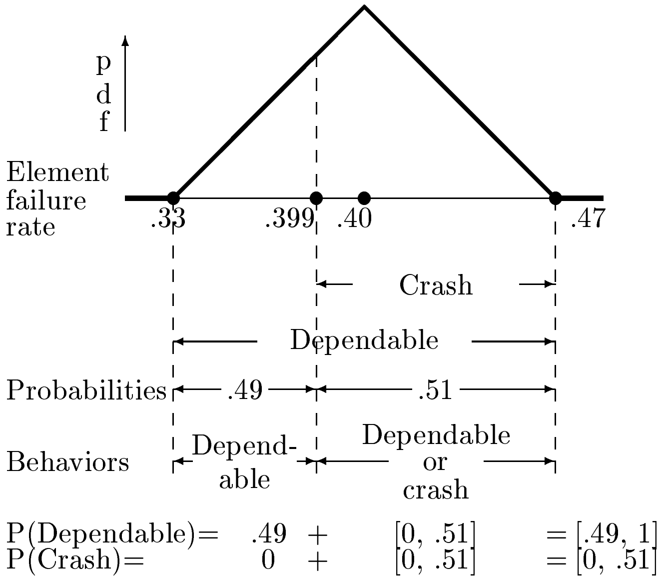

Figure 2: An isosceles pdf is used to derive probability ranges for behaviors of a system.

The domain of possible element failure rates is partitioned into two intervals which are each consistent with one or both of the qualitative behaviors called "dependable" and "crash". "Crash" is inconsistent with low element failure rates in the left portion of the pdf; "dependable" appears plausible for any possible element failure rate. This allows inferring intervals bounding the probabilities of each behavior, as illustrated by the figure: the left portion of the pdf has a probability mass of 0.49 which is assigned to the dependable behavior; the rest with a probability of 0.51 cannot be unambiguously assigned to a behavior, so each behavior is assigned its share, known only to be within the interval $[0, 0.51]$.

tails are another commonly used pdf. The method of this paper is capable of handling arbitrary pdfs, given code for their associated integrals (i.e. their cumulative distribution functions). Figure **??** exemplifies how probabilities of behaviors are bounded.

2.1 Finding the consistency of a behavior

It is necessary to determine, for each interval in the partition of the pdf domain (or in the case of more than one pdf-described model inputs, for each element in the *cartesian product* of the partitions), which of the qualitative behaviors the interval may be consistent with. Partitioning may be done unintelligently [Berleant 90], but it is useful to make the partition wisely, so that the partition boundaries have some correspondence to boundaries of regions of the pdf domain space such that values within a region are all plausible for the same subset of behaviors.

The method for achieving these objectives is as follows:

1. *Represent the behaviors as constraint networks.* This is done by simulating the model to automatically produce behavior models, using the *Q3* program [Berleant and Kuipers 91][1]. The behavior models are represented as constraint networks consisting of the dependencies of the various model variables upon each other, instantiated for each time point in the simulation, as well as integration constraints that use values at a time point to constrain values in neighboring time points. A constraint network describing one behavior of the model of figure **??** is shown in figure **??**.

2. Label the constraint network nodes with intervals, which are 1) the quantitative model specifications when these specifications are intervals, 2) the pdf domains when the specifications are pdfs, and 3) intervals describing the

[1] *Q3* derives from a previous program *Q2* [Kuipers and Berleant 88] which in turn derives from QSIM [Kuipers 84].

