Hospital Bed-Capacity and Emergency-Physician Risk Management — Strategies to Design Pandemic Contingency Plans

Mehmet Sahinoglu* and Ferhat Zengul

***Abstract*—This article employs a discrete event simulator, *CLOURAM* (Cloud Risk Assessor and Manager), so to estimate risk indices in modern-day *Cloud* computing setting applicable to Hospital Healthcare Service Networks. This innovative approach has not been implemented earlier using a *Cloud* framework for digital queuing simulation. The article also innovatively examines emergency-physician management strategy through *MCQS* (Multi-Channel Queuing Simulation) and Hospital Scheduling. The macro-level goal is to assess and manage risk with tangible mitigation targets and to improve the operational quality of interconnected health care services for crucial needs such as improving the critical bed-count and dire physician-availability to meet growing demands towards designing pandemic contingency plans. The proposed methods are applied to five randomly selected States. The raw data originated from the national repository of States' hospital networks. Such in-depth analyses not only assess the bed- and physician-inadequacy risk, but also foster feasibility plans by conducting cost and benefit analysis for future provisions of infrastructural needs to improve networked-healthcare services with cost-saving justifications. The results indicate that if physician-scarcities' and bed-shortfalls' admission and discharge input data can be traced to the States' healthcare networks, the administrative and financial analysts can timely benefit from proactive digital simulations. *JIT* (Just-in-time) simulations would similarly help toward the States' *CON* (Certificate of Need) laws, which require the capital expenditures' approval by State health planning agencies to avoid unnecessary duplications of healthcare investment against wasteful practices.**

***Index Terms*—Simulation software, hospitals national repository, cost and benefit, physician- and bed-capacity, emergency, risk**

I. Introduction and Motivation

Cloud computing is one of the vital research topics of the new century because it focuses on offering a variety of computing services conveniently and prudently through the internet, the largest of all online networks. A quantitative risk assessment, such as per the *QoS* (Quality of Service) in such enterprises, proves indispensable in modern trends. *Cloud* computing's *QoS* can be challenging to measure, not only qualitatively, but most importantly, quantitatively. An index-based *Cloud*-networked simulation is favorable to the intractably lengthy calculations by the theoretical Markov models, overly-limited in scope [1].

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Cloud computing will be implemented to healthcare service networks to form a *Cloud* backbone in this research article. For such purposes, a detailed *Cloud*-based math-statistical queuing simulation modeling is presented. This research study proposes an algorithmic, discrete-event simulated cost and benefit analysis in the realm of queuing principles to estimate hospitals healthcare service oriented *Cloud* network's bed-capacity indices by mimicking feasible scenarios. It similarly plans to run a computationally intensive discrete-event simulation software to queuing patients for managing critical emergency-physician needs, provided cost and benefit analyses. The article plans to concurrently run an economic analysis to identify the cost of operating the queuing system and then, develop a cost-optimal decision for the count of physicians to employ on an hourly operating cost basis to justify demand at times of emergency [2]. Digital simulations allow policy-makers to proactively prepare States' *CON* laws for investment. Popular illustrations of *Cloud* Computing in Fig. 1 allude to ref. [3]:

Fig. 1. Illustrative CLOUD (Hospital Healthcare Network) Computing.

The *Cloud* model's central idea for on-demand (or in-service) access to a shared pool of resources is to utilize the *JIT* resources instead of depending on local servers to run applications or provide data access. In the proposed framework of hospitals, the healthcare industry modeled as a *Cloud* network poses no exception to the wider sense of *Cloud* computing. *CLOURAM* software, whereas, acts to benefit for estimating the bed-inadequacy risks, and mitigating those risks by providing cost and benefit analyses on planning and deployment of future bed-capacity needs. This article will help assess a critical risk that hospitals faced all over the World and USA, resulting from insufficient planning to abruptly rising bed- and physician-demands [4]. The problem addressed is of great importance considering the dire need for optimizing hospitals' bed-capacities and physician-count, especially during the *COVID*-19 pandemic that culminated to its peak damage in mid-2020 prior to invention of life-saver vaccinations such as BioNTECH [5].

II. Methods, Survey, and Input Data Management

Motivations: A) To assess and manage risk of bed-shortages by deploying bedding requirements justified by the associated cost and benefit analysis to facilitate the States' *CON* laws with *CLOURAM* per *Appendix* button #13. B) To economize emergency-physician planning with *MCQS* and Hospital Scheduling per *Appendix* buttons #25 and #27. For both, Poisson arrivals and negative exponential service times by *M/M/k* (Poisson/Negative Exponential/*k* #channels) queuing on *FCFS (*First-Come-First-Served) are used [2].

A. Assessment and Management of Risk of Bed-Shortages with Cost and Benefit

The task of quantifying the lack of service due to the bed-shortages using the *LOLP* (Loss of Load or Loss of Service Probability) in a defined hospital healthcare network gains momentum. Authors positively affirm that there already exist *Cloud* applications albeit on a commercial and big-data basis, such as works like Sahoo *et al*. simulating healthcare employing CloudSim simulator [6]. *Cloud* computing is not a new concept in healthcare in an administrative sense, such that the adoption of *Cloud* technology has been increasing at an unexpected pace. As recent data shows, the global market for the general frame of *Cloud* technologies in the healthcare industry is expected to grow by ~$26 billion during 2020-2024 [7]. The required input data for this study, whereas, includes the *AHA* (American Hospital Association) annual survey [8] and *IHME* (The Institute for Health Metrics and Evaluation)'s *COVID*-19 projections for 2020 [9]. In-depth probabilistic modeling of *Cloud* computing can be found in [10]. Moreover, this article conducts a digital time-dependent, time-clocked, discrete event simulation in the framework of a *Cloud*. It compares available bed vs. patient demand in the realm of hospital healthcare network's patients' queuing algorithm based on admission and discharge mechanism in the *CLOURAM* software. This article also serves to design new strategies for optimal stockpiling medical supply (e.g. beds) and allocation for vital personnel demand such as physicians [11].

Summing lack of bed-capacity hours yields *LOLE* (Loss of Load Expected), i.e. an expected number of hours of the Loss of Load (Service). Load or service here implies bed-demand. *LOLP*=*LOLE*/*NHRS*, where *NHRS*=8760h, and *d*=LOLE/f indicates how long on the average, a loss of patient service due to bed-inadequacy endures before a spare bed is found. Frequency of deficiency is calculated by dividing the count of deficiencies by 8760h. Eq. (1) summarizes all:

$$LOLE = \text{f(Annual Frequency of Occurrences of Deficiencies)} \times \text{d(Average Hourly Duration of a Deficiency)} \quad (1)$$

From the provided data initially, the *OCR* (Occupancy Rate) input is calculated in dividing the total inpatient days by the product of bed-count and 365 days. The *OCR* is the ratio of the number of beds occupied. The bed-demand is calculated in multiplying the hospital's installed bed-count by its *OCR*. Bed-demand determines the patient-demanded number of actual beds in hospitals. The data from hospital raw data mainly includes the hospitals' year, patients' admission and discharge, inpatient days and hospital bed-demand. Eqs. (2) to (12) serve to build the input parameters. The *LOS* symbolizes a patient's average length of stay in days.

Capacity Value: Number of installed beds or bed-counts per group, e.g., 175 beds (2)

Groups: 1 *to …n* types of hospitals. Number of such identical groups, e.g., *n*=50 groups or 50 hospitals. (3)

Components: 1 to …*m*: How many such hospitals of identical bed-capacity, e.g. *m*=5; in the article, all *m*=1. (4)

Weibull Shape: β=1, i.e., Weibull *pdf* (probability density function) with its unity shape parameter to imply Negative Exponential (λ) *pdf* to be used. (5)

Failure Rate: Hospitalization arrivals' or patient's admission rates, e.g., λ=0.1/h (1 every 10h), $\lambda < \mu$. (6)

Repair Rate: De-hospitalization, departure, or patient's discharge rate, e.g., μ=0.2/h (1 every 5h), $\mu > \lambda$. (7)

AHD (American Hospital Directory) survey includes organizational, operational, financial, and market-level information of *U.S.* hospitals, but what's still missing was the patients' admission and discharge rates [12]. The discharge rate (h^{-1}) is calculated from the total count of inpatient days divided by the product of *LOS* and 8760h. Once the results are tabulated, bed-demand sum is calculated and used as the constant load for the *CLOURAM* input parameter. The sum of bed-counts are also verified by the software output in the form of total installed capacity, e.g. in Fig. 2. Once the calculations finalized, input templates for the *CLOURAM* are extracted from those tabulations of *AHD*'s *EXCEL* files. *CLOURAM* receives the input data as follows, recursively.

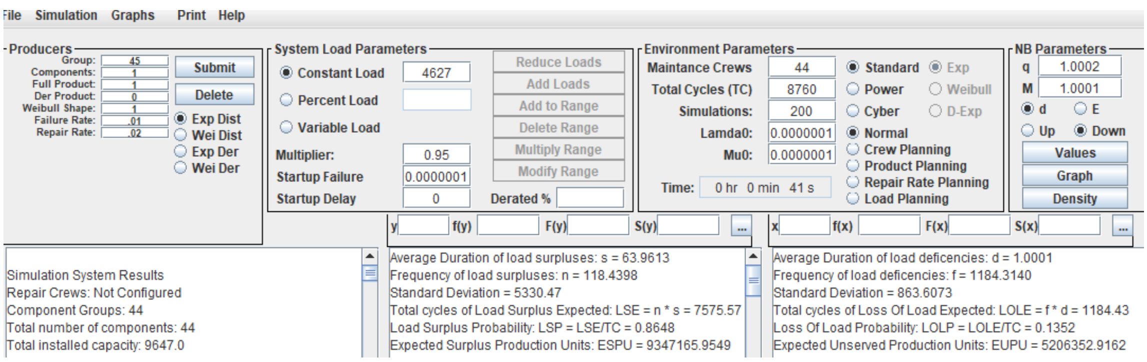


Fig. 2. State of *AL* hospitals network *CLOUD* simulation output *LOLE* ≈ 1184 h (LOLP≈13.52%) for *LOS*=2 days with installed bed-capacity: 9647 and constant load (due to *OCR*) of 4627 beds demanded, and Multiplier: 0.95 (load curbing ratio) leading to 4396 beds below the red central line in Fig. 3.

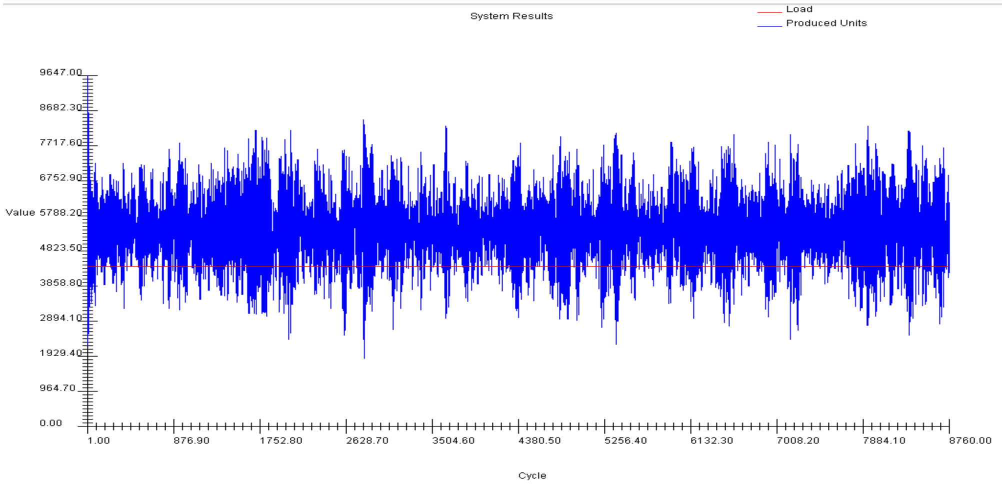


Fig. 3. State of *AL CLOUD* simulation deficiency (below the central red line = 4396 beds) plot with a total of ~1184h of bed-inadequacy in a year.

Occupancy Rate: OCR (unitless) = Bed Demand/Bed-Count = Inpatient days / (365 × bed-count) (8)

Bed Demand (# of beds needed) = *OCR* × Bed-Count = Inpatient days / 365 days (9)

Patient Admission Rate (h^{-1}) = #Patient Admissions /8760h (10)

Patient Discharge Rate (h^{-1}) = Inpatient days / (*LOS* × 8760h), where *LOS* = 2 (or 3) days upon choice (11)

LOS in days = Inpatient days / Total #Discharges (12)

The authors use *Cloud* computing discrete (not continuous) event simulation to research hospital network bed-resourcing by employing a queuing algorithm based on patients being admitted and discharged. If the available reserve bed capacity (Installed Bed Capacity−Bed Outages−Bed Demands) has less than a zero margin, an undesirable deficiency or bed-count shortage occurs. Sample data is no less than n=31 (prototype) and around n=50 (accepted norm) hospitals to display a statistically robust behavior for a Normal *pdf* approximation to the summed missing bed-count's purely Poisson *pdf* with q≈1 (Fig. 3's upper right corner) for *AL* State: *LOL* (Loss of Load) ~ Normal (μ = *LOLE* ≈ 1184h, σ ≈ 864h) with 68% of time of the *LOL* lying within one standard deviation of the *LOLE*, i.e. $\mu \pm \sigma$: (320h, 2048h). The input templates are finalized, and are loaded to the *CLOURAM* using the *Cloud* button #13 in *Appendix*. The constant load is the sum of the bed demands for the hospitals. *Cloud*-based digital simulation software, *CLOURAM*, assesses the bed-inadequacy index, which is *LOLP* (Loss of Load or Lack of Service) risk by conducting ≥100 years of simulation per annum (8760h). The risk management is conducted cost-optimally to mitigate *LOLP* index. Noteworthy details are:

i) Not all data sets for the States are available for the same calendar year due to different project undertakings by different project analysts. Years show differences per 2010, 2014 and 2018. Therefore, the performances of the States are not being compared to one another in terms of healthcare service efficacy owing to different years and sampling styles.

ii) *LOS* = 2 days was accepted as a norm through Table I–V since the higher *LOS* days are unrealistic and pessimistic.

iii) The cost examples in Table VI were avoiding loss (−) but aiming for profit (+). Profit is not always possible. However, the breakeven cost values were calculated for when the income trend reversed from positive to negative, or else.

iv) The bed-capacity graphs are fully plotted when the *LOLP*<0.15. The hospitals' identities are hidden for privacy. Varying simulation runs such as from n=100 to 200, or to 10,000 years whereas yielded slight differences converging to the true estimate, but intensive computations lasted longer.

v) The States' healthcare networks are assumed to be within easy reach of one another rather than too far away to enable the patients to be moved via medically equipped helicopters (or ambulances in prime condition) at hospitals' helipads ready to act to compensate for missing beds. The urgently needy patients are transferred in case of emergency.

vi) The patients' data refer to pre-*COVID* projected ahead.

1) States' hospital cases and varying scenarios

This article will quantitatively study five randomly selected States based on *EXCEL*-enabled hospital repository data banks from *AHD* and more to observe how the input data are processed to arrive at results where the five worst hospital bed-shortages were in *CT*, *MA*, *NJ*, *NY* and *RI* [13]. Table VI exhibits the calculated statistics of the networked-hospital healthcare indices for the *MI* (Northern), *TX* (Southern), *AZ* (South-Western), South-Eastern (*AL*) and Eastern (*PA*) dispersed under watch "where hospitals in the U.S. are under siege" [14]. Admission interarrival and discharge sojourn times are simulated by *Negative Exponential pdf* (λ) as a special case of the Weibull *pdf*, i.e. Wei (β=1, α=λ^{-1}).

Footnote of Table VI should state: For the cost and benefit analysis, a 1 million dollars ($1,000,000 or $1*M*) potential benefit is assumed per 1% rise of bed-availability of the hospital network regarding any State. For example, in the 3rd row of Table VI, i.e. *MI* state, *LOLP* (COL.8) drops to 0.26604909 (Fig. 4) from 0.28553231 (Fig. 5) with %1.948 improvements, roughly equal to 1.948% × $1*M* ≈ $1.948*M* benefit, and 200 new beds cost, 200 × $7500 ≈ $1.5*M*. The overall profit is $1.948*M* – $1.5*M* ≈ $448*K* in Table VI's ROW 3, COL.9 for *MI* under profit per Fig. 4 using Table III.

For the exceeded optimal step in Fig. 4, if *LOLP* newly drops to ~0.25684 from ~0.28553 with ~%2.869 improvements, Benefit ≈ 2.869% × $1M ≈ $2.869M. The State of *MI*'s 300 new beds cost 300 × $7500 ≈ $2.25M. The final Profit ≈ $2,689*M* – $2.25*M* ≈ $619*K* is in Table VI, ROW 3, COL.13.

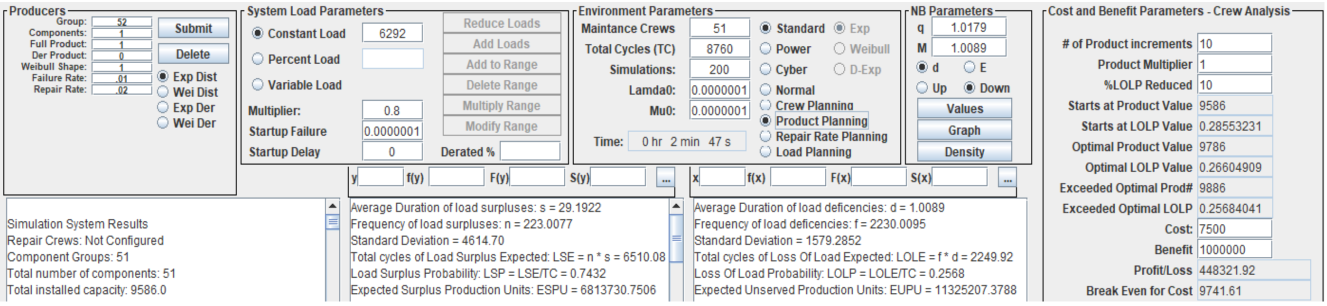


Fig. 4. State of *MI* hospitals *CLOUD* simulation bed–size (product) planning outcomes using input Table III.

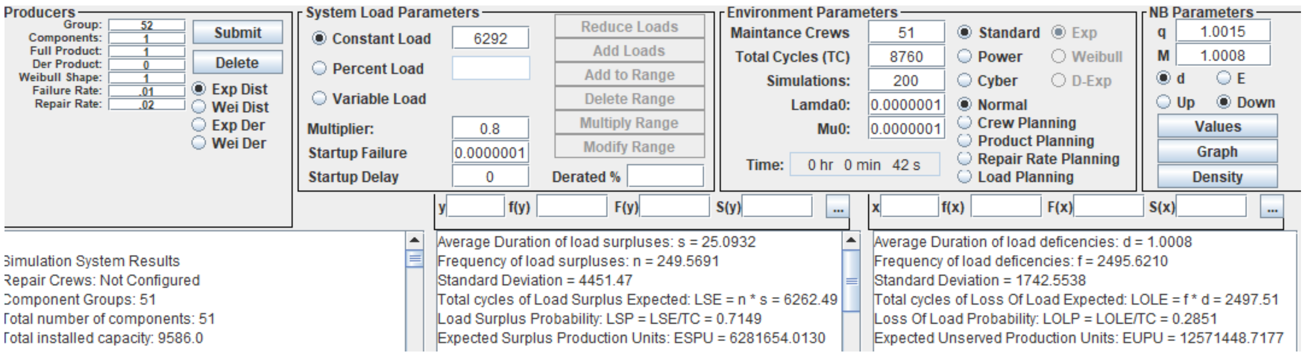


Fig. 5. State of *MI* Hospitals Network *CLOUD* Simulation Output *LOLE*=2498h (*LOLP*=28.5%) for *LOS*=2 days with installed bed-capacity=9586 and constant load (due to *OCR*) of 6292 beds demanded and Multiplier: 0.8 (load curbing ratio) of 6292 leading to 5034 beds below the central red line in Fig. 6.

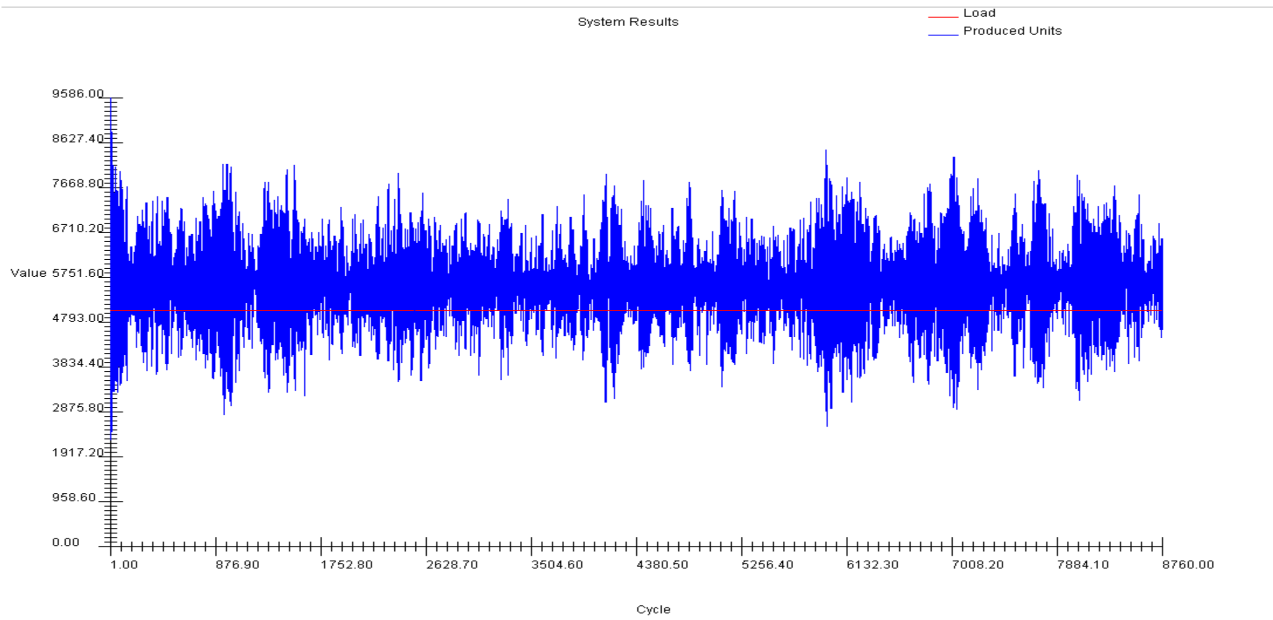


Fig. 6. State of *MI CLOUD* simulation deficiency (below the central red line =5034 beds) plot with a total of ~2498h of bed-inadequacy in a year.

