



A Statistical Approach for Estimating Casualty Rates During Combat Operations

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Report No. 13-61

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80th MORS Symposium
Working Group (15) - Casualty Estimation and Force Health Protection, June 14, 2013

Descriptors: OIF, OEF, combat, wounded-in-action, distribution functions, and casualty rates

This work was supported by the U.S. Navy Bureau of Medicine and Surgery under Work Unit No. N1202. The views expressed in this work are those of the authors and do not reflect the official policy or position of the Department of the Navy, Department of Defense, or the U.S. Government. Approved for public release; distribution is unlimited.

Abstract

Estimating casualties during military operations is critical in planning the medical response to military operations. Casualties dictate medical requirements, supplies, and staffing. Casualty data, which includes wounded in action (WIA), and disease and nonbattle injury (DNBI) casualty rates, are expressed as the rate per thousand of the population at risk per day. Casualty rate estimation processes vary considerably for WIA and DNBI and are typically estimated using computer programs. The emphasis of this paper is on the development of WIA casualty rates and their distributions using mixture model distribution functions. This paper compares the distribution of WIA casualty rates from various combat units involved in combat operations in Afghanistan and Iraq.

Post-2004 casualty data were obtained from the Theater Medical Data Store, which is the authoritative in-theater database for service members' medical information. This database allows patient disposition tracking and displays longitudinal medical record information. Data prior to 2004 were obtained primarily from previously published technical reports, casualty counts from medical records, and casualty logs from various medical treatment facilities.

Casualty occurrence variability poses analytic challenges since the range of casualties can be as few as 1 per day to as high as 50 per day, as evidenced during the second battle of Fallujah. In this paper, random variables from lognormal, exponential, gamma, and Weibull distributions were generated and compared with the actual distribution of the casualty rates evidenced from selected combat units who saw recent combat in Afghanistan and Iraq. Goodness-of-fit tests were used to compare the accuracy of the probability distributions with the empirical data. After the rates and distributions were determined, daily casualty estimates were generated and modeled using a mixture model consisting of the underlying distribution and a Poisson distribution. One of the main advantages of using mixture models is that multistage hierarchy systems are often easier to model because one distribution's parameters become parameters for the other distribution. This paper defines a new approach to WIA casualty rate determination, contrasts that approach with past research, and provides insight into the approach's assumptions and limitations, as well as the importance of casualty rate estimation.

Introduction

Projecting illness and injury incidence during military operations is an essential element in medical resource planning. The Joint Staff Surgeons annually request service-specific casualty estimates through the combatant commands to establish expected patient workloads. Joint health service logistic support requires casualty estimates to determine the requirements for Class VIII medical supplies. For example, the Marine Air Ground Task Force Planner's Reference Manual (2001), section *Part IV Staff Planning Factors and Considerations*, contains a designated area for casualty rate estimation. Additionally, military medical planning and analysis tools such as the Joint Medical Planning Tool (formerly known as the Tactical Medical Logistics Planning tool) require casualty estimates to assist in determining the needed operating room beds, medical supplies, evacuation assets, and staffing for theater-level medical treatment facilities (MTFs). The casualty data consist of wounded-in-action (WIA) and disease and nonbattle-injury (DNBI) casualty rates expressed as the rate per thousand of the population at risk (PAR) per day. Casualty rate estimation processes vary considerably for WIA and DNBI and are typically estimated using computer software programs.

Casualty rate estimates can be refined through a number of adjustment factors, including type or number of troops engaged, battle intensity, geographical region, and the type or phase of an operation. Adjustment factors are coefficients that significantly influence casualty occurrences and require extensive data to quantify (Dupuy 1990). Examples of adjustment factors are weather, terrain, posture (offensive or defensive attacks), troop size, opposition strength, surprise of attack, sophistication of enemy, and pattern of operations. Although, the derivation and estimation of the adjustment factors are important elements in casualty estimation they have less impact on the probability distribution function of the casualty rates. For example, the WIA casualty rates of Battle of Okinawa were reported to be represented by an exponential distribution (O'Donnell & Blood 1993). Similarly, the WIA casualty rates from the major combat phase from Operation Iraqi Freedom (OIF) also fit an exponential distribution, as reported in this study. Consequently, this paper is limited to an examination and derivation of the distribution of the WIA casualty rates.

