

# Predicting the Reliability of a Complex System Using an Artificial Neural Network

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**Abstract.** The capability to predict the reliability of complex systems that must be deployed without overly prolonged or expensive testing is of increasing importance to the military test and evaluation community. The presentation of subsystem reliability data to an artificial neural network is a critical factor in the capability of such networks to produce accurate system predictions. By producing a matrix of values corresponding to subsystem reliabilities, using a zero (0) for a nonexistent parallel resource and a one (1) for a nonexistent series subsystem, it was possible to train an artificial neural network to accurately predict the overall system reliability.

## Introduction

**Background.** The definition of reliability of a system is usually stated in straightforward terms as "...the probability that the system will not fail during delivery of service" (Reibman and Veeraraghavan, 1991), or alternatively, that the overall system performance figure of merit will not enter failure mode between the time a service is requested and when that service is delivered (Sun et al 2001). To determine the reliability of a complex system for which the reliability of individual subsystems is known can be difficult, depending on the configuration of the subsystems and the distribution of nodes (e.g., workstations in a communications network). In relatively simple systems, series relationships act as a logical AND gate. Both subsystems must operate successfully in order to have a successful overall system operation. Parallel (i.e., redundant) subsystems act as a logical (inclusive) OR gate. One or the other of the two subsystems (or both) must operate successfully in order to have a successful overall subsystem operation. This simplified approach may not be applicable to system optimization but can work well with straightforward systems (Liu, 1998). This can lead to an assessment of overall system reliability in substantially less time than other approaches (e.g., Monte Carlo simulation).

However, systems are rarely simple. Combinations of series and parallel relationships and interdependencies between subsystems complicate the problem of determining overall system reliability. Furthermore, reliability measurement usually does not consider system degradation, where degradation is defined as substandard operation that impairs overall system operation but may not cause what is known in military testing as a mission critical failure (i.e., a failure of an overall system that would force the cancellation of a mission). The problem of degradation involves subsystem testing to determine the probability of obtaining a result (e.g., voltage, frequency, or other parameter) that is outside established system parameters but is not sufficiently far away from acceptable values to cause a mission critical failure, although some of

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the system results for certain combinations of inputs will be unavailable or incorrect, and may have a less than critical impact on the successful completion of a military mission (e.g., forcing the system users to perform some manual calculations). This type of system, known as a noncoherent system, “takes into account the failures caused by the underproduction of units or services and the failures that are caused by overproduction as well” (Sun, Han, and Levendal, 2001).

A format was developed to present reliability values for subsystem components of complex systems to an artificial neural network (ANN) for the purpose of predicting overall system reliability as suggested by (Coit and Smith, 1995). The format developed includes the capability to describe the probability of critical failure and subcritical failure for subsystems that may have serial or parallel relationships in complex configurations. The reliability of a number of sample systems was obtained and the parameters and results used as training input to an ANN. The ANN was used to predict the reliability of other complex systems and the results were compared to programmatic calculations.

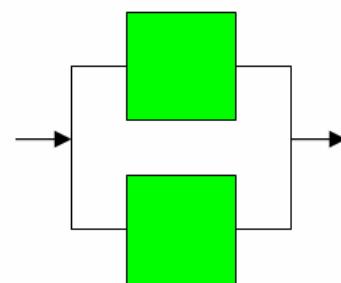
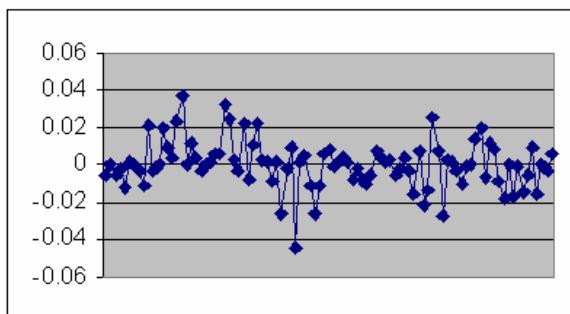
For the research described herein, the ANN tool used was *NeuroShell2®*, a commercially available software product produced and distributed by Ward Systems Group, Inc. The choice of this ANN tool was based primarily on *NeuroShell2®*'s ability to train the network without overtraining (i.e., memorizing a pattern). The training data is compared to a test data set that is randomly selected (using a feature built in to *NeuroShell2®*) and removed from the initial data set. The best fit compared to the test data set is retained, regardless of how much better the fit against the training data set becomes as training progresses. The final results of the network are then applied to a production data set that is also a randomly selected data set that is removed from the original data set prior to commencement of actual training. Thus, the production set that is used to show final comparisons consists of data that has never been seen by the network prior to the final comparison (Ward Systems Group, 1996).