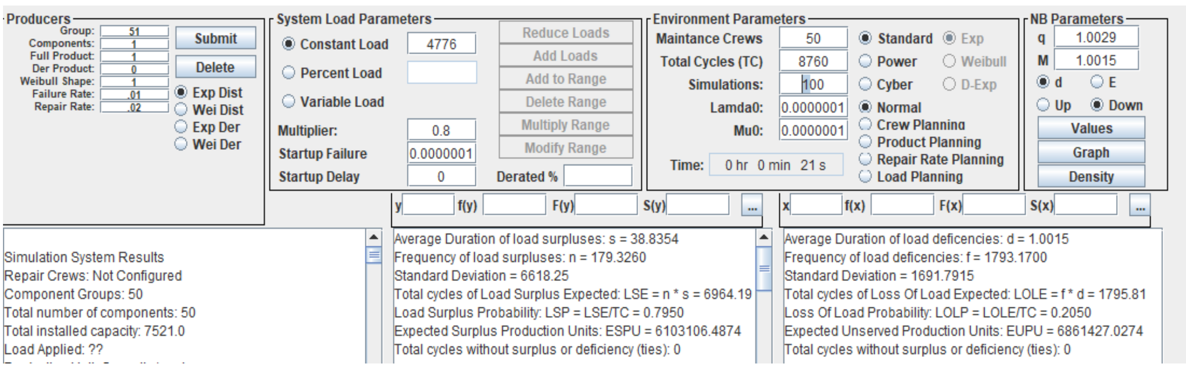


Fig. 7. State of *AZ* hospitals network *CLOUD* simulation output *LOLE* ≈ 1796h (*LOLP* = 20.5%) for *LOS*=2 days with installed bed-capacity=7521 and constant load (due to *OCR*) of 4776 beds demanded and Multiplier: 0.8 (load curbing ratio) of 4776 leading to 3821 beds below the central red line in Fig. 8.

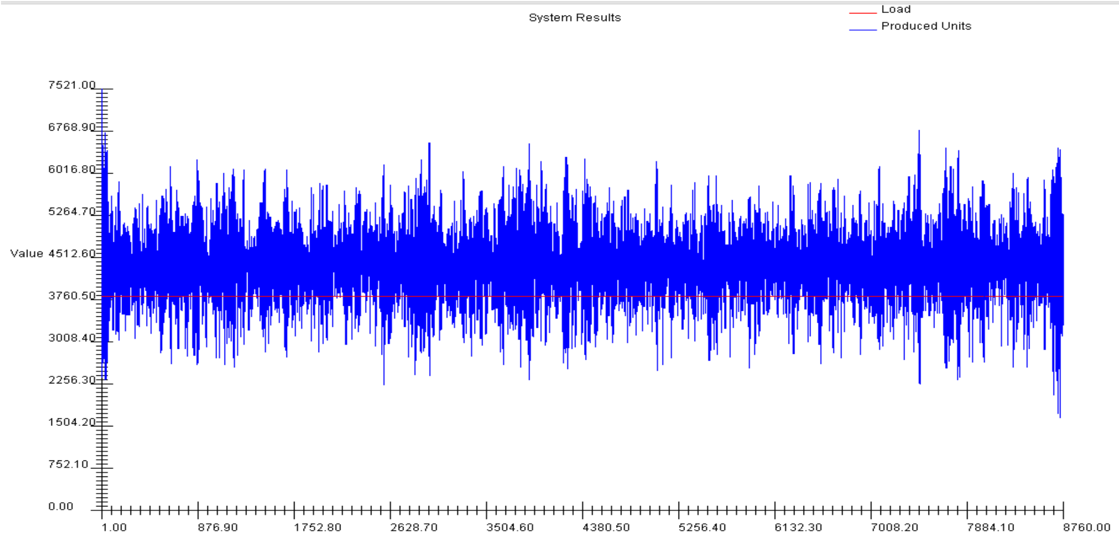


Fig. 8. State of *AZ CLOUD* computing simulation deficiency (below the central red line = 3821 beds) plot with a total ~1796h of bed-inadequacy in a year.

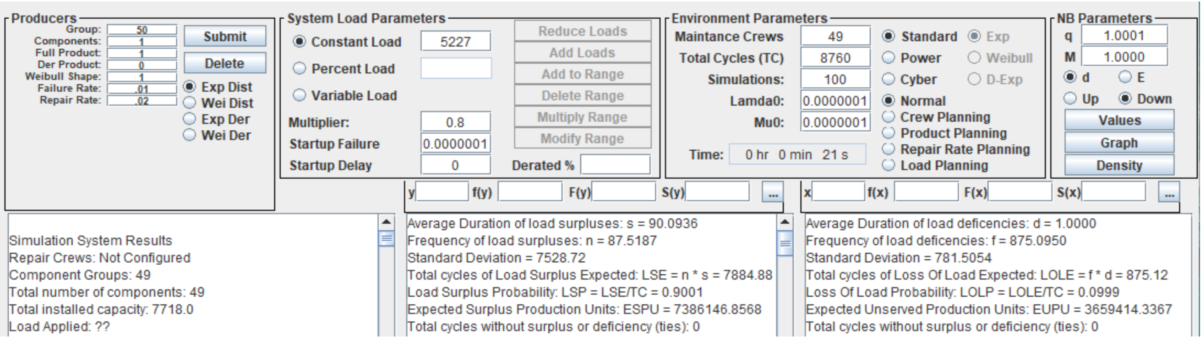


Fig. 9. State of *PA* hospitals network *CLOUD* simulation output *LOLE* ≈ 875h (*LOLP* ≈ 9.99%) for *LOS*=2 days with installed bed-capacity=7718 and constant load (due to *OCR*) of 5227 beds demanded and Multiplier: 0.8 (load curbing ratio) of 5227 yielding 4182 beds below the central red line in Fig. 10.

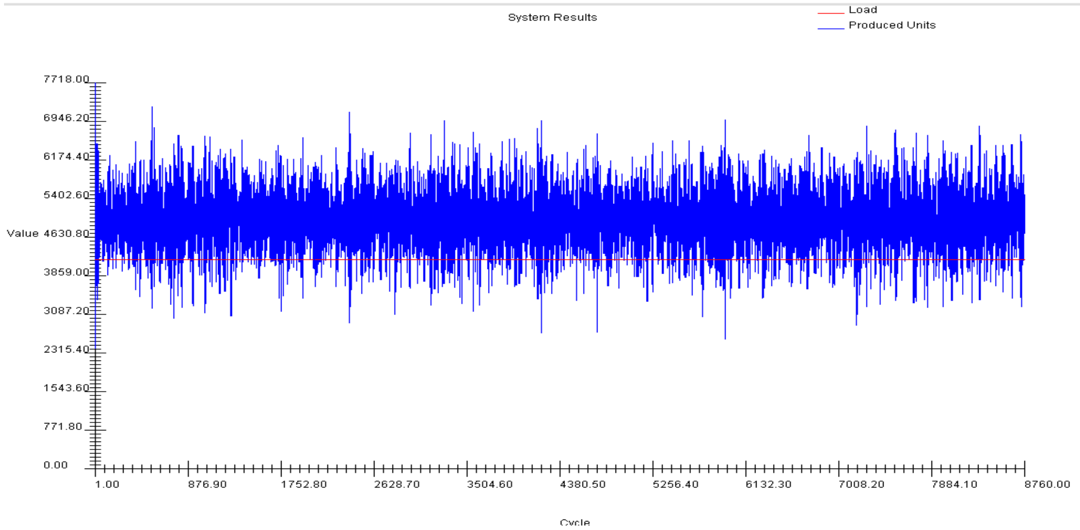


Fig. 10. State of *PA CLOUD* computing simulation deficiency (below the red line =4182 beds) plot with a total of ~875h of bed-inadequacy in a year.

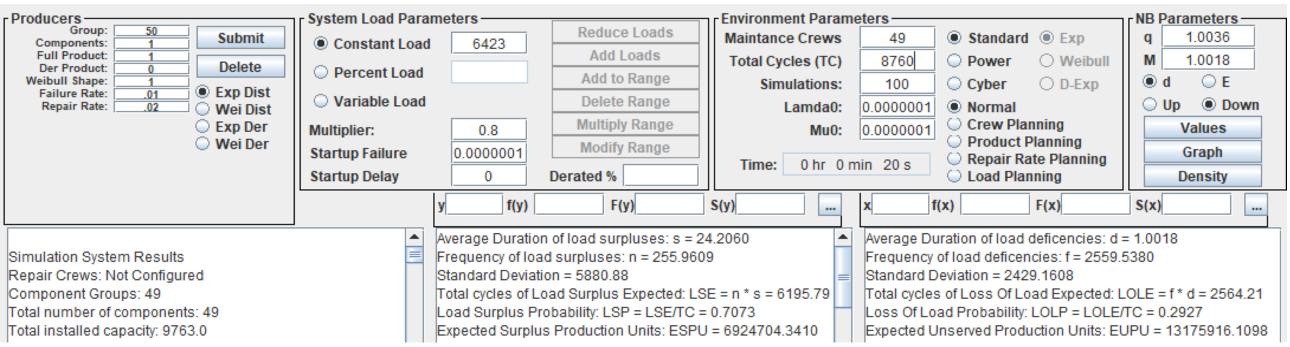


Fig. 11. State of *TX* hospitals network *CLOUD* simulation output *LOLE* ≈ 2564h (*LOLP* ≈ 29.3%) for *LOS*=2 days with installed bed-capacity=9763 and constant load (due to *OCR*) of 6423 beds demanded and Multiplier: 0.8 (load curbing ratio) of 6423 yielding 5138 beds below the central red line in Fig. 12.

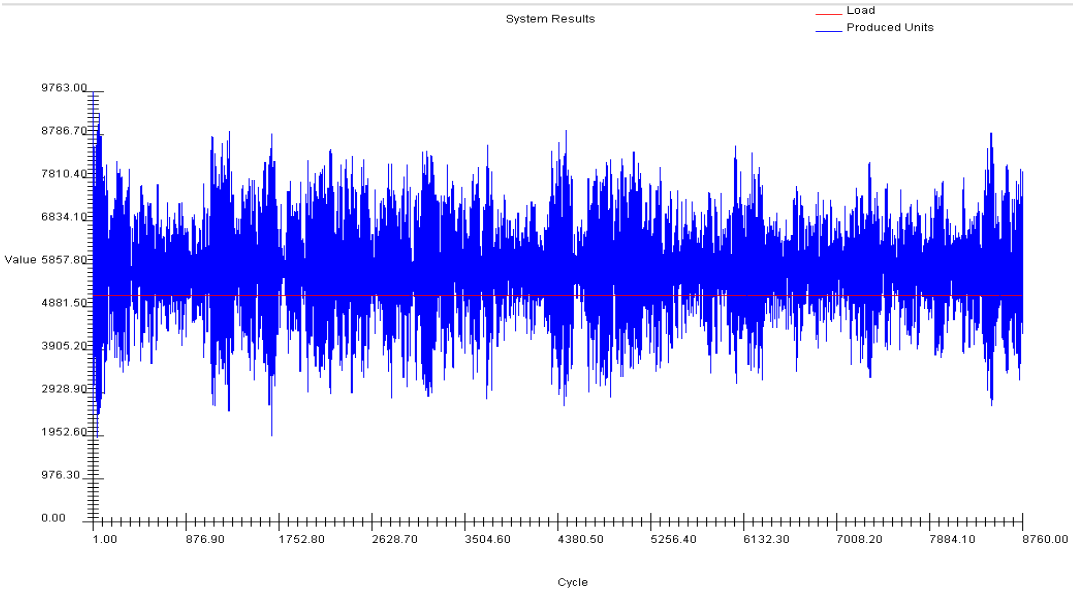


Fig. 12. State of *TX CLOUD* simulation deficiency (below the central red line = 5138 beds) plot with a total 2564h of bed-inadequacy in a year.

2) Interpretative clarifications for the five different states: standard algorithmic approach

In the following sections, one will observe pertinent interpretations for the five different randomly selected States as indicated by the columnar numerical input and output entries of Table VI. The following list of input data and output results follow the indicated sequence through Table I–V:

a) Hospital Network Input: Tables I–V.

b) Cloud *LOLP* Index Output: Fig. 2, Figs. 5–8.

c) Bed-Count Time-Series*:* Figs. 3, 6, 8, 10, 12.

d) Analytical Bed-Count Planning*:* Figs. 4, 13–16.

e) Plotted Bed-Count Planning: Figs. 17–21.

Standard Algorithm: Given one of USA's randomly selected hospital networks in Table VI, as analyzed from input Tables I–V; follow the input steps in the indicated manner for State per *AHA*, *IHME* and *AHD* [8, 9, 12].

i) The randomly selected microcosm of hospitals of a hypothetical contiguous State (*AL*) covered 44 to 51 beds.

ii) The *OCR* multiplied by the individually installed beds sum up to the total bed-demand per year.

iii) A computationally feasible *X*% of the bed-demand yielding #*Y* beds, is taken as a constant load of demanded beds to be serviced per year.

Follow the output steps in the following manner for any hypothetical State of USA in Figs. 2–21.

i) Obtain the *LOLP* index for the risk assessment step (Figs. 2–12).

ii) Improve the *LOLP* index by deploying #*Z* new beds while each new bed is assumed to cost $*W* (Fig. 4, Figs. 13–16).

iii) The improved *CLOURAM* software risk (Fig. 4, Figs. 13–16) yielded *LOLP* ≈ *U* % equivalent to *LOLE* ≈ *V* hours.

iv) The improved *CLOURAM software* showed a profit of ~$*P* at a breakeven cost of ~$*B* implying that unless the breakeven cost/bed exceeds ~$*B*, the Profit (+) prevails.

v) Figs. 13, 17; 14, 18; 4, 19; 15, 20; 16, 21 show alternatives when #*Q* more beds instead of less. *CLOURAM* yielded *LOLP* ≈ *U*% with *LOLE* ≈ *V* hours with ~$*P* profit if $1*M* is gained per every 1% *LOLP* improved.

vi) Figs. 3, 8, 6, 10, 12 are the oscillatory plots of number of beds on hourly basis with the central red line indicating the cut-off level between the adequate and deficient bed-counts.

3) The state of Alabama hospitals network (Table VI, Row 1; Table I, Cols. 1 to 7; Figs. 2, 3, 13, 17, 22, 23)

Follow the input steps in the following manner for the State of *AL* as instructed in subsection II-A.2's standard algorithm:

i) The forty-four randomly selected hospitals for the State of *AL* (Table VI, ROW 1, COL.2) covered 9,647 beds.

ii) The *OCR* (Table I, ROW 1, COL.3), multiplied by the individually installed beds sum up to the actual number of bed-demands, 4,627 beds (Table I, ROW 1, COL.4) per year.

iii) A computationally feasible 95% (below which *CLOURAM* can feasibly yield solutions) of the bed-demand, 4,396 beds/h, is the curbed constant bed-demand (Fig. 2's input Multiplier = 0.95). Fig. 3 is the time-series of bed-counts.

Follow the output steps in the following manner for the State of *AL* as instructed in subsection II-A.2's algorithm:

i) When *AL*'s input template in Fig. 2 was utilized, the *CLOURAM* software solution was *LOLP* ≈ 13.55% with *LOLE* ≈ 1,184h (Table VI, ROW 1, COL.5) and σ ≈ 864h.

ii) The *AL* hospital network desires to improve by deploying 700 new beds (Table VI, ROW 1, COL.6) while each additional bed-cost is assumed to be $5,000 (Table VI, ROW 1, COL.7).

iii) *CLOUD* software risk in Fig. 13 was *LOLP* ≈ 9.66% equivalent to *LOLE* ≈ 852 hours (Table VI, ROW 1, COL.8).

iv) Fig. 13 software showed a profit of [(13.55−9.66) × $1*M*] – [$5000 × (10,347−9,647)] = $397*K* (Table VI, ROW 1 COL.9) after 700+ beds at a breakeven cost of ~$5,566 (Table VI, ROW 1 COL.10) implying that unless the paraphernal cost per bed exceeds ~$5,566, then the overall profit prevails.

v) Figs. 13 and 17 show alternatives that when 800 more beds (Table VI, ROW 1, COL.11) instead of 700 (Table VI, COL.6), *CLOURAM* software yielded *LOLP* ≈ 9.15% with *LOLE* ≈ 802 hours (Table I, ROW 1, COL.12) for $407*K* profit (Table VI, ROW 1, COL.13) if $1*M* gain per every 1% *LOLP* increase.

vi) Fig. 3 is the annual oscillatory plot of number of bed-counts on an hourly basis with the central red line marking the cut-off level between adequate and deficient bed supplies.

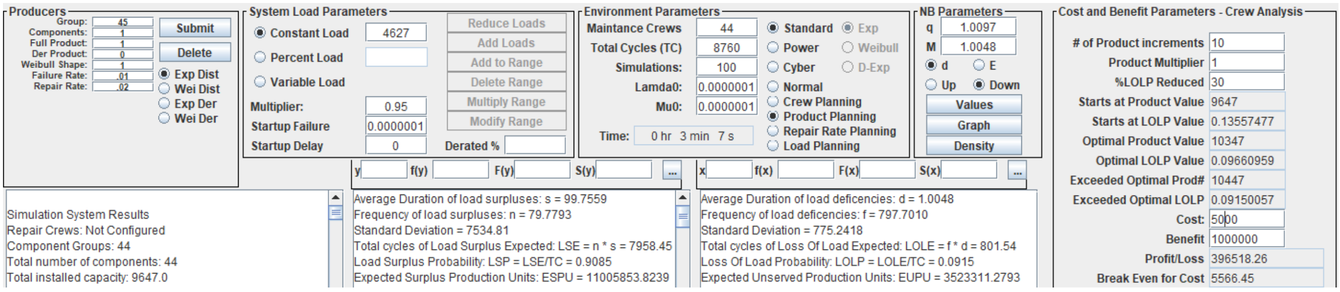


Fig. 13. State of *AL* hospitals *CLOUD* simulation bed-count (product) planning outcomes from Table I input data.

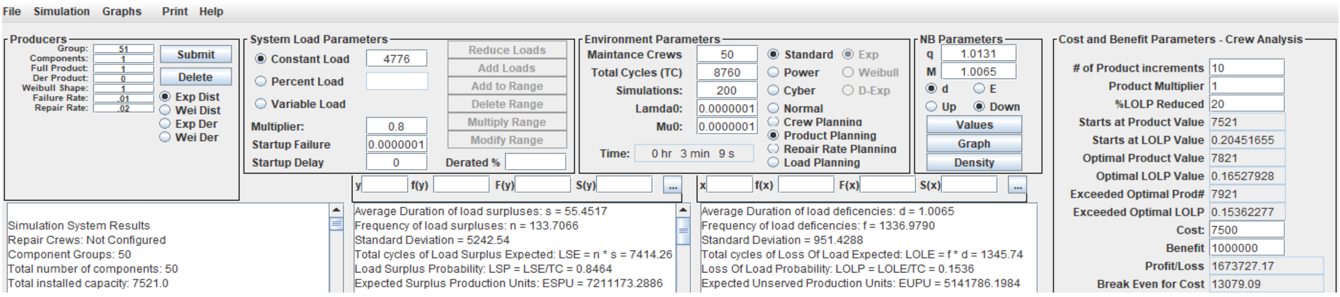


Fig. 14. State of *AZ* hospitals *CLOUD* simulation bed-capacity (product) planning outcomes from Table II input data.

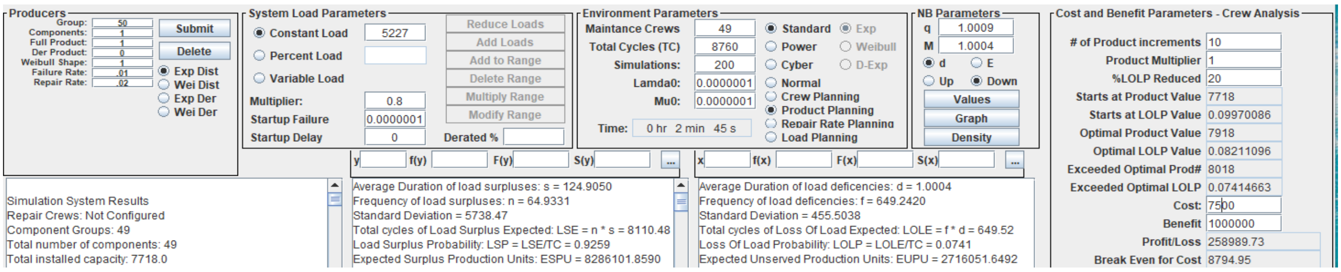


Fig. 15. State of *PA* hospitals *CLOUD* simulation bed-count (product) planning outcomes from Table IV input data.