The U.S. military employs tiered medical care architecture to treat casualties in theater. First responder care is administered at or near the front, followed by forward resuscitative care, and, after evacuation, theater hospitalization for the more seriously wounded. Prior to 2004, data from forward MTFs (first responder and forward resuscitative care) were rarely electronically captured. Consequently, casualty estimates were often reverse engineered through multiplicative factors applied to the theater hospital data to obtain the casualty estimates for forward medical care. With the increased information technology capabilities and medical systems (e.g., Joint Patient Tracking Application, Global Expeditionary Medical System, TRANSCOM Regulating and Command and Control Evacuation System [TRAC2ES], Composite Health Care System, Armed Forces Health Longitudinal Technology Application–Theater) data are captured forward of theater hospitalization. These data are uploaded to the Theater Medical Data Store (TMDS), allowing for more accurate projections of workload requirements, not only at theater hospitals but at forward MTFs as well.

Computer-aided estimation tools have been developed based on previous research in casualty estimation. The Ground Forces and Casualty Forecasting System (Blood, Zouris, & Rotblatt 1997) and the Casualty Incidence Rate Calculator & Injury Type (Zouris et al. 2013) tools are two such efforts. Algorithm refinements in these and other tools are now possible due to the abundant casualty data contained in TMDS. These refinements are currently being incorporated into the Medical Planners' Toolkit (NHRC 2013).

The papers cited above discuss the advantages of using mathematical functions to model casualty occurrences, identify trends and patterns of variability, and emphasize the importance of using statistical approaches for estimating casualty rates during combat operations. It has long been known that casualty rates are a function of several factors, including, among others, the phase of an operation. It has been shown that similar operations conducted under similar conditions will exhibit casualty rates and wound distributions that are comparable to each other (Wing 2013, unpublished paper). It is this fact that makes prediction of future casualty rates based on empirical data so compelling. In this paper, a mixture model is developed and used to represent the presence of subpopulations within the overall population. While problems associated with "mixture distributions" relate to deriving the properties of the overall population from those of the subpopulations, "mixture models" are used to make statistical inferences about the properties of the subpopulations given only observations on the pooled population, without subpopulation identity information. This paper demonstrates the relationship of operational phase to WIA casualty rate using several examples from Operation Enduring Freedom (OEF) and OIF.

Method

Random variables from lognormal, exponential, gamma, and Weibull distributions were generated and compared with the actual distribution of the casualty rates evidenced from selected subpopulations (phases) in combat from recent Afghanistan and Iraq operations. Goodness-of-fit tests were applied to compare the probability distribution fit with the empirical data. After the rates and distributions were determined, daily casualty estimates were generated and modeled using a mixture model, based on the underlying distribution(s), and a Poisson distribution. The phases depicted in Table 1 were chosen as representative subpopulations because they offer examples of (very) low, medium, and high combat periods observed in OIF/OEF operations.

Table 1
Select OIF/OEF Combat Phases

Phase	Unit	Duration
OIF: Major combat	MEF	Mar–Apr 2003
OIF: The second battle of Fallujah	2 RCT	Nov–Dec 2004
OIF: The Surge	2 BN	Feb–Jul 2007
OEF: 2011	1 BN	Apr–Aug 2011

Note. BN = Battalion; MEF = Marine Expeditionary Force; OEF = Operation Enduring Freedom; OIF = Operation Iraqi Freedom; RCT = Regimental Combat Team.

Casualty Rate Formula

At its simplest, WIA casualty rate estimation is based on the number of casualties, duration of the operation in days, and PAR. Since casualty rates are expressed as the number of casualties per 1,000 population per day, the relationship is specified as (1) below.

