Prediction of Wear Rate of Polyethylene Bearing in Total Hip Replacement Implants using Linear Regression Model

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Abstract

For total hip replacement implant bearings, pin-on-disc (PoD) studies are commonly performed to quantify wear of different bearing material. However, it is difficult to compare polyethylene wear results from multiple PoD trials, which may lead to knowledge being lost. In the present work, a machine learning based linear regression model is trained by quantifying the error encountered during model training. The linear regression model is able to predict the wear rate of polyethylene bearing material with the accuracy of 95% when compared with the actual wear rate of polyethylene bearing material taken from literature.

Keywords. Total hip replacement, artificial intelligence, linear regression, polyethylene wear rate, Pin-on-disk test.

1. INTRODUCTION

The bones present in human body are made up of strongest material, but bone fractures come into existence as external forces are applied or the individuals suffer from osteoporosis and femur necrosis. Despite the ability of the associated tissues to mend themselves, some bone injuries are permanent and irreversible [1-3]. Hip injury is a significant and regular occurrence that can be extremely debilitating, resulting in permanent disability. Hip fracture related injuries are anticipated to grow to about 6.26 million worldwide by 2050 [4]. As many person with hip joint related illness struggle to even do daily chores, hip replacement surgery has gained its popularities. In 'total hip replacement surgeries', the hip joint is replaced by an artificial metallic and polymer based joint, which transfer bodyweight to the femur [5]. The primary goal of hip replacement is to alleviate discomfort and increase mobility. The total hip replacement implants are composed of metallic femoral and polymer bearing cup component which are intended to restore the function and relieve pain of hip joint [6]. The most prevalent bearing material in total hip replacement implants [7] is metal-on-polyethylene (MoP), which typically pairs a metallic femoral head with a polymer based acetabular cup. Polyethylene wear debris has the potential to promote osteolysis (bone weakening) [8], which may make the implant loosemechanically unstable [9]. Several attempts were made by researchers all across the world to enhance the mechanical and tribological properties of polyethylene liners viz. crosslinking and vitamin E blending to the polyethylene. In vitro and in vivo show that high crosslinking of polyethylene and blending of vitamin E produce less wear as compared to conventional ultrahigh molecular weight polyethylene (UHMWPE) [10, 11].

Pin-on-disc (PoD) wear studies are prevalent approaches for quantifying, comparing, and ranking wear of various polymer based bearing materials [12]. On the other hand, computational wear modelling could be a remedy to the POD tests shortcomings. Many mathematical wear models have been formulate d and available in the literature, and are used to assess the wear of polyethylene based bearing materials. Machine learning-based algorithm is another major modelling approach that scientists, engineers, and researchers in the field of wear modelling are considering these days. It may also be used to estimate the mechanical and tribological properties of composites and medical-graded polymers [13-16]. Materials scientists, on the other hand, have made strides in recent years by having used machine learning approaches in conjunction with experimental dataset to make it easier to model complex material connections, components structure, and the mechanical attributes that go with them [17]. These data-driven models allow the comparison of exisitng datasets with the newly developed ones. Prediction of new outcomes based on previously learned information, which would be difficult or time-consuming to gather otherwise using conventional research procedures(@vipin please revise this sentence) [18]. One of the advantages of machine learning is that some models can be trained on massive amounts of data, also known as "big data." The more data the underlying model is trained on, the more accurate its predictions get [19], which improves the usage of these models in decision making. Decision trees, support vector machines, regression analysis, and Bayesian networks are among the ML models employed [20, 21]. In addition, a subset of machine learning known as "deep learning" has been developed, which comprises models based on artificial neural networks (ANNs) for evaluation of wear performance of total knee replacement implants. These models have the advantage of not requiring humans to preprocess the data; instead, they can evaluate raw inputs and determine which attributes are most significant for a study. Thus, the aim of the current study is to use machine learning based linear regression method to create a model which should be able to make predictions of wear rate of polyethylene based bearing materials. A model similar to this may be used to enhance PoD wear tests and discover previously unknown correlations between polyethylene wear rate and PoD operation parameters.

2. MATERIALS AND METHOD

2.1. Linear regression model

The relationship between the feature and actual dependent values can be given as

$$y = b_0 + b_1 x_1 + e \qquad (1)$$

The estimated regression model takes the following form:

$$y = b0 + b_1 x_1 \qquad (2)$$

and the following relationship is used to compute the regression error:

$$e = y - y \qquad (3)$$

where, y and y are the actual dependent value and estimated dependent variable, x_1 and b_0 are the explanatory factor and intercept term, b_1 and e are the sensitivity of y to factor x and regression error terms respectively. Figure 1 depicts the entire flow chart of the methods used to train and test the network. The training and testing of this network entails multiple processes, including the data collection, data split into training and testing datasets, definition of machine learning model, error computations, and ultimately testing the network with a new input dataset.

