Stochastic Simulation of Cyber CLOUD and Power Grid

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***Abstract*—Conventionally in Cyber CLOUD and/or Power Grid modeling and simulation; failure and repair rates of servers or generators and of transmission lines or links, as well as load (demand) on the system are collected as deterministic input constants from field studies. CLOURAM mimics a Cyber- or Power generation (links assumed 100% reliable) system, where digital event simulation (DES) is applied to draw failure and repair times and load for production units. Their assigned failure and repair rates and load cycle remain constant across the simulation runs. In this "Stochastic" modified version of CLOURAM through Stochastic Simulation of a Grid or a CLOUD, i.e. the failure and repair rates and the load are not any longer constants, but random deviates simulated from selected probability distributions. The CLOUD metrics with the proposed Stochastic Simulation approach are compared very favorably to those of previously non-Stochastic Simulation benchmark cases with deterministic rates and load cycle. Then one can study the producer and link simulations with various probability density functions to mimic the grid operation of Power and Cyber systems.**

Index Terms—**Bayesian Gamma, uniform, DES, LOLP.**

I. Introduction

For a Power or Cyber Grid scenario, the following features are provided; that is, the analyst is expected to:

1) Input failure and repair rates of power generator or cyber servers' (producers) and transmission lines' (links).
2) Study the effect of different load distributions using stochastic simulation. We use Normal probability density.
3) Examine the effect of different failure and repair distributions using stochastic simulation Times to failure and repair probability distributions to be supported are Gamma (Empirical Bayesian) and Uniform densities.

II. Methodology

In the following studies, the large power or cyber CLOUD system of 348 units (data95.txt) will be taken as an example as in Fig. 1 to follow up and compare in the rest of the article [1]. See Fig. 1 descriptions in Appendix.

Stochastic Simulation (SS)' is added to Simulation in CLOURAM (**CLO**Ud **R**isk **A**ssessment & **M**anagement) studied as in Fig. 1. NSS: Non-Stochastic Simulation. LOLP:

Loss of Load Probability = Loss of Load Expected/1 year or exposure period in years.

User inputs normally collected grid data in one of the following ways:

1. Input wizard in a dialog by dialog approach.
2. Manual entry for each group filling out the cubicles.
3. Import data that was saved earlier from data files.

Next, we study the following steps in the article:

A) Benchmarks to verify the SS software operation where inputs of averages default to NSS solutions as in Fig. 1.

B) Non-benchmark cases that follow the Cyber CLOUD or Power Grids after the verification. Then, use different inputs unequal to those of benchmarks, either more or less, to see the effect of SS with links appended to the production only.

III. Numerical Applications to Stochastic Simulation to Verify the Nonstochastic Default

A. Times to Failure and Repair are Negative Exponential

The following Fig. 3 displays the initial screen when the user clicks the Stochastic Simulation (SS) after importing the CLOUD data such as data95.txt shown in Fig. 1 and Fig. 2.

To activate the dialogue box, click on group 1 in the Update column above right that calls for the first group's failure rate (28/1000) and repair rate (552/10000) that are defaulted input values in Fig. 1. Do the same for 2^{nd} to 24^{th} groups. Note, this article will study various input data assumptions to run a Stochastic Simulation. For producer group 1 with failure rate = 0.028 and repair rate = 0.0552, flat (non-informative) parameters are c = ksi= d = eta = 0, a = 28, and X_T = 1000, b = 552 and Y_t = 10000 as field data inspired from a large CLOUD input, data95.txt [1]. To generate random failure and repair rates, an empirical Bayesian Gamma distribution is used [2]. The failure and repair dates are drawn from Gamma simulators: λ~ Gamma ($a+c$, $(ksi+X_T)^{-1}$) and μ~Gamma($b+d$, $(eta+y_T)^{-1}$). Firstly, link distributions are 'None' (100% reliable) as no Grid exists. Load distribution is assumed Normal density with Mean and Std. Dev. computed from the given deterministic load cycle. When the 24^{th} updating action is done as in Fig. 4, click Simulate System as in Fig. 2.