(1)

Determination of Phases

For this paper, WIA casualty rates for OEF and OIF operations were determined based on representative combat phases, determination of phase duration, identification of the participating units involved, and analysis of the daily casualty counts. The phases selected took into account the peak involvement of combat activity and the availability of electronic medical records to verify the cause of injury and the specific combat unit(s) involved. Department of Defense casualty reports were used to identify the periods that had peak involvement of combat activity as evidenced from high casualty counts. Since planners base medical requirements on the 95th percentile estimates, these "phases" are more relevant (Wojcik et al 2004). From these criteria, the major OIF combat phase (March–April 2003), the second battle of Fallujah (November–December 2004), the troop surge in OIF (February–July 2007, described as the Surge), and high combat activity periods in OEF (April–August 2011) were selected.

Numerator Data—Pre-2004

The injury data for the OIF major combat phase (March–April 2003) were obtained from Marines seen at the Shock Trauma Platoons, Forward Resuscitative Surgical Systems, surgical companies, fleet hospitals, and Landstuhl Regional Medical Center. The data consisted of diagnostic codes in *International Classification of Diseases, Ninth Edition* (ICD-9) format, which provided cause, date, and severity of injury. TRAC2ES data and Personnel Casualty Reports were used to validate and verify information.

Numerator Data—Post-2004

The injury data for all the other phases (post-2004 data) were obtained primarily from the TMDS, which is the largest and most comprehensive expeditionary medical data warehouse. The TMDS was merged with additional data sources to create a comprehensive medical profile for each occurrence. No single data source exists that tracks patients from the point of injury, through acute care, and on through definitive care. Therefore, various data sets were used to generate a comprehensive hybrid database that capitalized on individual databases strengths (Zouris et al. 2011). The resulting hybrid database provides a single, more accurate, highly representative database depicting WIA events and casualty counts.

Denominator Data

The PAR data were compiled from the Defense Manpower Data Center (DMDC), Contingency Tracking System. The DMDC documents all completed Overseas Contingency Operations deployment events from the DMDC Contingency Tracking System Deployment File. This file contains one record for each deployment event, including the beginning date of deployment, the end date of deployment, the location country, and deployment duration.

Goodness-of-Fit Tests

Goodness-of-fit tests were used to test if observed casualty rate distributions from each phase could be represented by gamma, exponential, lognormal and Weibull distributions, but results only showing significance or marginal significance are reported. All statistical procedures were conducted using SAS software (version 9.3 for Windows, SAS Institute Inc., Cary, NC). The casualty generation was then modeled using a Poisson distribution. The input parameter for Poisson was obtained from the random variate from the initial fitted distribution. Unlike most statistical tests, we want to accept the null hypothesis, that is when $p > \alpha$ ($\alpha = .05$ usually is the significance level). The larger the *p* value, the less likely the distribution fit occurred by chance, assuming the null hypothesis is true.

H_0: The data follow the specified distribution.

Ha: The data do not follow the specified distribution.

Implementing Mixture Model Derivation

After the rates and distributions for each phase were determined, daily casualty estimates were generated and modeled using a mixture model consisting of the underlying distribution and a Poisson distribution.

Results

The casualty rates were calculated using formula (1) for each phase and are tabulated in Table 2. For all phases examined in this study, the second battle of Fallujah resulted in the highest average casualty rate (1.04) and the OIF major combat phase the lowest (0.14). Goodness-of-fit tests were performed for each phase and are examined in detail in the following sections. In addition, percentile distributions of the observed data are compared with the statistical distribution to enable the reader to visualize the estimates at various percentiles. In medical planning, upper percentile estimates are used rather than mean estimates to reduce risk (Zouris & Blood 2000; Wojcik et al. 2004).

Previous research indicated that WIA casualties were characterized by a nonstationary Poisson process best approximated by an exponential distribution (O'Donnell & Blood 1993). This study shows and confirms that the WIA rates can be approximated by an exponential distribution, but it can also be approximated by lognormal and gamma distributions as well.

