This review article will explore the innovative and popular theme of engineering modeling and simulation, predominantly in the manufacturing industry and cybersecurity world, citing severe challenges, advantages and time- and budget saving solutions and its future. The power of simulation is not an exaggeration but an understatement. The favorable outcomes since the advent of digital computers and software revolution could not have been achieved, especially without the multiple benefits of statistical simulation, which underlies the widespread use of modeling and simulation in engineering and sciences, stretching from A (Astronomy) to Z (Zoology). This refers not only to research findings in verifying a certain piece of theory, such as that of the recently discovered Higgs Boson, but in testing new products to innovate new discoveries so as to make our universe a more peaceful place by modeling and simulating the future projects and taking precautions before disasters occur. The review explores a cross section of engineering modeling and simulation practices illustrating a window of numerical examples.

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help him towards his discovery of the distribution of the correlation coefficient and to bolster his faith in his so-called $t$-distribution.\textsuperscript{2} A.N. Kolmogorov in 1931 showed the relationship between Markov stochastic processes and certain integro-differential equations. Stanislaw Ulam at Los Alamos labs performed simulation in 1945 during the WWII in the bomb-building Manhattan Project before proposing the Teller-Ulam thermonuclear weapon design. Ulam suggested first the ‘Russian Roulette’ and ‘splitting’ methods, for evaluating complicated mathematical integrals for nuclear chain reactions that later led to the systematic Monte Carlo methods by von Neumann, Metropolis and others. John von Neumann explored the behavior of neutron chain reactions in fission devices using statistical sampling methods in 1948 (such as the acceptance–rejection method) employing the newly developed electronic computing techniques. Neumann proposed the agent-based Von Neumann Machine,\textsuperscript{3} a theoretical machine capable of reproduction following detailed instructions to copy itself. Ulam suggested a machine as a collection of cells on a grid. The idea intrigued von Neumann, who created the first of the devices later termed, cellular automaton.\textsuperscript{4}  John Conway constructed the well-known Game of Life,\textsuperscript{5} operated in a virtual world in the form of a two-dimensional checkerboard. A team headed by N. Metropolis using the ENIAC Computer in 1948 carried out what’s contemporarily known as modern Monte Carlo calculations.

Computer simulation has been widely used in engineering systems to validate the effectiveness of tentative decisions regarding a new plan or schedule, or its outcomes, without actually experiencing the actual conditions, which could in actuality cost more resources or partial to full destruction such as in the simulation of the nuclear bomb. In a book titled, Simulation Engineering, by Jim Ledin in 2001,\textsuperscript{6} the author outlines his twofold purpose as follows: (1) simulation engineering (SE) is the application of engineering discipline to the development of good simulations. (2) Similarly, SE occurs when simulations become part of an engineering process when applied as tools to develop better products and test processes with a greater efficiency for different types of complex embedded systems. The latter purpose (2) is the subject matter of this review article. The IEEE June 2012 Spectrum issue, emphasized that the Modeling and Simulation effect is a creative and time-saving topic of interest ranging from automotive engineering of hybrid vehicles to finding solutions to treating nuclear waste, and upgrading the nuts and bolts of the Electrical Power (Smart) Grid and moreover, supercomputing research.\textsuperscript{7}

**GENERIC THEORY—CASE STUDIES ON GOODNESS OF FIT FOR UNIFORM NUMBERS**

A formal scientific theory of simulation, to verify a validated model so as to mimic a physical or a social system, does not exist in terms of conventional math-statistical theorems and their subsequent proofs. However, heuristic modeling formalisms at an advanced level for engineers through cellular automaton for Monte Carlo and Discrete Event Simulations are studied by Zeigler et al.\textsuperscript{8} (Ch. 4), although these formalisms do not lend themselves to easy algorithmic implementations for practicing engineers or scientists as this review article purports to. Moreover, the fundamental process of verifying sequences of uniform deviates from an associated generator where Ho: Uniform Random Sequence is (quasi) random versus Ha: Sequence is not random, is an accepted technique. For instance, $\chi^2$ tests, such as those by Leven and Wolfowitz\textsuperscript{9} and Knuth,\textsuperscript{10} are popularly well-accepted math-statistical scientific practices to theorize the verifiability of uniform random numbers essential to the realm of statistical simulation. In order to clarify the validation of the above stated Ho: Random Sequence versus Ha: Not Random Sequence, the commercial JAVA code’s uniform number generator will be tested for randomness, as illustrated in a series of screenshots from Figures A1–A9 in Appendix A by using Stewart’s JAVA program to implement Knuth’s technique.\textsuperscript{11} The results show that by law of large numbers for only $n \geq N \approx 50,000$; $E(\theta) \rightarrow 0.5$ with probability 1, for $\theta \sim Uniform(0, 1)$ from the uniform number generator imbedded in the Java code, ‘Ho: Random Sequence’ is not rejected. Therefore $n = 50,000$ runs is a new standard for attaining quasirandomness; not 5000 anymore as practiced in 1980s.

**WHY CRUCIAL TO ENGINEERING—MANUFACTURING AND CYBER DEFENSE ISSUES**

The power of simulation is prevalent as the audio-visual Ref 12 favorably explains certain topics related to production and manufacturing engineering. In ‘Modeling and Simulation in Manufacturing and Defense Systems Acquisition’, the Board on Manufacturing and Engineering Design (BMED) emphasized the importance of modeling and simulation in not only making the right decisions but also incurring fewer expenses.\textsuperscript{13} Similarly, the Wychavon (UK) council has adopted manufacturing industry’s simulation model to reduce waste and
improve performance. Since the US manufacturing industry is challenged by increased global competition and price erosion, one can benefit from manufacturing simulation to eliminate bottlenecks, enhance lean manufacturing, optimize capacity planning and optimize production output. In an Annotated Discrete Event Simulation Bibliography, there exist 325 articles on manufacturing simulation as cited in Ref 15. A certain bibliography displays 112 publications on ‘Load Models for Power Flow and Dynamic Performance Simulation’ by the IEEE Transactions on Electric Power Systems.

On the contrary, there are fewer simulation studies in cybersecurity-and-defense-related theoretical and applied research. In their 2007 article as titled, ‘Cyber Attack Modeling and Simulation for Network Security Analysis’, the authors Kuhl et al. discuss a simulation modeling approach to represent computer networks and intrusion detection systems (IDS) to efficiently simulate cyber-attack scenarios in order to test and evaluate cyber security systems. You-Tube-based audio-visual Cybersecurity Simulation roundtable underlines the power of simulation in cybersecurity scenarios. Under ‘War game reveals US lacks cyber-crisis skills’ in a war game, sponsored by a nonprofit group and attended by former top-ranking national security officials, laid bare that the US government lacks answers to such key questions. Former Clinton press secretary Joe Lockhart said that people would be scared by the simulation but he added, ‘...that’s a good thing.’ Sahinoglu in his 2007 Wiley textbook, Trustworthy Computing: Analytical and Quantitative Engineering Evaluation, considers modeling and simulation of individual components and systems toward assessment of security risk, in addition to his publications where theoretical models are confirmed using Monte Carlo and Discrete event simulation runs. Further, certain manufacturing- and cybersecurity-themed examples will be reviewed through working details of how the modeling should be validating the physical model and the subsequent simulation computationally verifying the solutions accurately and cost effectively. These reviews are the tips of the iceberg, as industries will continue to design and discover new products and services by M&S.

Figure 1 displays the interaction between the process of building a model by focusing on the interplay between (1) experimental results, (2) simulation results, and (3) theoretical predictions as displayed in Ref 25. A favorable example of this interplay is presented in a recent WIREs article titled Cloud Computing (Figure 8, p. 55), which displays an experimental scenario for a trivial Cyber Cloud. On the other hand Ref 26 (Figure 9, p. 57) outlines the Markovian theoretical predictions followed by the simulation results for the same scenario of two 1-GB units serving a constant load of 1.5 GB for 13 cycles. The resulting availability of this small Cloud: (1) 0.307 for Experimental, (2) 0.305 for Simulation after 1 million runs, or trials and (3) 0.331 for Markov Theoretical, allowing a negligible error content, which diminishes to less than 3% as the size of the experiment increases from a few to many hundreds of units. In the event of large cyber CLOUDS such as those with 398 units, the authors showed that the experimental approach was infeasible, and theoretical result was not mathematically tractable. However, supercomputer-driven programming worked for days regarding the basic two-state assumptions, crunching $2^{398}$ ($\gg 10^{100}$) Markov states to 93.8% reliability. DES result was a satisfactorily comparable 90.5%.

