Lifetime Estimation of Composite Bone Joint Screws

A. Khalatbari, K. Jenab, A. Varvani-Farahani

***Abstract*— Background: Bone screws are crucial elements in treating many types of open/closed fractures and arthroplasties in different joints in the body. The life time of many plates used in the fracture treatment are dependent on the screws function. The fracture of screws at any point of their lifetime will cause failure of the treatment for that specific pathology. This may lead to increase risk of new surgeries, osteomyelitis and less commonly septic arthritis. These complications not only have a negative impact on patient's quality of life, increase comorbidity and mortality but also increase health care cost significantly.**

Method: We study the lifetime of bone joint screws made up of biostable (polysulfone) and biosorbable (poly-lactide-co-glycolide) polymer composite materials. The lifetime estimations under in vitro conditions were calculated based on extremely small sample size. A computational intelligent model has been developed to estimate the lifetimes, which is superior to least square and real-coded Genetic Algorithm methods, specifically, for a small sample size of data. Retrospectively, 76 X-rays with screw fracture indication (37 polysulfon screws and 39 poly-lactide-co-glycolide screws) constitute the sample size in this study. The funding sources were provided by the office of research services at Ryerson University.

Results: The proposed model is a robust method because it does not converge to a local optimum, and also it does not need the use of differential calculus facilitating the computational implementation. The findings make a significant contribution to reliability of composite implants.

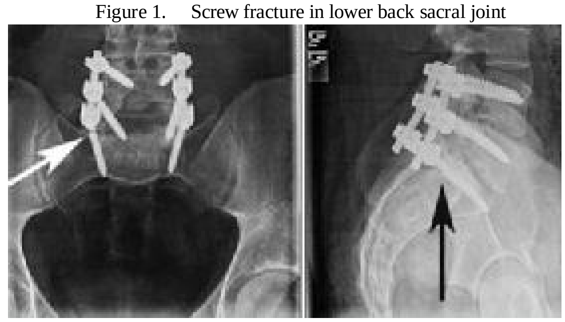
Conclusion: The application of this model for two types of composite materials used for bone joint screws proves that polysulfone screws lifetime is better than that of poly-lactide-co-glycolide screws. Therefore, using the poly-sulfone screws could decrease the health related complications such as new surgeries and osteomyelitis.

***Index Terms*— Intelligent computational, Lifetime analyzing; Composite materials, Composite bone joints, X-ray diagnosis.**

I. INTRODUCTION

Screws used in bone surgery are the types of implants, which fulfill the function of joining elements during bone healing process. As shown in Figure 1, the fracture of screws at any point of their lifetime will cause the failure of the treatment for that specific pathology. This may lead to increase risk of new surgeries, osteomyelitis and less commonly septic arthritis. Prediction of the screw lifetime is a significant factor in optimization and warranty [1, 2]. The life span of a screw, which is measured from some specified time until it fails, is presented by the continuous random variable 't'. One distribution that has been used extensively in recent years, to deal with such problems of reliability and life-testing, is the Weibull distribution. This was introduced by Weibull, who proposed it in connection with his studies on strength of material.

Figure 1. Screw fracture in lower back sacral joint



The cumulative distribution function for the 2-parameter Weibull is:

$$F(t) = 1 - e^{-\alpha^* t^b} \tag{1}$$

Where 't' denotes time to failure, b is the shape parameter, and $h = 1/a^{1/b}$ is scale parameter.

It is widely known that Maximum Likelihood Estimation (MLE) estimators are asymptotically unbiased with the minimum variance. Therefore, the maximum likelihood estimation is a commonly used technique for parameter estimation. It is indicated that MLE is superior to the estimation of a scale population parameter because the accuracy of MLE is better when the number of samples is increased [3]. MLE attempts to determine the Weibull parameter values a^* and b^*, where the likelihood function is a maximum. The likelihood function $L(a,b)$ is given by:

$$L(a,b) = \prod_{i=1}^{n} f(t;a,b) \tag{2}$$

Where n is number of data points.