Table 2
Selected Phases of Combat Operations During OIF and OEF Among Marine Corps Units

Phase	Size	Duration	Days	Average PAR	WIA counts	Average rate
OIF: Major combat	MEF	Mar–Apr 2003	41	49,154	273	0.14
OIF: The second battle of Fallujah	2 RCTs	Nov–Dec 2004	59	9,127	558	1.04
OIF: The Surge	2 BN	Feb–Jul 2007	180	2,664	122	0.25
OEF: Peak casualty counts	1 BN	Apr–Aug 2011	122	1,115	139	1.02

Note. BN = Battalion; MEF = Marine Expeditionary Force; OEF = Operation Enduring Freedom; OIF = Operation Iraqi Freedom; PAR = population at risk; RCT = Regimental Combat Team; WIA = wounded in action.

Major Combat Phase in OIF (March–April 2003)

Chi-square goodness-of-fit tests for this phase were conducted using lognormal, exponential, gamma, and Weibull distributions and were significant for both gamma (χ^2 = 2.87, p = .58, df = 4) and exponential (χ^2 = 2.68, p = .67, df = 4) distribution functions (Tables 3 and 4). Although the gamma distribution provides a good model for` the distribution of WIA rates, the exponential is the simpler model to implement.

Table 3
Chi-Square Comparison of Exponential (β = 0.136) and Observed Wounded in Action Rates During the Major Combat Phase

WIA rate interval	Observed n = 41 (%)	Expected n = 41 (%)	Total n = 82 (%)
[0, .025)	10 (24.39)	10.5 (25.61)	20.5 (25.0)
[.026, .075)	6 (14.63)	6.9 (16.83)	12.9 (15.73)
[.075, .15)	14 (34.15)	10 (24.39)	24 (29.27)
[.15, .25)	5 (12.19)	7.1 (17.32)	12.1 (14.76)
[.30, ∞)	6 (14.63)	6.5 (15.85)	12.5 (15.2)

Note. $\chi 2$ = 2.36, df = 4, p = 0.67

Table 4
Chi-Square Comparison of Gamma (α = 1.26, β = 0.12) and Observed Wounded in Action Rates During the Major Combat Phase

WIA rate interval	Observed n = 41 (%)	Expected n = 41 (%)	Total n = 82 (%)
[0, .025)	10 (24.39)	7.9 (19.27)	17.9 (21.83)
[.026, .075)	6 (14.63)	6.9 (16.83)	12.9 (15.73)
[.075, .15)	14 (34.15)	11.1 (26.43)	25.1 (30.61)
[.15, .25)	5 (12.19)	8.2 (20.0)	13.2 (16.10)
[.30, ∞)	6 (14.63)	7.0 (17.07)	13.0 (15.85)

Note. $\chi 2$ = 2.36, df = 4, p = 0.67.

The gamma distribution requires two parameters (α = shape and β = scale) as opposed to the exponential, which requires only the scale parameter. The shape and scale of the gamma distribution must be estimated using the method of moments or through maximum likelihood estimation. The shape and scale parameters were obtained using SAS. The scale of the exponential is equal to the mean (β = μ), which is easy to estimate, and when the shape parameter (α) is 1, the gamma distribution reduces to the exponential distribution.

Table 5 shows the fit of the two models compared with the observed data. Both distributions are good models for the distribution of WIA casualty rates during the major combat phase. Also, there is a great deal of variability in the rates as evidenced by the range of percentile estimates.

Table 5
Gamma and Exponential Distribution Percentiles Compared With Observed WIA Rates During the Major Combat Phase

	Gamma (α = 1.26, β =	Exponential (β = 0.136)

Percentile	Observed	0.12) estimates	estimates
5	0.000	0.002	0.007
10	0.020	0.012	0.014
25	0.040	0.042	0.039
50	0.102	0.099	0.094
75	0.163	0.191	0.188
90	0.284	0.307	0.312
95	0.351	0.393	0.406
99	0.750	0.589	0.625

Second Battle of Fallujah in OIF (November–December 2004)

The goodness-of-fit tests for the second battle of Fallujah were significant for both lognormal ($\chi2 = 2.78$, $df = 4$, $p = 0.59$) and exponential ($\chi2 = 4.45$, $df = 4$, $p = 0.35$) distribution functions (Tables 6 and 7). The lognormal distribution provides a good model for the distribution of WIA rates; however, the exponential is the simpler model to implement. The alpha (2) and beta (3) parameters for the lognormal distribution can be estimated using the following formulas, where the $\mu_n = 1.04$ and $\sigma_n = 1.36$ are the sample mean and standard deviation of the data.