The SS with n = 100 years of simulation outputs the Fig. 5's LOLP = 5.50%, nearly the same as NSS's benchmark of 5.51% in Fig. 1 as clarified in the Appendix. Therefore, the benchmark is verified. Then any combinations of a, c, ksi, X_T for λ (failure rate), and b, d, eta, y_T for μ (repair rate) can be input as data for the 24 production groups totaling to 348 units of data95.txt example, in regarding the negative exponential for the failure and repair times.

Manuscript received October 10, 2014; revised May 15, 2015.

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DOI: 10.7763/IJCTE.2017.V9.1109

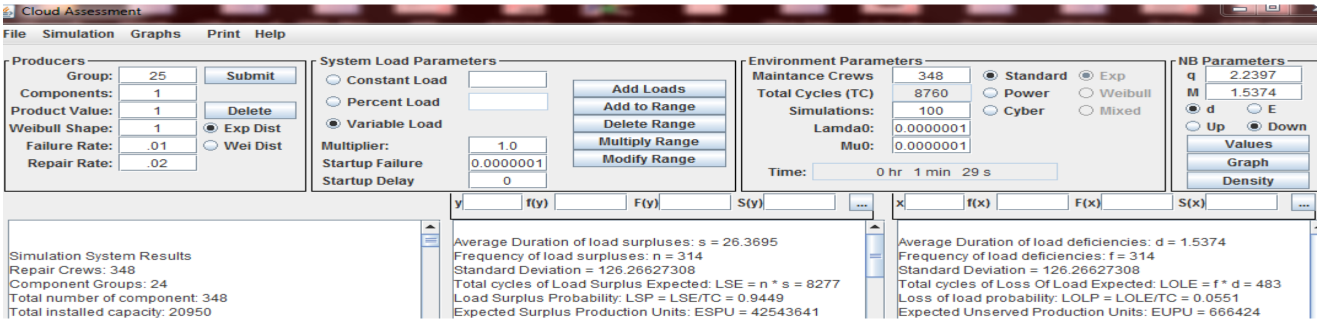

Fig. 1. LOLE=5.51% benchmark index used for Fig. 2 to 12 for a large CLOUD system of 348 units (data95.txt).

B. Times to Failure and Repair Are Weibull Distributed

Now it's time for assuming the times to failure and repair are Weibull distributed. For group1 with failure scale = 35.72 = $(0.028)^{-1}$ and repair scale = 18.12 = $(0.0552)^{-1}$, where both shapes=1 (special case) defaulting to negative exponential, parameters are c = ksi = d = eta = 0 (flat priors), a = 28, X_t =1000, b = 552 and Y_t = 10000 in Fig. 6.

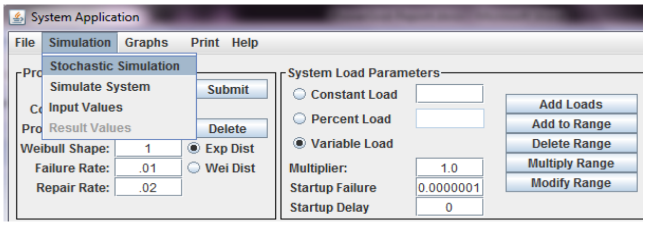

Fig. 2. Appending Stochastic Simulation to CLOURAM in Fig. 1.