**Thesis.** The thesis is that it is possible to present a generic reliability description of the subsystems comprising a system in such a way that an artificial neural network (ANN) can process the data file presented.

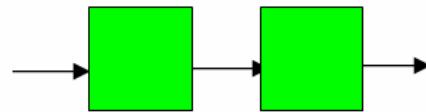
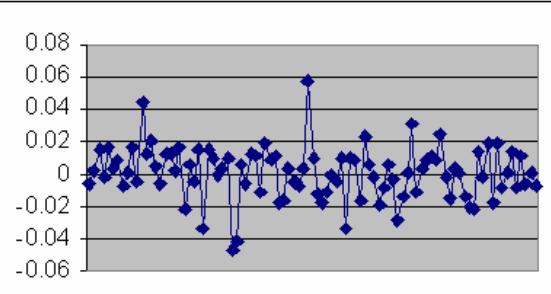
**Initial test of ANN.** As an initial test of the capability of an ANN to predict system reliability, some simple systems were modeled and data produced for presentation to an ANN. The following three charts illustrate the fact that an ANN is capable of predicting the reliability of a simple system. Note that the coefficients of correlation between actual and predicted reliability for these three systems were above +0.997.

## **Description**

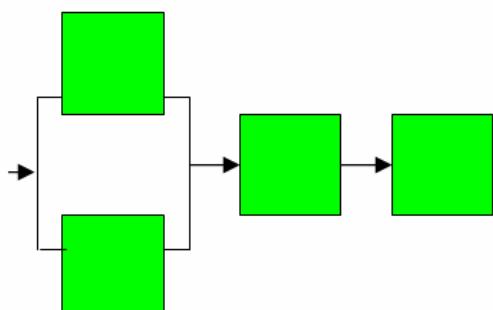
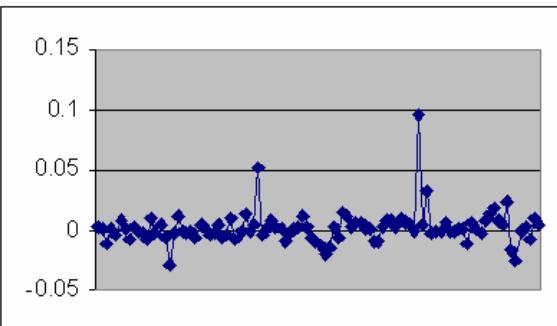
**Representation.** The representation of subsystems must be sufficiently generic to allow for a variety of combinations and also must allow for the calculation of degraded output.



**Figure 1. Residual values for simple parallel system ( $r=.9988$ )**



**Figure 2. Residual values for simple series system ( $r=.9978$ )**



**Figure 3. Residual values for combination series-parallel system ( $r=.9981$ )**

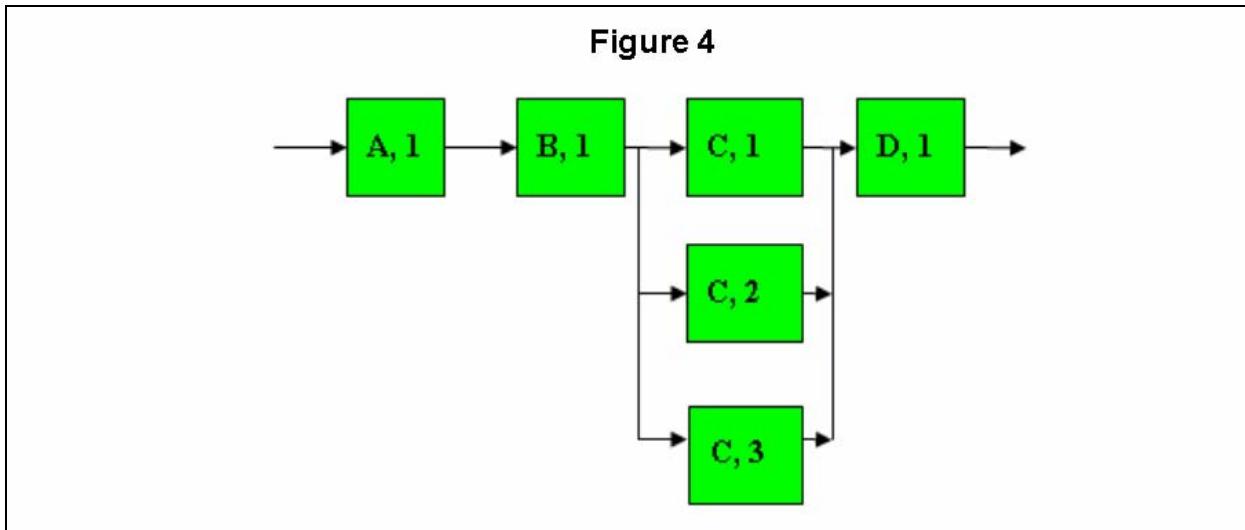
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To allow for this representation, since it cannot be determined in advance whether the relationship between subsystem elements is serial or parallel, or how many elements there are in each configuration, a matrix of elements with dimensions that will encompass the most complex subsystem can be used.