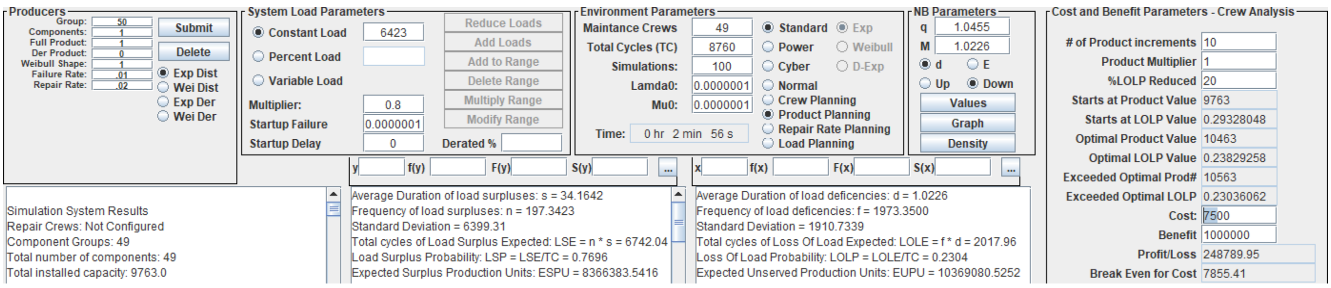


Fig. 16. State of *TX* hospitals *CLOUD* simulation bed-count (product) planning outcomes from Table V input data.

4) Cloud queuing simulation of planning for hospitals' networked-services deployed bed-capacity

It is timely to review a description of *CLOURAM*'s architecture in terms of its computational building blocks [15]. What happens when the statewide or U.S.-wide hospital networks administration managers plan to increase the bed-capacity to avoid bottlenecks in the possible event of a real-life emergency such as the notorious *COVID*-19 pandemic?

At what level should they stop adding and installing extra beds to achieve an optimal *ROI* (Return on Investment) or one with a feasible cost and benefit analysis [16]? The goal is to optimize the quality of a hospital *Cloud*-based operation and, therefore, what to do? Namely, at the risk management level so as to economize the customer service quality by reserve planning of the additional bed-capacity cost and benefit (and the resultant Profit or Loss) will follow this step. Let's follow the algorithmic steps to the generic product- or bed-capacity plan for the *AL* State in input Table I and Fig. 2 per Appendix:

Step 1: *Normal Button*: This is selected for risk assessment step's input data in Fig. 2 to observe *LOLP* ≈ 13.52%.

Step 2: *Product (Bed) Planning*: This button is selected as in Fig. 13 for the risk management step's input data.

Step 3: *# of Product Increments*: This in default is given as 10, which indicates the number of product intervals required to plot the extra bed deployment performance graph.

Step 4: *Product Multiplier*: This in default is given as 1, which indicates the default number of components (=100) multiplied for the horizontal axis, such as 1×100=100 beds or 2×100=200 beds or 3×100=300 beds, or 10×100=1,000 beds for extra bed units incremented in the *CLOURAM* For example, change the product multiplier from 1 to 100 to get a range of 100×100=10*K*, 200×100=20*K*,...,80*K*, 90*K*, 100*K*.

Step 5: *%LOLP Reduced*: This in Fig. 13 is 30% feasibly given. For *MI*, 10% (Fig. 4); for *AZ*, *PA* and *TX*, 20% (Figs. 14-16). This says, if the difference between the starting and the next-optimized *LOLP* value is larger than e.g. ~30% of the latter, the capacity value stops at *LOLP no*t exceeding the ~30% of the *LOLP* (≈13.55%) due to a new simulation run.

Step 6: *Starting Product (#Beds) Value:* 9647 is the initially installed total bed-capacity in Fig. 13 and Fig. 17.

Step 7: *Starting LOLP Value*: ~13.55% is the *LOLP* value for the initial total bed-capacity of 9647 in Fig. 13 and Fig. 17.

Step 8: Optimal Product (#Beds) Value: Stops the product when 10,347 is the optimal capacity as in Fig. 13 and Fig. 17 give product (bed-count) plan which increases the beds in the *AL* hospital network by 700 (= 10,347 − 9,647).

Step 9: *Optimal LOLP Value:* ~ 9.66% is optimal if at least ~30% of the initial ~13.55% is achieved in Fig. 13 and Fig. 17. ~$397*K* is profited in Table VI's COL. 9 since [(13.557477 − 9.660959) % × $1M] − [700 × 5,566] ≈ $397K

Step 10: *Exceeded Optimal Products#*: 10,447(= 9,647 + 800) beds is the total installed capacity at the end of the reserve product planning, exceeding beyond the target if not satisfied with the preceding optimal value.

Step 11: *Exceeded Optimal LOLP Value:* ~9.15% is the *LOLP* index for the total bed-capacity of 10,447 for one more attempt around and exceeding beyond the planning target.

Step 12: Cost in Fig. 13 given as $5,000 per bed in Table VI, ROW 1, COL.7, which indicates the dollar amount of the investment expense for one additional bed towards extra production- or bed-capacity.

Step 13: *Benefit* is given as $1,000,000 per 1% increase for bed-capacity efficiency per Table VI's footnote defined in II.A.1 This value indicates the dollar gained to improve the annual serviceability, i.e. as accrued by 1% decrease in the Loss of Load Probability, *LOLP*. See Fig. 13 and Fig. 17.

Step 14: Here is a brief recap of the algorithm for adding new beds for the State of *AL*:

Total Capacity Value (=9647) is the original installed bed-capacity before incrementing more beds.

Profit or loss (≈ $397K) indicates whether there is a Profit (+) or Loss (−) from the preceding steps 2 to 13.

Breakeven Cost (~$5566) indicates the calculated cost amount for one bed above which the profit becomes a loss.

Solution for AL exceeded optimality is as follows in Table VI, ROW 1 for the *COLS.* 11 to 13:

Benefit (B) = ($\Delta LOLP$ = 0.13557477−0.09150057) × 100% × $1,000,000 = $4,407K gained. Cost(C) = (10447−9647) × $5000 ≈ 800 × $5,000 = $4M.

Therefore, Benefit(B) − Cost(C) ≈ $407K roughly is the hand-calculated and rounded-off profit as in Table VI, ROW1, COL.13. So, Table VI, ROW 1, COL. 11 shows the increase from an initial 9,647 beds to 10,447 with 800 more beds added as the new bed-capacity. As a result of the new extra bed-capacity, the *Loss of Load Probability* favorably drops to *LOLP* ≈ 9.15% from *LOLP* ≈ 13.55% initially.

Step 15: Cost and benefit analysis initially showed a profit of ~$397*K* in Fig. 13 with +700 beds for an optimal increase of bed-count in Table VI, ROW 1, COL. 9. This comes with a breakeven cost per each additive bed, as shown to be roughly $5,566 instead of the initial input of $5,000. This implies that if the break-even cost per each additional bed ~$5,566, not $5,000 as an arbitrary placeholder, the "Benefit – Cost" difference (positive Profit or negative Loss) outcome would come to even out to the zero Loss or Profit (≈$0).

A core summary of the hospital *CLOURAM* discrete event simulation application boils down to the contents of the pair of Figs. 13 and 17 (*AZ:* Figs. 14, 18; *PA*: Figs. 15, 20; *MI*: Figs. 4, 19; *TX*: Figs. 16, 21) in the case of randomly sampled *AL* hospitals where the central red threshold line reveals: *LOLE* ≈ 1,184h and frequency of loss ≈1,184 (unitless); hence, yielding an average duration of loss ≈ 1h by equation (1) of II.A per Fig. 2. This is interpreted as the sum of hours to recuperate due to bed–unavailability, or the sum of deficiencies under the red threshold in the varying hourly time-series per annum of 8760h. The standard deviation of *LOLE*, ~864h, in Fig. 2 outcome will diminish owing to more simulation runs from 100 years' up to >1000s. *EUPU* (Expected Unserved Production Units/year) ≈ 5,206,353 beds/year, found at the right hand bottom corner of Fig. 2, signifies the #bed-hours to be salvaged by the hospital, had the annual average bed-capacity index been quasi–perfect to patients' demands with an ideal zero defect. If this implies that the *LOLP* so drops down to 0% from 13.52%, and if the hospital plans and premeditates $1*M* profit per 1% drop of unavailability, the overall profit is $13.52*M*. The State-wide hospital network can profit 13.52*M* / $5,000 (cost/bed) ≈ 2,700 beds in the context of a static index. Dynamic index, however, shows that $13.52*M* / 5,206,353 bed-h (by Fig. 2's *EUPU*) ≈ $2.6 per bed-h should be profited by the hospital's daily services. This example for a dynamic index argument is valid for other States' EUPU values in the coming sections.

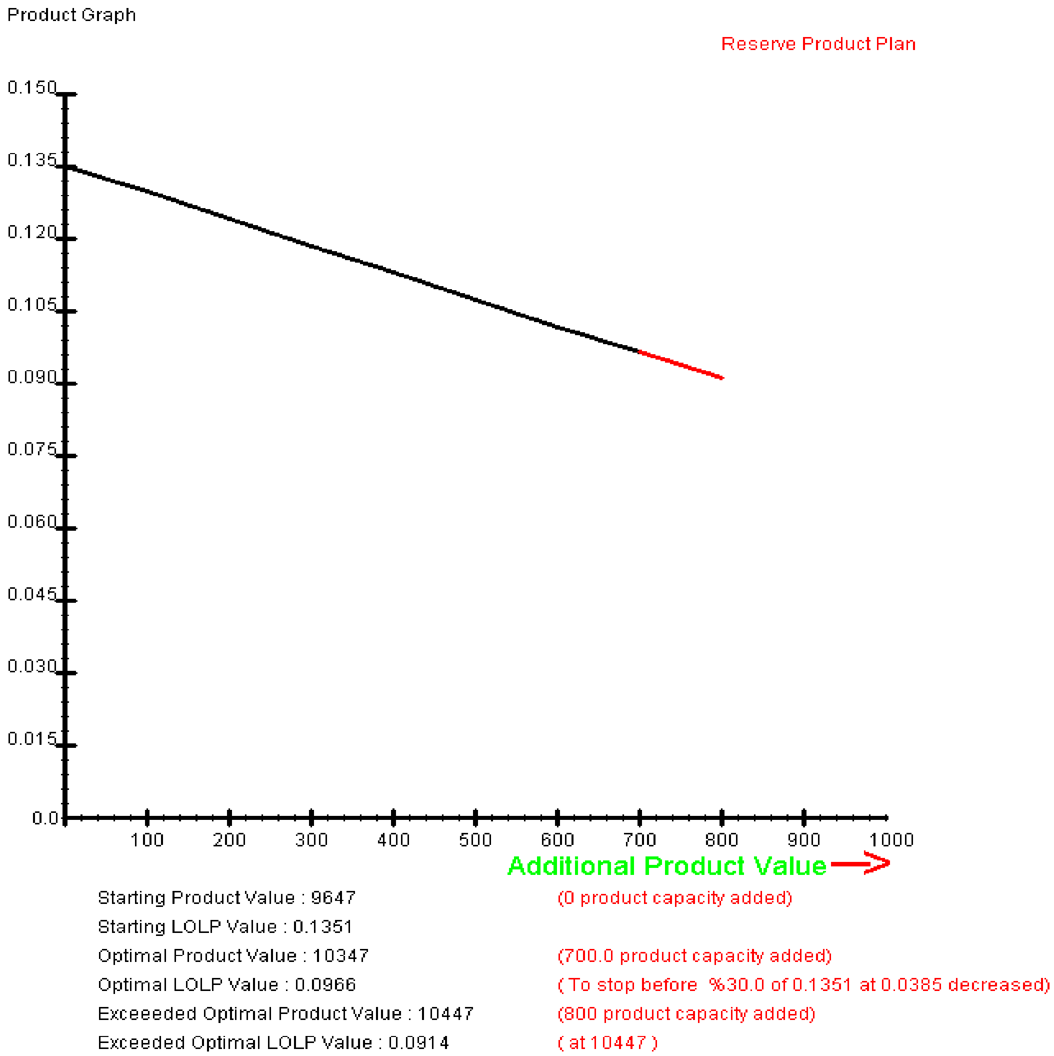


Fig. 17. State of *AL* hospitals' *CLOUD* computing simulation for the bed-count planning's full-plotted diagram using Fig. 7 with 700 and 800+ beds respectively, justified by the cost and benefit analysis obtained from Table I input data.

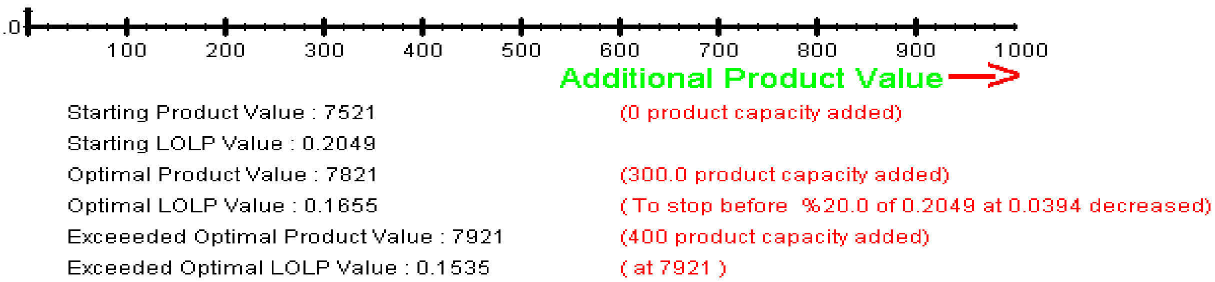


Fig. 18. State of *AZ* hospitals' *CLOUD* computing simulation for the bed-count planning's line-plotted diagram using Fig. 11 with 300+ and 400+ beds respectively, justified by the cost and benefit analysis obtained from Table II input data.

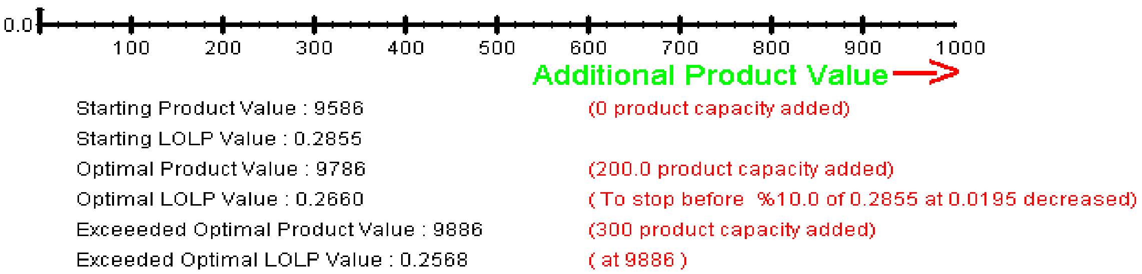


Fig. 19. State of *MI* hospitals' *CLOUD* simulation for the bed-count planning's line-plotted diagram using Fig. 15 with 200+ and 300+ beds respectively, justified by the cost and benefit analysis obtained from Table III input data.

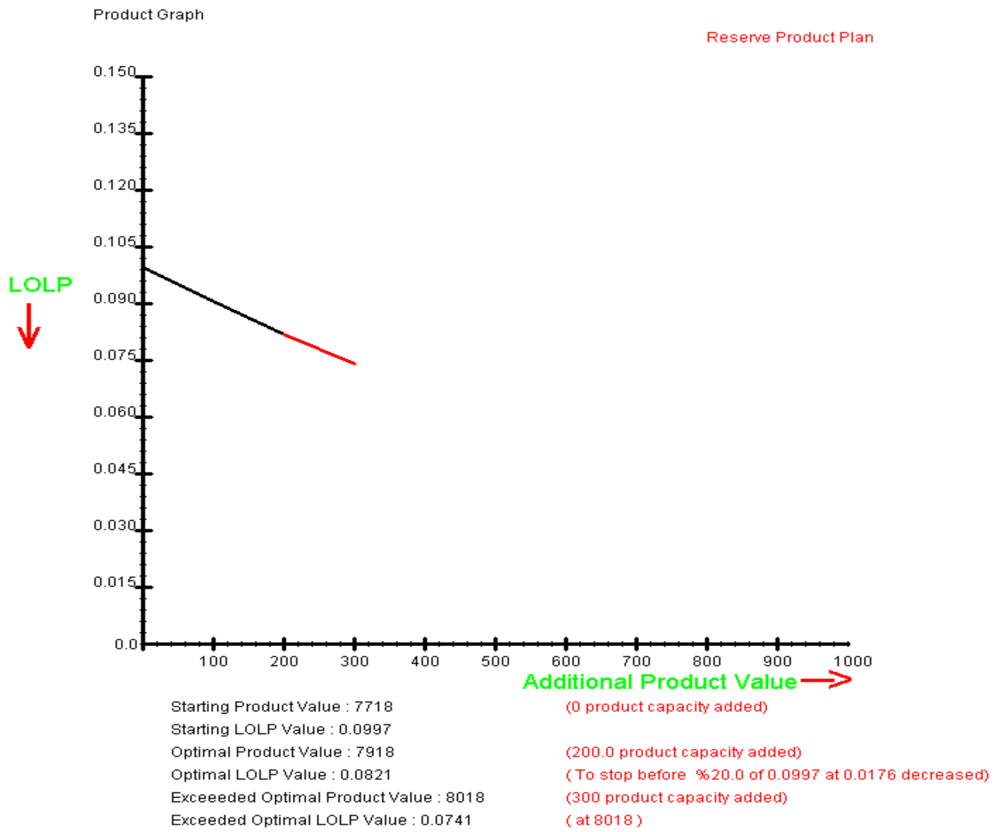


Fig. 20. State of *PA* hospitals *CLOUD* computing simulation for the bed-capacity planning's full-plotted diagram using Fig. 19 with 200+ and 300+ beds respectively, justified by the cost and benefit analysis obtained from Table IV input data.

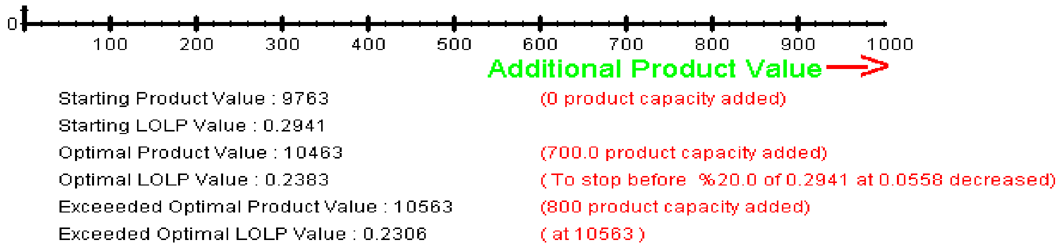


Fig. 21. State of *TX* hospitals *CLOUD* simulation for the bed-capacity planning's line-plotted diagram using Fig. 23 with 700+ and 800+ beds respectively, justified by the cost and benefit analysis obtained from Table V input data.

5) *Tables and figures for bed-capacity risk*

Refer to Tables I-X and Figs. 2–23, in III.A's bed-capacity-oriented input data and output computations.

B. *Assessment and Management of Emergency Physician-Scarcity Risk with Cost and Benefit*

Section II.-B. supported by Tables I–XXIII (except for Table VI) and Fig. 24 [2, 22] which studied the bed-shortfalls, is quite justifiably concerned with the provision of another but equally decisive significant factor of a hospital healthcare network. This is no other than the emergency physician-count at epochs of epidemics as evidenced by recent events. Table XI, fundamentally independent of Table VI, outlines input data and output solutions for all five different States from a lack of personnel (i.e. physicians) perspective. Table XI is a compact tabulation of all five States' input data of descriptive *COLS.* 1 to 3 followed by *COLS.* 4 to 5, such as: Patient's Admission's and Patient Discharge's Poisson rates (λ and μ) in turn, and negative exponential mean times referring to *MTTA* (Mean Time to Admission) and *MTTD* (Mean Time to Discharge). Table XI has the number of #Waiting out of the daily patient or bed- demand and *W* (the average time a unit spends in the system) when k=1 or k=2 or k=3 physicians or doctors are available as in the *MCQS* and Hospital Scheduling software of *Appendix* referring to buttons #25 and 27.

The principal author's *MCQS* is also software for financial banking. It can be adapted to a hospital emergency-ward setting. For an average e.g. *AL* clinic's arrival: λ (admission) and service: μ (discharge) rates, use Table I caption. For other States' averaged λ and μ rates, use captions of Tables II–V.