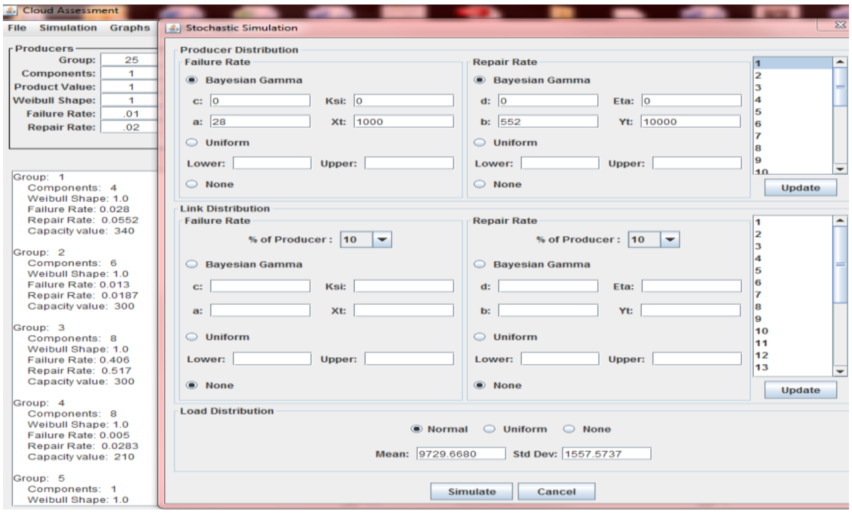

Fig. 3. The dialogue box to start the Stochastic Simulation (time to failure and repair data are in Neg. Exponential, not Weibull).

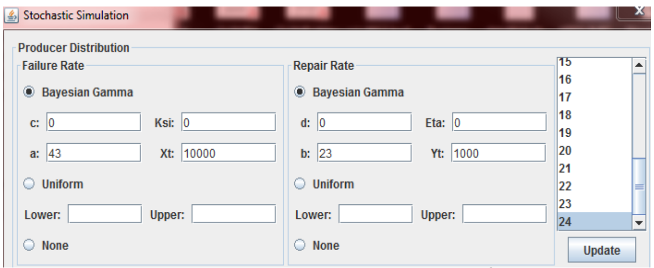

Fig. 4. The Fig. 3 screen above to end the SS at the 24th update (time to failure and repair data are in Negative Exponential).

Then we update from 1st group up to the 24th and as in Section III-A, with 'None' for links and Normal assumption for the load with the same Mean and Std, Dev. Then, we click Simulate button at the bottom of Fig. 6. After 1.5 minute run time for n = 100 years, we get in Fig. 7, LOLP = 5.89% ≈ 5.51% of Fig. 1. LOLP benchmark for Weibull assumption has been met. Another n = 10000 (30 min) study with Weibull produced LOLP = 6%. Any Weibull input of failure and repair times can be entered.

C. Link Distributions (Failure and Repair Times from Negative Exponential or Weibull) with Uniform Density

First, transmission failures and repair times are computed when the producer or generator data are from Negative Exponential or Weibull. One marks the producers' failure and repair rates as 'None', meaning remaining the same, not to be updated. Then, the link failure rate= ±10% of the producers' failure and repair rates to do a benchmark analysis will be conducted as in Fig. 8, where Update SS input from 1st to 24th groups.

We simulate for n = 1000 runs in 4 min 18 sec and we achieve LOLP = 5.7% in Fig. 9, similar to 5.55% in Fig. 1 benchmark. This shows the benchmark study is validated for the links. Namely, ±10% increase of failure rates of links has been offset or neutralized by an equal increase in the repair rates. A similar analysis can be conducted using the Weibull assumption as conducted for Neg. Exponential in Fig. 9. Weibull input data in Fig. 10 for n = 1000 after 3 min led to a favorable LOLP = 5.66%. One may enter lower and upper values for Uniform density at will from a field search for the most general input case.

D. Link Distributions (Failure and Repair Data Are from Negative Exponential or Weibull) with Bayesian Gamma

So far, benchmarks were validated in A, B and C. Now for D, we can use the Bayesian Gamma for links when Negative Exponential is assumed. We activate symmetric data increases by upping the failure and repair rates each for 10% to counterbalance and offset each other's rise toward the Fig. 1's NSS benchmark results. The LOLP = 5.43% is nearly 5.51% with with links activated having ±10% less/more failure and ±10% less/more repair rates of the production units for n = 1000. We will do the same for Weibull link distribution with Bayesian Gamma to validate the benchmark results. We will update similar to those of Negative Exponential We achieve almost the same where LOLP = 5.55% not budging much from the benchmark of LOLP = 5.51% of Fig. 1 since the 10% rises for both failure and repair rates did not alter the benchmark LOLP by offsetting each other to verify the case study for Weibull. Output boxes are not shown for D due to space limitations.