For each element, the following data will be provided.

- The reliability for complete failure with reference to other parallel elements
- The reliability for complete failure with reference to other serial elements
- The reliability for degraded operation with reference to other parallel elements
- The reliability for degraded operation with reference to other serial elements

As an example of how this data format could be used, consider the following system.



The largest dimensions of this system are 4 columns and 3 rows. A  $4 \times 3$  matrix can be used to represent this system. Unused elements in parallel will have a reliability of 0 (an open circuit) and unused elements in series will have a reliability of 1 (a permanent connection). Unused elements are [A,2],[A,3],[B,2],[B,3],[D,2], and [D,3].

The data format would be  $Rs[A,1]$ ,  $Rp[A,1]$ ,  $Rsd[A,1]$ ,  $Rpd[A,1]$ ,  $Rs[A,2]$ ,  $Rp[A,2]$ ,  $Rsd[A,2]$ , ...,  $Rpd[D,3]$ .  $Rs$  represents the serial reliability for total failure, and  $Rp$  represents the parallel reliability for total failure.  $Rsd$  represents the serial reliability for degraded failure, and  $Rpd$  represents the parallel reliability for degraded failure.

To test the ability of an artificial neural network to predict the overall reliability of subsystems with different configurations, data was generated for 1500 different system configurations. A sample data set (with reliability values selected at random) for the system shown above is.

**Figure 5. Sample Data Set with Reliability Values**

.2,.4,0,0,1,1,0,0,1,1,0,0,.3,.3,0,0,1,1,0,0,1,1,0,0,1,1,.25,.2,1,1,.2,.4,1,1,.33,.42,.45,.5,0,0,1,1,0,0,1,  
1,0,0

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This approach allows for the presentation of data in a standard format so that the ANN can process the data. The ANN software used for this investigation is not capable of handling data sets with different record lengths. This approach avoids that obstacle to ANN processing.

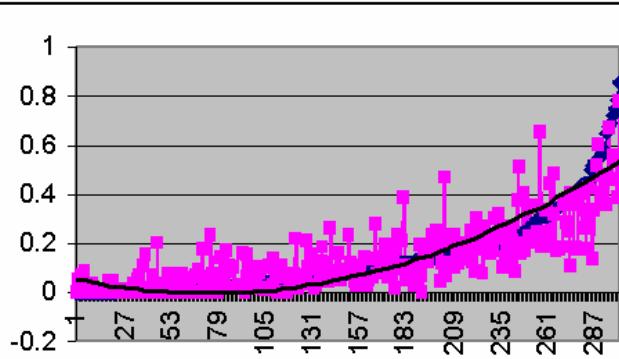
Including threshold values for every subsystem that indicate the impact on critical and subcritical reliability for any degradation in any other subsystem extends the data set further. For the 4 x 3 system pictured in Figure 1, there would be an additional 24 values in the data record (12 values for critical failure impact and 12 values for subcritical failure impact). These values would be subtracted from subsystem reliability as the signal propagates through the system, and prior to the final calculation of overall system reliability.

**Data generation.** An algorithm was developed that prepared a formatted file of 1500 data records using random values of reliability for the subsystems involved, and using different configurations of parallel and serial relationships between subsystems. A portion of the file is shown below.