A CROSS SECTION OF MODELING AND SIMULATION ISSUES IN MANUFACTURING

Simulation use in production is not new. For the sake of a few examples, various authors from 25 years ago published articles on simulating flexible manufacturing systems (FMS), machine utilizations and production rates, and modeling of Automated Manufacturing Systems (AMS). Given the advances in pervasive computing regarding communication networks, as well as recently popularized large scale cloud computing in cyber networks; quantitative risk assessment of a manufacturing unit and their network availability have become challenging tasks. An often overlooked fact is that many real-life grid units such as routers or servers in cyber physical systems to the manufacturing assemblies in automotive or avionics, etc. and the intricate telephony networks (wired or wireless), and water-supply networks or hydroelectric dams, do not operate in an idealized simple setting of either full or zero capacity. This fact therefore necessitates the inclusion of degrees of derated (in-between UP and DOWN states) capacity. Because of lack of closed-form solutions in the three-state model including DERATED as opposed to that of the conventional UP-and-DOWN dichotomous two-state model, a summary of three or multistate system inferential analysis will be reviewed by using Monte Carlo simulations. This process will employ the empirical Bayesian principles to estimate the full and derated availability probability distributions. The historical failure and repair data, or operating (full or derated) and nonoperating hours, as the input data, will
be used along with prior parameters for an empirical Bayesian analysis. The results satisfactorily lend themselves to statistical inference for multiple states other than the traditional binary assumption (UP or DOWN), an outcome which can prove very useful to the manufacturing industry. In the past, various articles have studied a similar problem. For instance, ‘A Hybrid Markov system dynamics approach for availability analysis of degraded systems’ by Rao et al; similarly, Lins and Droguett study ‘Multi-objective Optimization of Availability and Cost in Repairable Systems Design Via Genetic Algorithms and Discrete Event Simulation.’ Reliability and Availability Analysis of Three-state Device Redundant Systems with Human Errors and Common-cause Failures’, by Shah and Dhillon studies somewhat similar but still different topics. The primary difference between the above listed three references and this review article is the empirical Bayesian treatment of the three states to estimate their probability distributions by Monte Carlo simulations based on the Sahinoglu–Libby probability density function, originally derived independently by both Sahinoglu and Libby in 1981. The closest among these three articles, that is, by Rao et al. uses only four transition rates in a three-state Markov model whereas Sahinoglu’s model uses all six transitions. However, this review article’s simulation approach is even more powerful and flexible as the application can be extrapolated based on identical principles to four or more states, whereas reference by Rao et al. deals solely with differential equations limited in scope. Others, Lins et al. and Shah et al. are on slightly different but not identical topics; all of which do not employ modeling and simulation techniques or generate closed form statistical probability density function (p.d.f.) expressions and derivations.

**Modeling and Simulation of Multistate Production Units and Systems in Manufacturing**

Most research articles or books on reliability theory are devoted to traditional binary reliability models allowing for only two possible states for a system and its components: perfect functionality or complete failure. However, many real-world systems are composed of multistate components which have different performance levels and several failure modes with varying effects on the entire system performance. Such systems are called multistate systems (MSS). Examples of MSS are cyber systems where the unit performance is characterized by the data processing speed or server gigabyte capacity and similar to electric power systems, where the generating unit performance is depicted by its generating capacity. In the electric power supply system of generating facilities, each generator can function at different levels of capacity with a given probability. This may result from the outages of several auxiliaries such as pulverizers, water pumps, fans, boilers, etc. Billinton and Allan describe a three state 50 MW generating unit. The performance rates (generating capacity) corresponding to these three states and probabilities of the three states which sum to unity are presented as follows: Probability of State 1 (50 MW capacity) = 0.960, Probability of State 2 (30 MW capacity) = 0.033 and Probability of State 3 (0 MW capacity) = 0.007. Therefore, the reliability analysis of MSS is much more complex compared to binary-state systems. From the mid-1970s until now, various books and research articles focusing on MSS reliability were published. However, these works are deterministic, and not probabilistic, thus not lending themselves to probability distribution functions other than a single summary measure.
Therefore statistical inference cannot be conducted. This article reviews methodology for the estimation of the probability distributions of three-state (now including a new derated or degraded state beyond the binary assumption of UP or DOWN) repairable hardware units or components by using Monte Carlo simulations in employing the statistical random number generation techniques.

The power of simulation once again flexes its muscle as a favorable exit out of this theoretical impasse. The Monte Carlo technique remains the only available feasible way to solve the proposed three-state problem, whose math-statistical closed-form solution does not actually exist. This is mainly because the three-state Markov model’s random variables’ (UP, DOWN, DER) probability distributions cannot be derived through math-statistical transformations due to mathematical intractability and lack of sufficient statistical theory. The probability density function of the Forced Outage Rate (FOR) was earlier analyzed in a textbook by the primary author, who designated that the Sahinoglu–Libby (SL) probability model can be used if certain underlying assumptions hold. Libby and Novick independently have studied multivariate generalized beta distributions for utility assessment; however their analysis was for only two-states similarly, not for multistate hence the term, G3B: Generalized 3-Parameter Beta. The failure two-states similarly, not for multistate hence the term, utility assessment; however their analysis was for only studied multivariate generalized beta distributions for approximated using their associated moments.

Down the three-state Markov model’s random variables’ (UP, DOWN, DER) probability distributions have been cited in Refs 33–37 for a first by deriving its cumulative density function (c.d.f.), i.e. \( G_Q(q) = P(Q \leq q) = P(\lambda/\lambda + \mu \leq q) \). Then, taking its derivative to obtain \( g_Q(q) \) as per Eqs (5A.1)–(5A.18) in Appendix 5A, on pp. 26–32 of Ref 20 and Ref 33, p. 1487, and also in Ref 34; \( g_Q(q) \) is as follows:

\[
g_Q(q) = \frac{\Gamma(a + b + c + d)}{\Gamma(a + c)\Gamma(b + d)} \times (\xi + x_T)^{a+c}(\eta + y_T)^{b+d}(1-q)^{b+d-1}q^{a+c-1} \left[ \eta + y_T + q(\xi + x_T - \eta - y_T) \right]^{a+b+c+d} 
\]

(skipping steps)

\[
\frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} (1-q)^{\beta-1}q^{\alpha-1} \left[ \frac{1}{1+q(L-1)} \right]^{\alpha+\beta} L^a. 
\]

(1)

Note that \( g_Q(q) \) is the p.d.f. of the random variable \( Q = \text{FOR} \), where \( \alpha = a + c, \beta = b + d, \beta_1 = \xi + x_T, \) and \( \beta_2 = \eta + y_T; \) and \( 0 \leq q \leq 1 \). If \( L = (\beta_1/\beta_2) \) for SL (\( \alpha, \beta, L \)) or \( \beta_1 = \beta_2 \), the usual two-parameter beta p.d.f. is obtained. An alternative original derivation of the same p.d.f. termed under generalized multivariate beta distribution is given by Libby in 1981 and 1982. The expression in Eq. (1) can also be reformulated in terms of SL (\( \alpha = a + c, \beta = b + d, \) \( L = (\beta_1/\beta_2) \)), as follows:

\[
g_Q(q) = \frac{L^{a+c}q^{a+c-1}(1-q)^{b+d-1}}{B(b + d, a + c)[1 - (1 - L)q]^{a+b+c+d}}, \quad (2)
\]

where

\[
B(b + d, a + c) = \frac{\Gamma(a + c)\Gamma(b + d)}{\Gamma(a + b + c + d)}, \quad \text{and} \quad L = \frac{\xi + x_T}{\eta + y_T}. 
\]

Note if \( L = 1 \), Sahinoglu-Libby p.d.f. reduces to a standard Beta (\( \alpha, \beta \)) p.d.f. See Figure 2 for ‘r = availability’ and ‘q = unavailability’ confidence plots where \( r = 1 - q \). Densities of SL (or G3B) distributions have been cited in Refs 33–37 for a variety of \( L \) values. From a strictly mathematical point of view, the presence of the parameter \( L \) allows the SL p.d.f. to take a variety of shapes besides the standard Beta(\( \alpha, \beta \)) where \( L = 1 \). For example, when \( \alpha = \beta \), the standard Beta(\( \alpha, \alpha \)) is symmetric with a mean at 0.5. However, the SL (\( \alpha, \alpha, L \)
distribution is not necessarily so, and can be skewed positively or negatively, depending on \( L > 1 \) and \( L < 1 \) respectively, because the mode, skewness, and kurtosis of SL random variable now also depend on \( L \). For \( 0 < L < 1 \), the SL p.d.f. stays below the plot of the related standard Beta near zero but crosses the latter to become the greater of the two p.d.f.s at a point:

\[
y_0 = \left[ 1 - L^{a_1/(a_1 + a_2)} \right]^{-1} - (1 - L)^{-1}. \tag{4}
\]