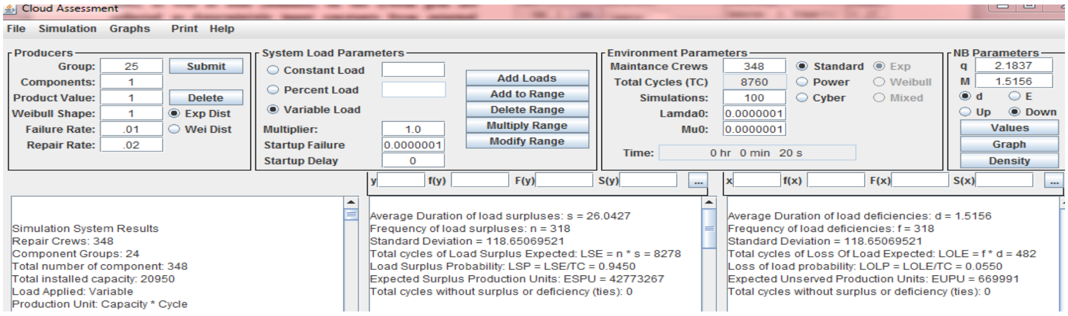

Fig. 5. LOLP = 5.5% for benchmark Fig. 3, Fig. 4 after SS.

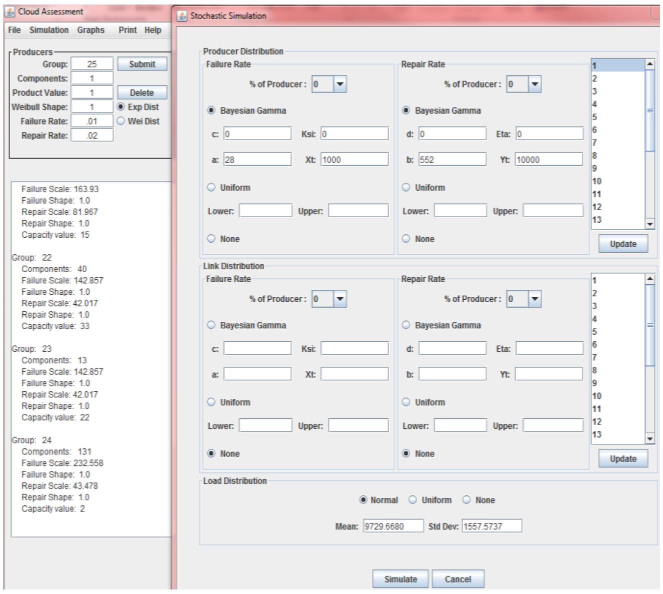

Fig. 6. Input box when failure and repair times are from Weibull.

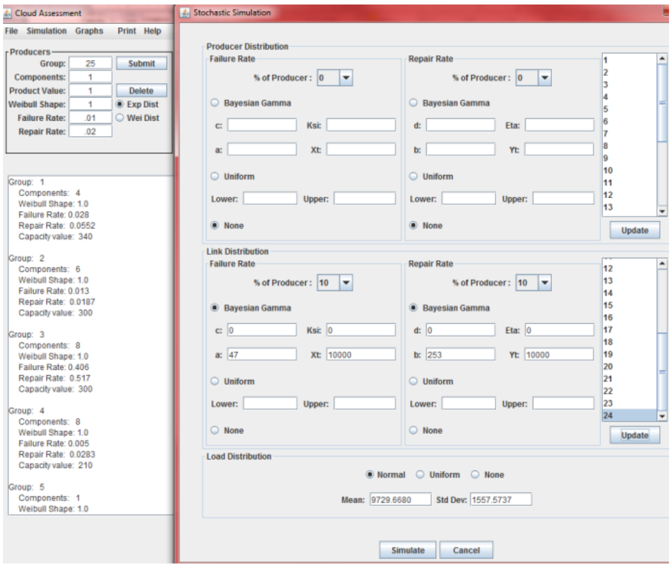

Fig. 8. If uniform is used, default values are ± 10% of the rates for lower and upper limits for producers with Neg. Exponential.