The pursuant *COLS.* 6, 7 and 8 that denote the number of patients queuing (#Waiting) for any of the five States' daily #bed demands, also symbolized as the number of simulation runs for each State in their respective *MCQS* outcomes. The capitalized letter *W* (average system time) in *MCQS*-related tables when multiplied by their respective admission rate (λ) will find the average #system units, i.e. *L* (Little's Eq.) = λw in *COLS.* 9, 10 and 11. This is evidenced by Tables VII–X for k=1, 2 or 3 physicians for the State of *AL*. This finally leads to *COLS.* 12, 13 and 14 to yield the general equation of *TC*:

$$TC \text{ (Total Cost)} = C_{\text{waiting}}*L + C_{\text{service}}*k,\ k = \text{\#physicians} \quad (13)$$

For an example, $C_{waiting}$=$1,000 since the loss or premature departure of an over-waiting patient can cause the hospital emergency-ward a financial loss of roughly $1,000 with health insurance-related plus co-pay expenses for an hour of consultation. $C_{service}$=40/h by any attending emergency physician roughly brings his/her annual salary to $350,400 during an 8760h-long service period to 40$/h x 8760h≈$350*K* for *k*(#physicians) =1. Fig. 24 carries an important message as such, evident from Table XI's *COLS.* 12, 13 and 14 because after employing *k* (#channels) = 1 physician, the overall hospital's *TC* (total cost) of employing *k*=2 physicians drops, and one more hire yielding *k*=3 again raises the hospital *TC*. Fig. 24 out of scale clarifies graphically that *TC* reaches an inflection point roughly at a certain channel evident from Table XI to judge that *k*=2 is a cost-optimal count of physicians to employ in an emergency setting with the scenario input data here provided.

III. Conclusions, Comparisons and Contrasts with Other Works

A. Conclusions

The objectives of this article's computationally intensive simulations are: a) To assess the bed-shortage-risk in hospitals by providing a cost and benefit analysis; and b) To assess the physician-inadequacy risk in the hospital emergency wards during epidemics and thus, manage in the most economic manner a much-needed cost-optimal physician-count, a fact recently exposed to the entire world after an unprecedented *COVID*-19 onslaught reaching 6.3M deaths in June 2022 [5].

Appendix outlines how the reader can install the CyberRiskSolver to run the *CLOURAM* and *MCQS*, and Hospital Scheduling apps created by the principal author [1]. Tables I, VII–X, and Tables II–V, XII–XXIII display the individual five States' outcomes tabulated by the input and output columns of the pivotal summary rows and columns of Tables VI and XI. This article, as Section II: METHODS, SURVEY, AND INPUT DATA MANAGEMENT's initiating paragraph describes, proposes an application of a) *CLOURAM* and b) *MCQS*, both discrete event simulators, in the realm of hospital healthcare networks servicing an influx of queuing patients. Both computationally intensive simulation software use Poisson count of patient arrivals and Weibull patient service times with their scale parameter β=1, thus yielding a Negative Exponential *pdf*.

The motivation of this article is that once the distinct State-wide hospitals systems are treated as a centralized *Cloud*-network of healthcare services within the structure of patients being involved in a queuing episode, and once the patients are admitted for seeking cure to their ailments and maladies; the risk assessment and management of the lack of physicians and bed-shortage at hospitals take over the severest priority. Thus, how to improve or mitigate the unsatisfactory risk follows suit, justified by their corresponding cost and benefit analyses, which were covered and discussed throughout sections II-A.1 to II-A.5, and Tables I-V, and Figs. 2, 3, 13, 17, 22–24. The primary goal of this article is to assess and then, manage the bed-capacity and physician-scarcity risks where cost and benefit parameters are introduced to discern the extent of profit or loss in need-based State hospital networks. Best practices dictate counter-measurable precautions to mitigate the undesirable risk of bed- and physician-inadequacy to facilitate useful *CON* laws [19, 20].

Therefore, equally significant *What-If* scenarios [15, 16] previously reviewed in Section II.A.4. are, i) How does one profit more by *Cloud* computing in optimizing the bed-capacity resources? ii) How does one save and profit from *Cloud* computing by optimizing to manage the load cycle while varying the load multiplier constant (≤1) as practiced in Figs. 2, 4, 5, 7, 9, 11, 13–16. This novel research effort makes a tangible contribution to healthcare service's dual bed and physician capacity planning initiatives, given the financial and quality implications of *COVID*-19 pandemic on hospitals with unimaginable levels of aggressive, albeit professional competition in the healthcare industry [17].

TABLE I: STATE OF ALABAMA (AL) RANDOMLY SAMPLED HOSPITALS NETWORK INPUT DATA SPREADSHEET* EXPECTED ADMISSION RATE: 1.92/H, MEAN TIME: 0.52H, EXPECTED DISCHARGE RATE: 5.23/H, MEAN TIME: 0.19H
AL STATE INPUT DATA SETS FOR BED- AND PHYSICIAN-COUNT RELATED ANALYTICAL OUTPUT
STATE OF ALABAMA (AL) FOR THE YEAR 2018

Order (1-44)	Total # Hospital Beds	Occupancy Rate (OCR)	Total #Bed Demands per year	Admission Rate hour^{-1}	Discharge Rate hour^{-1} (LOS=2)	Discharge Rate hour^{-1} (LOS=3)
1	252	0.50	126	1.263	2.629	1.753
2	83	0.36	30	0.399	0.617	0.411
3	270	0.60	161	0.163	3.348	2.232
4	129	0.09	12	0.877	0.245	0.163
5	231	0.39	91	0.877	1.889	1.259
6	595	0.35	209	2.904	4.364	2.909
7	204	0.51	104	0.607	2.174	1.449
8	156	0.02	3	0.054	0.069	0.046
9	145	0.55	80	0.769	1.673	1.115
10	46	0.09	4	0.094	0.091	0.061
11	264	0.43	113	0.890	2.359	1.573
12	235	0.65	152	1.265	3.169	2.113
13	327	0.80	262	2.162	5.454	3.636
14	99	0.28	28	0.457	0.577	0.385
15	47	0.23	11	0.189	0.224	0.150
16	141	0.75	106	0.914	2.206	1.471
17	167	0.04	7	0.153	0.144	0.096
18	358	0.47	169	0.058	3.521	2.347

19	185	0.07	12	0.200	0.252	0.168
20	28	0.15	4	0.064	0.085	0.056
21	90	0.58	52	0.511	1.082	0.721
22	879	0.77	678	4.857	14.118	9.412
23	183	0.67	123	1.127	2.572	1.715
24	259	0.25	65	0.810	1.363	0.909
25	49	0.07	4	0.123	0.076	0.050
26	669	0.60	402	3.132	8.374	5.583
27	349	0.57	197	1.691	4.113	2.742
28	209	0.78	163	1.034	3.397	2.265
29	149	0.91	136	0.762	2.839	1.892
30	176	0.80	141	1.150	2.944	1.963
31	389	0.60	233	2.123	4.860	3.240
32	270	0.75	203	1.473	4.232	2.821
33	184	0.08	15	0.317	0.311	0.207
34	207	0.35	73	0.965	1.527	1.018
35	515	0.41	210	1.634	4.365	2.910
36	89	0.24	21	0.235	0.448	0.298
37	218	0.13	28	0.466	0.574	0.382
38	163	0.30	48	0.822	1.003	0.669
39	178	0.43	77	0.742	1.598	1.065
40	115	0.14	16	0.171	0.331	0.220
41	54	0.12	6	0.185	0.133	0.089
42	187	0.17	32	0.319	0.662	0.441
43	33	0.30	10	0.128	0.205	0.137
44	71	0.11	8	0.232	0.170	0.113
	9647		**4627**			

TABLE II: STATE OF ARIZONA (AZ) RANDOMLY SAMPLED HOSPITALS NETWORK INPUT DATA SPREADSHEET* EXPECTED ADMISSION RATE: 1.78/H, MEAN TIME: 0.56H, EXPECTED DISCHARGE RATE: 4.55/H, MEAN TIME: 0.22H
AZ STATE INPUT DATA SETS FOR BED- AND PHYSICIAN-COUNT RELATED ANALYTICAL OUTPUT
STATE OF ARIZONA (AZ) FOR THE YEAR 2010

Order (1-50)	**Total # Hospital Beds**	**Occupancy Rate(OCR)**	**Total #Bed Demand per year**	**Admission Rate hour^{-1}**	**Discharge Rate hour^{-1} (LOS=2)**	**Discharge Rate hour^{-1} (LOS=3)**
1	48	0.48	23	0.142	0.487	0.325
2	22	0.42	9	0.078	0.193	0.129
3	583	0.69	404	4.109	8.468	5.645
4	51	0.58	30	0.048	0.622	0.415
5	500	0.75	377	3.715	7.908	5.272
6	59	0.60	35	0.558	0.744	0.496
7	23	0.35	8	0.096	0.167	0.111
8	111	0.56	62	0.712	1.302	0.868
9	224	0.87	196	2.058	4.104	2.736
10	15	0.53	8	0.030	0.166	0.110
11	60	0.72	43	0.133	0.907	0.605
12	144	0.39	56	0.599	1.184	0.789
13	16	0.38	6	0.072	0.127	0.085
14	19	0.74	14	0.222	0.295	0.197
15	139	0.59	82	0.916	1.714	1.143
16	172	0.56	97	0.840	2.029	1.353
17	25	0.27	7	0.068	0.142	0.095
18	16	0.44	7	0.028	0.149	0.099
19	72	0.37	27	0.384	0.557	0.371
20	25	0.46	11	0.037	0.239	0.159
21	180	0.55	99	0.938	2.081	1.387
22	65	0.56	36	0.216	0.761	0.057
23	70	0.24	17	0.188	0.357	0.238
24	74	0.72	53	0.157	1.116	0.744
25	345	0.62	213	1.430	4.459	2.973
26	20	0.33	7	0.132	0.137	0.091
27	338	0.73	247	0.013	5.181	3.454
28	80	0.75	60	0.248	1.252	0.834
29	85	0.75	63	0.263	1.330	0.887
30	266	0.72	193	1.919	4.039	2.693
31	100	0.63	63	0.830	1.323	0.882
32	24	0.32	8	0.064	0.160	0.107
33	225	0.64	144	1.084	3.020	2.013
34	301	0.59	178	0.409	3.741	2.494
35	134	0.53	71	0.874	1.485	0.990
36	15	0.06	1	0.013	0.020	0.013
37	59	0.40	23	0.319	0.489	0.326
38	8	0.33	3	0.053	0.055	0.036
39	21	0.26	5	0.048	0.114	0.076

40	496	0.67	331	2.930	6.943	4.628
41	110	0.58	64	0.696	1.340	0.893
42	54	0.50	27	0.100	0.568	0.379
43	373	0.63	234	2.314	4.901	3.267
44	449	0.58	262	2.380	5.488	3.659
45	422	0.79	331	2.620	6.948	4.632
46	236	0.72	170	0.601	3.557	2.371
47	19	0.28	5	0.064	0.113	0.076
48	25	0.43	11	0.162	0.223	0.149
49	333	0.53	176	1.999	3.684	2.456
50	270	0.66	178	2.111	3.724	2.482
	7521		**4776**			

TABLE III: STATE OF MICHIGAN (*MI*) RANDOMLY SAMPLED HOSPITALS NETWORK INPUT DATA SPREADSHEET* EXPECTED ADMISSION RATE: 2.45/H, MEAN TIME: 0.41H, EXPECTED DISCHARGE RATE: 6.02/H, MEAN TIME: 0.17H
MI STATE INPUT DATA SETS FOR BED-AND PHYSICIAN-COUNT RELATED ANALYTICAL OUTPUT
STATE OF MICHIGAN (MI) FOR THE YEAR 2010

Order (1-51)	Total # Hospital Beds	Occupancy Rate (OCR)	Total #Bed Demands per year	Admission Rate hour^{-1}	Discharge Rate hour^{-1} (LOS=2)	Discharge Rate hour^{-1} (LOS=3)
1	44	0.60	27	0.041	0.553	0.368
2	25	0.28	7	0.089	0.144	0.096
3	80	0.55	44	0.101	0.917	0.611
4	391	0.75	291	2.712	6.072	4.048
5	387	0.64	248	2.312	5.171	3.447
6	989	0.69	683	6.343	14.226	9.484
7	141	0.64	91	0.355	1.886	1.257
8	530	0.72	383	3.586	7.971	5.314
9	65	0.55	36	0.493	0.740	0.493
10	49	0.35	17	0.220	0.357	0.238
11	560	0.75	421	3.700	8.770	5.847
12	620	0.73	452	3.832	9.425	6.283
13	20	0.14	3	0.041	0.057	0.038
14	208	0.71	147	1.193	3.062	2.041
15	96	0.79	75	0.221	1.572	1.048
16	84	0.61	51	0.404	1.069	0.712
17	96	0.89	85	0.018	1.779	1.186
18	74	0.75	56	0.134	1.162	0.775
19	119	0.42	50	0.478	1.040	0.694
20	68	0.35	24	0.251	0.497	0.332
21	24	0.31	7	0.101	0.154	0.102
22	24	0.20	5	0.071	0.099	0.066
23	37	0.31	12	0.175	0.242	0.161
24	348	0.18	63	0.239	1.322	0.881
25	221	0.73	161	0.058	3.362	2.242
26	188	0.60	113	0.500	2.352	1.568
27	335	0.78	260	2.487	5.413	3.609
28	220	0.54	118	0.947	2.468	1.645
29	157	0.53	83	0.873	1.721	1.147
30	80	0.40	32	0.304	0.662	0.441
31	49	0.30	15	0.207	0.310	0.206
32	38	0.26	10	0.100	0.203	0.136
33	203	0.54	110	1.057	2.300	1.533
34	25	0.38	10	0.104	0.199	0.132
35	65	0.80	52	0.082	1.086	0.724
36	62	0.31	19	0.226	0.400	0.267
37	268	0.68	181	1.419	3.773	2.515
38	306	0.67	206	1.929	4.285	2.856
39	39	0.36	14	0.193	0.296	0.197
40	25	0.17	4	0.060	0.086	0.058
41	25	0.31	8	0.107	0.161	0.107
42	78	0.56	44	0.472	0.909	0.606
43	407	0.82	332	2.603	6.918	4.612
44	73	0.61	44	0.064	0.921	0.614
45	214	0.54	116	1.158	2.421	1.614
46	77	0.67	51	0.330	1.071	0.714
47	244	0.69	169	1.458	3.529	2.353
48	319	0.82	261	0.351	5.434	3.623
49	394	0.77	303	3.183	6.305	4.203
50	355	0.79	280	2.364	5.830	3.887
51	40	0.47	19	0.120	0.388	0.259
	9586		**6292**			

TABLE IV: STATE OF PENNSYLVANIA (*PA*) RANDOMLY SAMPLED HOSPITALS NETWORK INPUT DATA SPREADSHEET* EXPECTED ADMISSION RATE: 0.97/H, MEAN TIME: 1.03H, EXPECTED DISCHARGE RATE: 3.91/H, MEAN TIME: 0.26H
PA STATE INPUT DATA SET FOR BED- AND PHYSICIAN-COUNT RELATED ANALYTICAL OUTPUT
STATE OF PENNSYLVANIA (PA) FOR THE YEAR 2010

Order (1-49)	**Total # Hospital Beds**	**Occupancy Rate (OCR)**	**Total #Bed Demands per year**	**Admission Rate hour^{-1}**	**Discharge Rate hour^{-1} (LOS=2)**	**Discharge Rate hour^{-1} (LOS=3)**
1	158	0.71	112	0.96	2.32	1.55
2	80	0.75	60	0.20	1.25	0.83
3	109	0.86	94	0.65	1.95	1.30
4	448	1.07	480	1.00	10.01	6.67
5	68	0.44	30	0.19	0.63	0.42
6	36	0.47	17	0.12	0.35	0.24
7	40	0.42	17	0.11	0.35	0.23
8	146	0.95	138	0.54	2.88	1.92
9	32	0.48	15	0.09	0.32	0.21
10	73	0.47	34	0.11	0.71	0.47
11	150	0.64	96	0.84	2.00	1.34
12	152	0.69	106	0.51	2.20	1.47
13	165	0.47	78	0.66	1.63	1.08
14	96	0.48	46	0.42	0.96	0.64
15	25	0.57	14	0.16	0.30	0.20
16	42	0.74	31	0.03	0.65	0.43
17	254	0.62	158	1.31	3.30	2.20
18	95	0.50	47	0.31	0.99	0.66
19	145	0.44	63	0.48	1.32	0.88
20	76	0.60	45	0.49	0.94	0.63
21	141	0.64	91	0.77	1.89	1.26
22	25	0.52	13	0.13	0.27	0.18
23	150	0.51	76	0.56	1.59	1.06
24	44	0.61	27	0.08	0.55	0.37
25	59	0.93	55	0.29	1.14	0.76
26	276	0.65	179	1.57	3.73	2.48
27	20	0.24	5	0.04	0.10	0.07
28	254	0.55	140	1.17	2.91	1.94
29	130	0.61	80	0.75	1.66	1.11
30	164	0.71	116	0.98	2.42	1.61
31	496	0.60	299	2.12	6.24	4.16
32	96	0.79	76	0.13	1.58	1.06
33	58	0.58	33	0.10	0.70	0.46
34	374	0.59	222	0.51	4.62	3.08
35	312	0.72	224	2.33	4.67	3.11
36	312	0.72	224	2.33	4.67	3.11
37	312	0.72	224	2.33	4.67	3.11
38	234	0.54	126	1.23	2.62	1.75
39	95	0.56	53	0.24	1.11	0.74
40	224	0.71	158	1.54	3.30	2.20
41	209	0.50	104	1.15	2.17	1.45
42	30	0.34	10	0.10	0.21	0.14
43	335	0.88	296	0.04	6.17	4.11
44	250	0.75	188	0.03	3.92	2.61
45	278	0.78	216	0.01	4.50	3.00
46	59	0.57	34	0.38	0.71	0.47
47	224	0.61	136	1.36	2.83	1.89
48	65	0.81	53	0.16	1.10	0.73
49	102	0.85	86	0.11	1.80	1.20
	7718		**5227**			

TABLE V: STATE OF TEXAS (*TX*) RANDOMLY SAMPLED HOSPITALS NETWORK INPUT DATA SPREADSHEET* EXPECTED ADMISSION RATE: 2.13/H, MEAN TIME: 0.47H, EXPECTED DISCHARGE RATE: 7.81/H, MEAN TIME: 0.13H
TX STATE INPUT DATA SET FOR BED- AND PHYSICIAN-COUNT RELATED ANALYTICAL OUTPUT
STATE *OF TEXAS (TX) FOR THE YEAR 2014*

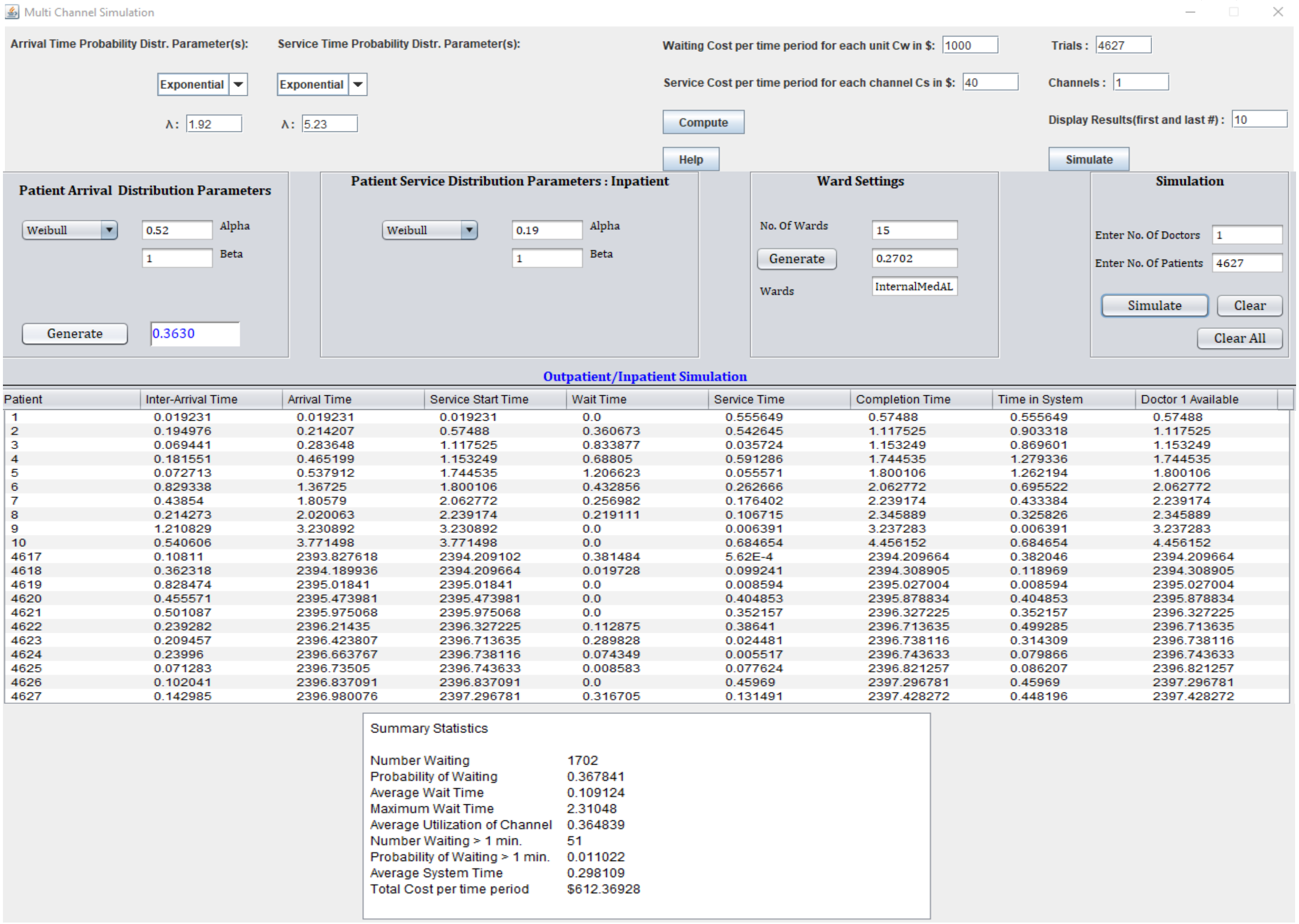
Order (1-49)	**Total # Hospital Beds**	**Occupancy Rate (OCR)**	**Total #Bed Demands per year**	**Admission Rate hour^{-1}**	**Discharge Rate hour^{-1} (LOS=2)**	**Discharge Rate hour^{-1} (LOS=3)**
1	65	0.48	31	0.424	0.652	0.435
2	381	0.08	31	0.086	0.651	0.434
3	25	0.53	13	0.079	0.274	0.183
4	34	0.73	25	0.101	0.516	0.344
5	30	0.07	2	0.011	0.045	0.030
6	209	0.63	131	1.018	2.731	1.821
7	40	0.40	16	0.155	0.335	0.223
8	53	0.39	21	0.210	0.435	0.290
9	875	0.75	655	1.321	13.645	9.096
10	241	0.62	149	1.147	3.108	2.072
11	167	0.53	88	0.961	1.833	1.222
12	553	0.64	353	2.615	7.357	4.905
13	16	0.73	12	0.048	0.243	0.162
14	24	0.87	21	0.014	0.437	0.291
15	25	0.31	8	0.121	0.164	0.109
16	237	0.65	155	1.620	3.232	2.154
17	15	0.34	5	0.077	0.107	0.071
18	923	0.69	641	4.280	13.345	8.897
19	679	0.65	444	3.760	9.257	6.171
20	562	0.63	357	2.905	7.433	4.956
21	766	0.79	606	3.746	12.618	8.412
22	422	0.73	310	2.174	6.452	4.302
23	718	0.77	551	3.697	11.481	7.654
24	62	0.85	53	0.071	1.096	0.731
25	66	0.95	63	0.204	1.310	0.874
26	381	0.90	345	0.106	7.183	4.789
27	70	0.68	48	0.514	0.996	0.664
28	85	0.38	32	0.448	0.669	0.446
29	78	0.38	30	0.228	0.624	0.416
30	121	0.37	45	0.553	0.938	0.625
31	142	0.61	87	1.021	1.816	1.211
32	148	0.21	31	0.407	0.649	0.432
33	86	0.53	46	0.531	0.952	0.635
34	101	0.61	62	0.570	1.293	0.862
35	44	0.38	17	0.220	0.351	0.234
36	58	0.86	50	0.303	1.045	0.697
37	92	0.72	66	0.498	1.380	0.920
38	314	0.85	266	0.290	5.550	3.700
39	55	0.61	34	0.194	0.698	0.466
40	35	0.41	14	0.055	0.299	0.200
41	80	0.54	43	0.229	0.897	0.598
42	58	0.86	50	0.303	1.045	0.697
43	92	0.72	66	0.498	1.380	0.920
44	55	0.61	34	0.194	0.698	0.466
45	11	0.25	3	0.040	0.058	0.038
46	35	0.41	14	0.055	0.299	0.200
47	266	0.61	162	1.359	3.367	2.245
48	44	0.31	14	0.068	0.287	0.192
49	124	1.00	124	0.525	2.575	1.717
	9763		**6423**			