The reverse action holds true for \( L > 1 \) with the same crossing point, \( y_0 \). The major drawback to the distribution is that there is no closed form for finite estimates of the moments. The moment generating function for the univariate SL distribution is an infinite series.\(^{36,37}\)

Three-State Sahinoglu Probability Model of Production Units (Monte Carlo Simulation)

In studying large capacity generation (power) or production (or cyber-physical) units, it may be necessary to consider the probabilities associated with one or more forced derated-outage states as in multistate, rather than considering the unit as being either available or unavailable.\(^{40-42,44,45}\) In summary, there are gray areas or in-between capacities which are called derated or degraded states. However in this review article, we will only consider a single derated state rather than multiple ones, which may well exist in practice such as in 50%, 60%, or 75% derated capacity. But now, we have not only full-FOR but also derated-FOR (or DFOR), that will be equal to the total derated operating time over the total exposure time. That is, \( DFOR = DER \) time/\( UP \) time + \( DER \) time + \( DOWN \) time). It is also well documented that any calculated \( FOR \) or \( DFOR \) is not only a constant but also a specific single realization of its random variable.\(^{20}\) The probability density function of the \( FOR \) by empirical Bayesian analysis was identified in Section Two-State Sahinoglu-Libby Probability Model of Production Units (Closed-Form Solution) to be the Sahinoglu–Libby (SL) probability density, where certain underlying assumptions hold. However, we shall review above and beyond a traditional closed-form two-state SL; namely, a three-state SL where the transition rates are gamma distributed (see derivations in subsections of Three-State Sahinoglu...
Probability Model of Production Units (Monte Carlo Simulation). Let us examine and review the following state space diagram in Figure 3 by Billinton from his textbook.\textsuperscript{44} Let \( \lambda = \) transition rate from \( UP \) (fully operational) to \( DOWN \) (forced outage) state; \( \mu = \) transition rate from \( DOWN \) to \( UP \) state; \( \delta = \) transition rate from \( UP \) to \( DER \) (partially forced outage) state; \( \beta = \) transition rate from \( DER \) (partially forced outage) to \( UP \) state; \( \alpha = \) transition rate from \( DER \) to \( DOWN \) state; \( \gamma = \) transition rate from \( DOWN \) to \( DER \) state. Using Figure 3 given, by changing to the Greek variables from the Latin originals (a–l) cited in the same reference\textsuperscript{44} (p.156, Fig. 4.2), the time-dependent but steady state probabilities of occupying one of the three states are given as follow from (5)–(7), assuming negative exponential densities for each state’s sojourn time, which will converge to:

\[
P(UP) = \text{FOR} = \frac{\mu \beta + \mu \gamma + \alpha \beta}{\text{DENOMINATOR}}, \tag{5}
\]
\[
P(DERATED) = D\text{FOR} = \frac{\delta \mu + \delta \alpha + \lambda \mu}{\text{DENOMINATOR}}, \tag{6}
\]
\[
P(DOWN) = 1 - P(UP) - P(DERATED) = \frac{\lambda \beta + \lambda \gamma + \delta \gamma}{\text{DENOMINATOR}}, \tag{7}
\]

where

\[
\text{DENOMINATOR} = \mu \beta + \mu \gamma + \alpha \beta + \lambda \beta + \lambda \gamma + \delta \mu + \delta \alpha + \lambda \mu + \delta \gamma. \tag{8}
\]

A closed form solution of the three-state SL is intractable and analytically impossible in this setting with six random variables, as compared solely to the two variables in Section Two-State Sahinoglu-Libby Probability Model of Production Units (Closed-Form Solution). We will therefore have to simulate the \( P(UP) \), \( P(DER) \) and \( P(DOWN) \) from Eqs (5)–(7) by generating the recursive Monte Carlo simulated deviates of the state transition rates. Empirical Bayesian analysis will be pursued through deriving first the conditional posterior densities of the six transition rates from subsections of Three-State Sahinoglu Probability Model of Production Units (Monte Carlo Simulation), and using random uniforms for generating the transitions that constitute the probabilities in Eqs (5)–(7). See Figure 4 for a sample draft scenarios to illustrate transitions of Figure 3.

**UP-to-DOWN Failure Transition Rate (\( \lambda \)), for example, from \( x_1 \) to \( w_1 \), or \( x_2 \) to \( w_2 \) in Figure 4**

Let \( a = \) number of occurrences of \( UP \) (operating) times before \( DOWN \) (recovery)

\[
x_T = \sum x_i = \text{total UP (operating) times before going DOWN (recovery) for } 'a' \text{ such occurrences.}
\]

\[
\lambda = \text{full UP-to-DOWN rate.}
\]

\[
\xi = \text{shape parameter of gamma prior for the full failure rate } \lambda.
\]

\[
\xi = \text{inverse scale parameter of gamma prior for the full failure rate } \lambda.
\]

Now let the failure rate, \( \lambda \) have a gamma prior distribution:

\[
\theta_1(\lambda) = \frac{\xi^\xi}{\Gamma(\xi)} \lambda^{\xi-1} \exp(-\lambda \xi), \lambda = 0. \tag{9}
\]

The joint likelihood of the \( UP \)-time random variables is

\[
f(x_1, x_2, \ldots, x_d | \lambda) = \exp(-x T \lambda), \tag{10}
\]

the joint distribution of data and prior becomes:

\[
k(\lambda, x) = f(x_1, x_2, \ldots, x_d, \lambda)
\]

\[
= \frac{\xi^\xi}{\Gamma(\xi)} \lambda^{a+c-1} \exp[-\lambda(x_T + \xi)]. \tag{11}
\]

Thus, the posterior distribution for the random variable \( \lambda \) is

\[
b_1(\lambda | x) = \frac{\xi^\xi}{\Gamma(\xi)} \lambda^{a+c-1} \exp[-\lambda(x_T + \xi)]
\]

\[
\times \frac{\xi^\xi}{\Gamma(\xi)} (x_T + \xi)^{-1} \Gamma(a + c)
\]

\[
= \frac{1}{\Gamma(a + c)} (x_T + \xi)^{a+c-1} \exp[-\lambda(x_T + \xi)], \tag{12}
\]
which is also distributed as $\text{Gamma}[a + c, (x_T + \xi)^{-1}]$. Note that $\mathbf{x}$ is a vector.

**DOWN-to-UP Recovery Transition Rate ($\mu$), for example, from $y_1$ to $x_1$, or $y_2$ to $z_1$ in Figure 4**

Let $b =$ number of occurrences of DOWN (recovery) times before UP (operating)

\[ Y_i \sim \mu e^{-\mu y} \]

\[ y_T = \sum Y_i = \text{total DOWN (recovery) times before going UP for 'b'} \text{ many such occurrences} \]

$d =$ shape parameter of gamma prior for the full recovery rate $\mu$

$\eta =$ inverse scale parameter of gamma prior for the full recovery rate $\mu$

Now let the full recovery rate, $\mu$, have a gamma prior distribution:

\[ \theta_2(\mu) = \frac{\eta^d}{\Gamma(d)} \mu^{d-1} \exp(-\mu \eta), \mu > 0. \quad (13) \]

The joint likelihood of the DOWN-time random variables is

\[ f(y_1, y_2, \ldots, y_b | \mu) = \mu^b \exp(-y_T \mu). \quad (14) \]

The joint distribution of data and prior becomes:

\[ k(y, \mu) = f(y_1, y_2, \ldots, y_b | \mu) \]

\[ = \frac{\eta^d}{\Gamma(d)} \mu^{b+d-1} \exp[-\mu (y_T + \eta)]. \quad (15) \]

Thus, similarly skipping two intermediate steps, the posterior distribution for $\mu$ is

\[ b_2(\mu | y) = \frac{1}{\Gamma(b + d)} (y_T + \eta)^{b+d-1} \exp[-\mu (y_T + \eta)], \]

(16)

which is also distributed as $\text{Gamma}[b + d, (y_T + \eta)^{-1}]$. Note that $\mathbf{y}$ is a vector.

**UP-to-DER Failure Transition Rate ($\delta$), e.g. from $z_1$ to $u_1$, or $z_2$ to $s_2$ in Figure 4**

Let $\alpha =$ number of occurrences of UP times before DER

\[ z_T = \sum Z_i = \text{total UP times before going DER} \]

for ‘$\alpha$’ many of such occurrences.

\[ Z_i \sim \delta e^{\delta z}. \]

$\delta =$ UP-to-DER failure rate.