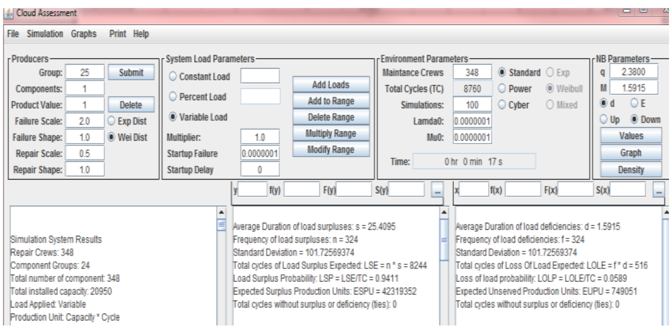

Fig. 7. LOLP = 5.89% for Weibull Fig. 6 data as benchmark.

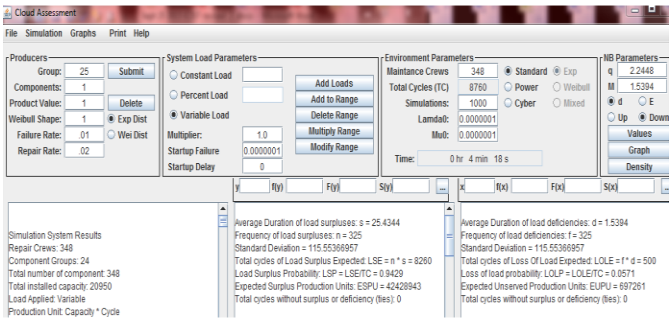

Fig. 9. Output of LOLP = 5.7% with Neg. Exp. of Fig. 7. applied.

IV. Stochastic Simulation Applied to Real-Life Cyber or Power Grids Where Links and Producers' (Generators) Input Data Changes Are Asymmetric

After the validation and verification processes in Section III, we need to work on asymmetric Cyber CLOUD or Power Grid scenarios for the system performance with generation and transmission components merged. We will use the same as in Fig. 1 benchmark, i.e. CLOUD system of 348 units (data95.txt) to compare or contrast new results.

A. With the Neg. Exponential Input for Failure and Repair Rates Using Uniform Distribution for Links

Non-Benchmark SS Analyses will constitute those such as in a real life grid scenario where the non-equally ($\lambda \geq \mu$) added link failure and repair data to the existing generation or production will likely increase the LOLP. We expect the composite link to transmit the production to consumers. Assume that each cyber production or power generating unit has its links' failure and repair rates as composite values, either inspired by the producer's data given for each group or hard-coded new. We assume that each production unit is linked to its entire perimeter for supplying the generated energy or production, and transmitting it to its peripheral. We will in the same order as above take up the data1995.txt and add link data assumed to be of both Uniform and Bayesian Gamma where 30% (lower limit = 15%, upper limit = 45%) rise in the failure rate and 10% (lower limit = 5%, upper limit = 15%) rise in the repair rate are entered. All data are first related to Negative Exponential for both production and transmission in Fig. 11. LOLP has deteriorated to 8.92% from a benchmark of 5.5% in Fig. 1. Since all other factors are controlled, links are failing faster than repaired in an example we have selected.

B. With the Neg. Exponential Input for Failure and Repair Rates Using Bayesian Gamma Distribution for Links

This time, although the product failure and repair time distributions are still simulated from the Negative Exponential, the links are assumed to carry Bayesian Gamma with unequal percentage rises to the disfavor of the links' repair activity. We observe in Fig. 12, the Bayesian Gamma used for the links with +30% for the failure, and +10% for the repair unfavorably gave LOLP = 13.7% as expected. Due to space limitations, we will not display the Weibull versions of A and B, however they do not show any different trends as before.