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Table 6
Chi-Square Comparison of Lognormal ($\mu_n = -0.49$, $\sigma_n = 1.01$) and Observed Wounded in Action Rates During the Second Battle of Fallujah

WIA rate interval	Observed $n = 59$ (%)	Expected $n = 59$ (%)	Total $n = 118$ (%)
[0, .33)	20 (33.90)	15.9 (26.87)	35.9 (30.38)
[.33, .55)	11 (18.64)	11.1 (18.75)	22.1 (18.70)
[.55, 1.2)	13 (22.03)	17.1 (29.04)	30.1 (25.54)
[1.2, 2.6)	9 (15.25)	10.4 (17.72)	19.4 (16.49)
[2.6, ∞)	6 (10.17)	4.5 (7.63)	10.5 (8.90)

Note. $\chi2 = 2.78$, $df = 4$, $p = 0.59$.

Table 7
Chi-Square Comparison of Exponential(β = 1.04) and Observed Wounded in Action Rates During the Second Battle of Fallujah

WIA rate interval	Observed n = 59 (%)	Expected n = 59 (%)	Total n = 118 (%)
[0, .33)	20 (33.90)	16.1 (27.27)	36.1 (30.59)
[.33, .55)	11 (18.64)	8.2 (13.91)	19.2 (16.28)
[.55, 1.2)	13 (22.03)	16.2 (27.41)	29.2 (24.72)
[1.2, 2.6)	9 (15.25)	13.7 (23.28)	22.7 (19.26)
[2.6, ∞)	6 (10.17)	4.8 (8.13)	10.8 (9.15)

Note. $\chi 2 = 4.45$, $df = 4$, $p = 0.35$.

Table 8 shows the fit of the two models compared with the observed data. Both distributions are good models for the distribution of WIA casualty rates during the major combat phase. The 75th percentile for the observed and exponential (β = 1.04) random variable are nearly identical (1.205 ≈ 1.213).

Table 8
Lognormal and Exponential Distribution Percentiles Compared With Observed Wounded in Action Rates During the Second Battle of Fallujah

Percentile	Observed	Lognormal (μ_n = -0.49, σ_n = 1.01) estimates	Exponential (β = 1.04) estimates
5	0.110	0.053	0.117
10	0.219	0.109	0.169
25	0.329	0.298	0.311
50	0.548	0.718	0.615
75	1.205	1.437	1.213
90	2.630	2.386	2.237
95	4.492	3.104	3.227
99	6.245	4.772	6.416

The Surge in OIF (February–July 2007)

The goodness-of-fit test for the Surge phase was marginally significant ($\chi 2 = 7.06$, $df = 3$, $p = 0.07$) for a gamma distribution using the chi-square goodness-of-fit tests shown in Table 9. The upper percentile estimates are good approximations, which are typically more important for medical planning purposes. The 90th percentile estimate from the observed data was 5.95 compared with 5.39 from the simulated data (Table 10).

Table 9
Chi-Square Comparison of Observed Wounded in Action Rates and Simulated Gamma (0.74, 0.24) Random Variables

WIA rate interval	Observed n = 184 (%)	Expected n = 184 (%)	Total n = 368 (%)
[0,.26)	150 (81.52)	147.2 (80.0)	297.2 (80.76)
[.26, 595)	11 (5.98)	20.4 (11.1)	31.4 (8.54)
[.595, 1.01)	13 (7.06)	9.2 (5.0)	22.2 (6.04)
[1.01, ∞)	10 (5.43)	7.2 (3.9)	17.2 (4.66)