The goal is to find a vector that maximizes the likelihood function $L(a,b)$. Generally, the values of a^* and b^* are

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computed numerically using either Newton-Raphson (NR) algorithm method or bisection method, however, these methods do not always work and may run into problems in several cases. The NR algorithm may converge to a local but not to a global maximum. It might also converge either to a local minimum or cycle between two points. Therefore, it will converge to an unpromising value, if the starting of the algorithm is close to unknown parameter instead of the true value. These unpromising estimates are carried out through the iterative procedure, hence producing skewed (or biased) values for the parameter estimates. Thomas et al., indicated some drawbacks of MLE for the estimation of 2-parameter Weibull Distribution [4]. Skinner et al., also recommended the use of the Least Square Estimation (LSE) for small sample sizes as compared to MLE [5]. The LSE based on Weibull Probability Plot (WPP) is one of the most basic methods used for estimating the Weibull parameters. The common procedure of this method is based on using the least squares regression of Y on X. the procedure minimizes the sum of squares of the vertical residuals to fit a straight line of data points on WPP in order to calculate the least square estimators. However, this method is known to be biased. In the existing literature, the least squares regression of X on Y (minimizing the sum of squares of the horizontal residuals), has been used by the Weibull researchers [6]. The LSE method is a very popular technique used to compute estimations of parameters and to fit data. In LSE, the unknown values of a and b parameters in the regression function are estimated by finding numerical values of the parameters. This minimizes the sum of the squared deviations between the observed responses $\hat{F}(t_i)$ and the functional portion of the model $F(t_i)$. Mathematically, the least squares criterion (i.e., SSE) is minimized to obtain the parameter estimates, i.e.,

$$Min\ SSE = \sum_{i=1}^{n}\left[F(x_i) - \hat{F}(x_i)\right]^2 \tag{3}$$

This minimization takes place by taking partial derivatives of SSE with respect to a and, b , setting each partial derivative equal to zero, and solving the resulting system of two equations with two unknowns. Furthermore, it is difficult to exactly picture the accuracy of parameter estimator of the LSE. Generally, iterative methods are often used. These methods search in a stepwise fashion for the best value of parameters. For two parameter Weibull distribution, they turned out to be good methods provided that an appropriate initial point is available. However, these methods are not recommended for estimating three parameter Weibull distributions because they may not guarantee global optimality with certainty. A stochastic optimization algorithm known as simulated annealing [7] can overcome the local maxima problem at least in theory.

Nevertheless, this algorithm may not be a feasible option in practice as it may take a realistically long time to find the solution. All above, the need of a promising approach for Weibull-parameter estimation has motivated us to develop a computational intelligence based approach, which provides a feasible option in theory as well as in practice to estimate the lifetime of bone joint screws.

II. Intelligence Based Model

Thomas et al., utilized real-coded GA to estimate the parameters of Weibull distribution and compared it to MLE [4]. They finally concluded that the real-coded GA was superior to MLE regarding accuracy of the two parameter Weibull distribution. Their results showed that the parameter estimated values obtained by the real-coded-GA were better than those of the MLE parameter estimates in each of their four cases. However, after the study and implementation of this real-coded GAs, we observed that there are some weaknesses in implementation of real-coded GAs. Firstly, a major drawback of GAs observed is, if an inappropriate initiate solution population is chosen, it leads the converging fitness function to a local minimum. Consequently, it can be a very time intensive process to leave (dig itself out of) the local minimum and move to the global minimum. Secondly, the genes from a few comparatively highly fit (but not optimal) individuals may rapidly come to dominate the population that causes it to converge to a local maximum. Once the population has converged, the ability of the GA to continue the search for better solutions is effectively eliminated. Only “mutation” remains to explore entirely new ground, and this simply performs a slow, random search. Figure 2 illustrates the newly developed model for estimating Weibull parameters. This figure demonstrates how the evolutionary operators are combined with the statistical methods to estimate the Weibull parameters. In order to compare the model to the LSE and Real- coded GA, the following simulation based on Monte Carlo simulation has been performed [8].