$e =$ shape parameter of gamma prior for the UP-to-DER failure rate $\delta$.

$\Delta =$ inverse scale parameter of gamma prior for the UP-to-DER failure rate $\delta$.

Now let the UP-to-DER failure rate $\delta$ have a gamma prior distribution:

\[ \theta_3(\delta) = \frac{\Delta^e}{\Gamma(e)} \delta^{e-1} \exp(-\delta \Delta), \delta > 0. \quad (17) \]

Thus, similarly skipping two intermediate steps, the conditional posterior density of $\delta$ becomes:

\[ b_3(\delta | z) = \frac{1}{\Gamma(o + e)} (z_T + \Delta)^{o+e-1} \exp[-\delta (z_T + \Delta)], \]

(18)

which is also distributed as $\text{Gamma}[o + e, (z_T + \Delta)^{-1}]$. Note that $\mathbf{z}$ is a vector.

**DER-to-UP Recovery Transition Rate ($\beta$), for example, from $u_1$ to $x_2$, or $u_2$ to $z_2$ in Figure 4**

Let $k =$ number of occurrences of DER times before UP

\[ u_T = \sum U_i = \text{total DER failure times before going UP for 'k'} \text{ many of such occurrences} \]

\[ U_i \sim \beta e^{-\beta u}. \]

$\beta =$ DER-to-UP recovery rate.
\( \phi \) = shape parameter of gamma prior for the DER-to-UP recovery rate \( \beta \).

\( f \) = inverse scale parameter of gamma prior for the DER-to-UP recovery rate.

Now let the DER-to-UP recovery rate \( \beta \) have a gamma prior distribution:

\[
\theta_4(\beta) = \frac{\phi^f}{\Gamma(f)} \beta^{f-1} \exp(-\beta \phi), \beta > 0. \tag{19}
\]

Thus, similarly skipping two intermediate steps, the conditional posterior density of \( \beta \):

\[
b_4(\beta | w) = \frac{1}{\Gamma(k + f)} (u_T + \phi)^{k+f-1} \exp(-\beta(u_T + \phi)),
\tag{20}
\]

which is also distributed as Gamma \( k + f, (u_T + \phi)^{-1} \). Note that \( u \) is a vector.

**DER-to-DOWN Failure Transition Rate (\( \alpha \)); for example, from \( s1 \) to \( y2 \), or \( s2 \) to \( y3 \) in Figure 4**

Let \( j \) = number of occurrences of DER failure times before DOWN

\[ s_T = \sum_j s_j = \text{total DER failure times before going DOWN for '} j \text{' many such occurrences.} \]

\[ s_i = \alpha e^{-a s_i}. \]

\( \alpha \) = DER-to-DOWN failure rate.

\( g \) = shape parameter of gamma prior for DER-to-DOWN failure rate \( \alpha \).

\( \psi \) = inverse scale parameter of gamma prior for DER-to-DOWN failure rate \( \alpha \).

Now let the DER-to-DOWN failure rate \( \alpha \) have a gamma prior distribution:

\[
\theta_5(\alpha) = \frac{\psi^g}{\Gamma(g)} \alpha^{g-1} \exp(-\alpha \psi), \alpha > 0. \tag{21}
\]

Thus, similarly skipping two intermediate steps, the conditional posterior density of \( \alpha \):

\[
b_5(\alpha | s) = \frac{1}{\Gamma(j + g)} (s_T + \psi)^{j+g-1} \exp(-\alpha(s_T + \psi)),
\tag{22}
\]

which is also a Gamma \( j + g, (s_T + \psi)^{-1} \). Note that \( s \) is a vector.

**DOWN-to-DER Recovery Transition Rate (\( \gamma \)), e.g. from \( w1 \) to \( s1 \), or \( w2 \) to \( u2 \) in Figure 4**

Let \( p \) = number of occurrences of DOWN times before DER

\[ w_T = \sum_1^p W_i = \text{total DOWN times before going DER for '} p \text{' many such occurrences.} \]

\[ W_i \sim \gamma e^{-\gamma w_i}. \]

\( \gamma \) = DOWN-to-DER recovery rate.

\( \lambda \) = shape parameter of gamma prior for the DOWN-to-DER recovery rate \( \gamma \).

\( b \) = inverse scale parameter of gamma prior for the DOWN-to-DER recovery rate \( \gamma \).

Now let the DOWN-to-DER recovery rate \( \gamma \) have a gamma prior distribution:

\[
\theta_6(\gamma) = \frac{\lambda^b}{\Gamma(b)} \gamma^{b-1} \exp(-\gamma \lambda), \gamma > 0. \tag{23}
\]

Thus, similarly skipping two intermediate steps, the conditional posterior density of \( \gamma \):

\[
b_6(\gamma | w) = \frac{1}{\Gamma(p + b)} (w_T + \pi)^{p+b-1} \exp(-\gamma(w_T + \pi)),
\tag{24}
\]

which is also distributed as Gamma \( p + b, (w_T + \pi)^{-1} \). Note that \( w \) is a vector.

**Statistical Simulation of Three-State Units to Estimate the Density of UP, DOWN, and DER**

Table 1 displays the input data as tabulated for the following example covering the first five episodes of six different sojourn times (see Figures 3 and 4).

The cumulative probabilities of states are calculated by Monte Carlo Simulation method using input from Table 1 as follows in Tables 2–4 for UP, DOWN, and DER states in 100, 1000, and 10,000 simulation runs, respectively. Figures 5–7 using Eqs (5)–(7) will convert these tabulations into cumulative frequency plots utilizing the six transitions of Figure 3 in subsections of Three-State

**TABLE 1 | An Input Data Example for the Monte Carlo Simulations of UP, DOWN, and DER States for the first 5 episodes (#Events)**

| #Events | Exposure Time | Shape Parameter | Scale Parameter | Transition Rate |
|---------|---------------|----------------|----------------|----------------|
| \( a = 5 \) | \( x_T = 25 \) | \( c = 0.2 \) | \( \xi = 1 \) | \( \lambda \) |
| \( b = 5 \) | \( y_T = 5 \) | \( d = 2 \) | \( \eta = 0.5 \) | \( \mu \) |
| \( o = 5 \) | \( z_T = 10 \) | \( e = 1 \) | \( \Delta = 0.5 \) | \( \delta \) |
| \( k = 5 \) | \( u_T = 20 \) | \( f = 0.5 \) | \( \theta = 1 \) | \( \sigma \) |
| \( j = 5 \) | \( s_T = 10 \) | \( g = 1 \) | \( \psi = 0.5 \) | \( \alpha \) |
| \( p = 5 \) | \( w_T = 15 \) | \( h = 2 \) | \( \pi = 1 \) | \( \gamma \) |
### TABLE 2 | UP STATE EQ(5)

| Cumulative Density | <0.1 | <0.2 | <0.3 | <0.4 | <0.5 | <0.6 | <0.7 | <0.8 |
|---------------------|------|------|------|------|------|------|------|------|
| 100 simulation runs |
| Total count         | 0    | 2    | 19   | 62   | 92   | 100  | 100  | 100  |
| Cumulative Probability | 0    | 0.02 | 0.19 | 0.62 | 0.92 | 1    | 1    | 1    |
| 1000 simulation runs |
| Total count         | 0    | 21   | 185  | 597  | 885  | 978  | 998  | 1000 |
| Cumulative Probability | 0    | 0.021| 0.185| 0.597| 0.885| 0.978| 0.998| 1    |
| 10,000 simulation runs |
| Total count         | 0    | 187  | 2000 | 5874 | 8815 | 9816 | 9984 | 10,000|
| Cumulative Probability | 0    | 0.0187| 0.2  | 0.5874| 0.885| 0.978| 0.998| 1    |

### TABLE 3 | DERATED STATE EQ(6)

| Cumulative Density | <0.05 | <0.1 | <0.15 | <0.2 | <0.25 | <0.3 | <0.35 | <0.4 | <0.45 |
|---------------------|-------|------|-------|------|-------|------|-------|------|-------|
| 100 simulation runs |
| Total count         | 0     | 10   | 43    | 80   | 97    | 100  | 100   | 100  | 100   |
| Cumulative Probability | 0     | 0.1  | 0.43  | 0.8  | 0.97  | 1    | 1     | 1    | 1     |
| 1000 simulation runs |
| Total count         | 0.34  | 181  | 552   | 829  | 954   | 984  | 995   | 998  | 999   |
| Cumulative Probability | 0.034 | 0.181| 0.552 | 0.829| 0.954 | 0.984| 0.995 | 0.998| 0.999 |
| 10,000 simulation runs |
| Total count         | 34    | 1893 | 5894  | 8543 | 9545  | 9882 | 9960  | 9989 | 9999  |
| Cumulative Probability | 0.0034| 0.1893| 0.5894| 0.8543| 0.9545| 0.9882| 0.996 | 0.9989| 0.9999|