TABLE VI: INPUT DATA AND OUTPUT SOLUTIONS FOR AL, AZ, MI, PA, AND TX ON BED-CAPACITY MANAGEMENT (*APPENDIX* BUTTON #13)

1	2	3	4	5	6	7	8	9	10	11	12	13
NETWORKED HOSPITALS IN STATES	#GROUPS= #HOSPITALS (#BEDS)	DAILY #BED DEMAND for COL.2	CURBED #BED DEMAND (curb%) for COL.3	LOLP (unitless) (LOLE hour) for COL.2	#BEDS+ ADDED for COL.5	$COST Per BED for COL.6	LOLP unitless (LOLE hour) for COL.6	PROFIT(+) or LOSS(-) for COL.6	BREAKEVEN BED $COST for COL.6	#BEDS+ ADDED for COL.5	LOLP unitless (LOLE hour) for COL.11	PROFIT(+) or LOSS(-) for COL.11
*AL**	44 (9647)	4627	4396 (95%)	0.1355 (1184 h)	700	$5,000	0.0966 (852 h)	$397K	$5,566	800	0.0915 (802 h)	$407K
*AZ**	50 (7521)	4774	3821 (80%)	0.205 (1796 h)	300	$7,500	0.165 (1445 h)	$1674K	$13,079	400	0.154 (1346 h)	$2089K
*MI**	51 (9586)	6292	5034 (80%)	0.286 (2498 h)	200	$7,500	0.266 (2330 h)	$448K	$9,742	300	0.257 (2251 h)	$619K
PA	49 (7718)	5227	4182 (80%)	0.0999 (875 h)	200	$7,500	0.0821 (719 h)	$259K	$8,795	300	0.0741 (649 h)	$310K
TX	49 (9763)	6423	5138 (80%)	0.293 (2564 h)	700	$7,500	0.238 (2085 h)	$249K	$7,855	800	0.230 (2018 h)	$292K

(*Indicates those States in Table VI with *CON* programs in place from Fig. 22; in collecting States' data, *PA* and *TX* were not known to be non-*CON* States)

TABLE VII: DISCRETE EVENT SIMULATION OF *AL* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD'S TOTAL COST, $TC(K=1) \approx \$612$



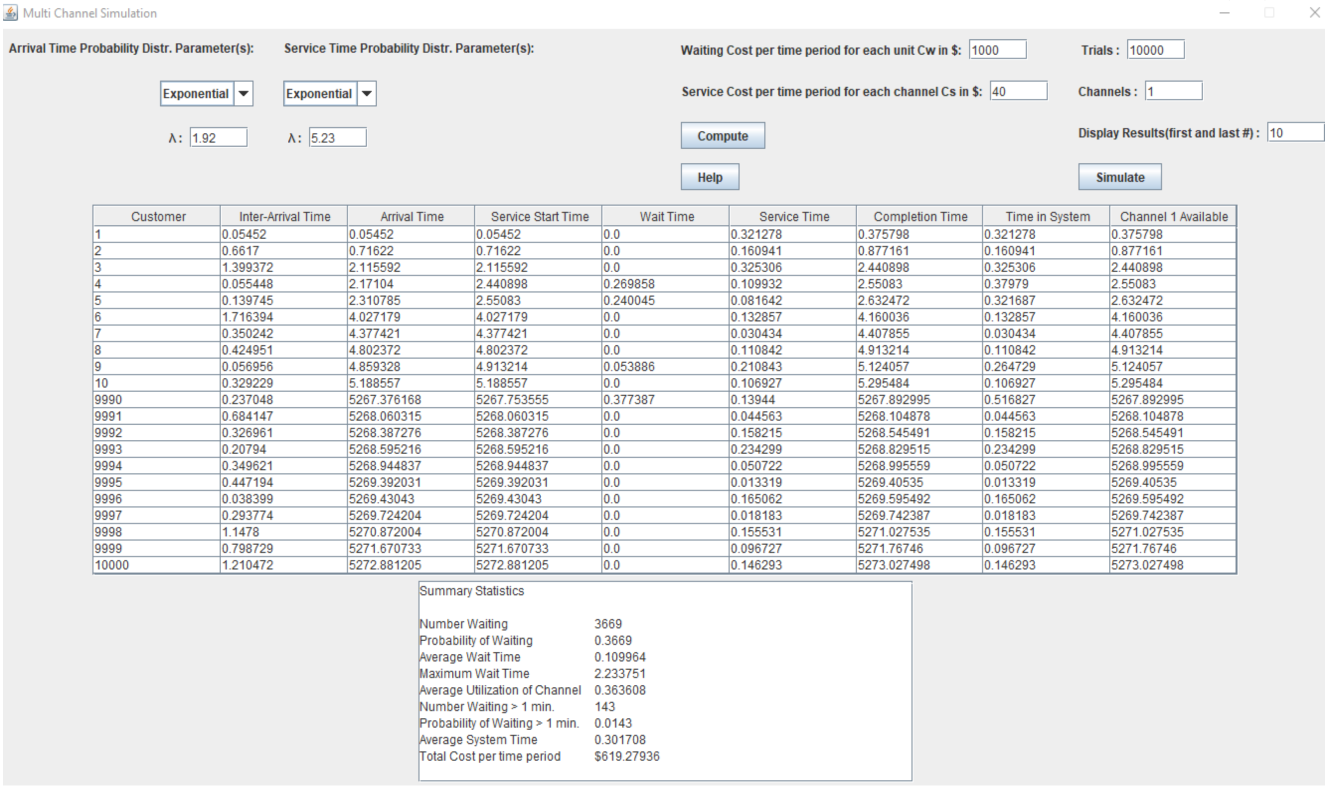
Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available
1	0.019231	0.019231	0.019231	0.0	0.555649	0.57488	0.555649	0.57488
2	0.194976	0.214207	0.57488	0.360673	0.542645	1.117525	0.903318	1.117525
3	0.069441	0.283648	1.117525	0.833877	0.035724	1.153249	0.869601	1.153249
4	0.181551	0.465199	1.153249	0.68805	0.591286	1.744535	1.279336	1.744535
5	0.072713	0.537912	1.744535	1.206623	0.055571	1.800106	1.262194	1.800106
6	0.829338	1.36725	1.800106	0.432856	0.262666	2.062772	0.695522	2.062772
7	0.43854	1.80579	2.062772	0.256982	0.176402	2.239174	0.433384	2.239174
8	0.214273	2.020063	2.239174	0.219111	0.106715	2.345889	0.325826	2.345889
9	1.210829	3.230892	3.230892	0.0	0.006391	3.237283	0.006391	3.237283
10	0.540606	3.771498	3.771498	0.0	0.684654	4.456152	0.684654	4.456152
4617	0.10811	2393.827618	2394.209102	0.381484	5.62E-4	2394.209664	0.382046	2394.209664
4618	0.362318	2394.189936	2394.209664	0.019728	0.099241	2394.308905	0.118969	2394.308905
4619	0.828474	2395.01841	2395.01841	0.0	0.008594	2395.027004	0.008594	2395.027004
4620	0.455571	2395.473981	2395.473981	0.0	0.404853	2395.878834	0.404853	2395.878834
4621	0.501087	2395.975068	2395.975068	0.0	0.352157	2396.327225	0.352157	2396.327225
4622	0.239282	2396.21435	2396.327225	0.112875	0.38641	2396.713635	0.499285	2396.713635
4623	0.209457	2396.423807	2396.713635	0.289828	0.024481	2396.738116	0.314309	2396.738116
4624	0.23996	2396.663767	2396.738116	0.074349	0.005517	2396.743633	0.079866	2396.743633
4625	0.071283	2396.73505	2396.743633	0.008583	0.077624	2396.821257	0.086207	2396.821257
4626	0.102041	2396.837091	2396.837091	0.0	0.45969	2397.296781	0.45969	2397.296781
4627	0.142985	2396.980076	2397.296781	0.316705	0.131491	2397.428272	0.448196	2397.428272

Summary Statistics

Number Waiting	1702
Probability of Waiting	0.367841
Average Wait Time	0.109124
Maximum Wait Time	2.31048
Average Utilization of Channel	0.364839
Number Waiting > 1 min.	51
Probability of Waiting > 1 min.	0.011022
Average System Time	0.298109
Total Cost per time period	$612.36928

The following outcome with 10,000 runs is almost identical to a preceeding Table IV with 4627 trials, since simulation results will end up roughly the same as long as #runs > ~500, since results vary from #runs to more unless 100*M* times causing subtle changes, i.e. Prob. of Waiting: 0.3669 (for 4627 runs) ≈0.3678 (for 10*K* runs) when #runs increased 20-fold, i.e. a comparatively negligible increase.

TABLE VIII: DISCRETE EVENT SIMULATION OF *AL* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD'S TOTAL COST: $TC(K=1) \approx \$619$



Customer	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Channel 1 Available
1	0.05452	0.05452	0.05452	0.0	0.321278	0.375798	0.321278	0.375798
2	0.6617	0.71622	0.71622	0.0	0.160941	0.877161	0.160941	0.877161
3	1.399372	2.115592	2.115592	0.0	0.325306	2.440898	0.325306	2.440898
4	0.055448	2.17104	2.440898	0.269858	0.109932	2.55083	0.37979	2.55083
5	0.139745	2.310785	2.55083	0.240045	0.081642	2.632472	0.321687	2.632472
6	1.716394	4.027179	4.027179	0.0	0.132857	4.160036	0.132857	4.160036
7	0.350242	4.377421	4.377421	0.0	0.030434	4.407855	0.030434	4.407855
8	0.424951	4.802372	4.802372	0.0	0.110842	4.913214	0.110842	4.913214
9	0.056956	4.859328	4.913214	0.053886	0.210843	5.124057	0.264729	5.124057
10	0.329229	5.188557	5.188557	0.0	0.106927	5.295484	0.106927	5.295484
9990	0.237048	5267.376168	5267.753555	0.377387	0.13944	5267.892995	0.516827	5267.892995
9991	0.684147	5268.060315	5268.060315	0.0	0.044563	5268.104878	0.044563	5268.104878
9992	0.326961	5268.387276	5268.387276	0.0	0.158215	5268.545491	0.158215	5268.545491
9993	0.20794	5268.595216	5268.595216	0.0	0.234299	5268.829515	0.234299	5268.829515
9994	0.349621	5268.944837	5268.944837	0.0	0.050722	5268.995559	0.050722	5268.995559
9995	0.447194	5269.392031	5269.392031	0.0	0.013319	5269.40535	0.013319	5269.40535
9996	0.038399	5269.43043	5269.43043	0.0	0.165062	5269.595492	0.165062	5269.595492
9997	0.293774	5269.724204	5269.724204	0.0	0.018183	5269.742387	0.018183	5269.742387
9998	1.1478	5270.872004	5270.872004	0.0	0.155531	5271.027535	0.155531	5271.027535
9999	0.798729	5271.670733	5271.670733	0.0	0.096727	5271.76746	0.096727	5271.76746
10000	1.210472	5272.881205	5272.881205	0.0	0.146293	5273.027498	0.146293	5273.027498

Summary Statistics

Number Waiting	3669
Probability of Waiting	0.3669
Average Wait Time	0.109964
Maximum Wait Time	2.233751
Average Utilization of Channel	0.363608
Number Waiting > 1 min.	143
Probability of Waiting > 1 min.	0.0143
Average System Time	0.301708
Total Cost per time period	$619.27936

TABLE IX: DISCRETE EVENT SIMULATION OF *AL* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD'S TOTAL COST: $TC(\kappa=2) \approx \$456$

Multi Channel Simulation

Arrival Time Probability Distr. Parameter(s): Exponential λ: 1.92
Service Time Probability Distr. Parameter(s): Exponential λ: 5.23
Waiting Cost per time period for each unit Cw in $: 1000
Service Cost per time period for each channel Cs in $: 40
Trials : 4627
Channels : 2
Display Results(first and last #) : 10
Compute | Help | Simulate

Patient Arrival Distribution Parameters: Weibull, Alpha 0.52, Beta 1; Generate 0.3630

Patient Service Distribution Parameters : Inpatient: Weibull, Alpha 0.19, Beta 1

Ward Settings: No. Of Wards 15; Generate 0.2702; Wards InternalMedAL

Simulation: Enter No. Of Doctors 2; Enter No. Of Patients 4627; Simulate | Clear | Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available	Doctor 2 Available
1	0.725848	0.725848	0.725848	0.0	0.19234	0.918188	0.19234	0.918188	0.0
2	0.050447	0.776295	0.776295	0.0	0.120387	0.896682	0.120387	0.918188	0.896682
3	0.055281	0.831576	0.896682	0.065106	0.014329	0.911011	0.079435	0.918188	0.911011
4	0.465647	1.297223	1.297223	0.0	0.212161	1.509384	0.212161	1.509384	0.911011
5	0.382723	1.679946	1.679946	0.0	0.053157	1.733103	0.053157	1.733103	0.911011
6	0.209958	1.889904	1.889904	0.0	0.176051	2.065955	0.176051	2.065955	0.911011
7	1.379161	3.269065	3.269065	0.0	0.289154	3.558219	0.289154	3.558219	0.911011
8	0.196981	3.466046	3.466046	0.0	0.133887	3.599933	0.133887	3.558219	3.599933
9	0.193489	3.659535	3.659535	0.0	0.199787	3.859322	0.199787	3.859322	3.599933
10	0.051605	3.71114	3.71114	0.0	0.13695	3.84809	0.13695	3.859322	3.84809
4617	0.141483	2400.402183	2400.402183	0.0	0.194159	2400.596342	0.194159	2400.596342	2400.163472
4618	0.390891	2400.793074	2400.793074	0.0	0.032441	2400.825515	0.032441	2400.825515	2400.163472
4619	1.503957	2402.297031	2402.297031	0.0	0.187827	2402.484858	0.187827	2402.484858	2400.163472
4620	1.179644	2403.476675	2403.476675	0.0	0.198078	2403.674753	0.198078	2403.674753	2400.163472
4621	0.958172	2404.434847	2404.434847	0.0	0.084141	2404.518988	0.084141	2404.518988	2400.163472
4622	0.230639	2404.665486	2404.665486	0.0	0.075399	2404.740885	0.075399	2404.740885	2400.163472
4623	1.456163	2406.121649	2406.121649	0.0	0.257273	2406.378922	0.257273	2406.378922	2400.163472
4624	0.740052	2406.861701	2406.861701	0.0	0.077202	2406.938903	0.077202	2406.938903	2400.163472
4625	1.180274	2408.041975	2408.041975	0.0	0.225854	2408.267829	0.225854	2408.267829	2400.163472
4626	1.246505	2409.28848	2409.28848	0.0	0.214315	2409.502795	0.214315	2409.502795	2400.163472
4627	0.428167	2409.716647	2409.716647	0.0	0.033392	2409.750039	0.033392	2409.750039	2400.163472

Summary Statistics

Number Waiting	247
Probability of Waiting	0.053382
Average Wait Time	0.005749
Maximum Wait Time	0.735143
Average Utilization of Channels	0.18258
Number Waiting > 1 min.	0
Probability of Waiting > 1 min.	0.0
Average System Time	0.19569
Total Cost per time period	$455.7248

TABLE X: DISCRETE EVENT SIMULATION OF *AL* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD'S TOTAL COST: $TC(\kappa=3) \approx \$491$

Multi Channel Simulation

Arrival Time Probability Distr. Parameter(s): Exponential λ: 1.92
Service Time Probability Distr. Parameter(s): Exponential λ: 5.23
Waiting Cost per time period for each unit Cw in $: 1000
Service Cost per time period for each channel Cs in $: 40
Trials : 4627
Channels : 3
Display Results(first and last #) : 10
Compute | Help | Simulate

Patient Arrival Distribution Parameters: Weibull, Alpha 0.52, Beta 1; Generate 0.3630

Patient Service Distribution Parameters : Inpatient: Weibull, Alpha 0.19, Beta 1

Ward Settings: No. Of Wards 15; Generate 0.2702; Wards InternalMedAL

Simulation: Enter No. Of Doctors 3; Enter No. Of Patients 4627; Simulate | Clear | Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available	Doctor 2 Available	Doctor 3 Available
1	1.425888	1.425888	1.425888	0.0	0.091375	1.517263	0.091375	1.517263	0.0	0.0
2	0.36943	1.795318	1.795318	0.0	0.317342	2.11266	0.317342	2.11266	0.0	0.0
3	0.024712	1.82003	1.82003	0.0	0.04707	1.8671	0.04707	2.11266	1.8671	0.0
4	0.093507	1.913537	1.913537	0.0	0.026006	1.939543	0.026006	2.11266	1.939543	0.0
5	0.697556	2.611093	2.611093	0.0	0.21053	2.821623	0.21053	2.821623	1.939543	0.0
6	0.195147	2.80624	2.80624	0.0	0.101968	2.908208	0.101968	2.821623	2.908208	0.0
7	0.642189	3.448429	3.448429	0.0	0.02494	3.473369	0.02494	3.473369	2.908208	0.0
8	1.610394	5.058823	5.058823	0.0	0.083954	5.142777	0.083954	5.142777	2.908208	0.0
9	0.95652	6.015343	6.015343	0.0	0.325979	6.341322	0.325979	6.341322	2.908208	0.0
10	0.339957	6.3553	6.3553	0.0	0.03962	6.39492	0.03962	6.39492	2.908208	0.0
4617	0.097082	2364.943523	2364.943523	0.0	0.145796	2365.089319	0.145796	2365.262272	2365.089319	2333.629758
4618	0.655779	2365.599302	2365.599302	0.0	0.126147	2365.725449	0.126147	2365.725449	2365.089319	2333.629758
4619	0.391013	2365.990315	2365.990315	0.0	0.059072	2366.049387	0.059072	2366.049387	2365.089319	2333.629758
4620	1.331093	2367.321408	2367.321408	0.0	0.285872	2367.60728	0.285872	2367.60728	2365.089319	2333.629758
4621	0.220949	2367.542357	2367.542357	0.0	0.310105	2367.852462	0.310105	2367.60728	2367.852462	2333.629758
4622	0.892097	2368.434454	2368.434454	0.0	0.064444	2368.498898	0.064444	2368.498898	2367.852462	2333.629758
4623	0.671853	2369.106307	2369.106307	0.0	0.186433	2369.29274	0.186433	2369.29274	2367.852462	2333.629758
4624	2.620092	2371.726399	2371.726399	0.0	0.334702	2372.061101	0.334702	2372.061101	2367.852462	2333.629758
4625	0.270086	2371.996485	2371.996485	0.0	0.020166	2372.016651	0.020166	2372.061101	2372.016651	2333.629758
4626	0.221503	2372.217988	2372.217988	0.0	0.02456	2372.242548	0.02456	2372.242548	2372.016651	2333.629758
4627	1.012887	2373.230875	2373.230875	0.0	0.076803	2373.307678	0.076803	2373.307678	2372.016651	2333.629758