Note. $\chi 2 = 7.06$, $df = 3$, $p = 0.07$

Table 10
Percentile Comparisons of Gamma Distribution and Observed Wounded in Action Rates During the Surge

Percentile	Observed	Gamma ($\alpha = 0.74$, $\beta = 0.24$) estimates
5	0.00	0.000
10	0.00	0.000
25	0.00	0.000
50	0.00	0.028
75	0.251	0.183
90	0.595	0.539
95	1.006	0.876
99	1.784	1.775

OEF in 2011

The goodness-of-fit test for the OEF phase showed a significance level ($\chi^2 = 5.31$, $df = 4$, $p = .26$) for a gamma distribution (Table 11). The observed data were compared with a gamma distribution ($\alpha = 0.24$, $\beta = 4.26$). The majority of data contain zeroes, as evidenced by the 50th percentile of the observed data equal to zero. The percentile estimates are shown in Table 12.

Table 11
Chi-Square Comparison of Gamma (0.24, 4.26) and Observed Wounded in Action Rates 2011

WIA rate interval	Observed n = 121(5)	Expected n = 121(%)	Total
[0,.5)	83 (68.6)	77.33 (63.91)	160.3 (66.25)
[.5,2)	19 (15.7)	24.54 (20.28)	43.54 (17.99)
[2,3)	5 (4.13)	6 .46 (5.33)	11.46 (4.73)
[3,5)	4 (3.31)	6.50 (5.37)	10.5 (4.34)
[5,∞)	10 (8.26)	6.18 (5.11)	16.18 (6.69)

Note. $\chi 2 = 5.31$, $df = 4$, $p = 0.26$.

Table 12
Percentile Comparisons of Gamma Distribution and Observed Wounded in Action Rates During OEF 2011

Percentile	Observed	Gamma (α = 0.24, β = 4.26) estimates
5.0	0.00	0.00
10.0	0.00	0.00
25.0	0.00	0.00
50.0	0.00	0.08
75.0	1.09	0.53
90.0	2.18	1.95
95.0	3.26	3.81
99.0	7.62	11.32

Mixture Models Results

After the rates were modeled, the generation of the daily number of casualties was modeled using a mixture model of the exponential distribution or gamma and a Poisson distribution. The counts from the mixture model and actual counts are shown in Table 13. The simulated WIA casualty counts were effectively generated from a negative binomial distribution, which is a gamma–Poisson mixture distribution where the mixing distribution of the Poisson rate is a gamma distribution. The mixture model is summarized in the following formula.

(4) Daily number of WIA casualties = Poisson (λ) where

$\lambda \sim$ Exponential(β) * PAR/1,000 or

$\lambda \sim$ Gamma(α, β) * PAR/1,000

Table 13
Simulated Casualty Counts Using a Mixture Model

Operation	Phase	Days	F	Mixture Poisson (F)	Actual WIA
OIF: Major combat	Mar–Apr 2003	41	Exponential (β = 0.14)	267	273
OIF: The second battle of Fallujah	Nov–Dec 2004	59	Exponential (β = 1.02)	570	558
OIF: The Surge	Feb–July 2007	180	Gamma (α = 0.74, β = 0.24)	117	122
OEF: Peak casualty counts	Apr–Aug 2011	180	Gamma (α = 0.24, 4.26)	175	167

Conclusions

We found that WIA casualty rates can be modeled using an exponential or a gamma distribution across four representative combat phases from OIF and OEF. We have assumed that the four combat phases are representative of the combat operations over the past decade in Iraq and Afghanistan. Additional phases could have been proposed and examined and the results may have been different from what we obtained. We also found that the WIA casualty counts can be simulated using a Poisson mixture model, where the mixing distribution of the Poisson rate is the WIA casualty rate distribution. Statistical chi-square goodness-of-fit tests were used to select the WIA casualty rate probability distributions for the combat phases. The proposed casualty rate distributions were validated by the close correspondence of the Poisson mixture model simulated casualty counts to the actual casualty counts.