**Figure 6. Sample results**

```
0 0 0 0 .7865 .2115332 .3710606 .314864 0 0 0 0 .3517857 .46512  
.1474822 .7499236 0 0 0 .1224546 .6921564 0 0 .7832942 .8320953  
.8008459 .7854704 0 0 0 .8302999 .7336618 0 0 .2955675 .2903464 1 0  
.27994 .3840686 0 0  
.4564432 .3308239 .1905266
```

**Figure 7. Predicted Reliability (trend line) vs. Actual Reliability of Production Data Set ( $r=0.82$ )**



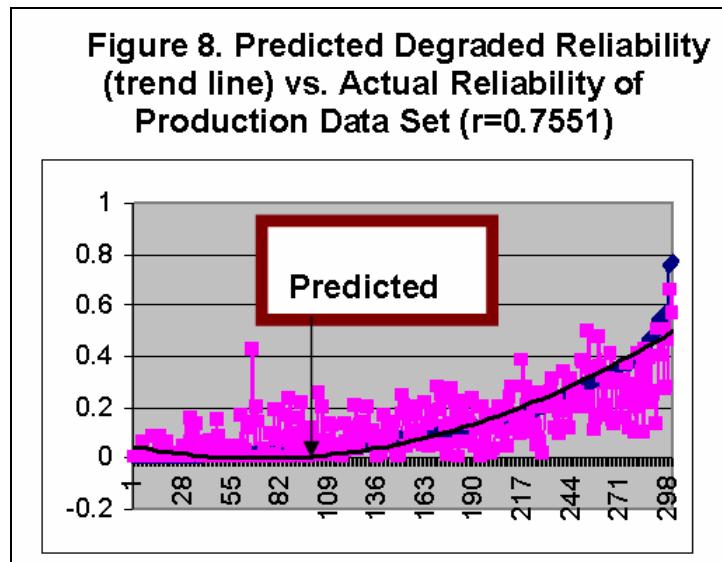
Fifteen hundred data sets were produced with random values (using the built-in pseudorandom number generator in Microsoft® Excel) for fully operational and degraded reliability. Three hundred data sets were randomly selected for a test set, and an additional 300 data sets were randomly selected as a production set. The remaining 900 data sets were used as a training data set for the ANN. Results were kept for the best match to the test set, which avoided the problem of overtraining the ANN (i.e., memorizing the pattern) (Ward Systems Group 1996).

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The resulting relationship was then applied to the production set, which consisted of data that the ANN had not been previously exposed to during training. The results (using a trend line to represent the predicted values) are shown in Figure 7.

The value of the coefficient of correlation for a complex system was not as high as it was for simple systems, but there is still a substantial agreement ( $r = 0.82$ ) between predicted and actual values. The coefficient of correlation is more than 43 times greater than the standard error of the coefficient of correlation, which indicates significance at the .05 level for a sample size of 300.

**Degradation.** Prediction of the degraded performance reliability yielded the following results.



This is significant at the .05 level for a sample size of 300.

## Further Work

Additional investigation into the relationship between full and degraded performance and the ability of an ANN to predict generic system reliability is needed. There is also a need to study  $k$ -out-of- $n$  systems, as well as systems where interactions between subsystems are defined by the output of one subsystem becoming the input of another subsystem, or by the output of a subsystem being fed back as a (stabilizing) portion of the input to that same subsystem.

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## **Biography**

Alan L. Breitler is a graduate student at the University of Maryland University College pursuing a Master's Degree in Information Technology. He recently retired from full time employment after a career as a software developer and analyst in government and industry that spanned 40+ years. Alan currently is a consultant for the US Navy and teaches computer science courses as an adjunct faculty member at Trinity College in Washington, DC and the extension program for Florida Institute of Technology at the Patuxent River Naval Air Station, Patuxent River, MD. Dr. Breitler holds a Ph.D. from Catholic University.

Crystal D. Sloan is a principal of EagleRidge Technologies, Inc. (ertin.com), a Rockwood, Tennessee consulting and e-commerce firm, contributor to a number of books on computing, and a recipient of the Microsoft® MVP award. From 1999 until his death in July 2003, Ms. Sloan also worked with the late Dr. William H. McCumber on the development and teaching of Web-based graduate classes at the University of Maryland University College (UMUC); she continues to assist with classes there. Past projects include development of systems for the space shuttle, medical applications, and radiation monitoring of nuclear plants, many medical laboratory instruments, and numerous business applications. Ms. Sloan holds a S.B. in Mathematics from M.I.T.