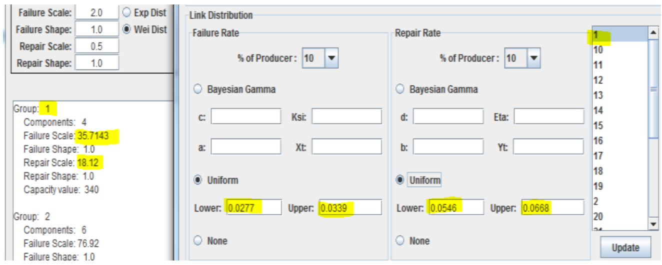

Fig. 10. Dialog box when the producer probability distribution is Weibull and link probability distribution in 10% Uniform.

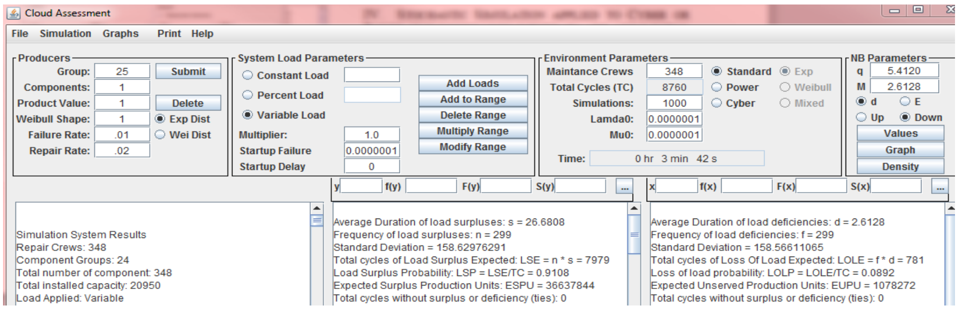

Fig. 11. Uniform distribution for the links' failure and repair rates, LOLP=8.92% worse than the benchmark LOLP = 5.5% for n = 1000 years with 8 min runtime.

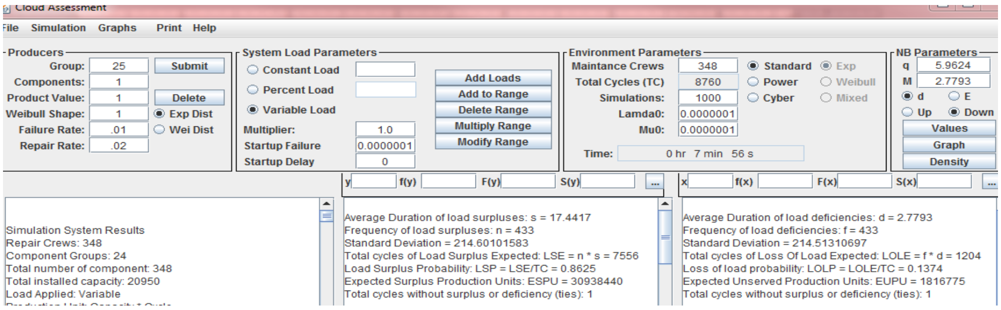

Fig. 12. Bayesian Gamma used for the links where 30% for the failure and 10% for the repair gave LOLP 13.7%.

V. Conclusion and Discussions, and How to Apply Stochastic Simulation to a Cyber or Power Grids

Traditionally, in Cyber CLOUD or Power Grid modeling, data regarding failure and repair rates, as well as the servers' or generators' transmission lines or links, and load (demand) cycle are supplied as deterministic inputs through field data collection sources. CLOURAM is a risk assessment and management tool that simulates and manages the entire cyber- or generation grid. Through what is termed as Stochastic Simulation of Grid or CLOUD parameters such as failure and repair rates of power generators or cyber servers, and the client-demanded load cycle, we validate and verify for the non-stochastic CLOURAM software through benchmarks such as in Fig. 1 so that SS runs are deemed accurate.