### TABLE 4 | DOWN STATE EQ(7)

| Cumulative Density | <0.1 | <0.2 | <0.3 | <0.4 | <0.5 | <0.6 | <0.7 |
|---------------------|------|------|------|------|------|------|------|
| 100 simulation runs |
| Total count         | 0    | 5    | 19   | 66   | 90   | 100  | 100  |
| Cumulative Probability | 0    | 0.05 | 0.19 | 0.66 | 0.9  | 1    | 1    |
| 1000 simulation runs |
| Total count         | 1    | 48   | 252  | 639  | 902  | 995  | 1000 |
| Cumulative Probability | 0.001| 0.048| 0.252| 0.639| 0.902| 0.995| 1    |
| 10,000 simulation runs |
| Total count         | 13   | 364  | 2435 | 6161 | 9032 | 9899 | 10,000|
| Cumulative Probability | 0.0013| 0.0364| 0.2435| 0.6161| 0.9032| 0.9899| 1    |

*Sahinoglu Probability Model of Production Units (Monte Carlo Simulation) covering Eqs (9)–(24).*

Plots shown in Figure 8 are the extrapolated JAVA versions of the EXCEL applications in Figures 5–7. Consequently a more detailed graphical JAVA version of the probability density plots with $n = 100,000$ simulation runs are displayed in Figures 9 and 10 to illustrate statistical centrality.
and location measures. The input data covering the first $n = 5$ events or episodes of each of six different sojourn times, as a hypothetical example in Table 1 are symbolically displayed in Figure 4, as derived from Markov state diagram shown in Figure 3. Consequently, results of Tables 2–4 and Figures 5–7 are plotted for each of the three states (UP–DOWN–DER) c.d.f. in Figure 8. Given the input tabulation in Table 1, the JAVA program will compute the popular statistical measures of three random variables as plotted in Figures 9 and 10. Probability density functions of the three states from Eqs (5)–(7) with a mean and a standard deviation, obtained by incremental piecewise calculations in

**Figure 5** | $P(UP)$ Cumulative reliability plot with 10,000 Monte Carlo simulation runs.

**Figure 6** | $P(DER)$ Cumulative reliability plot with 10,000 Monte Carlo simulation runs.

**Figure 7** | $P(DOWN)$ Cumulative reliability plot with 10,000 Monte Carlo simulation runs.
FIGURE 8 | The input data in Table 1, and simulation results in Tables 2–4 and Figures 5–7 display the cumulative reliability plots of the three states for UP (r), DER (d), and DOWN (q).

Figure 8 from the c.d.f.s of Figures 5–7 will follow:

\[ f(UP) \sim \text{Normal}(0.267, 0.107), \]
\[ f(DER) \sim \text{Normal}(0.433, 0.1) \]
\[ f(DOWN) \sim \text{Normal}(0.299, 0.106). \]

Note that the 90% confidence limits for the three Markov states computed in Figure 9 are as follow:

\[ \{UP_u = 0.12, \quad UP_L = 0.46\}, \quad \{DER_u = 0.27, \quad DER_L = 0.60\}, \quad \{DOWN_u = 0.14, \quad DOWN_L = 0.49\}, \]

Assume the random variables, \( y \sim \text{Gamma} (\alpha_1 = a + c, \beta_1 = \xi + x_T) \), and \( r v, z \sim \text{Gamma} (\alpha_2 = b + d, \beta_2 = \eta + y_T) \), where the random variable \( q = y/(y + z) \) has the p.d.f. and c.d.f. respectively,

\[
gQ(q) = \frac{\Gamma(m' + n')}{\Gamma(m')\Gamma(n')} q^{m'-1} (1-q)^{n'-1} \left[ \frac{b'}{a' + q(b' - a')} \right]^{m'+n'},
\]

(27)
\[ G_Q(q) = 1 - G_{F_{2m',2n'}} \left[ \frac{a' n'}{b' m'} (q^{-1} - 1) \right] \]

\[ = P[F_{2m',2n'} > C_1 = (q^{-1} - 1)]. \quad (28) \]

Re-substituting for \( n' = a + c, \ m' = b + d, \ b' = \xi + x_T \) and \( a' = \eta + y_T \), we obtain for (27)

\[ g_Q(q) = \frac{\Gamma(a + b + c + d)}{\Gamma(a + c)\Gamma(b + d)} (\eta + y_T)^{b + d} (\xi + x_T)^{a + c} \]

\[ \times \frac{(1 - q)^{b + d - 1} q^{a + c - 1}}{[\eta + y_T + q' (\xi + x_T - \eta - y_T)]^{a + b + c + d}}. \quad (29) \]

where Snedecor’s F-Distribution used in Eq. (28) can be found in Ref 47. By the inverse transform approach, find the constant \( C_1 = \text{inverse of } F_{2m',2n'}(1 - u_i) \) as in Eq. (28), by equating the c.d.f. value \( G_Q(q) \) to a random uniform number, \( u_i \) for \( i = 1, \ldots, N \) (large), as follows.

\[ C_1 = \frac{a' n'}{b' m'} (q^{-1} - 1) \rightarrow q^* \]

\[ = \frac{a' n'}{a' n' + C_1 b' m'}, 0 < q^* < 1, \quad (30) \]

where \( q^* \) is the SL (\( \alpha = a + c, \ \beta = b + d, \ L = L_1/\beta_2 \)) random deviate for \( q \) (unavailability). Note, \( u_i \) are uniform \((0,1)\) for \( i = 1, \ldots, N \) (large). Figure 11 shows relationships between popular distributions for statistical simulations.

**Example of SL Simulation for Modeling Network of 2 Two-State (UP-DN) Units**

Given the following simplest series system of two identical components in Figure 12, whose default operational probability for each is \( P(\text{UP}) = 0.9 \) and hence \( P(\text{System}) = 0.9^2 = 0.81 \). We now force these units have their unavailability r.v. distributed with SL displayed as in Figure 2’s l.h.s. column, where \( g_Q(q) \) is formulated as follows: SL (\( \alpha = a + c, \ \beta = b + d, \ L = (\xi + x_T)(\eta + y_T) \)) = SL (\( \alpha = 10 + 0.02 = 10.02, \ \beta = 10 + 0.1 = 10.1; \ L = (1 + 1000)/(1 + 111.1) = (1001/112.1) = 9.7234 \)). Use the SL random deviate simulator for \( q \) in Eq. (30), where \( q_i \) are to be independently SL distributed (Table 5). Historical failure and repair data are given in Figure 2. The flat deterministic outcome is 0.92 = 0.81 whereas SL-distributional input-output relationship is unknown due to the closed-form derivation of the product of random variables being not available. Since Eqs (25) and (26) are not closed form solutions and tedious numerical integration is needed, Monte Carlo simulation can be the only solution for much larger networks if analytical tools are not available\(^{45} \) (pp. 196–197, Figures 4 and 5) where analytical integration becomes an impossible task.

**Example of Another SL Simulation for Modeling Network of 7 Two-State (UP-DN) Units**

For the sake of a convenient example, a feasible and probable seven-node complex architectural style is taken\(^{20} \) (p. 254) with failure and repair history including the prior parameters displayed on the l.h.s. with 10 each ups and downs lasting 1000 and 111.1h, respectively, in Figure 13. The author assumes for the hypothetical control architecture an identical SL-distribution for its unavailability as displayed in Table 6 employing historical data for its components simulated 1000 times in 100- tuples of networks. This means 100,000 simulation runs overall. The analytical result being unknown for a complex system as the 7-node network depicted in Figure 13, the resulting simulation is 0.785 as in Table 6.

In the June 2012 issue of the IEEE Computer with ‘Computing in Asia’ as the cover feature, an article titled ‘Computing for the Next-Generation Automobile’ displays three hybrid vehicle architectural styles: series, parallel and series-parallel, and then the (Toyota) Prius integrated THS II control architecture. It is mentioned that most vehicles today come with more than 50 embedded computer components, called electronic control units (ECUs)\(^{7} \) (pp. 34–35).