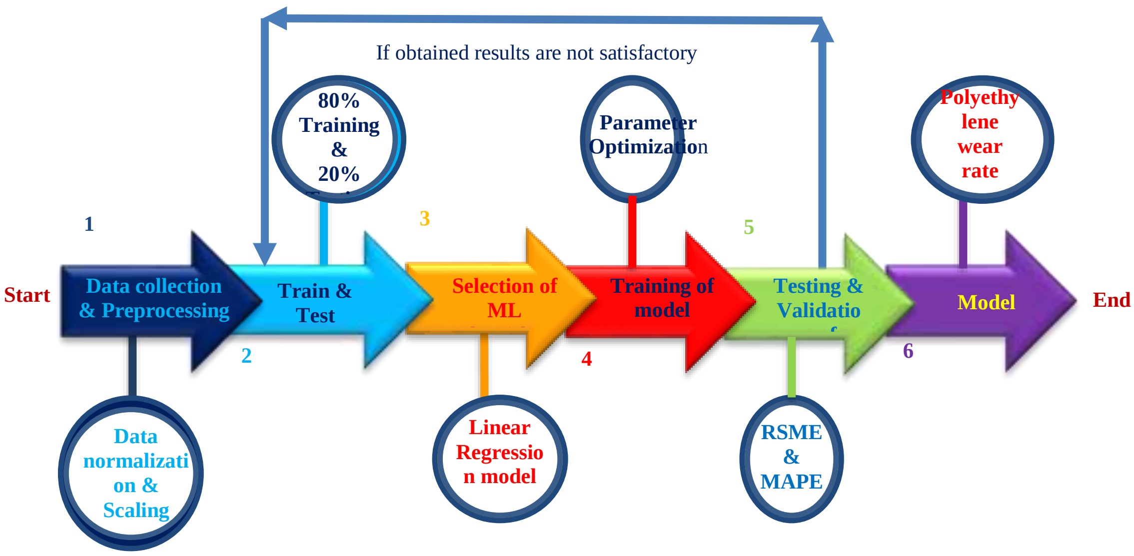

Figure 1. A flowchart showing the process of developing a linear regression algorithm

2.2. *Modelling Performance Criteria*

A) Mean Square Error

The root mean square error is defined as

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_i)^2$$

where,symbols have the same meaning as explained earlier in section 2.1.

2.3. *Data Collection and Preprocessing*

The experimental raw dataset, based on POD test, of all parameters and polyethylene wear rate is collected from available literature. After acquired dataset is scaled and normalized to ease the linear regression model training, normalized dataset is split into training and testing dataset. The 80% of available dataset is used for training and 20% for testing of linear regression model respectively.

The kernel density estimate plots are used to observe the probability distribution of variables. These have been s in Fig. 2. Kernel density estimation (KDE) is a non-parametric method of estimating a probability density function of a random variable. Kernel density estimation is fundamentally data smoothening problem in which statistical predictions are obtained from a discrete dataset. The statistical properties viz: minimum (min), maximum (max) and standard deviation (std) of all wear parameters that affects the wear of polyethylene acetabular cup in total hip replacement are summarized in Table 1.