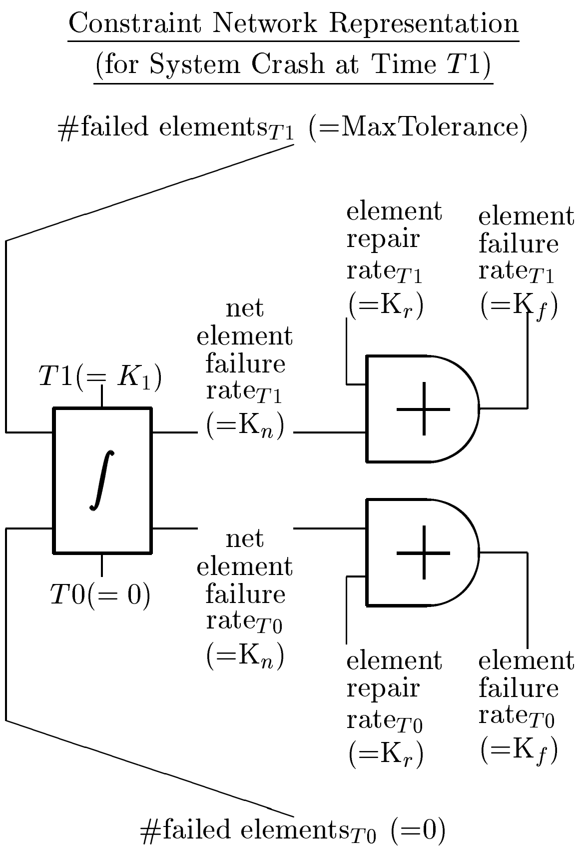

Figure 3: Constraint network representing a behavior of the model of figure **??**.

boundary conditions imposed by the behavior itself. The boundary conditions in figure **??** are, $T1 = K_1$ and $\#\text{failed elements}_{T1} = MaxTolerance$; sample values for K_1 and MaxTolerance as well as other model inputs are given in table **??**. (Note that an interval may be quite weak, e.g. $[0, \infty]$.)

3. Propagate the quantitative information throughout the constraint network, allowing it to settle using Waltz filtering [Davis 87].

4. Examine (automatically) the settled constraint network to see if, for the behavior represented by the network, the inferred plausible values for the pdf are a subinterval of the domain of the pdf. If so, values outside the subinterval are inconsistent with the behavior represented by the network, and the boundaries of the subinterval should be used in partitioning the domain.

5. The probability of each behavior is bounded as illustrated in figure **??**.

3 Discussion and Conclusions

This work has described a method for bounding probabilities of qualitative behaviors, given partial quantitative model specifications in the form of intervals and pdfs. Previous work on finding probabilities of behaviors has appeared in Yeh [1990], Doyle and Sacks [1989], and DeCoste [1990]. Monte Carlo simulation can also be used for this purpose. However, these techniques do not handle partial quantitative model specifications as flexibly as the method reported here: previously reported methods cannot handle quantitative specifications for which some specifications are intervals and others are pdfs. A more detailed discussion of previous work appears in the longer version of this paper [Berleant and Chandra 91].

The need for dependability analysis has become necessary for the development of next generation,

Dependability analysis results

element failure rate $\in$ [.033,.047]	element failures tolerated $\in$ [60,80]	element repair rate $\in$ [.007,.012]	$p(working)$ (dependable behavior), time = 1800
$\frown$ ($\wedge$)	†	†	> 0.49 (0.48)
†	$\frown$ ($\wedge$)	†	> 0.34 (0.32)
$\frown$ ($\wedge$)	$\frown$ ($\wedge$)	†	> 0.66 (0.65)

Table 1: Some dependability results for the 1-tank dependability model of figure **??**. Two pdf shapes were tested. Results for an isosceles shape, $\wedge$, are shown in parentheses.
Key:
$\wedge$designates an isosceles pdf with base defined by the associated interval.
$\frown$designates a trimmed Gaussian pdf with 4 standard deviations within the associated interval, the tails outside trimmed off, and the area normalized to 1.
† indicates no pdf, just the interval.
Note that the shape of the pdf makes a difference in the results. With repair rate also described by a pdf (not shown) there was no further improvement in inference due to excess width in interval calculations [Moore 79]. However, use of recent semi-numerical techniques [Berleant and Kuipers 91] is expected to help.

high-performance computer systems. We have described a technique for bounding the probabilities of qualitatively meaningful behaviors. This allows using what knowledge is actually available to describe values of model inputs, whether it be in the form of numbers, intervals, probability distributions or a some of each. The technique was demonstrated on a simple model, and provided dependability bounds not easily obtainable otherwise, as other methods cannot work as flexibly with partial quantitative model specifications.

The idealized dependability model used here was checked by comparing the results with a considerably more complex Markov model requiring precise inputs, analyzed using the HARP tool. The results were similar to those predicted by the model used here, given precise numerical model specifications. Results for a Markov model given quantitative model specifications in the form of intervals and pdfs are not available; we plan to investigate the use of such partial quantitative information in Markov models in future research.

The technique appears to have utility and to merit further investigation in other domains requiring probabilistic bounds on qualitative alternatives given limited information about value, such as risk and decision analysis.

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