Summary Statistics

Number Waiting	45
Probability of Waiting	0.009726
Average Wait Time	0.001493
Maximum Wait Time	0.379182
Average Utilization of Channels	0.124985
Number Waiting > 1 min.	0
Probability of Waiting > 1 min.	0.0
Average System Time	0.193129
Total Cost per time period	$490.80768

TABLE XI: INPUT DATA AND OUTPUT SOLUTIONS FOR AL, AZ, MI, PA AND TX ON DOCTORS-CAPACITY MANAGEMENT (*APPENDIX* BUTTON #25)
[1]*AL* Tables I, VII-X; [2]*AZ* Tables II, XII-XIV; [3]*MI* Tables III, XV-XVII; [4]*PA* Tables IV, XVIII-XX; [5]*TX* Tables V, XXI-XXIII

1	2	3	4	5	6	7	8	9	10	11	12	13	14
NETWORKED STATES	#GROUPS (#HOSPITALS)	DAILY #BED DEMAND	Admissions λ (MTTA)	Discharge μ (MTTD)	#Waiting (W) # Doctors (1)	#Waiting (W) # Doctors (2)	#Waiting (W) # Doctors (3)	L= λ W # Doctors (1)	L= λ W # Doctors (2)	L= λ W # Doctors (3)	$TC=C_{Waiting}\times L+C_{Service}\times k$ # Doctors (1)	# Doctors (2)	# Doctors (3)
[1]*AL**	44 (9647)	4627	1.92/h (0.52 h)	5.23/h (0.19 h)	1702 (0.298)	247 (0.195)	45 (0.193)	0.57216	0.3744	0.37056	↑$612.37	↓$455.73	↑$490.81
[2]*AZ**	50 (7521)	4776	1.78/h (0.56 h)	4.55/h (0.22 h)	2509 (0.375)	445 (0.231)	25 (0.226)	0.66750	0.41118	0.40228	↑$707.36	↓$491.92	↑$523.00
[3]*MI**	51 (9586)	6292	2.45/h (0.41 h)	6.02/h (0.17 h)	2540 (0.273)	460 (0.173)	54 (0.169)	0.66885	0.42385	0.41405	↑$708.09	↓$504.76	↑$534.62
[4]*PA*	49 (7718)	5227	97/h (1.03 h)	3.91/h (0.26 h)	1300 (0.337)	137 (0.253)	9 (0.246)	0.32689	0.24541	0.23862	↑$367.48	↓$325.23	↑$359.05
[5]*TX*	49 (9763)	6423	2.13/h (0.47 h)	7.81/h (0.13 h)	1696 (0.172)	229 (0.133)	18 (0.129)	0.36636	0.28329	0.27477	↑$406.70	↓$361.79	↑$359.05

(MTTA: Admission Mean Time = λ^{-1}; MTTD: Discharge Mean Time = μ^{-1}; L = Avg system units, W_q = Avg waiting time, W = Avg system time, C_W = \$1,000, C_S = \$40)

TABLE XII: DISCRETE EVENT SIMULATION OF *AZ* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD'S TOTAL COST: $TC(k=1) \approx \$707$

Patient Arrival Distribution Parameters
Weibull | 0.56 Alpha | 1 Beta
Generate 0.4918

Patient Service Distribution Parameters : Inpatient
Weibull | 0.22 Alpha | 1 Beta

Ward Settings
No. Of Wards 15
Generate 0.2869
Wards InternalMedAZ

Simulation
Enter No. Of Doctors 1
Enter No. Of Patients 4776
Simulate | Clear | Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available
1	0.394855	0.394855	0.394855	0.0	0.2133	0.608155	0.2133	0.608155
2	0.001168	0.396023	0.608155	0.212132	0.059972	0.668127	0.272104	0.668127
3	0.03746	0.433483	0.668127	0.234644	0.204045	0.872172	0.438689	0.872172
4	0.066544	0.500027	0.872172	0.372145	0.161005	1.033177	0.53315	1.033177
5	0.154918	0.654945	1.033177	0.378232	0.581879	1.615056	0.960111	1.615056
6	0.00861	0.663555	1.615056	0.951501	0.14918	1.764236	1.100681	1.764236
7	0.190174	0.853729	1.764236	0.910507	0.201181	1.965417	1.111688	1.965417
8	0.640279	1.494008	1.965417	0.471409	0.490257	2.455674	0.961666	2.455674
9	0.711549	2.205557	2.455674	0.250117	0.069219	2.524893	0.319336	2.524893
10	0.112588	2.318145	2.524893	0.206748	0.016274	2.541167	0.223022	2.541167
6282	0.323913	3480.639271	3480.639271	0.0	0.083889	3480.72316	0.083889	3480.72316
6283	1.102764	3481.742035	3481.742035	0.0	0.015869	3481.757904	0.015869	3481.757904
6284	0.755861	3482.497896	3482.497896	0.0	0.038666	3482.536562	0.038666	3482.536562
6285	1.013357	3483.511253	3483.511253	0.0	0.112052	3483.623305	0.112052	3483.623305
6286	0.110581	3483.621834	3483.623305	0.001471	0.033688	3483.656993	0.035159	3483.656993
6287	0.207566	3483.8294	3483.8294	0.0	0.195628	3484.025028	0.195628	3484.025028
6288	1.486322	3485.315722	3485.315722	0.0	0.036438	3485.35216	0.036438	3485.35216
6289	0.139821	3485.455543	3485.455543	0.0	0.479973	3485.935516	0.479973	3485.935516
6290	1.001559	3486.457102	3486.457102	0.0	0.085036	3486.542138	0.085036	3486.542138
6291	0.200464	3486.657566	3486.657566	0.0	0.156947	3486.814513	0.156947	3486.814513
6292	0.734565	3487.392131	3487.392131	0.0	0.200458	3487.592589	0.200458	3487.592589

Summary Statistics

Number Waiting	2509
Probability of Waiting	0.39876
Average Wait Time	0.148909
Maximum Wait Time	2.342348
Average Utilization of Channel	0.407829
Number Waiting > 1 min.	189
Probability of Waiting > 1 min.	0.030038
Average System Time	0.374923
Total Cost per time period	$707.36294

TABLE XIII: DISCRETE EVENT SIMULATION OF *AZ* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD'S TOTAL COST: $TC(K=2) \approx \$492$

Patient Arrival Distribution Parameters
Weibull | 0.56 Alpha | 1 Beta
Generate 0.4918

Patient Service Distribution Parameters : Inpatient
Weibull | 0.22 Alpha | 1 Beta

Ward Settings
No. Of Wards 15
Generate 0.2869
Wards InternalMedAZ

Simulation
Enter No. Of Doctors 2
Enter No. Of Patients 4776
Simulate | Clear | Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available	Doctor 2 Available
1	0.667219	0.667219	0.667219	0.0	0.007008	0.674227	0.007008	0.674227	0.0
2	0.372689	1.039908	1.039908	0.0	0.47935	1.519258	0.47935	1.519258	0.0
3	0.453088	1.492996	1.492996	0.0	0.213578	1.706574	0.213578	1.519258	1.706574
4	1.508628	3.001624	3.001624	0.0	0.072462	3.074086	0.072462	3.074086	1.706574
5	0.124452	3.126076	3.126076	0.0	0.308918	3.434994	0.308918	3.434994	1.706574
6	0.244569	3.370645	3.370645	0.0	0.040568	3.411213	0.040568	3.434994	3.411213
7	1.175073	4.545718	4.545718	0.0	0.044823	4.590541	0.044823	4.590541	3.411213
8	1.49476	6.040478	6.040478	0.0	1.9E-5	6.040497	1.9E-5	6.040497	3.411213
9	1.686585	7.727063	7.727063	0.0	0.092452	7.819515	0.092452	7.819515	3.411213
10	0.070286	7.797349	7.797349	0.0	0.353864	8.151213	0.353864	7.819515	8.151213
6282	1.868131	3526.890136	3526.890136	0.0	0.090601	3526.980737	0.090601	3526.980737	3525.182729
6283	0.427383	3527.317519	3527.317519	0.0	0.170237	3527.487756	0.170237	3527.487756	3525.182729
6284	0.354565	3527.672084	3527.672084	0.0	0.252351	3527.924435	0.252351	3527.924435	3525.182729
6285	0.413176	3528.08526	3528.08526	0.0	0.08883	3528.17409	0.08883	3528.17409	3525.182729
6286	0.758833	3528.844093	3528.844093	0.0	0.096619	3528.940712	0.096619	3528.940712	3525.182729
6287	0.453171	3529.297264	3529.297264	0.0	0.299512	3529.596776	0.299512	3529.596776	3525.182729
6288	0.839722	3530.136986	3530.136986	0.0	0.067924	3530.20491	0.067924	3530.20491	3525.182729
6289	1.661197	3531.798183	3531.798183	0.0	0.511108	3532.309291	0.511108	3532.309291	3525.182729
6290	0.475424	3532.273607	3532.273607	0.0	1.052569	3533.326176	1.052569	3532.309291	3533.326176
6291	0.19205	3532.465657	3532.465657	0.0	0.143684	3532.609341	0.143684	3532.609341	3533.326176
6292	0.868059	3533.333716	3533.333716	0.0	0.014472	3533.348188	0.014472	3533.348188	3533.326176

Summary Statistics	
Number Waiting	445
Probability of Waiting	0.070725
Average Wait Time	0.010238
Maximum Wait Time	0.726318
Average Utilization of Channels	0.196781
Number Waiting > 1 min.	0
Probability of Waiting > 1 min.	0.0
Average System Time	0.231416
Total Cost per time period	$491.92048

TABLE XIV: DISCRETE EVENT SIMULATION OF *AZ* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD'S TOTAL COST: $TC(k=3) \approx \$523$

Patient Arrival Distribution Parameters
Weibull 0.56 Alpha; 1 Beta
Generate 0.3630

Patient Service Distribution Parameters : Inpatient
Weibull 0.22 Alpha; 1 Beta

Ward Settings
No. Of Wards 15
Generate 0.2702
Wards InternalMedAZ

Simulation
Enter No. Of Doctors 3
Enter No. Of Patients 4776
Simulate Clear Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available	Doctor 2 Available	Doctor 3 Available
1	0.338419	0.338419	0.338419	0.0	0.073831	0.41225	0.073831	0.41225	0.0	0.0
2	0.246582	0.585001	0.585001	0.0	0.300587	0.885588	0.300587	0.885588	0.0	0.0
3	0.618952	1.203953	1.203953	0.0	0.101616	1.305569	0.101616	1.305569	0.0	0.0
4	1.15809	2.362043	2.362043	0.0	0.013826	2.375869	0.013826	2.375869	0.0	0.0
5	0.008505	2.370548	2.370548	0.0	0.112861	2.483409	0.112861	2.375869	2.483409	0.0
6	0.084326	2.454874	2.454874	0.0	0.068863	2.523737	0.068863	2.523737	2.483409	0.0
7	0.030812	2.485686	2.485686	0.0	0.156881	2.642567	0.156881	2.523737	2.642567	0.0
8	0.175808	2.661494	2.661494	0.0	0.090476	2.75197	0.090476	2.75197	2.642567	0.0
9	0.197437	2.858931	2.858931	0.0	0.580063	3.438994	0.580063	3.438994	2.642567	0.0
10	0.035805	2.894736	2.894736	0.0	0.086813	2.981549	0.086813	3.438994	2.981549	0.0
4766	0.021654	2691.041475	2691.041475	0.0	0.182518	2691.223993	0.182518	2691.348789	2691.225232	2691.223993
4767	0.642005	2691.68348	2691.68348	0.0	0.216322	2691.899802	0.216322	2691.899802	2691.225232	2691.223993
4768	1.100643	2692.784123	2692.784123	0.0	0.086341	2692.870464	0.086341	2692.870464	2691.225232	2691.223993
4769	0.502346	2693.286469	2693.286469	0.0	0.316728	2693.603197	0.316728	2693.603197	2691.225232	2691.223993
4770	0.424665	2693.711134	2693.711134	0.0	0.665016	2694.37615	0.665016	2694.37615	2691.225232	2691.223993
4771	0.678779	2694.389913	2694.389913	0.0	0.243901	2694.633814	0.243901	2694.633814	2691.225232	2691.223993
4772	0.616049	2695.005962	2695.005962	0.0	0.197055	2695.203017	0.197055	2695.203017	2691.225232	2691.223993
4773	0.677605	2695.683567	2695.683567	0.0	0.811379	2696.494946	0.811379	2696.494946	2691.225232	2691.223993
4774	0.039631	2695.723198	2695.723198	0.0	0.35466	2696.077858	0.35466	2696.494946	2696.077858	2691.223993
4775	0.137013	2695.860211	2695.860211	0.0	0.210824	2696.071035	0.210824	2696.494946	2696.077858	2696.071035
4776	0.342707	2696.202918	2696.202918	0.0	0.333418	2696.536336	0.333418	2696.494946	2696.536336	2696.071035

Summary Statistics	
Number Waiting	25
Probability of Waiting	0.005235
Average Wait Time	9.7E-4
Maximum Wait Time	0.379194
Average Utilization of Channels	0.133465
Number Waiting > 1 min.	0
Probability of Waiting > 1 min.	0.0
Average System Time	0.226446
Total Cost per time period	$523.07388

TABLE XV: DISCRETE EVENT SIMULATION OF *MI* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD TOTAL COST: $TC(k=1) \approx \$708$

Patient Arrival Distribution Parameters
Weibull 0.41 Alpha; 1 Beta
Generate 0.4074

Patient Service Distribution Parameters : Inpatient
Gamma 0.17 Alpha; 1 Beta

Ward Settings
No. Of Wards 15
Generate 0.2842
Wards InternalMedMI

Simulation
Enter No. Of Doctors 1
Enter No. Of Patients 6292
Simulate Clear Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available
1	0.253613	0.253613	0.253613	0.0	0.171803	0.425416	0.171803	0.425416
2	0.266942	0.520555	0.520555	0.0	0.173067	0.693622	0.173067	0.693622
3	0.140249	0.660804	0.693622	0.032818	0.0466	0.740222	0.079418	0.740222
4	1.018271	1.679075	1.679075	0.0	0.013742	1.692817	0.013742	1.692817
5	1.337372	3.016447	3.016447	0.0	0.090879	3.107326	0.090879	3.107326
6	0.800163	3.81661	3.81661	0.0	0.391855	4.208465	0.391855	4.208465
7	0.269711	4.086321	4.208465	0.122144	0.404323	4.612788	0.526467	4.612788
8	1.036682	5.123003	5.123003	0.0	0.320132	5.443135	0.320132	5.443135
9	0.172177	5.29518	5.443135	0.147955	0.2103	5.653435	0.358255	5.653435
10	0.630054	5.925234	5.925234	0.0	0.035024	5.960258	0.035024	5.960258
6282	0.901589	2586.180885	2586.180885	0.0	0.36123	2586.542115	0.36123	2586.542115
6283	0.277368	2586.458253	2586.542115	0.083862	0.284157	2586.826272	0.368019	2586.826272
6284	0.243558	2586.701811	2586.826272	0.124461	0.181078	2587.00735	0.305539	2587.00735
6285	0.252175	2586.953986	2587.00735	0.053364	0.490777	2587.498127	0.544141	2587.498127
6286	0.427279	2587.381265	2587.498127	0.116862	0.087527	2587.585654	0.204389	2587.585654
6287	0.306933	2587.688198	2587.688198	0.0	0.29776	2587.985958	0.29776	2587.985958
6288	0.035336	2587.723534	2587.985958	0.262424	0.31192	2588.297878	0.574344	2588.297878
6289	0.458648	2588.182182	2588.297878	0.115696	0.029911	2588.327789	0.145607	2588.327789
6290	0.133168	2588.31535	2588.327789	0.012439	0.080707	2588.408496	0.093146	2588.408496
6291	0.378134	2588.693484	2588.693484	0.0	0.290039	2588.983523	0.290039	2588.983523
6292	0.310426	2589.00391	2589.00391	0.0	0.10521	2589.10912	0.10521	2589.10912

Summary Statistics	
Number Waiting	2540
Probability of Waiting	0.403687
Average Wait Time	0.107124
Maximum Wait Time	1.971807
Average Utilization of Channel	0.40249
Number Waiting > 1 min.	50
Probability of Waiting > 1 min.	0.007947
Average System Time	0.272691
Total Cost per time period	$708.09295

TABLE XVI: DISCRETE EVENT SIMULATION OF *MI* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD TOTAL COST: $TC(K=2) \approx \$505$

Patient Arrival Distribution Parameters

Weibull | 0.41 Alpha | 1 Beta

Generate | 0.4074

Patient Service Distribution Parameters : Inpatient

Gamma | 0.17 Alpha | 1 Beta

Ward Settings

No. Of Wards: 15

Generate | 0.2842

Wards: InternalMedMI

Simulation

Enter No. Of Doctors: 2

Enter No. Of Patients: 6292

Simulate | Clear | Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available	Doctor 2 Available
1	0.202531	0.202531	0.202531	0.0	0.011915	0.214446	0.011915	0.214446	0.0
2	1.213169	1.4157	1.4157	0.0	0.015413	1.431113	0.015413	1.431113	0.0
3	0.05898	1.47468	1.47468	0.0	0.327648	1.802328	0.327648	1.802328	0.0
4	0.797193	2.271873	2.271873	0.0	0.036724	2.308597	0.036724	2.308597	0.0
5	0.32011	2.591983	2.591983	0.0	0.080871	2.672854	0.080871	2.672854	0.0
6	0.024493	2.616476	2.616476	0.0	0.334762	2.951238	0.334762	2.672854	2.951238
7	0.132391	2.748867	2.748867	0.0	0.003365	2.752232	0.003365	2.752232	2.951238
8	0.031209	2.780076	2.780076	0.0	0.235201	3.015277	0.235201	3.015277	2.951238
9	0.584108	3.364184	3.364184	0.0	0.173239	3.537423	0.173239	3.537423	2.951238
10	1.215042	4.579226	4.579226	0.0	0.028259	4.607485	0.028259	4.607485	2.951238
6282	1.257364	2559.264634	2559.264634	0.0	0.172789	2559.437423	0.172789	2559.437423	2558.250626
6283	0.032055	2559.296689	2559.296689	0.0	0.230447	2559.527136	0.230447	2559.437423	2559.527136
6284	1.279771	2560.57646	2560.57646	0.0	0.054862	2560.631322	0.054862	2560.631322	2559.527136
6285	1.225356	2561.801816	2561.801816	0.0	0.381942	2562.183758	0.381942	2562.183758	2559.527136
6286	0.752145	2562.553961	2562.553961	0.0	0.105645	2562.659606	0.105645	2562.659606	2559.527136
6287	0.002939	2562.5569	2562.5569	0.0	0.001652	2562.558552	0.001652	2562.659606	2562.558552
6288	0.570113	2563.127013	2563.127013	0.0	0.095744	2563.222757	0.095744	2563.222757	2562.558552
6289	0.442478	2563.569491	2563.569491	0.0	0.170313	2563.739804	0.170313	2563.739804	2562.558552
6290	0.325919	2563.89541	2563.89541	0.0	0.00517	2563.90058	0.00517	2563.90058	2562.558552
6291	0.321717	2564.217127	2564.217127	0.0	0.155239	2564.372366	0.155239	2564.372366	2562.558552
6292	0.423905	2564.641032	2564.641032	0.0	0.221527	2564.862559	0.221527	2564.862559	2562.558552

Summary Statistics

Number Waiting	460
Probability of Waiting	0.073109
Average Wait Time	0.00806
Maximum Wait Time	0.612214
Average Utilization of Channels	0.203046
Number Waiting > 1 min.	0
Probability of Waiting > 1 min.	0.0
Average System Time	0.17337
Total Cost per time period	$504.7565

TABLE XVII: DISCRETE EVENT SIMULATION OF *MI* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD TOTAL COST: $TC(K=3) \approx \$535$