**A REVIEW OF MODELING AND SIMULATION IN CYBERSECURITY**

Modeling and simulation (M&S) is a vital tool that can be leveraged for process improvement, and technology/capability development and evaluation. It is the process of designing a model of a system and conducting simulated experiments to preview and predict system behavior and evaluate optimal strategies for system operation. A short review of approaches will be covered in the world of cyber security on MC or DES. With the cyber security breaches rampant in the world, some of the most creative solutions to counteract these problems can be obtained by digital simulation faster, safer and cheaper than they can be resolved in the physical labs. In his related article, Rinaldi highlights M&S as a crosscutting initiative to increase the security of critical infrastructures.\(^{48} \) Their Strategy states that modeling, simulation, and analysis must be employed to ‘develop creative approaches and enable complex
decision support, risk management, and resource investment activities to combat terrorism at home. Rinaldi concludes that the multidisciplinary science of interdependent infrastructures is immature, and requires M&S to mature it, and adds that they are developing, among others, at Sandia Labs the following techniques. Aggregate Supply and Demand (What-if Analyses), Dynamic Simulations, and ABM, which at a macro level similar to cellular automata, is out of scope for this review. Some examples of M&S and DES, in the cybersecurity field will follow.
Monte-Carlo Value-at-Risk Approach by Kim et al. in Cloud Computing

Based on today’s volatile market conditions, the ability to generate accurate and timely risk measures has become critical to operating successfully, and necessary for survival. Value-at-Risk (VaR) is a market standard risk measure used by senior management and regulators to quantify the risk level of a firm’s holdings. However, the time-critical nature and dynamic computational workloads of VaR applications make it essential for computing infrastructures to handle bursts in computing and storage resources needs. This requires on-demand scalability, dynamic provisioning, and the integration of distributed resources.

A VaR calculation will typically start after the end of the trading day, when market data and final positions have been verified. It must be complete, and updated risk numbers must be available, before the start of the next trading day. As the number and complexity of positions change, the computational requirements for the calculation can change significantly, however the completion deadline of the beginning of the next trading day remains fixed. Furthermore, as market conditions change, a firm may want to vary the number of Monte Carlo scenarios run (and thus the resolution of the calculation), which will add additional variability to the computation time. Specifically, the authors demonstrate how the Comet Cloud autonomic computing engine can support online multiresolution VaR analytics, a candidate for Cloud architecture by integrating of private and Internet cloud resources.49

Monte Carlo and Discrete Event Simulations in Sahinoglu’s Security-Meter (SM) Risk Model

Four examples will be studied regarding Monte Carlo (MC) and Digital Event Simulation in the field of Cybersecurity.

Example for Security Meter Risk Modeling and Simulation

Assume two vulnerabilities and two threats in a $2 \times 2 \times 2$ set up as in Figure 14.20,22

Let $X$ (total number of cyber-attacks detected) $= 360$/year and let $X_{11} = 98$, $X_{12} = 82$, $X_{21} = 82$, $X_{22} = 98$.

Let $Y$ (total number of attacks undetected) $= 10$/year and let $Y_{11} = 2$, $Y_{12} = 3$, $Y_{21} = 3$, $Y_{22} = 2$.

When we keep Figure 14 in sight, we obtain the risk ratios and $ECL$ (Expected Cost of Loss) as follow.

$$P_{11} = \frac{X_{11} + Y_{11}}{X_{11} + Y_{11} + X_{12} + Y_{12}} = \frac{100}{185} = 0.54,$$

TABLE 5 | Simulation of a Simple Series Network using SL-Distributed Unit Unavailability in figure 12

| Properties | Direct Values |
|------------|--------------|
| Up-Dn #a   | 10           | C 0.02 |
| Dn-Up #b   | 10           | Ksl 1.0 |
| Cum. a (Xt)| 1000         | D 0.1 |
| Cum. b (Yt)| 111.11       | Eta 1.0 |

79,617 successes out of 100,000 simulation runs.
NETWORK RELIABILITY = 0.79617
NETWORK UNRELIABILITY = 0.20383
Each of the 100 networks simulated 1000 times totaling to 100,000 runs in 65.444 seconds.

TABLE 6 | Simulation of a Complex Production Network using SL-Distributed Unit Unavailability in figure 13

| Properties | Direct Values |
|------------|--------------|
| Up-Dn #a   | 10           | C 0.02 |
| Dn-Up #b   | 10           | Ksl 1.0 |
| Cum. a (Xt)| 1000         | D 0.1 |
| Cum. b (Yt)| 111.11       | Eta 1.0 |

78,476 successes out of 100,000 simulation runs.
NETWORK RELIABILITY = 0.78476
NETWORK UNRELIABILITY = 0.21524
Each of the 100 networks simulated 1000 times in 148.36 seconds.

FIGURE 13 | Complex network of seven units with input data, where source: $s = 1$ and target: $t = 7$. 
Figure 14 | Simplest $2 \times 2 \times 2$ tree diagram for two threats and for two vulnerabilities in a cyber-risk scenario.

\[ P_{12}(\text{threat 2 probability for vulnerability 1}) = \frac{(X_{12} + Y_{12})}{(X_{11} + Y_{11} + X_{12} + Y_{12})} = \frac{85}{185} = 0.46, \quad (32) \]
\[ P_{21}(\text{threat 1 probability for vulnerability 2}) = \frac{(X_{21} + Y_{21})}{(X_{21} + Y_{21} + X_{22} + Y_{22})} = \frac{85}{185} = 0.46, \quad (33) \]
\[ P_{22}(\text{threat 2 probability for vulnerability 2}) = \frac{(X_{22} + Y_{22})}{(X_{21} + Y_{21} + X_{22} + Y_{22})} = \frac{100}{185} = 0.54, \quad (34) \]
\[ P_1(\text{vulnerability 1}) = \frac{(X_{11} + Y_{11} + X_{12} + Y_{12})}{(X_{11} + Y_{11} + X_{12} + Y_{12} + X_{21} + Y_{21} + X_{22} + Y_{22})} = \frac{185}{370} = 0.5, \quad (35) \]
\[ P_2(\text{vulnerability 2}) = \frac{(X_{21} + Y_{21} + X_{22} + Y_{22})}{(X_{11} + Y_{11} + X_{12} + Y_{12} + X_{21} + Y_{21} + X_{22} + Y_{22})} = \frac{185}{370} = 0.5. \quad (36) \]

The probabilities of LCM (Lack of Countermeasure) and CM (Countermeasure) where CM + LCM = 1 for the vulnerability-threat pairs demonstrated in Figure 14.

\[ P(LCM_{11}) = \frac{(Y_{11})}{(X_{11} + Y_{11})} = \frac{2}{100} = 0.02, \quad \text{hence, } P(CM_{11}) = 1 - 0.02 = 0.98, \quad (37) \]
\[ P(LCM_{12}) = \frac{(Y_{12})}{(X_{12} + Y_{12})} = \frac{3}{85} = 0.035, \quad \text{hence, } P(CM_{12}) = 1 - 0. \quad (38) \]
\[ P(LCM_{21}) = \frac{(Y_{21})}{(X_{21} + Y_{21})} = \frac{3}{85} = 0.035, \quad \text{hence, } P(CM_{21}) = 1 - 0.035 = 0.965, \quad (39) \]
\[ P(LCM_{22}) = \frac{(Y_{22})}{(X_{22} + Y_{22})} = \frac{2}{100} = 0.02, \quad \text{hence, } P(CM_{22}) = 1 - 0.02 = 0.98. \quad (40) \]

We place the estimated input values for the security meter in Figure 14 to calculate total residual risk.

Therefore, once you build the probabilistic model from the empirical data, as above, which should verify the final results, you can forecast or predict any ‘taxonomic’ activity whether it is the number of vulnerabilities or threats or crashes as in Table 7. For the study above, the total number of crashes is 10 out of 370 total events, which gives a ratio of 10/370 = 0.0270 to verify the final results in Figure 14.

Using this probabilistically accurate model, we can predict what will happen in a different setting or year for a newly given explanatory set of data as in Table 7. If a clue suggests to us a future 1000 total episodes and 500 episodes of vulnerabilities of $V_1$, then by the avalanche effect, we can fill in all the other blanks, such as for $V_2 = 500$. Then (0.5405) (500) = 270.2 of $T_1$ and (0.4595)(500) = 229.7 of $T_2$. Out of 270.2$T_1$ episodes, (0.02)(270.2) = 5.4054 for LCM, were yielding to 5.4 crashes. Therefore, antivirus devices or firewalls have led to 264.8 preventions or saves. Again for $T_2$ of $V_1$: (0.035)(229.7) = 8.1 crashes and (0.965)(229.7) = 221.6 saves. The same holds for the $V_2$ due to symmetric data in this example depicted in Table 7. If the asset is $2500 and the criticality constant is 0.4, then the ECL (expected cost of loss) is demonstrated in Figure 14 following above calculations. Also,

\[ ECL = \text{Residual Risk} \times \text{Criticality} \times \text{Asset} \]
\[ = (0.0269)(0.4)(2500) = 26.9. \quad (41) \]
The analyst is expected to simulate a cyber-component’s (such as a server) tree-diagram 10 consecutive times from the beginning of the year (e.g., 1/1/2013) until the end of 1000 years (i.e., 12/31/3012) in an 8,760,000 h period, with a life cycle of crashes or saves for a total of 10 × 1000 = 10,000 simulation runs. The input data is tabulated in Table 7 to conduct the generation of random deviates. At the end of this planned time period, the analyst will fill in the elements of the tree diagram for a 2 × 2 × 2 security meter’s tree diagram model as in Figure 14.  