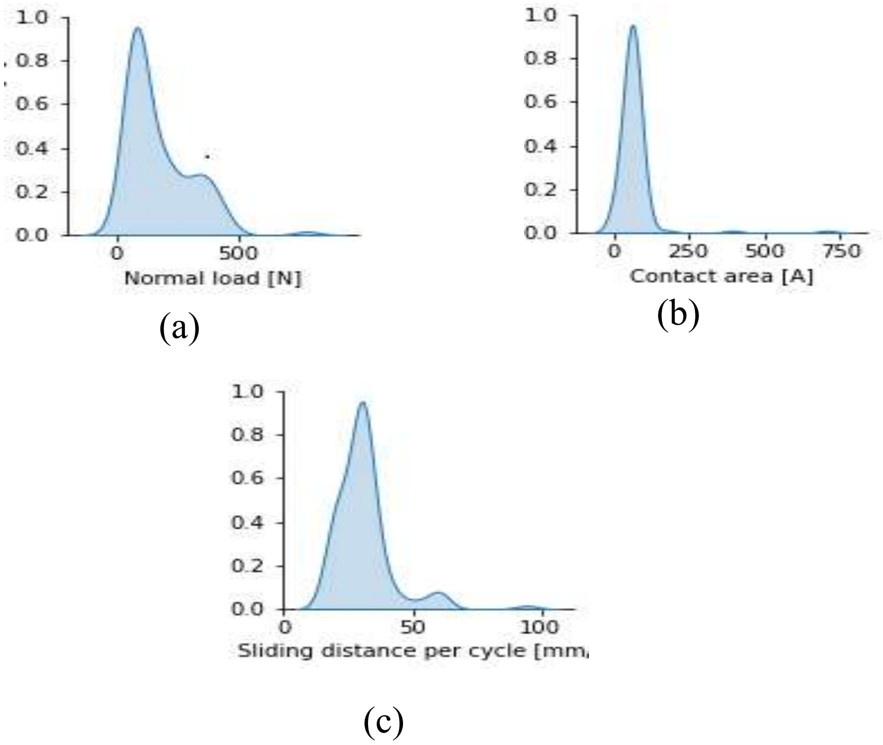

Figure 2. Schematic diagram of kde distribution of variable

Table. 1 Statistical parameters of wear variable and Polyethylene wear rate

	count	mean	std	min	max
Normal load [N]	103.0	168.915495	132.329401	7.00	777.546
Contact area [A]	103.0	69.954466	74.238209	7.07	706.860
Sliding distance per cycle [mm/C]	103.0	30.899320	11.088335	17.76	94.250

The linear regression model was trained by considering mean square error and 'Adam' as loss function and optimization function respectively. The value of learning rate was taken 0.1 during whole model training.

3. Results and Discussion

The training and validation losses obtained during dataset training are shown in Figure 3. The regression model can fit the training dataset accurately when there are only a few instances, say two or three. However, when more new instances are added to the model, it begins to fit incorrectly. The ultimate purpose of a regression model is to reduce the error that it produces while comparing predictions with real time data. The learning curve descends smoothly and steeply for each epoch before flattening out at the end. As the number of instances and epochs progresses, both training and validation curves matches

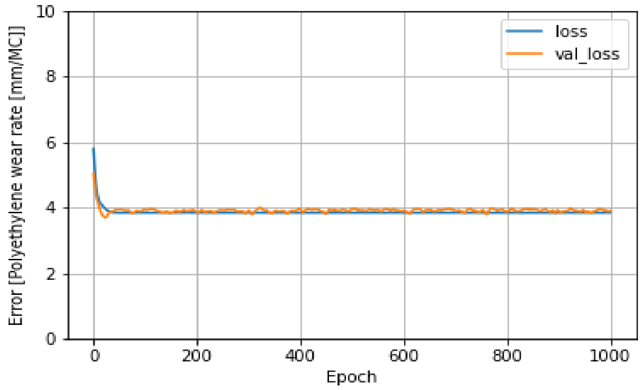

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Figure 3. The schematic diagram of regression vs number of epochs (@vipin please make this figure in origin)

The actual and predicted values of polyethylene wear rate using linear regression model have been shown in Fig. 4. As explained earlier, for a few starting instances, the model has the capability to predict a data accurately but as training of model proceeds, the model starts to manifest over-fitting and under-fitting of input dataset. Upon further training of regression model, it starts to fit the data accurately and manifests good convergence. This behaviour of model is just because of training data may have some noise. Therefore, before training of regression model, all the noise and the irregularities present in the input dataset should be removed by applying scaling and data filtering procedures.

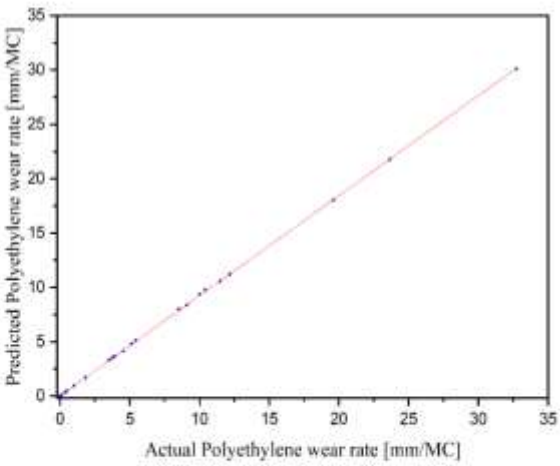

Figure 4. Scattering diagrams between predicted polyethylene wear rate and actual polyethylene with linear regression model with normal load as input variable. (Please prepare this graph in better way in origin, increase the data point size to visibly big)

In the current work only one variable i.e. normal load is considered on hip wear. In practical applications the effect of other variables viz., contact area, also exists. Therefore, to enhance the prediction capabilities of the current model more variables should be incorporated in this linear regression model. Further, the experimental dataset used for training of the model is also very small, therefor a large dataset should be used for better prediction of polyethylene wear rate in total hip replacements implants.

4. CONCLUSION

The polyethylene wear rate is estimated using a linear regression model technique with normal load as an input variable in this study. The aim of this study is to see how effective a linear regression model may be in tribological analysis in the setting of total hip replacement. When compared to standard polyethylene wear rate, it is established that the proposed model has a prediction accuracy of 95%. Thelinear regression model is suitable for obtaining perfect tuning between input variables and target values.

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Biographies

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