Overview and Reference Document for Operational Experience Results and Databases Trending

1 Introduction

Trend methods differ depending on the nature of the data under study. When raw data, such as counts of failures and either demands or operating times are available for each fiscal year, a more complicated calculation is performed than ordinary least squares regression because the failures are discrete and the variances in the data are not the same from year to year.

Also, because all of the data considered in this study represent either probabilities that must lie between zero and 1, or rates that must be non-negative, the linear models are applied to simple functions of the observed data.

Table 1 provides an overview of the trending methods for various types of data. Subsections below provide further details, including specific references to thorough explanations in Reference 1. Two sections at the end provide reference information in the form of a glossary of terms and a list of acronyms.

2 Trend Method for Data that Includes Event Counts

To create the trend charts, the failure counts and associated number of demands or mission times from EPIX for each fiscal year from 1998 to 2006 were obtained for the applicable failure modes. A Bayesian update was applied separately for each failure mode or event type and year. A beta prior distribution was used for the failure-to-operate probability, and a gamma prior distribution was selected for the spurious operation rates. The means of the prior distributions were based on a pooling of the component or event type data for the years going into the plot, but other aspects of the prior distributions were relatively flat, so that the prior distributions did not create large changes in the data. The probability counts were taken to be binomial in each year, while Poisson data in each year were assumed for the rates. The specific priors used were the "constrained noninformative" distributions (CNID) described in Reference 1, Sections 6.2.2.5.3 and 6.3.2.3.3. The Bayesian update process is straight-forward for the beta/binomial and gamma/Poisson prior/likelihood pairs because the posterior distributions are in the same family of probability distributions as the prior distributions. The Bayesian update process was performed in order to obtain yearly estimates that are all strictly greater than zero.

In the plots, the means of the posterior distributions from the Bayesian update process were trended across the years. The posterior distributions were also used for the vertical bounds for each year. The 5^{th} and 95^{th} percentiles of these distributions give an indication of the relative data variation within each year?. When there are no failures, the interval tends to be larger than the interval for years when there are one or more failures. The larger interval reflects the uncertainty that comes from having little information in that year's data. Such uncertainty intervals are determined by the prior distribution. In each plot, a relatively "flat" constrained noninformative prior distribution (CNID) is used, which has large bounds.

Table 1. Trend methods.

Type of data	Web pages having the data type	Examples	Distribution whose 5th and 95th percentiles form the vertical bars	Trend model	Method for estimating slope and intercept
Raw data: failures or other event counts in time (occurrence rates or failure rates) (see Section 2)	All types of component performance, initiating events, fires	Rate for failure to run or for spurious operation; frequency of demands per reactor year	Perform Bayesian updates of the gamma constrained noninformative prior distribution (CNID)[a] using each year's total occurrences or failures (f_i) and operating or standby time (T_i). The CNID prior distribution mean is $\mu=(f + 0.5)/T$, where $f=\sum f_i$, and $T=\sum T_i$. The resulting posterior distribution mean for the i^{th} year is $(f_i + 0.5) / (0.5/\mu + T_i)$.	$\log[R(t)] = a + b\, t$, where $R(t)$ is the mean of the rate for the t^{th} year. The fitted $R(t)$ is $\exp(a + b\, t)$.	Iteratively reweighted least squares, with weights inversely proportional to the estimated variance of the log of the Bayesian updated rate in each year.
Raw data: failures on demand (probabilities) (see Section 2)	All types of component performance	Probability of failure to start, probability of failure to open/close	Perform a Bayesian updates of the beta CNID using the each year's failures (f_i) and demands (D_i). The CNID prior distribution mean is $\mu= (f + 0.5)/(D + 1)$, where $f=\sum f_i$, and $D=\sum D_i$. The resulting posterior distribution mean for the i^{th} year is $(f_i + \alpha) / [(\alpha / \mu) + D_i]$, where α is a computed number based on μ that lies between 0.3 and 0.5 when μ is <0.5.	$\text{logit}[P(t)] = a + b\, t$, where $P(t)$ is the mean of the probability for the t^{th} year and $\text{logit}[P] \equiv \log[P/(1-P)]$. The fitted $P(t)$ is $\exp(a+bt)/[1+\exp(a+bt)]$.	Iteratively reweighted least squares, with weights inversely proportional to the estimated variance of the logit of the Bayesian updated probability in each year.
Unavailabilities (down times divided by total required times) (see Section 3)	Component performance (MDP, TDP, EDG)	Total (planned & unplanned) maintenance unavailability for EDG	Find the beta distribution which has the same mean and variance as the sample mean and variance estimated from the train unavailabilities in each year.	$\text{logit}[U(t)] = a + b\, t$, where $U(t)$ is the unreliability for the t^{th} year. If the p-value for a statistical test for the significance of the slope was lower, $U(t) = a + b\, t$ was used directly.	Ordinary least squares