Recall that the rates are the reciprocals of the means for the assumption of a negative exponential probability density function to represent the distribution of time to crash. For example, if \( \lambda = 98 \) per 8760 h, the mean time to crash is 8760/98 = 89.38 h. Use the input as in Table 7.  

We observe a result of \( TRR = 0.0269 \approx 0.027 \) in Figure 15. Using the same data, as projected, we get the same results in Figure 16 as in Figure 15. That is, \( TRR = 0.0269 \approx 0.027 \). Therefore, DES and MC results were identical to four decimals as expected.  

### Table 7: The Deterministic Estimates of the SM Parameters in Figure 15 and Figure 16 Given the Total Number of Attacks  

| Total Attacks | VB Attacks | % Crashes | Saves | Threat | Events | % Crashes | Saves | Risk | Post Pct | Post vb |
|---------------|------------|-----------|-------|--------|--------|-----------|-------|------|----------|---------|
| 370           | v1         | 185       | 5     | 180    | v1.t1  | 100.0     | 54.05 | 2.0  | 98.0     | 0.005405 | 20.00   | 0.0500000 |
|               | v1.t2      | 85.0      | 45.95 | 3.0    | 82.0   | 0.008108  | 30.00 | 0.0500000 |
| 1000          | v1         | 500       | 50.00 | 14     | 486    | v1.t1     | 270.2 | 54.05 | 5.4054   | 264.8... | 0.005405 | 20.00   | 0.0500000 |
|               | v1.t2      | 229.7     | 45.95 | 8.1081 | 221.6... | 0.008108 | 30.00 | 0.0500000 |
|               | v2         | 500       | 50.00 | 14     | 486    | v2.t1     | 270.2 | 54.05 | 5.4054   | 264.8... | 0.005405 | 20.00   | 0.0500000 |
|               | v2.t2      | 229.7     | 45.95 | 8.1081 | 221.6... | 0.008108 | 30.00 | 0.0500000 |

### Monte Carlo (Static Time-Independent) Simulation using a Continuous Uniform p.d.f.  

In another cyber setting, with three vulnerabilities \( (V_1, V_2, V_3) \) with four threat levels for \( V_1 \), three threat levels each for \( V_2 \) and for \( V_3 \); the following upper and lower risk values for \( U(a,b) \) are assumed to be available for each vulnerability, threat and corresponding LCM variables, as follow in Table 8. Selected upper and lower uniformly distributed example values are very close to reduce variation. Theoretical derivations for \( TRR \)’s mean and variance are by MAPLE software using are as follow.  

\[
M := 0.260432113, \quad V := 0.0000144453852, 
\]

as copied from MAPLE outcomes, are tabulated in Table 8:

\[
M := 0.05040004790 + 0.03247999996 
+ 0.0033600000913 + 0.0028000000577 
+ 0.03717999068 + 0.003380000475 
+ 0.00790399736 + 0.03494401504 
+ 0.06903005201 + 0.01895400665. 
\]

### Discussion

Tables 9 and Figure 17 provide the comparative analytical MAPLE tabulations and Monte Carlo Simulations below. The means are almost identical to \( 10^{-6} \) identical and standard deviations are only \( 9 \times 10^{-3} \) apart. This alone shows the predictive power of modeling and simulation for cyber security studies in Section A Review of Modeling and Simulation in Cybersecurity in addition to those of production or manufacturing engineering in Section A Cross Section of Modeling and Simulation Issues in Manufacturing. Therefore, \( ECL = \text{Final Risk} \times \$8K = 0.26 \times 0.4 \times \)

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**FIGURE 15** | DES results of the $2 \times 2 \times 2$ security meter sampling design.

**FIGURE 16** | The Monte Carlo (MC) simulation results of the $2 \times 2 \times 2$ security meter sampling design.

**TABLE 8** | Simulation Input Data for the SM’s Uniformly Distributed $U(a, b)$, $TRR = \sum_{i=1}^{10} RR_i = 0.26$

| Vulnerability Threat Lack of Countermeasure | Residual Risk ($RR_i$) |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| Lower Upper | Lower Upper | Lower Upper | Expected |
| 0.34 0.36 | 0.47 0.49 | 0.29 0.31 | **0.0504** |
| 0.15 0.17 | 0.57 0.59 | | **0.0324** |
| 0.31 0.33 | 0.02 0.04 | | **0.0033** |
| 0.03 0.05 | 0.19 0.21 | | **0.0028** |
| 0.25 0.27 | 0.21 0.23 | 0.64 0.66 | **0.0371** |
| 0.01 0.03 | 0.64 0.66 | | **0.0033** |
| 0.75 0.77 | 0.03 0.05 | | **0.0079** |
| 0.38 0.40 | 0.31 0.33 | 0.27 0.29 | **0.0349** |
| 0.58 0.60 | 0.29 0.31 | | **0.0690** |
| 0.08 0.10 | 0.53 0.55 | | **0.0189** |

$8K = 0.104173 \times 8K = 833.38$ is the expected cost of loss to redeem if no risk is desired. How to mitigate the accrued risk from unwanted to a tolerable risk percentage is detailed in Refs 24 and 50.

**DISCUSSION AND CONCLUSION**

The power of simulation is evident from countless number of contemporary research works in addition to industrial and military undertakings to save time...
and budget. Besides nondestructively ‘learning the truth’ before ‘unexpected things happen’ in the real-world sense at an incomparably cost effective setting; the science and art of M&S cracks the code for numerous challenging problems where analytical derivations or formulae prove inutil of by reaching a dead-end. The objective of applying simulation is to strengthen the advantages of the IT corporate circles and reduce the disadvantages, mainly because of the economic pressure and time constraints in the business world. A gamut of modeling and simulation practices in the Armed Forces flank can be advantageously utilized to plan saving time and resources so as to avoid wasting a tight budget for ‘the most bang for the buck’ before new projects are hastily commissioned, only to see that they are not what to get the job done in a disappointing finale. Uses of simulation in medical oncology or else, as well as its impact in the area of computational finance are only some of its virtually endless applications.51,52

Following a brief introduction and running a best-kept-secret historical perspective to the origins of simulation, the author reviews the literature as to why the art and science of modeling and simulation are crucial to today’s engineering world. The review further focuses on the currently popular manufacturing and cyber defense issues, to cite a few examples if not all, to set the stage for the rest of the plentiful engineering avenues.

On the manufacturing or production front, the author in response to then-in-2007-unsolved homework question 5.5 on p. 256 from his Wiley textbook,20 reviews the set of techniques to generate the multistate probability distribution model of an important pillar of trustworthiness, that is, availability. Namely, when the availability (or reliability) of a unit is at stake, and while the unit possesses three operational states with a derated state added beyond the usual two-state binary or dichotomous assumption, conventional applications do not suffice. Therefore, it is worth to review the fact that the primary difference between other related works30–32 and author’s empirical Bayesian treatment of the three states of a repairable hardware unit is to estimate the p.d.f.s of these three states by using Monte Carlo simulations.38,39 The closest article to this one uses only four transition rates in a three-state Markov model whereas the reviewed Monte Carlo model uses all six transitions.30 This reviewed statistical simulation approach is powerful and flexible, whereas Ref 30 deals with differential equations limited in scope. Other close references deal with different topics; however none use any simulation techniques.31,32

It is currently infeasible to find closed form solutions for the random variables of \( U_P \), \( DER \), and \( DOWN \) expressed by Eqs (5)–(8) because of a multiplicity of sums and products of gamma
random variables expressed in the denominator term of Three-State Sahinoglu Probability Model of Production Units (Monte Carlo Simulation). In the final analysis shown in Statistical Simulation of Three-State Units to Estimate the Density of UP, DOWN and DER, the resulting distributions for the three parameters, UP, DER and DOWN are approximated by normal distributions. The outcome distributions in A Cross Section of Modeling and Simulation Issues in Manufacturing are quasisymmetrical with \( E \) (Mean) and \( M \) (median) almost equal, although slightly right-skewed because \( \text{Mean} \approx \text{Median} > \text{Mode} \). The reviewed Sahinoglu–Libby, a.k.a., SL (\( \alpha, \beta, L \)) is the continuous probability density function of the unavailability (or availability when duly reparametrized) of a two-state unit. For those units whose life time can be decomposed into operating (UP), derated (DER), and nonoperating (DOWN) states in a three-state setting, sojourn times are assumed to be distributed according to the generalized gamma p.d.f. where both shape and scale parameters are non-identical. The resultant density plots in Figures 12 and 13, following extensive statistical simulations in A Cross Section of Modeling and Simulation Issues in Manufacturing, are approximately symmetric normal despite a spike for the mode. These plots definitely qualify to pass goodness-of-fit tested for Normal p.d.f. Because of infeasibility of closed form analytical solutions for the explained three-state version; the Monte Carlo simulation technique is rightfully selected as a mathematically tractable model to calculate the \( UP \), \( DER \), and \( DOWN \) probabilities for a three-state repairable hardware unit.