A. *Database generation*

The high performance of the computational model is evaluated by means of the Monte Carlo simulation. The Weibull Parameters (a_i, b_i) were selected randomly between 10^{-6} and 10^{-2} range, and between 0.5 and 3.5 range for a and b, respectively. The Monte Carlo inversion method consists of a pseudo-random number generator to generate models in a priori model space. Using some quantitative criteria to decide the acceptability of models, it computes the forward solution for each model and compares measured and modeled data [8]. We applied this method to produce screw random failure time based on a distribution like Weibull-Distribution.

B. *Confidence intervals*

In order to limit the large search space, we applied a statistical method namely “Confidence bounds” [9]. Figure 3 illustrates how the limitation of Weibull parameter is taking place.

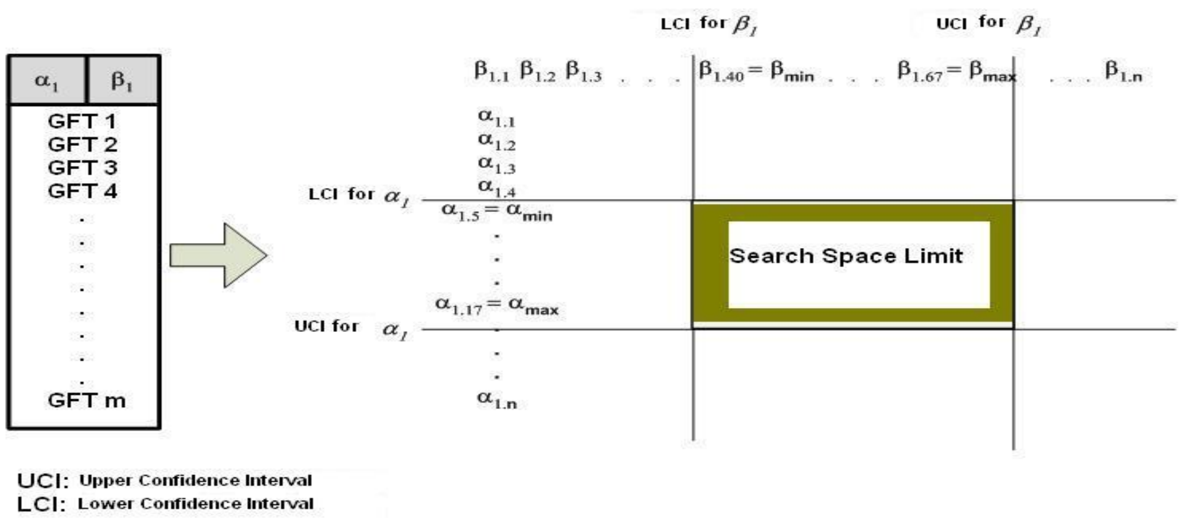

Figure 3 Search space limit

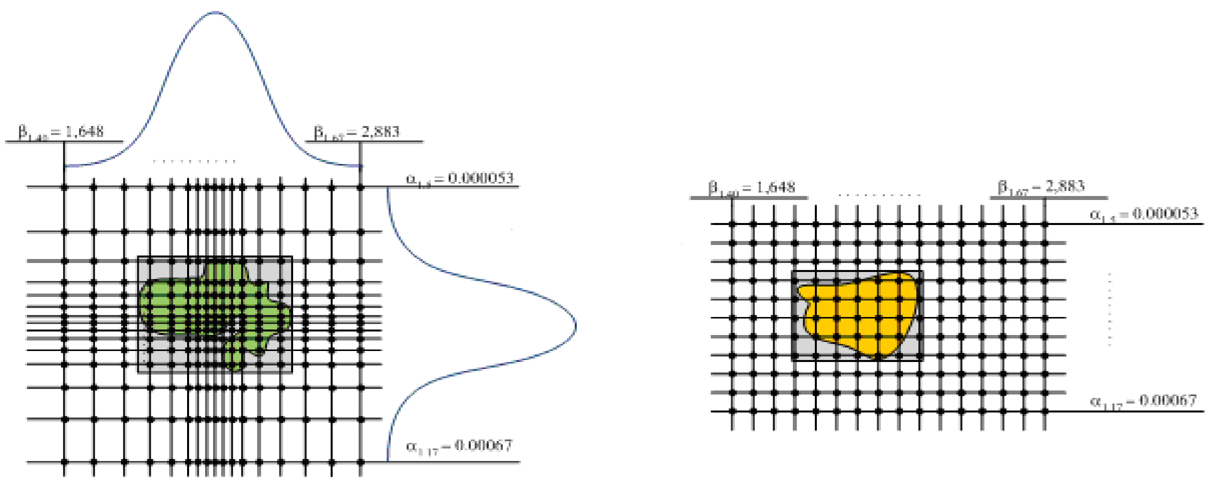

Figure 4 Confining procedure using combination of deterministic operators and Gaussian operators

The limitation of search space is performed in 3 steps. In Step 1, the upper and lower confidence interval of each sample data is obtained by means of the Beta distribution. In Step 2, the upper and lower confidence interval is fitted to a Weibull-distribution. The parameters of lower confidence interval ($a_{\min}, b_{\min}$) and the parameters of upper confidence interval ($a_{\max}, b_{\max}$) are easily estimated using linear regression.

A. *Intelligence based search*

The boundaries of different Parameters (a_i, b_i) are assumed to be known and kept constant in the Monte Carlo simulation by means of the determination of Confidence Intervals . After the confinement of search space using confidence intervals, the first iteration that is the LDC attempts to constitute a rough search concurrently. The places searched by deterministic crossover are regarded as the parent solution.