Type of data	Web pages having the data type	Examples	Distribution whose 5th and 95th percentiles form the vertical bars	Trend model	Method for estimating slope and intercept
Unreliabilities (system-level failures to start and run, or failures to start and run for the required mission time) (see Section 4)	System studies and the EDG component	Probability of AFW system failing to start	The empirical distribution made up of all the unreliability values simulated in Saphire for the year (using the Latin hypercube sampling method).	logit[U(t)] = a + b t, where U(t) is the unreliability for the t^{th} year. If the p-value for a statistical test for the significance of the slope was lower, U(t) = a + b t was used directly.	Ordinary least squares

a. The CNID is a relatively “flat” prior distribution that is constructed to have little influence on the posterior distribution, other than that its mean value is specified.

The trends themselves were modeled using a log model for rates and a logit model for probabilities. More specifically, for rates, the fitted model is

$$log(R_i) = a+bi, \quad (1)$$

where "R_i" is an estimated mean for the plotted failure rate in the i^{th} year. For the failure-to-operate probability, the model is

$$logit(P_i) = log[P_i/(1-P_i)] = a+bi, \quad (2)$$

where, as the equation shows, $logit(P_i)$ is defined as the logarithm of $[P_i/(1-P_i)]$. In this equation, P_i is the estimated mean of the failure-to-start probability for the i^{th} year. The log and logit transformations ensure that the rates remain positive and the failure probabilities lie between zero and one.

A further refinement in the regression calculations comes from the fact that inferences based on simple regression assume that the variances of the data in each year are the same across years. With count data underlying the failure rates and probabilities, the variances are known to differ. An iterative reweighted least-squares procedure, described in Sections 7.2.4.6 and 7.4.4.5 of Reference 1, accounts for this variation.

The horizontal curves plotted around the regression lines in the graphs form simultaneous confidence bands for the fitted lines. They are based on the asymptotic normality of the estimates of the intercept and slope coefficients, which make the fitted $\hat{a} + \hat{b}\,i$ data normally distributed also. On the scale of the linear data, bounds that have a 90% probability of containing the entire regression line are computed. The bounds are larger than ordinary confidence intervals for the trended values because they form a band that has a 90% probability of containing the entire line. The values are translated back to the scale of the rates and probabilities using the relationships, $\hat{R}_i = \exp(\hat{a} + \hat{b}\,i)$ and $\hat{P}_i = \exp(\hat{a} + \hat{b}\,i) / [1 + \exp(\hat{a} + \hat{b}\,i)]$. Details of this calculation are presented in the Reference 1 sections mentioned above. In the Data Tables section at the end of each document, these bounds are labeled as the "Lower (5%)" and "Upper (95%)" values in the "Regression Curve Data Points" columns.

In the lower left hand corner of the trend figures, the regression p-values are reported. They come from a statistical test on whether the slope of the regression line might be zero. Low p-values indicate that the slopes are not likely to be zero, and that trends exist.

3 Unavailability Trend Method

The mean for each year is the samples mean calculated from the train-level unavailabilities for that year. The vertical bar spans the calculated 5^{th} to 95^{th} percentiles of the beta distribution whose mean and variance agree with the sample mean and variance of the unavailabilities for that year.

For the trend graphs, two fits are performed; linear and logit.

The linear model uses the standard equation of the point-slope formula $Y=a+bt$ where Y is the random variable and t is a known quantity. In many applications, Y is a failure rate or failure probability and t is the year. A least squares fit is sought for the coefficients of the equation.

The logit model uses the equation of the point-slope formula $\ln[P/(1-P)] = a+bt$ where P is the random variable and t is the year. This model is useful when P is between 0 and 1, such as when P is a failure probability. If the P is a small probability, then the logit(P) is close to ln(P), and the logit model could be approximated by $\ln(P)=a+bt$. ~~an ordinary least squares fit is sought for the logit model~~ [Eq. (2)].

The fit that shows the lower P is used for the trend shown in the component performance study trend.

4 Unreliability Trend Method

The trend charts show the results of using data for each year based on selected system-specific failure probabilities and maintenance unavailability data over time. The uncertainty distribution and mean for each year vertical bar are the simulated percentiles and mean from the combined Latin-hypercube samples.

For the trend graphs, two fits are performed; linear and logit.

The linear model uses the standard equation of the point-slope formula $Y=a+bt$ where Y is the random variable and t is a known quantity. In many applications, Y is a failure rate or failure probability and t is the year. A least squares fit is sought for the coefficients of the equation.