WIA casualty rates have been previously modeled by an exponential distribution (O'Donnell & Blood 1993), and our research confirmed that the exponential distribution effectively modeled the OIF major combat phase and the second battle of Fallujah. However, the gamma distribution best modeled the OIF Surge and OEF 2011 phases. The exponential distribution is a special case of the gamma distribution (when the shape parameter, α, equals 1), and our research showed that the more flexible gamma distribution could be used to model WIA combat rates for any of the four representative combat phases. The simulated WIA casualty counts were effectively generated from a negative binomial distribution, which is a gamma–Poisson mixture distribution where the mixing distribution of the Poisson rate is a gamma distribution.

Further, in modeling the WIA casualty rates and counts, we have ignored any auto-correlation of the rates and counts (O'Donnell & Blood 1993; Zouris et al. 2013) and other adjustment factors (Dupuy 1990; Zouris et al. 2013). The WIA rate auto-correlations and adjustment factors will need to be included in any medical planning tool that estimates WIA casualty rates.

The current research draws on recent combat medical encounter data that are more accurate and abundant than at any other time in history, with the vastly improved electronic data collection mechanisms in place since 2004. This research is an extension and improvement from earlier work (O'Donnell & Blood 1993) that analyzed data drawn from unit diaries of Marine Corps battalions stationed in Okinawa and Korea operations.

For future research, we propose that that DNBI rates be estimated by combat phases as in the current study. The WIA combat casualty rate estimation process should be modified to include adjustment factors and daily auto-correlations.

U.S. Department of Defense medical planners need accurate percentile estimates of the WIA combat rates for estimating casualty workloads and associated patient streams from combat operations. This research estimated WIA casualty rates and counts using reliably coded data from more than a decade of recent combat operations in Afghanistan and Iraq. The results build on previous research and provide refined, empirically derived casualty rate estimates that will improve modeling and simulation in combat medical planning tools.

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REPORT DOCUMENTATION PAGE

1. REPORT DATE (DD MM YY)
10 12 13

2. REPORT TYPE
Technical Report

3. DATES COVERED (from – to)
May–Dec 2013

4. TITLE
A Statistical Approach for Estimating Casualty Rates During Combat Operations

5a. Contract Number:
5b. Grant Number:
5c. Program Element Number:
5d. Project Number:
5e. Task Number:
5f. Work Unit Number: N1202

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13-61

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10. SPONSOR/MONITOR'S ACRONYM(S)
BUMED/NMRC

11. SPONSOR/MONITOR'S REPORT NUMBER(s)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

Estimating casualties during military operations is critical in planning the medical response to military operations. Casualty occurrence variability poses challenges since the range of casualties can be as few as 1 to as high as 50 per day, as evidenced during the second battle of Fallujah. In this paper, random variables from lognormal, exponential, gamma, and Weibull distributions were generated and compared with the actual distribution of the casualty rates evidenced from selected combat units who saw recent combat in Afghanistan and Iraq.

We found that wounded-in-action (WIA) casualty rates can be modeled using an exponential or a gamma distribution across four representative combat phases from Afghanistan and Iraq. We also found that the WIA casualty counts can be simulated using a Poisson mixture model, where the mixing distribution of the Poisson rate is the WIA casualty rate distribution. Statistical chi-square goodness-of-fit tests were used to select the fitted WIA casualty rate probability distributions for the combat phases. The proposed casualty rate distributions were validated by the close correspondence of the Poisson mixture model simulated casualty counts to the actual casualty counts.

This paper defines a new approach to WIA casualty rate determination, contrasts that approach with past research, and provides insight into the approach's assumptions and limitations, as well as the importance of casualty rate estimation.

15. SUBJECT TERMS
OIF, OEF, combat, wounded-in-action, distribution functions, casualty rates, mixture model

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES
UNCL	UNCL	UNCL	UNCL	16

18a. NAME OF RESPONSIBLE PERSON
Commanding Officer

18b. TELEPHONE NUMBER (INCLUDING AREA CODE)
COMM/DSN: (619) 553-8429

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39-18