The mutation operator perturbs in every parent solution to create a new population. The best candidates will be selected based on the fitness function SSE. The best candidates let us know how much the search room will be confined as illustrated in Figure 4. In the next iteration, the confined search space will be searched by the means of the LDC more precisely in order to move from a possibly local minimum to the global minimum of SSE. If the stopping criterion is not met, further iterations and mutation will be performed more precisely.

III. LIFETIME PREDICTIONS FOR BONE JOINT SCREWS MADE OF POLYSULFONE AND POLY-LACTIDE-CO-GLYCOLIDE

To predict lifetimes for screws made of biostable (polysulfone) and biosorbable (poly-lactide-co-glycolide), the intelligence based model is used and its result is compared to the results of least SSE, and of real-coded GA. Retrospectively, X-rays of 37 polysulfone and 39 poly-lactide-co-glycolide screws with fracture indication have been pulled out from seven radiology departments. Both polymer and composite screws are manufactured by injection modling with geometry as shown in Figure 5. The data sets A and B represent the polysulfone screws and the poly-lactide-co-glycolide screws, respectively.

The numbers of sample and failure times in data set A are 37 and 6. For data set B, the numbers of sample and failure times are 39 and 12. As shown in Table 1, the SSE values of the intelligence based method for both data sets A and B are 0.037694 and 0.068198, which are less than those of other methods. Also, using this method, these results obtain through less iteration. For example, the numbers of iterations for data sets A and B are 37 and 21. Therefore, this comparative analysis proves the novelty and competence of the proposed method for the small sample size of data related to polymer and composite screws over the real-coded GA and the LSE. Also, based on the values of Weibull parameters, it can be concluded the polysulfone screws have better lifetime in vitro conditions.