The logit model uses the equation of the point-slope formula $\ln[P/(1-P)] = a+bt$ where P is the random variable and t is the year. This model is useful when P is between 0 and 1, such as when P is a failure probability. If the P is a small probability, then the logit(P) is close to ln(P), and the logit model could be approximated by $\ln(P)=a+bt$. ~~an ordinary least squares fit is sought for the logit model~~ [Eq. (2)].

The fit that shows the lower P is used for the trend shown in the component performance or system study trend.

5 Glossary

Constrained non-informative distribution (*CNID*)	A relatively “flat” prior distribution that is constructed to have little influence on the posterior distribution, other than that its mean value is specified.
Demand	An automatic or manual signal for the component to start or operate.
Demand rate	The number of demands divided by the operating time, in years.
Distribution	A function that describes the values a random variable or an uncertain quantity can take on and the associated probabilities. In this document, we use two families of distributions to describe uncertainty: beta distributions apply to quantities that lie in the interval from 0 to 1, and are used for failure probabilities and maintenance unavailabilities. Gamma distributions apply to quantities that are greater than or equal to zero, and are used for failure and occurrence rates. Particular distributions in each family are defined by two parameters, α and β.

Failed state (*of a component*)	A condition in which a component *could not* perform its function if it were to be demanded.
Failure (*of a component*)	A condition in which a component *does not* perform any one of its designed functions.
Failure mode	The specific function that a component fails to perform. Some examples, which may or may not apply to the equipment under consideration, are failure to start, failure to run, failure of a valve to open or close, and spurious operation (i.e. failure to remain in the desired state).
Failure on demand	Failure when a standby system is demanded. Modeled as a random event, having some probability, but unpredictable on any one specific demand.
Failure probability (*on demand*)	Probability of an entity (component, system, etc.) not responding when demanded to act (start, stop, open, close, etc.). Estimated as the number of failures divided by the number of times that the action was demanded.
Failure rate	Number of failures per unit time in a given time interval. The failure rate is such that the rate times some time interval is approximately the expected (or mean) number of failures in that period.
Failure to load and run	A failure mode for emergency diesel generators. Failure to load and run for the first hour.
Failure to open or close (*FTOC*)	A failure of the component to open, close, or operate. This failure mode is assigned to valves. The specification of either open, close, or operate acknowledges the uncertainty in failure data coding on what precise effect the failure had on that component.
Failure to run (*FTR*)	Used for normally running equipment. A failure of the component after the component has successfully started.
Failure to run ≤ 1 hour (*FTR≤1H*)	Used for normally standby equipment. A failure to run within the first hour of operation, given a successful start.
Failure to run > 1 hour (*FTR>1H*)	Used for normally standby equipment. A failure of the component after the component has run for 1 hour.
Failure to start (*FTS*)	A failure of the component to reach 90% of rated flow, speed, or position.
Industry-wide	This term means that the data were collected or pooled across all plants that have the component and/or system of interest. By doing so, it is recognized that components of varying types, sizes, manufacture, etc are included in the data set.

Least squares fit	Also known as ordinary least squares analysis, this is a method for fitting a function (such as a straight line) to data. It determines the values of the unknown quantities in the fitted model by minimizing the sum of the squares of the residuals (the differences between the fitted and observed values).
Linear model	The linear model uses the standard equation of the point-slope formula $Y=a+bt$ where Y is the random variable and t is a known quantity. In many applications, Y is a failure rate or failure probability and t is the year. A least squares fit is sought for the coefficients of the equation.
Logit model	The logit model uses the equation of the point-slope formula $\ln[P/(1-P)] = a+bt$ where P is the random variable and t is the year. This model is useful when P is between 0 and 1, such as when P is a failure probability. If the P is a small probability, then the logit(P) is close to ln(P), and the logit model could be approximated by $\ln(P)=a+bt$.
Loglinear model	The loglinear model fits $\ln(R) = a + bt$. This model is useful when R is greater than 0, such as when R is a failure rate.
Mean	The mean of a distribution is the weighted average of the outcomes, where the weights are the probabilities of the outcomes.
p-value	The probability that the data set would be as extreme as it is, if the assumed model is correct. It is the significance level at which the assumed model would barely be rejected by a statistical test. A small p-value indicates strong evidence against the assumed model.
Reliability	The reliability of a component or a system is the probability that it will perform its required functions under stated conditions for a stated period of time.
SAPHIRE API	An advanced programming interface to the SAPHIRE code. The API allows the user to analyze SPAR models using a programmatic interface. In this manner, the analysis takes place without opening and closing each SPAR model and the output is directed to text files, which facilitate further analysis.
Spurious operation (*SO*)	Any pre-defined change of state, such as a valve opening or closing, when this is action is not demanded.
Statistically significant	A trend or other departure from an assumed model is statistically significant if the test of the assumed model gives a p-value of 0.05 or smaller.