These summary measures are all shown in the plots of the JAVA applications throughout A Cross Section of Modeling and Simulation Issues in Manufacturing. Network applications for medium and large networks are studied using Monte Carlo simulations in references.\(^{20-24}\) After the analyses, the approximate closed form p.d.f.s can be estimated as shown in Statistical Simulation of Three-State Units to Estimate the Density of UP, DOWN, and DER because of the favorable results by normal probability plots. Researchers can utilize the results for their related research when deriving the p.d.f.s of their Markov states in other disciplines such as business, for example, banking.\(^{53}\) Currently, only deterministic probabilities can be calculated through Markov algebra, but not their probability densities. For example, a credit card is either closed (if less than a critical credit score), open (more than) or only conditionally usable for urgent cases (between lower and upper). The Bank actuarians may want to estimate the p.d.f.s of these three states to conduct statistical inference using customer-based empirical data by employing empirical Bayesian analysis. Multi-state systems such as in the case of four multiple derated states representing electric power turbines, as cited in Refs 20 (p. 280, Figure 6.26) and 45 (p. 201, Figure 10) can be derived. These estimators for unit availability can further be propagated to simulate the source-target availability for troublesome complex networks.

Regarding the cyber security science and engineering issues however, implementation of modeling and simulation compared to manufacturing industry is fairly new progressing at an experimental stage. This fact is not only because of involvement of human life and death situations in adversity, as compared to accidental casualties in the production world, but also because of lack of theoretical and experiential data base dating back to only 1990s since the launch of public internet. The author, by following examples in this area proceeds with currently popular VaR technique by Kim et al.\(^ {49}\) and Security Meter and CLOUD simulation tools (CLOURA) by Sahinoglu et al.\(^ {26}\) Monte Carlo VaR is costly to execute; it does not incorporate cost comparisons when taking measures. Consider a medium size firm holding positions in 20,000 different financial instruments. Running a 100,000 simulation Monte Carlo VaR calculation requires generating 2 billion simulated instrument prices. With a conservative estimate of 10 milliseconds per pricing, this calculation requires more than 5500 h of processor time over an 8 h window. The capital cost of hardware plus the operational cost for data center space, power, cooling and maintenance makes this cost prohibitive to all but the largest firms. However, scalable CLOURA is a very fast algorithm, that is, it can simulate a CLOUD system with 430 servers for 1000 years in less than 4 min.\(^ {26}\) SM simulations as in Tables 7–9 and Figures 15–17 and are relatively fast and accurate, comparable to their analytical counterparts.\(^ {20-22}\)

Overall M&S techniques abound, particularly face-saving in the case of theoretical impasses, and sometimes the only viable solutions in engineering and scientific applications. The multiples of positive results render M&S methods among the most useful and practical, as well as affordable algorithms of our time. If one day, humankind can make it to the surface of the red planet Mars, it will be possible because humans will have nondestructively travelled to Mars some tri-zillion times by riding on the cyber space...
through digital simulation rather than on the outer space. The author contends that positive solutions will realize for cancer and currently incurable diseases by crunching computationally intensive and nonlethal M&S techniques. The application of M&S to engineering, cyberspace and health informatics, however, is not an easy task with much progress remains to be done. This overview also aims to provoke thoughts and stimulate ideas for such goals by exploring interdisciplinary avenues through M&S using supercomputing.

Finally, one exam question in a Cybersecurity M.S. program’s midterm exam at AUM asked, ‘What would separate you in your future job if you took an M&S course, and others did not have any clue?’ The following four responses in Appendix B were gathered from candidates invariably all with a military background, either on active duty or retired USAF. The responses, as quoted, did demonstrate an awakening of mind on the timely significance of Modeling and Simulation in cyberspace and reliability and security engineering.

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APPENDIX A
See Figures A1–A9.

FIGURE A1 Uniform numbers testing; Ho: random versus Ha: not random for 500 runs. Ho is not rejected.

FIGURE A2 Uniform numbers testing; Ho: random versus Ha: not random for 500 runs. Ho is rejected. On the average, one out of 40 cycles of 500 runs = 20,000 simulations will end up rejecting Ho: random.

FIGURE A3 Uniform numbers testing; Ho: random versus Ha: not random for 5000 runs. Ho is NOT rejected.
**FIGURE A4** | Uniform numbers testing; Ho: random versus Ha: not random for 5000 runs. Ho is rejected. On the average, one out of 10 cycles of 5000 = 50,000 simulations will end up rejecting Ho: random.

**FIGURE A5** | Uniform numbers testing; Ho: random versus Ha: not random for 10000 runs. Ho is NOT rejected.

**FIGURE A6** | Uniform numbers testing; Ho: random versus Ha: not random for 10,000 runs. Ho is rejected. On the average, one out of 25 cycles of 10,000 = 250,000 simulations will end up rejecting Ho: random.
FIGURE A7 | Uniform numbers testing; Ho: random versus Ha: not random for 50,000 runs. Ho is NOT rejected. After 60 cycles $\times 50K = 3000K = 3,000,000$ simulations there is still no reject Ho = random sequence. This may signal a cut-off point of no rejection of random sequence from this point on. Safe threshold may be 50K for JAVA coding uniform random number generator.

FIGURE A8 | Uniform numbers testing; Ho: random versus Ha: not random for 100,000 runs. Ho is NOT rejected. After 50 cycles $\times 100K = 5000K = 5,000,000$ simulations, there is still no reject Ho = random sequence. This may signal still no rejection of random sequence from the earlier safe threshold: 50K for a JAVA coding uniform random number generator.

FIGURE A9 | Uniform numbers testing; Ho: random versus Ha: not random for 250,000 runs. Ho is not rejected. After 40 cycles $\times 250K = 10,000K = 10,000,000$ simulations there is still no reject Ho = Random Sequence. This may signal still no rejection of random sequence from the earlier safe threshold: 50K simulations for a JAVA coding uniform random number generator. Important Note: In this figure, buttons indicate: No of values = 250,000 (simulation runs), DF = 6 (Section on Generic Theory, by Knuth’s Technique\(^\text{10,11}\)), Significance level (Type-I error) = 5%, Total Runs: $41,606 \times 1 + 51,836 \times 2 + 23,059 \times 3 + 6583 \times 4 + 1482 \times 5 + 290 \times 6.093$ (average for $>6$) = 250,000, where bold numbers from 1 to $>6$ are calculated run sizes by Knuth’s method. $\chi^2$ calculated = 7.57 $< \chi^2$ critical value = 12.59. Do NOT reject Ho: random sequence.
APPENDIX B

(1) I would be able to provide practical feedback when designing a real world IT project (e.g., software). I could use the simulation to run tests on software before it is implemented on a network. This gives me an advantage over my colleagues, as I am able to safely determine correctness and efficiency of the software. (2) By using M&S, you are able to show your security risk and probability of occurrence within each area of cyber security. By also being the only one at your firm with the M&S experience you have put yourself in a great position for upward mobility or at the very least a project manager or lead with nondestructive testing. (3) If I had M&S background and coworkers did not, I would have the advantage to develop models and run various simulations to aid in my decision-making process. They would not have this capability and their probability of making the correct decisions would be reduced. Not only would my decisions have a greater chance of being correct, but even in the event a bad decision was made; I would have data to support my decisions where my co-workers would not. (4) Working in a Cybersecurity firm and having the knowledge of M&S enables one to experiment with probability of occurrences. This will enable me analyze potential return on investments by product or lifecycle costs. Lastly, being able to test new products and methods will assist me, and corporate management to make the right decisions based on modeling and simulation versus ‘gut’ feelings.