IV. Conclusion

Lack of subject with fracture of bone screws becomes crucial for LSE and real-coded GA estimation methods. Therefore, this study aims at developing a computational intelligence based model that is capable to estimate the lifetime of composite bone joint screws with extremely small sample size. The newly developed model shows significantly better results in comparison with LSE and real-coded GA. The application of this model for two types of composite materials used for bone joint screws proves that polysulfone screws lifetime is better than that of poly-lactide-co-glycolide screws. Therefore, using the polysulfone screws could decrease the health related complications such as new surgeries and osteomyelitis. This means less number of operation and hospitalization which not only has positive impact on family dynamics but also decreases the financial burden in the health care system.

V. Acknowledgment

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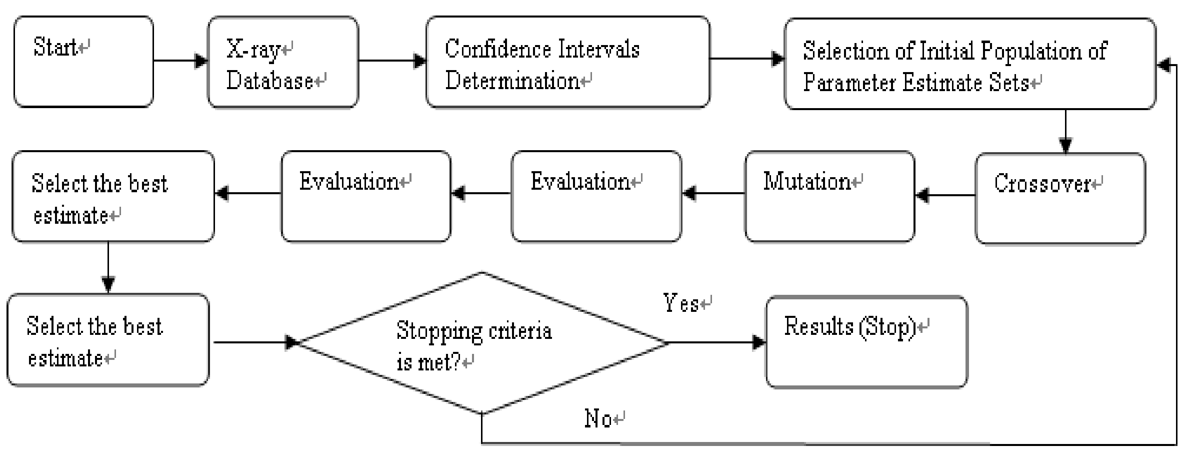

Figure 2 The statistical evolutionary approach for estimating Weibull parameters

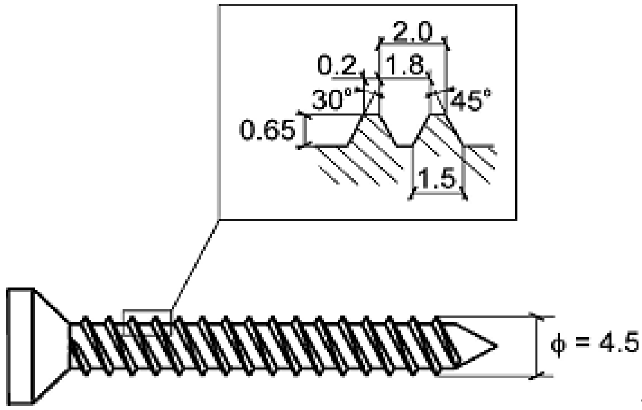

Figure 5 Geometry of joint screws

Data set	Method	*a*	*b*	**SSE**	**Best**
Data set A: Biostable (polysulfone)	LSE	0.0002842	0.81732	0.041128	
	Real-coded GA	0.0002993	0.82674	0.046712	
	Computational Intelligence based model	0.0027019	0.84979	0.037694	*
Data set B: Biosorbable (poly-lactide-co-glycolid e)	LSE	0.0025341	0.58232	0.075362	
	Real-coded GA	0.0027293	0.59281	0.082291	
	Computational Intelligence based model	0.0023111	0.60542	0.068198	*