Trend — A line fitted though the data using any of several techniques that shows a slope. The slope of the line can be used to interpret increasing, decreasing, or stable data. The slope of the line is tempered with the p-value, which indicates whether there is a statistical basis for the interpretation of increasing, decreasing, or stable data. When the p-value is not small, the assumed model or “null” hypothesis that the slope is zero is not rejected.

Unavailability (*UA*) (Maintenance) — The probability that a component/train is unavailable, out-of-service, when demanded. UA is calculated using the hours a train of components is unavailable due to test or maintenance over the reactor critical hours the plant experienced during the time period being evaluated.

Unreliability — One minus the reliability. That is, unreliability is the probability that the system will fail to complete its required mission (here defined to be 8-hours) when demanded. This includes the contributions of UA and any applicable failure modes, such as FTS, FTR≤1H, FTR>1H, FTR, FTOC, and SO.

Variance — The variance of a random variable measures the dispersion or spread in the distribution of data by averaging the squared deviations from the mean.

6 Abbreviations

AC	ac power
AFW	auxiliary feedwater
AHU	air handling unit
AOV	air-operated valve
BAT	battery
BUS	bus (electrical)
BWR	boiling water reactor
CBK	circuit breaker
CCF	common-cause failure
CCW	component cooling water
CDS	condensate system
CHL	chiller
CHW	chilled water system
CKV	check valve
CST	condensate storage tank
CTG	combustion turbine generator
CTS	condensate transfer system
CVC	chemical and volume control
DC	dc power
DDP	diesel-driven pump
EDG	emergency diesel generator
EPIX	Equipment Performance and Information Exchange
EPS	emergency power system
ESW	emergency or essential service water
FAN	fan
FTC	fail to close
FTFR	failure to transfer
FTLR	fail to load and run
FTO	fail to open
FTO/C	fail to open or close
FTOP	fail to operate
FTR	fail to run
FTR>1H	fail to run after 1 hour of operation
FTR≤1H	fail to run for 1 hour of operation
FTRO	failure to reopen
FTS	fail to start
FWS	firewater system

HOV	hydraulic-operated valve
HPCI	high-pressure coolant injection
HPCS	high-pressure core spray
HPI	high-pressure safety injection
HPSI	high-pressure safety injection
HTG	hydro turbine generator
HTX	heat exchanger
HVAC	heating, ventilating, and air conditioning
IAS	instrument air system
INL	Idaho National Laboratory
INPO	Institute of Nuclear Power Operations
ISO	isolation condenser
LCI	low-pressure coolant injection
LCS	low-pressure core spray
LER	licensee event report
LLOCA	large loss-of-coolant accident
LOAC	loss of ac bus
LOCA	loss-of-coolant accident
LOCCW	loss of component cooling water
LOCHS	loss of condenser heat sink
LODC	loss of dc bus
LOIA	loss of instrument air
LOMFW	loss of main feedwater
LOOP	loss of offsite power
LOSWS	loss of service water system
LPI	low-pressure injection
MDC	motor-driven compressor
MDP	motor-driven pump
MFW	main feedwater
MLOCA	medium loss-of-coolant accident
MOOS	maintenance-out-of-service
MOV	motor-operated valve
MSPI	Mitigating Systems Performance Index
MSS	main steam system
NRC	U.S. Nuclear Regulatory Commission
NSW	nuclear or normal service water
PDP	positive displacement pump
PMINJ	probability of multiple injections
PMP	pump volute
POD	pneumatic-operated damper
PORV	power-operated relief valve

PRA	probabilistic risk assessment
PWR	pressurized water reactor
RADS	Reliability and Availability Database System
RCIC	reactor core isolation cooling
RES	Office of Nuclear Regulatory Research
RCS	reactor coolant system
RHR	residual heat removal
RHRSW	residual heat removal service water
ROP	Reactor Oversight Program
SBO	station blackout
SEQ	sequencer
SGTR	steam generator tube rupture
SLOCA	small loss-of-coolant accident
SOV	solenoid-operated valve
SPAR	standardized plant analysis risk
SRV	safety relief valve
SWS	service water system
TBC	turbine building cooling water
TDP	turbine-driven pump
T&M	test and maintenance
TNK	tank

7 Reference

1. Atwood, C.L. et al., *Handbook of Parameter Estimation for Probabilistic Risk Assessment*, U.S. Nuclear Regulatory Commission, NUREG/CR-6823, September 2003.