Once the verification process was carried out successfully, i.e. the Grid or CLOUD non-SS (NSS) metrics using the earlier constants such as mean (expected) values were compared favorably to those employing deterministic input data. Subsequently, the producer (or generator) and link scenarios were studied such as in the event of the appended links no more being perfectly reliable, but operating with specified values through Uniform, or Bayesian Gamma input data assumptions. These were executed in the A and B subsections of Section IV. This innovative research illustrates that we can include, in lump-sum, the grid transmission (link) data as an averaging composite effect to estimate cyber or power CLOUD performance through a dynamic discrete event simulation algorithm. Additionally, this algorithm can be used for any other stochastic input assumptions, including the hard-coding of the desired input data, for the producers and the links. The versatility of the algorithm stems from a wide area of usage by leveraging the Weibull distribution, whose default is Negative Exponential and used extensively for electronic failure and repair histories. In the event of the non-existence of sophisticated data such as Weibull or similar, the analyst may use simple uniform deviations. For further research, the authors will seek the Power Grid or Cyber CLOUD data from industry to compare results [3]-[10].

This article also serves as a valuable reference to apply CLOUD computing simulation to Cyber CLOUD or Power Grids rather than to those with generation or production systems (without the transmission components or links) that comprised solely producers. Therefore it falls upon the analyst to use this innovative Stochastic Simulation algorithm to obtain dependable transmission input data from large Electric Power enterprises or ISPs (Internet Service Providers) for Cyber links by enhanced field research studies.

APPENDIX (ALSO APPLICABLE SIMILARLY TO FIGS. 5, 7, 9, 11 AND 12)

For Fig. 1, the production for 24 groups and load data for 8760 hours are entered. The system was interrupted f = 314 times each of which lasted on the average $d \approx 1.54$ hours (or cycles), overall of which led to LOLE (Loss of Load Expected, or Mean Number of Loss of Service Hours) = $f \, x \, d$ = 483 hours of Loss of Load or Service after n = 1000 runs or years. On the right hand side (rhs) column, the unreliability or LOLP=LOLE/8760hr are presented. The standard deviation of LOLE is 126.26 hours. However the LOLE (Loss of Load Expected) hours is not a perfect normal distribution but it is overly right skewed Compound Poisson ≈ NB (Negative Binomial) with M (mean) = 483 and q = Variance/Mean = $126.26^2/483 \approx 33$. Note, it is purely Poisson (not Compound) if q = 1. A static index LOLP (Loss of Load Probability) = 483/8760=0.0551 or 5.5 %. A dynamic index, EUPU (Expected Unserved Production Units) = 666,424 Gigabyte-Hours (Gigaflops for Cyber) or Mega-Watt hours (Mega-joules for Power) is recorded.

On the middle column, the reliability (versus unreliability on the right hand side) metrics are presented. The system operation was interrupted f = 314 times, each of which the uninterrupted operation lasted on the average d = 26.37 hours (or cycles), overall which led to LSE (Load Surplus Expected, or Mean Number of Operational Service Hours) = $n \, x \, d$ = 8277 or 8760 – LOLE= 8760 - 483 = 8277 hours of Operational Service. The standard deviation is 126.26 hours, the same as that of LOLE. However the LSE (Load Surplus Expected) hours is not a normal distribution but it is an only slightly right skewed Compound Poisson; rather NB (Negative Binomial) with M (mean) = 8277 and q = Variance/Mean = $126.26^2/8277 \approx 1.92$. Further, a static index LSP (Load Surplus Probability) = 8277/8760 = 0.9449 or 94.5%. A dynamic index, ESPU (Expected Surplus Production Units) = 42,543,641 Gigabyte-Hours (Gigaflops for Cyber) or Mega-Watt hours (Mega-joules for Power) is recorded.

On the left hand side (lhs), system input parameters are listed such as number of production groups: 24, total number of components: 348, and total installed capacity: 20950 Gigabytes (Cyber) or Megawatts (Power). Note that production: capacity*cycle (Cyber) and generation (Power) are interchangeably used, so are the producers and generators. Grid and CLOUD, Transmission and Link are two pairs of terms interchangeably used. The grid is used for Electric Power and CLOUD is used for the Cyber systems. However, there exist grids in Cyber ISPs [7], [8]. Power is one of five recognized CLOUDS in the literature; Cyber, Power, Water (Sewage), Telecom (Phone, TV), and Gas.

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