Patient Arrival Distribution Parameters

Weibull | 0.41 Alpha | 1 Beta

Generate | 0.3630

Patient Service Distribution Parameters : Inpatient

Weibull | 0.17 Alpha | 1 Beta

Ward Settings

No. Of Wards: 15

Generate | 0.2702

Wards: InternalMedMI

Simulation

Enter No. Of Doctors: 3

Enter No. Of Patients: 6292

Simulate | Clear | Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available	Doctor 2 Available	Doctor 3 Available
1	0.145091	0.145091	0.145091	0.0	0.011877	0.156968	0.011877	0.156968	0.0	0.0
2	0.509388	0.654479	0.654479	0.0	0.27149	0.925969	0.27149	0.925969	0.0	0.0
3	2.386066	3.040545	3.040545	0.0	0.048563	3.089108	0.048563	3.089108	0.0	0.0
4	0.253328	3.293873	3.293873	0.0	0.126529	3.420402	0.126529	3.420402	0.0	0.0
5	1.664216	4.958089	4.958089	0.0	0.037248	4.995337	0.037248	4.995337	0.0	0.0
6	0.297101	5.25519	5.25519	0.0	0.029663	5.284853	0.029663	5.284853	0.0	0.0
7	0.448399	5.703589	5.703589	0.0	0.140331	5.84392	0.140331	5.84392	0.0	0.0
8	0.005029	5.708618	5.708618	0.0	0.654764	6.363382	0.654764	5.84392	6.363382	0.0
9	0.851437	6.560055	6.560055	0.0	0.036812	6.596867	0.036812	6.596867	6.363382	0.0
10	0.167176	6.727231	6.727231	0.0	0.141382	6.868613	0.141382	6.868613	6.363382	0.0
6282	0.207842	2584.620192	2584.620192	0.0	0.290144	2584.910336	0.290144	2584.910336	2584.432588	2584.269453
6283	0.62696	2585.247152	2585.247152	0.0	0.061963	2585.309115	0.061963	2585.309115	2584.432588	2584.269453
6284	0.108096	2585.355248	2585.355248	0.0	0.230082	2585.58533	0.230082	2585.58533	2584.432588	2584.269453
6285	0.68996	2586.045208	2586.045208	0.0	0.028591	2586.073799	0.028591	2586.073799	2584.432588	2584.269453
6286	0.107776	2586.152984	2586.152984	0.0	0.064645	2586.217629	0.064645	2586.217629	2584.432588	2584.269453
6287	0.134445	2586.287429	2586.287429	0.0	0.110526	2586.397955	0.110526	2586.397955	2584.432588	2584.269453
6288	0.036129	2586.323558	2586.323558	0.0	0.276055	2586.599613	0.276055	2586.397955	2586.599613	2584.269453
6289	0.519402	2586.84296	2586.84296	0.0	0.076403	2586.919363	0.076403	2586.919363	2586.599613	2584.269453
6290	0.799537	2587.642497	2587.642497	0.0	0.278242	2587.920739	0.278242	2587.920739	2586.599613	2584.269453
6291	0.091849	2587.734346	2587.734346	0.0	0.139479	2587.873825	0.139479	2587.920739	2587.873825	2584.269453
6292	0.803806	2588.538152	2588.538152	0.0	0.105445	2588.643597	0.105445	2588.643597	2587.873825	2584.269453

Summary Statistics

Number Waiting	54
Probability of Waiting	0.008582
Average Wait Time	0.001345
Maximum Wait Time	0.317583
Average Utilization of Channels	0.136709
Number Waiting > 1 min.	0
Probability of Waiting > 1 min.	0.0
Average System Time	0.169233
Total Cost per time period	$534.62085

TABLE XVIII: DISCRETE EVENT SIMULATION OF *PA* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD TOTAL COST: $TC(K=1) \approx \$367$

Patient Arrival Distribution Parameters
Weibull | 1.03 Alpha | 1 Beta
Generate | 0.3630

Patient Service Distribution Parameters : Inpatient
Weibull | 0.26 Alpha | 1 Beta

Ward Settings
No. Of Wards | 15
Generate | 0.2702
Wards | InternalMedPA

Simulation
Enter No. Of Doctors | 1
Enter No. Of Patients | 5227
Simulate | Clear | Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available
1	0.078894	0.078894	0.078894	0.0	0.393455	0.472349	0.393455	0.472349
2	0.130878	0.209772	0.472349	0.262577	0.431992	0.904341	0.694569	0.904341
3	0.229228	0.439	0.904341	0.465341	0.231713	1.136054	0.697054	1.136054
4	0.141558	0.580558	1.136054	0.555496	0.467995	1.604049	1.023491	1.604049
5	3.009704	3.590262	3.590262	0.0	0.254596	3.844858	0.254596	3.844858
6	0.483148	4.07341	4.07341	0.0	0.068959	4.142369	0.068959	4.142369
7	0.729996	4.803406	4.803406	0.0	0.317056	5.120462	0.317056	5.120462
8	0.104319	4.907725	5.120462	0.212737	0.025848	5.14631	0.238585	5.14631
9	0.559696	5.467421	5.467421	0.0	0.307099	5.77452	0.307099	5.77452
10	0.262604	5.730025	5.77452	0.044495	1.198509	6.973029	1.243004	6.973029
5217	0.763785	5433.794609	5433.794609	0.0	0.227532	5434.022141	0.227532	5434.022141
5218	0.788632	5434.583241	5434.583241	0.0	0.182592	5434.765833	0.182592	5434.765833
5219	1.497757	5436.080998	5436.080998	0.0	0.469144	5436.550142	0.469144	5436.550142
5220	0.160278	5436.241276	5436.550142	0.308866	0.309793	5436.859935	0.618659	5436.859935
5221	2.85474	5439.096016	5439.096016	0.0	0.098334	5439.19435	0.098334	5439.19435
5222	0.617792	5439.713808	5439.713808	0.0	0.464833	5440.178641	0.464833	5440.178641
5223	0.812636	5440.526444	5440.526444	0.0	0.052785	5440.579229	0.052785	5440.579229
5224	0.04392	5440.570364	5440.579229	0.008865	0.125325	5440.704554	0.13419	5440.704554
5225	0.426513	5440.996877	5440.996877	0.0	0.246054	5441.242931	0.246054	5441.242931
5226	0.346406	5441.343283	5441.343283	0.0	0.00383	5441.347113	0.00383	5441.347113
5227	0.304324	5441.647607	5441.647607	0.0	0.167063	5441.81467	0.167063	5441.81467

Summary Statistics

Number Waiting	1300
Probability of Waiting	0.248709
Average Wait Time	0.082125
Maximum Wait Time	1.831644
Average Utilization of Channel	0.245395
Number Waiting > 1 min.	66
Probability of Waiting > 1 min.	0.012627
Average System Time	0.337606
Total Cost per time period	$367.47782

TABLE XIX: DISCRETE EVENT SIMULATION OF *PA* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD TOTAL COST: $TC(K=2) \approx \$325$

Patient Arrival Distribution Parameters
Weibull | 1.03 Alpha | 1 Beta
Generate | 0.4918

Patient Service Distribution Parameters : Inpatient
Weibull | 0.26 Alpha | 1 Beta

Ward Settings
No. Of Wards | 15
Generate | 0.2869
Wards | InternalMedPA

Simulation
Enter No. Of Doctors | 2
Enter No. Of Patients | 5227
Simulate | Clear | Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available	Doctor 2 Available
1	0.98263	0.98263	0.98263	0.0	0.445747	1.428377	0.445747	1.428377	0.0
2	0.266526	1.249156	1.249156	0.0	0.732576	1.981732	0.732576	1.428377	1.981732
3	0.20105	1.450206	1.450206	0.0	0.058135	1.508341	0.058135	1.508341	1.981732
4	1.18869	2.638896	2.638896	0.0	0.294423	2.933319	0.294423	2.933319	1.981732
5	0.767516	3.406412	3.406412	0.0	0.444793	3.851205	0.444793	3.851205	1.981732
6	0.790255	4.196667	4.196667	0.0	0.287562	4.484229	0.287562	4.484229	1.981732
7	3.916023	8.11269	8.11269	0.0	0.031042	8.143732	0.031042	8.143732	1.981732
8	0.566319	8.679009	8.679009	0.0	0.198093	8.877102	0.198093	8.877102	1.981732
9	1.510088	10.189097	10.189097	0.0	0.276729	10.465826	0.276729	10.465826	1.981732
10	0.90465	11.093747	11.093747	0.0	0.134139	11.227886	0.134139	11.227886	1.981732
5217	0.726918	5401.524513	5401.524513	0.0	0.145606	5401.670119	0.145606	5401.670119	5383.325771
5218	1.97051	5403.495023	5403.495023	0.0	0.482904	5403.977927	0.482904	5403.977927	5383.325771
5219	0.312996	5403.808019	5403.808019	0.0	0.033531	5403.84155	0.033531	5403.977927	5403.84155
5220	0.316086	5404.124105	5404.124105	0.0	0.346919	5404.471024	0.346919	5404.471024	5403.84155
5221	1.074875	5405.19898	5405.19898	0.0	0.575865	5405.774845	0.575865	5405.774845	5403.84155
5222	2.729881	5407.928861	5407.928861	0.0	0.122469	5408.05133	0.122469	5408.05133	5403.84155
5223	0.861626	5408.790487	5408.790487	0.0	0.05816	5408.848647	0.05816	5408.848647	5403.84155
5224	0.080346	5408.870833	5408.870833	0.0	0.145056	5409.015889	0.145056	5409.015889	5403.84155
5225	1.191116	5410.061949	5410.061949	0.0	0.049587	5410.111536	0.049587	5410.111536	5403.84155
5226	1.858656	5411.920605	5411.920605	0.0	0.102099	5412.022704	0.102099	5412.022704	5403.84155
5227	1.473235	5413.39384	5413.39384	0.0	0.432618	5413.826458	0.432618	5413.826458	5403.84155

Summary Statistics

Number Waiting	137
Probability of Waiting	0.02621
Average Wait Time	0.00325
Maximum Wait Time	0.886723
Average Utilization of Channels	0.120377
Number Waiting > 1 min.	0
Probability of Waiting > 1 min.	0.0
Average System Time	0.252812
Total Cost per time period	$325.22764

TABLE XX: DISCRETE EVENT SIMULATION OF *PA* HOSPITALS' COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD TOTAL COST: $TC(\kappa=3) \approx \$359$

Patient Arrival Distribution Parameters

Weibull | 1.03 Alpha | 1 Beta

Generate | 0.3630

Patient Service Distribution Parameters : Inpatient

Weibull | 0.26 Alpha | 1 Beta

Ward Settings

No. Of Wards: 15

Generate | 0.2702

Wards: InternalMedPA

Simulation

Enter No. Of Doctors: 3

Enter No. Of Patients: 5227

Simulate | Clear | Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available	Doctor 2 Available	Doctor 3 Available
1	2.268777	2.268777	2.268777	0.0	0.186824	2.455601	0.186824	2.455601	0.0	0.0
2	4.614782	6.883559	6.883559	0.0	0.0535	6.937059	0.0535	6.937059	0.0	0.0
3	0.050283	6.933842	6.933842	0.0	0.23058	7.164422	0.23058	6.937059	7.164422	0.0
4	0.511795	7.445637	7.445637	0.0	0.043528	7.489165	0.043528	7.489165	7.164422	0.0
5	4.937369	12.383006	12.383006	0.0	0.203342	12.586348	0.203342	12.586348	7.164422	0.0
6	0.053167	12.436173	12.436173	0.0	0.774478	13.210651	0.774478	12.586348	13.210651	0.0
7	0.108838	12.545011	12.545011	0.0	0.006071	12.551082	0.006071	12.586348	13.210651	12.551082
8	2.698615	15.243626	15.243626	0.0	0.120364	15.36399	0.120364	15.36399	13.210651	12.551082
9	1.157606	16.401232	16.401232	0.0	0.021585	16.422817	0.021585	16.422817	13.210651	12.551082
10	0.541487	16.942719	16.942719	0.0	0.17382	17.116539	0.17382	17.116539	13.210651	12.551082
5217	0.070049	5520.471981	5520.471981	0.0	0.597923	5521.069904	0.597923	5521.069904	5520.407375	5496.317396
5218	0.021034	5520.493015	5520.493015	0.0	0.30026	5520.793275	0.30026	5521.069904	5520.793275	5496.317396
5219	0.544313	5521.037328	5521.037328	0.0	0.030413	5521.067741	0.030413	5521.069904	5521.067741	5496.317396
5220	0.280547	5521.317875	5521.317875	0.0	0.164565	5521.48244	0.164565	5521.48244	5521.067741	5496.317396
5221	0.628504	5521.946379	5521.946379	0.0	0.388116	5522.334495	0.388116	5522.334495	5521.067741	5496.317396
5222	1.077637	5523.024016	5523.024016	0.0	1.105937	5524.129953	1.105937	5524.129953	5521.067741	5496.317396
5223	0.126619	5523.150635	5523.150635	0.0	0.207196	5523.357831	0.207196	5524.129953	5523.357831	5496.317396
5224	1.368137	5524.518772	5524.518772	0.0	0.014977	5524.533749	0.014977	5524.533749	5523.357831	5496.317396
5225	5.306861	5529.825633	5529.825633	0.0	0.248595	5530.074228	0.248595	5530.074228	5523.357831	5496.317396
5226	0.919994	5530.745627	5530.745627	0.0	0.976335	5531.721962	0.976335	5531.721962	5523.357831	5496.317396
5227	0.552771	5531.298398	5531.298398	0.0	0.485329	5531.783727	0.485329	5531.721962	5531.783727	5496.317396

Summary Statistics

Number Waiting	9
Probability of Waiting	0.001722
Average Wait Time	4.06E-4
Maximum Wait Time	0.134695
Average Utilization of Channels	0.077618
Number Waiting > 1 min.	0
Probability of Waiting > 1 min.	0.0
Average System Time	0.246444
Total Cost per time period	$359.05068

TABLE XXI. DISCRETE EVENT SIMULATION OF *TX* HOSPITALS COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD TOTAL COST: $TC(\kappa=1) \approx \$407$

Patient Arrival Distribution Parameters

Weibull | 0.47 Alpha | 1 Beta

Generate | 0.3630

Patient Service Distribution Parameters : Inpatient

Weibull | 0.13 Alpha | 1 Beta

Ward Settings

No. Of Wards: 15

Generate | 0.2702

Wards: InternalMedTX

Simulation

Enter No. Of Doctors: 1

Enter No. Of Patients: 6423

Simulate | Clear | Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available
1	1.106583	1.106583	1.106583	0.0	0.090819	1.197402	0.090819	1.197402
2	1.998712	3.105295	3.105295	0.0	6.11E-4	3.105906	6.11E-4	3.105906
3	0.20099	3.306285	3.306285	0.0	0.69483	4.001115	0.69483	4.001115
4	4.36E-4	3.306721	4.001115	0.694394	0.029961	4.031076	0.724355	4.031076
5	0.923843	4.230564	4.230564	0.0	0.190789	4.421353	0.190789	4.421353
6	0.175076	4.40564	4.421353	0.015713	0.136671	4.558024	0.152384	4.558024
7	0.139294	4.544934	4.558024	0.01309	0.065029	4.623053	0.078119	4.623053
8	0.224956	4.76989	4.76989	0.0	0.119511	4.889401	0.119511	4.889401
9	0.730582	5.500472	5.500472	0.0	0.039709	5.540181	0.039709	5.540181
10	0.451136	5.951608	5.951608	0.0	0.109123	6.060731	0.109123	6.060731
6413	0.147207	2984.003797	2984.057844	0.054047	0.053558	2984.111402	0.107605	2984.111402
6414	0.703892	2984.707689	2984.707689	0.0	0.069047	2984.776736	0.069047	2984.776736
6415	1.331633	2986.039322	2986.039322	0.0	0.320617	2986.359939	0.320617	2986.359939
6416	0.117457	2986.156779	2986.359939	0.20316	0.107487	2986.467426	0.310647	2986.467426
6417	0.970568	2987.127347	2987.127347	0.0	0.02326	2987.150607	0.02326	2987.150607
6418	0.570613	2987.69796	2987.69796	0.0	0.046415	2987.744375	0.046415	2987.744375
6419	0.366804	2988.064764	2988.064764	0.0	0.002835	2988.067599	0.002835	2988.067599
6420	0.423909	2988.488673	2988.488673	0.0	0.18942	2988.678093	0.18942	2988.678093
6421	0.942222	2989.430895	2989.430895	0.0	0.053999	2989.484894	0.053999	2989.484894
6422	0.650462	2990.081357	2990.081357	0.0	0.010113	2990.09147	0.010113	2990.09147
6423	0.354951	2990.436308	2990.436308	0.0	0.03814	2990.474448	0.03814	2990.474448

Summary Statistics

Number Waiting	1697
Probability of Waiting	0.264207
Average Wait Time	0.0457
Maximum Wait Time	1.126464
Average Utilization of Channel	0.271842
Number Waiting > 1 min.	3
Probability of Waiting > 1 min.	4.67E-4
Average System Time	0.172161
Total Cost per time period	$406.70293

TABLE XXII: DISCRETE EVENT SIMULATION OF *TX* HOSPITALS COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD TOTAL COST: $TC(\kappa=2) \approx \$362$

Patient Arrival Distribution Parameters

Weibull 0.47 Alpha
1 Beta
Generate 0.3630

Patient Service Distribution Parameters : Inpatient

Weibull 0.13 Alpha
1 Beta

Ward Settings

No. Of Wards 15
Generate 0.2702
Wards InternalMedTX

Simulation

Enter No. Of Doctors 2
Enter No. Of Patients 6423
Simulate Clear
Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available	Doctor 2 Available
1	0.037537	0.037537	0.037537	0.0	0.05543	0.092967	0.05543	0.092967	0.0
2	1.399884	1.437421	1.437421	0.0	0.229515	1.666936	0.229515	1.666936	0.0
3	0.377732	1.815153	1.815153	0.0	0.122963	1.938116	0.122963	1.938116	0.0
4	1.342839	3.157992	3.157992	0.0	0.034111	3.192103	0.034111	3.192103	0.0
5	0.380352	3.538344	3.538344	0.0	0.005276	3.54362	0.005276	3.54362	0.0
6	0.023686	3.56203	3.56203	0.0	0.101567	3.663597	0.101567	3.663597	0.0
7	0.821818	4.383848	4.383848	0.0	0.123751	4.507599	0.123751	4.507599	0.0
8	0.564228	4.948076	4.948076	0.0	0.068995	5.017071	0.068995	5.017071	0.0
9	0.925815	5.873891	5.873891	0.0	0.344623	6.218514	0.344623	6.218514	0.0
10	0.211393	6.085284	6.085284	0.0	0.030424	6.115708	0.030424	6.218514	6.115708
6413	0.009369	3023.106466	3023.106466	0.0	0.291256	3023.397722	0.291256	3023.147369	3023.397722
6414	0.89207	3023.998536	3023.998536	0.0	0.116337	3024.114873	0.116337	3024.114873	3023.397722
6415	0.979562	3024.978098	3024.978098	0.0	0.020801	3024.998899	0.020801	3024.998899	3023.397722
6416	0.186858	3025.164956	3025.164956	0.0	0.784454	3025.94941	0.784454	3025.94941	3023.397722
6417	0.575394	3025.74035	3025.74035	0.0	0.377522	3026.117872	0.377522	3025.94941	3026.117872
6418	0.316328	3026.056678	3026.056678	0.0	0.024729	3026.081407	0.024729	3026.081407	3026.117872
6419	0.514406	3026.571084	3026.571084	0.0	0.244794	3026.815878	0.244794	3026.815878	3026.117872
6420	0.059451	3026.630535	3026.630535	0.0	0.014947	3026.645482	0.014947	3026.815878	3026.645482
6421	0.505495	3027.13603	3027.13603	0.0	0.008042	3027.144072	0.008042	3027.144072	3026.645482
6422	0.489483	3027.625513	3027.625513	0.0	0.021643	3027.647156	0.021643	3027.647156	3026.645482
6423	0.233143	3027.858656	3027.858656	0.0	0.185733	3028.044389	0.185733	3028.044389	3026.645482

Summary Statistics

Number Waiting	229
Probability of Waiting	0.035653
Average Wait Time	0.003175
Maximum Wait Time	0.377443
Average Utilization of Channels	0.137645
Number Waiting > 1 min.	0
Probability of Waiting > 1 min.	0.0
Average System Time	0.132297
Total Cost per time period	$361.79261

TABLE XXIII: DISCRETE EVENT SIMULATION OF *TX* HOSPITALS COVID PATIENTS QUEUEING TO JUDGE EMERGENCY WARD TOTAL COST: $TC(\kappa=3) \approx \$395$

Patient Arrival Distribution Parameters

Weibull 0.47 Alpha
1 Beta
Generate 0.3630

Patient Service Distribution Parameters : Inpatient

Weibull 0.13 Alpha
1 Beta

Ward Settings

No. Of Wards 15
Generate 0.2702
Wards InternalMedTX

Simulation

Enter No. Of Doctors 3
Enter No. Of Patients 6423
Simulate Clear
Clear All

Outpatient/Inpatient Simulation

Patient	Inter-Arrival Time	Arrival Time	Service Start Time	Wait Time	Service Time	Completion Time	Time in System	Doctor 1 Available	Doctor 2 Available	Doctor 3 Available
1	1.529292	1.529292	1.529292	0.0	0.042419	1.571711	0.042419	1.571711	0.0	0.0
2	0.201764	1.731056	1.731056	0.0	0.402036	2.133092	0.402036	2.133092	0.0	0.0
3	0.791616	2.522672	2.522672	0.0	0.196213	2.718885	0.196213	2.718885	0.0	0.0
4	0.200552	2.723224	2.723224	0.0	0.261886	2.98511	0.261886	2.98511	0.0	0.0
5	0.774372	3.497596	3.497596	0.0	0.066973	3.564569	0.066973	3.564569	0.0	0.0
6	0.021487	3.519083	3.519083	0.0	0.169975	3.689058	0.169975	3.564569	3.689058	0.0
7	0.030472	3.549555	3.549555	0.0	0.049521	3.599076	0.049521	3.564569	3.689058	3.599076
8	0.514232	4.063787	4.063787	0.0	0.028625	4.092412	0.028625	4.092412	3.689058	3.599076
9	0.270058	4.333845	4.333845	0.0	0.119477	4.453322	0.119477	4.453322	3.689058	3.599076
10	0.008163	4.342008	4.342008	0.0	0.258727	4.600735	0.258727	4.453322	4.600735	3.599076
6413	0.389225	3072.192337	3072.192337	0.0	0.019835	3072.212172	0.019835	3072.212172	3071.83327	3067.07728
6414	0.501084	3072.693421	3072.693421	0.0	0.005231	3072.698652	0.005231	3072.698652	3071.83327	3067.07728
6415	0.606702	3073.300123	3073.300123	0.0	0.166658	3073.466781	0.166658	3073.466781	3071.83327	3067.07728
6416	0.951978	3074.252101	3074.252101	0.0	0.00163	3074.253731	0.00163	3074.253731	3071.83327	3067.07728
6417	0.078521	3074.330622	3074.330622	0.0	0.092692	3074.423314	0.092692	3074.423314	3071.83327	3067.07728
6418	0.892054	3075.222676	3075.222676	0.0	0.425801	3075.648477	0.425801	3075.648477	3071.83327	3067.07728
6419	0.095117	3075.317793	3075.317793	0.0	0.031207	3075.349	0.031207	3075.648477	3075.349	3067.07728
6420	1.423759	3076.741552	3076.741552	0.0	0.137454	3076.879006	0.137454	3076.879006	3075.349	3067.07728
6421	0.207291	3076.948843	3076.948843	0.0	0.324918	3077.273761	0.324918	3077.273761	3075.349	3067.07728
6422	0.3699	3077.318743	3077.318743	0.0	0.085225	3077.403968	0.085225	3077.403968	3075.349	3067.07728
6423	0.763347	3078.08209	3078.08209	0.0	0.032499	3078.114589	0.032499	3078.114589	3075.349	3067.07728

Summary Statistics

Number Waiting	18
Probability of Waiting	0.002802
Average Wait Time	4.69E-4
Maximum Wait Time	0.131022
Average Utilization of Channels	0.089758
Number Waiting > 1 min.	0
Probability of Waiting > 1 min.	0.0
Average System Time	0.12913
Total Cost per time period	$395.0469

Regarding the economic analysis of waiting lines, a manager may identify the cost of operating the waiting line system and then base the decision regarding the system design on a minimum hourly or daily operating cost. Before an economic analysis of a waiting line can be conducted, a total cost model, with the cost of waiting and the cost of service, must be developed. To develop a total cost model for waiting line, one begins by defining the core notation to be used [2]:

L = The average number of units (patients) in the system, $L=\lambda w$ (referred to as Little's Flow Equation #1)

C_w = Waiting (Queuing) Cost per time period of each unit

L_q = The average number of units in the queue, $L_q = \lambda w_q$ (referred to as Little's Flow Equation #2)

C_s = The service cost per time period for each channel (emergency–physician in this context)

k = The number of channels (#Emergency Physicians)

TC = The total cost per time period for an hourly visit by an e.g. emergency patient = $C_w \times L + C_s \times k$ by Eq. (13)

Then, the total cost, TC, is the sum of waiting cost and the service cost; where $L=\lambda w$ with λ=arrival rate and w= the average time a unit spends in the system such that $L_q= \lambda w_q$ denotes the average number of units in the waiting line (or queue). In the following for TC, C_W=\$1000 insurance fee per patient/h lost, C_S=\$40 hourly fee for the specialist (re: *COVID* care). In a hospital emergency ward, \$40/h × 8760h ≈ \$350*K* allocated for an emergency physician shown by the industry's compensation statistics.

The healthcare industry is among the top highly federal- and state-regulated industries [17]. By providing insights to the States' health planning agencies, this study alerts the potential hospital bed-needs as well as physician-hires through *CLOURAM* and *MCQS* as well as Hospital Scheduling algorithms within a framework of discrete event simulation models [18]. Currently, 35 states have *CON* State laws that require the approval of capital expenditures by States' health planning agencies, which aims to prevent duplication of services. and meet the need of the local communities [19]. This study should be especially useful in relation to the certificate of need-based States' laws, which governs the expansion of healthcare facilities and services, where Fig. 22 depicts a map of 35 States with *CON* Laws [20]. Overall, the *CLOURAM* and *MCQS*, and Hospital Scheduling provide insights into certain best practices for assessing, and proactively taking precautions to improve the undesirable and life-and-death risk of bed- and physician-inadequacy in hospitals—a task for health planning agencies by the States' *CON* laws. See *Appendix* for *CLOURAM* and MCQS, and Hospital Scheduling. Fig. 23's Chart Diagram mindfully shows the simple hospital management flow [21].

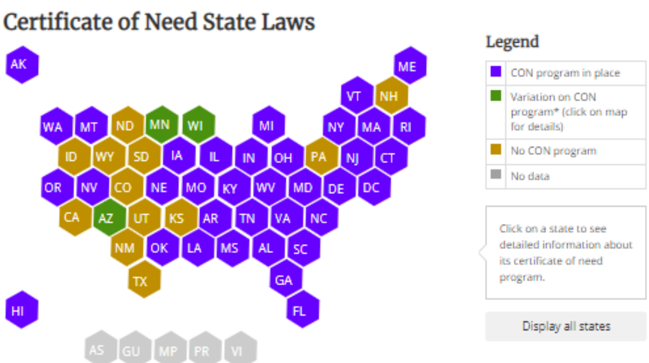


Fig. 22. States with the *CON* (Certificate of Need) Program in Place [20].

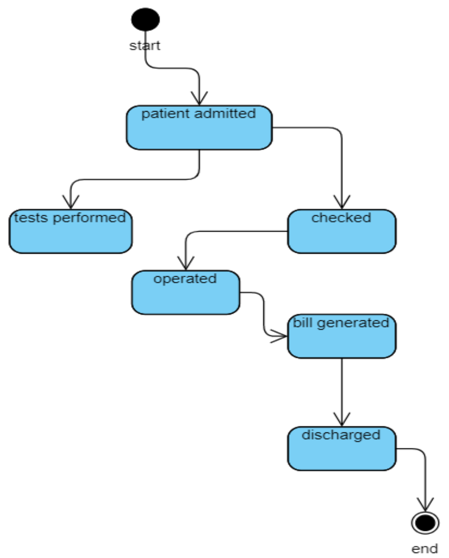


Fig. 23. State Chart Diagram for Hospital Management [21].

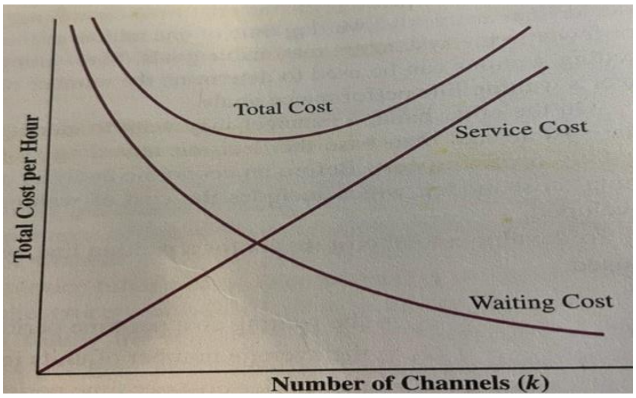


Fig. 24. The general trend of Waiting Cost, Service Cost, and Total-Cost Curves in Waiting Line Models from Table XI, such as for AL: TC(k=1) ≈ \$612 down to TC(k=2) ≈ \$456 and up to TC(k=3) ≈ \$491 yielding the best choice of k=2 doctors [2]. As for TX: TC(k=1) ≈ \$407 down to TC(k=2) ≈ \$362, then up to TC(k=3) ≈ \$395 yielding the most lucrative for k=2 doctors. States using the same cost parameters of Cw=\$1000 insurance fee and Cs=\$40/h fee for the specialist, k=2 proved optimal. Equation (13) is used.

For subsection II-B, Anderson *et al*. inspired by Agnithori and Taylor studied hospital staffing based on a multi-channel waiting line model [2, 22]. To further investigate the practicality of the two pivotal Tables VI and XI, based on the obvious fact that without adequate bed-count, the physicians are of no use. Thus, without the adequate supply of the emergency-physicians despite the abundance of beds, or vice versa, there is no added benefit. However, to synergize the independent Tables VI and XI, *CPNP* (Composite Patient Non-Denial Probability), e.g. for *AL*, is the cross product of probabilities of *BA*: bed-availability (Table VI, ROW 1, COL. 12) where P(*BA*) = 100%-9.15%= 90.85%, and the physician-availability (Table XI, ROW 1, COL.6) yielding the probability of the patients who are Not-Waiting: P(*NW*)=1−P(*W*)=1− (1702/4627) ≈ 100%−37%=63% for k=1, Next, the product of independent events, P(*BA*) × P(*NW*) = 90.85% × 0.63 = 57.24%. If P(*NW*)=1 is a perfect case, P(*BA*) remains as is, which never happens. This implies ~57 out of 100 patients will not be denied or ~43 denied. Likely, ~86 out of every 100 patients for k=2 will not be denied, or only 14 will be denied. Then P(*BA*) × P(*NW*) = (1-.0915) × [1-(45/4627)] ≈ .85% × 0.99≈90%, or 90 out of 100 for k=3 will not be denied, or 10 patients will be, due to physician- and bed-shortages despite a higher hospital cost than k=2. States' composite patient denials can be calculated for k = 1, 2 and 3. The proposed probabilistic index, *CPNP*, may invoke value-added alarms for *CON* laws. The patients' data allude to pre-*COVID*. The research will continue once the post-*COVID*-19 data is publicized to tell normal from the abnormal data.

B. Comparisons and Contrasts with Other Works

Several other works have been cited to predict hospital bed-and physician–capacity crises during or after the *COVID*-19 pandemic, as follow in six itemized sources, i to vi:

i) Deschepper *et al*. [23] used a Poisson distribution assumption for the number of newly admitted patients on each day with a multistate rather than 2-state, COVID-19 or non-COVID-19 (instead with possible transitions as Cohort, ICU Midcare, ICU Standard and ICU Ventilated) statistical model for the transitions to the different wards, discharge or death. These 203 piece of data used were from COVID-19 patients from April 20th to April 27th in 2020 by Monte-Carlo simulation of the capacity of beds by ward type over the upcoming 10 days, along with the worst- and best-case bounds using *R* statistical software (version 3.6.1).

ii) Römmele *et al.* [24] created a Monte Carlo simulation-based prognostic tool that provides the management of the University Hospital of Augsburg to plan and guide the disaster response for the pandemic. Especially the number of beds needed on isolation wards and intensive care units (*ICU*) were the biggest concerns. Using this information, Römmele *et al*. started Monte Carlo simulation with 10,000 runs to predict the range of the number of hospital beds needed, and favorably compared it with the available resources. 306 patients were treated with confirmed or suspected *COVID*-19, of which 84 needed treatment on the *ICU*. Using simulation-based forecasts, the required *ICU* and normal bed capacity at Augsburg University Hospital and the ambulance service in the period from 3/28/2020 to 6/8/2020 could be predicted with high degree of reliability. Simulations before the impact of the restrictions in daily life showed that one would have run out of ICU bed capacity within approximately one month.

iii) Rhodes *et al*. [25] hypothesized that in quantifying the numbers of critical care beds per country when corrected for population size were positively correlated with *GDP* (Gross Domestic Product) in Europe covering 7/2010 to 7/2011. Sources were identified in each country that could provide data on numbers of critical care beds. On average there were 11.5 critical care beds per 100,000 head of population with marked differences between Germany's 29 and Portugal's 4.

iv) Tippong *et al*. [26] considers healthcare coordination plans including the latest *COVID*-19 pandemic to have caused a shortage of healthcare resources and change in healthcare operations. This paper whereas provides a focused literature review of the *OR* (Operations Research) contributions in the coordination of healthcare systems during disasters on how to improve and manage the emergency medical response.

v) Weissman *et al*. [27] with an objective to estimate the timing of surges in clinical demand and the best- and worst-case scenarios of local *COVID*-19–induced strain on hospital capacity, designed a Monte Carlo simulation of a susceptible, infected model with a 1-day cycle. They concluded that this modeling tool can inform preparations for capacity strain during the early days of a pandemic. Current capacity across the 3 hospitals was defined as 1045 hospital beds, 253 ICU beds, and 183 ventilators, on the basis of internal estimates. Study was conducted in March 2020 within Philadelphia city.

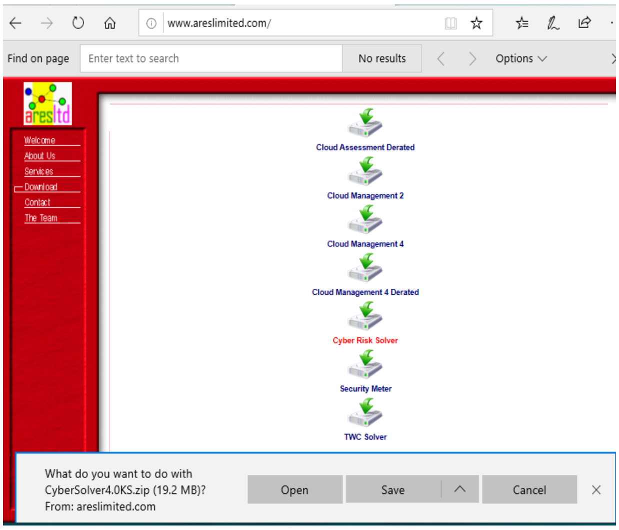
vi) Emanuel *et al*. [28] declared that among others in USA such as the scarcity of high-filtration N-95 masks and full-featured ventilators, South Korea in Daegu faced a hospital bed-shortage with some patients dying at home. While in UK protective gear requirements for health workers have been downgraded, causing condemnation among providers. How can medical resources be allocated fairly during a *COVID*-19 pandemic? They believe guidelines should be provided at a higher level of authority, both to alleviate physician burden and to ensure equal treatment without jeopardizing lives.

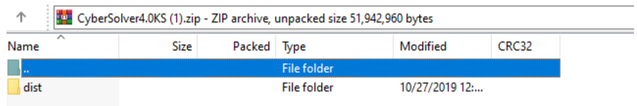
When the right moment arrives on what this contributing article proposes versus readers' plausible "So-What?" query, the two features are predominant: II.A) Risk assessment and management of bed-shortages, and II.B) Risk assessment and management of emergency (or e.g. pulmonary) physician-scarcities. Synthesizing instead of merely summarizing, the authors' contributions deserve to be compared and contrasted with other works in the current literature. Similarities and differences, or pros and cons, which one could outline as such are itemized in 10 categories as follow: *1)* This article proposes a macro-level design with a quasi-representative sample of five States (in USA) each with 44 to 51 networked-hospitals ranging from ~7500 to ~9800 installed beds during years of 2010 to 2018 yielding a high percentage of the installed beds as bed-demands according to the past patient visits obtained from *AHA* [8], *IHME* [9] and *AHD* [12] and similar resources in USA. *2)* Each State has an averaging (expected) effect of admission and discharge rates calculated. These rates are then utilized to evaluate the *CLOURAM* outcomes to design for bed-capacity and *MCQS* results to plan for physician-adequacy where each channel is a physician in residence. *3)* This genre of approach is not available in the literature so far as these authors have screened although Emanuel *et al.* [28] touches upon physician-scarcity but not offering a difference-making solution proposal. Tippong *et al.*'s research [26] is rather a review paper of *OR* considerations at large, not a specific solution oriented approach. In terms of bed-shortages where there exists multiplicity of micro-design studies within a particular University (Ghent or Augsburg etc.) hospital [23, 24] or of a city enclave such as Philadelphia [27], or Europe at large correlated with the nations' GDP [25], all which were beneficial during the hot-bed rampant pandemic. *4)* Deschepper *et al.* [23] for short-term predictions similar to authors' proposals used Poisson modeling with a multistate model whereas this article used a two-state model due to only COVID or non-COVID from the Johns Hopkins University data bank [29]. *5) CLOURAM* software from a macro-level perspective of five contiguous States' treats each state as in a *Cloud*-framework, interconnected and calculates the bed-count deficiency after at least 100 years of annual 8760h-long discrete event simulations. Though, similarities exist, others employ Monte Carlo simulations but may often last only for a short period of time ahead. Whereas, *CLOURAM* and *MCQS* are discrete-event-simulated cover a dynamic stochastic process, not static, ~1,000 or 10,000 more years ahead [1, 10, 18]. *6)* One other contrast between the two genre of approaches is that *CLOURAM* software uses the States' input data during the pre-*COVID* era before the advent of the pandemic at the outset of this research, whereas the other works used data at the scene of events at a limited scope. *7)* Another difference is that both of this article's approaches of risk management of bed- and physician-shortages follow a resource-optimization agenda in detail outlining the cost and benefit parameters in Tables VI and XI if additional beds or physicians are deemed necessary. *8)* This research is index oriented, i.e. besides the *LOLE* and *EUPU* of section II.A where loss of beds is the primary concern; whereas in II.B cost-optimal *k* count of physicians is introduced. In III.A, a probabilistic *CPNP* is defined utilizing Tables VI and XI in synergy for all States to compute the probability of a hospital network for not denying the needy patients. *9)* The *CON* laws for United States' future investments are critical. *10)* What does all this say at the terminal stage? This article differently yields a premeditated scientific message to design preventive and life-saving, remedial pandemic contingency plans for future on critical capacities, a process which was not feasible in 2020.

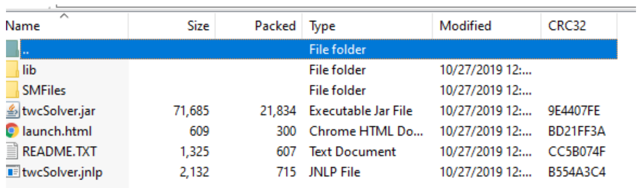
APPENDIX

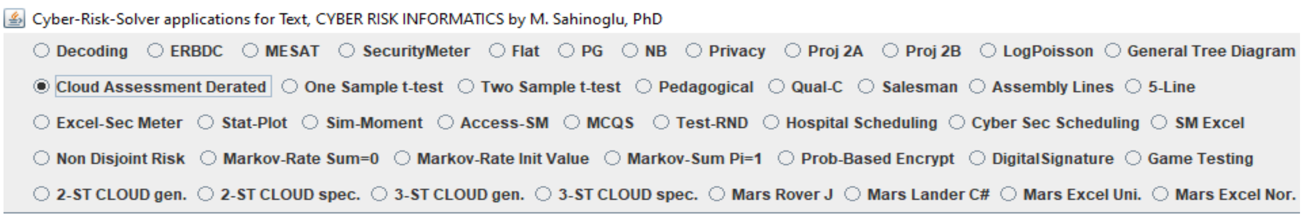
HOW TO INSTALL *CYBERRISKSOLVER* TO RUN THE *CLOUD ASSESSMENT DERATED* AND MCQS/HOSPITAL SCHEDULING:

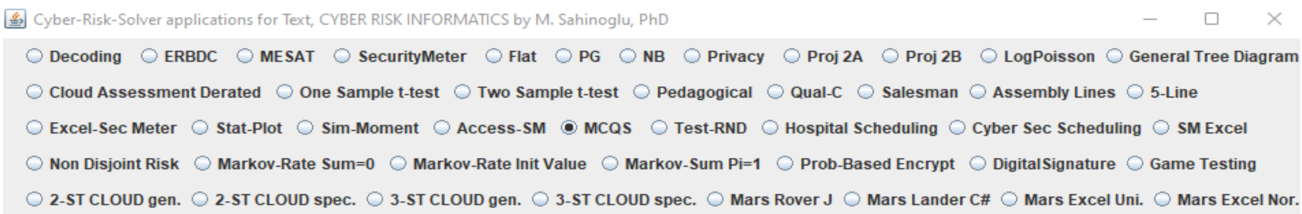
1. Click www.areslimited.com. Type in the user name: *mehmetsuna*, password: *Mehpareanne*, click OK.
2. Go to DOWNLOAD on www.areslimited.com for left hand side menu's 4th from the top.
3. Click on the Cyber Risk Solver in **red** and download the application which a ZIP file. Unzip or extract the downloaded application into C:\myapp folder. See C:\myapp\dist. Open a Command Prompt and go to C:\myapp\dist folder and run the command: //For Cyber Risk Solver, java –jar twcSolver.jar. Use license code: **EFE28SEP2020** for twcSolver.jar**.**
4. Click *Cloud Assessment Derated* and/or *MCQS* and Hospital Scheduling apps both (checked). Click Open. Enter input from Figs. 1-24 and Tables I-XXIII input and output data as deemed necessary.

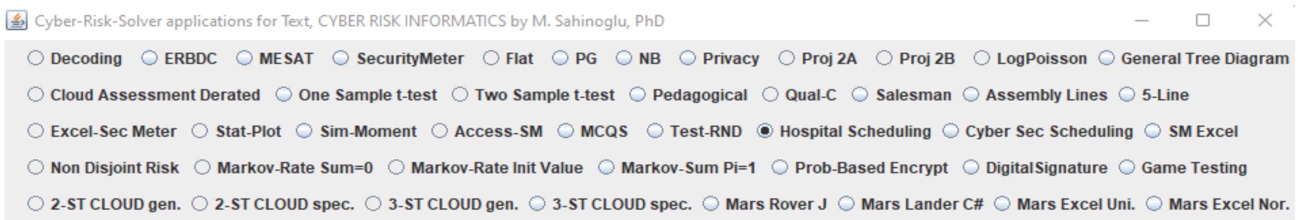












CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

The authors contributed to this article since 2019 before

COVID-19 in their strength areas; namely Dr. MS in creating the core methodology and simulation software, and Dr. FZ in UAB Health Administration's Health Care Management by finding *AHD* bed-capacity, data-mining and allocation limits.

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