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Comparative Analysis of Fracture Healing Predicted Using Mathematical Model and Soft Computing Technique

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Abstract

Exact diagnosis of Fracture Healing period is a challenging task to medical practitioners. Recent studies have addressed the problem of ‘fracture reunion prediction’ by different methods including electrical stimulation approaches. In this work, comparison of fracture healing period diagnosed using mathematical modeling of tibia fracture and Neural Network is presented. Using the electrical data recorded across 32 different tibia fracture patient’s empirical models like FOPDT (First order plus dead time), FOPDTZ (First order plus dead time and Zero) and higher order model were developed. The 32 patients were classified into 4 group’s namely fresh presentation, presentation after a medium delay, presentation after a long delay and facture with gap. Neural network was trained using electrical data recorded across different tibia fracture patients whose fracture site was stabilized using Teflon coated rings and a DC input voltage of 0.7V was applied via K-wires. A three layered feed forward neural network model designed using Levenberg-Marquett (LM) Back propagation training algorithm was able to predict the fracture reunion prediction with Relative Absolute Error (RAE) of 0.12 to 3.5.

Introduction

Increase in Road accidents has resulted in the most common injury namely the bone fractures treated by orthopedic surgeons. Fracture treatment involves lengthy period of lost man-days, with soaring expenditure involved in health care. The need is to exactly predict the time of healing i.e. when the bone has regained adequate strength to be loaded in the normal manner. However during the course of treatment of any fracture, it is complex to predict at which time exactly a given fracture has united. This knowledge of the exact time at which a fracture unites is vital for both the patient and the medical practitioner in order to reduce the immobilization time and re-fracture risk. Moreover, there is every chance of accidental mistakes so that a fracture may be loaded prematurely or unloaded long after the actual union. X-rays are used to determine fracture healing which has many demerits [1-5]. Recently electrical stimulation was tried as a method to diagnose fracture healing [6-8]. Still the closing assertion in the papers is that these fractures are in the process of healing. There is no exact prediction of fracture healing. In an attempt to simplify the fracture healing process, models have been proposed to relate all possible data and observation to understand this process better. Some authors have proposed a first order system, which has been tested and validated only on animals [9-12]. Sridevi et al[13] has designed and controlled non linear interaction process using soft computing technique. In our earlier work the prediction of healing period of a human tibia fracture across limb using first order mathematical model was demonstrated. The experimental data fitted a First order plus dead time Zero model (FOPDTZ) that coincide with the mathematical model of electrical simulated tibia fracture limb. Fracture healing diagnosis was proposed using model parameter process gain. Current stabilization in terms of process gain parameter becoming constant indicates the healing of fracture. An error analysis was performed and it was observed that the measured data correlated to the FOPDTZ model with an error of less than 2 percent. Prediction of fracture healing period was done by one of the identified model parameters namely process gain [14].

The above authors have not analyzed fracture-healing prediction using electrical data recorded across limb by soft computing technique. In this work fracture-healing predicted by FOPDT (First Order plus Dead time), FOPDTZ (First Order plus Dead Time with Zero), higher order empirical models and neural network is compared and error analysis performed. Models were validated using the real time electrical data to predict the exact instance at which a fracture has reunited completely. The predicted and actual performances were evaluated for various models.

Experimental Setup

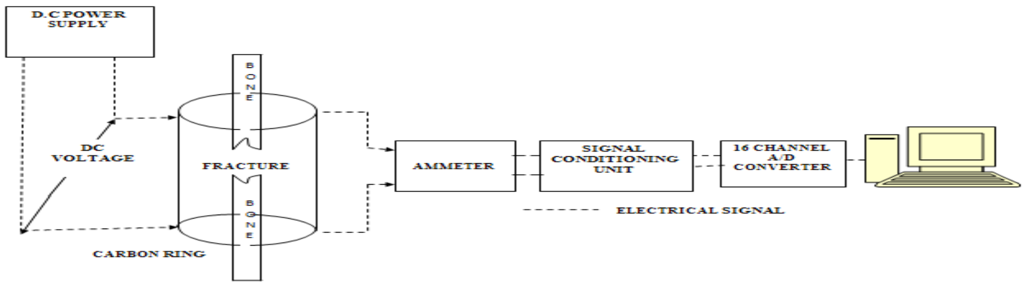


Figure 1a): Experimental Setup For Fracture Healing Prediction Analysis

Figure 1b): Photographic view of Experimental setup for fracture healing prediction analysis.

The experimental set-up for fracture healing prediction analysis is shown in Figure1a) and photographic view in Figure 1b).As fracture healing is a complicated process, data from the prospective study that was conducted (Kumaravel et al.2009) was used in this study. Open fractures of tibia were cleaned of debris and contaminants and were stabilized with four Teflon coated carbon ring Ilizarov external fixators. In these cases the healing was followed with clinical assessment and periodical X-rays till the endpoint of fracture union before the removal of rings. Additionally, all these patients also had application of DC electrical voltage in the range of 0.1-1.0 V in 0.1 V increments, across the two wires on either side of fracture. For safety reasons in the study, the maximum output current was kept not to exceed 1000 mA .The output data corresponding to 0.7V is taken for testing and training purpose for this study. The output current was recorded by an ammeter connected in series. The voltage was calibrated in terms of current using M/s AD Instrumentation 16 channel data acquisition card via signal conditioning unit. The card was connected to the USB port of the Pentium processor with an in built anti aliasing filter. The card supports 16 ADC and DAC channels in the range of ±15V. Program was developed in ‘C’ language to read and display the patient’s current rating in terms of mA. The graph was compared with the appearance of new bone in X-rays. The above methodology was carried upon 32 different patients at Thanjavur government medical college to predict the exact instance at which a fracture has united completely. The 32 patients were classified into 4 groups namely fresh presentation (patient was presented to practitioner within 2 weeks) , presentation after a medium delay (patient was presented to practitioner within a period more than 2 week but within 2 months) and presentation after a long delay (presented to practitioner after 2 months) and Fourth group were facture with gap. For all the four different groups (case) of patients same fracture healing pattern was obtained. The real time experimental data was shown in figure 2.In figure2. Case-1 shows the output response recorded during fracture treatment using DC electric simulation for one of the fresh presentation patient to the clinician. Case2 corresponds to response of a medium delay patient while Case3 corresponds to long delay more than 2 months. Case 4 shows the response of a patient presented with a fracture gap and was presented after 2 months delay to clinician.

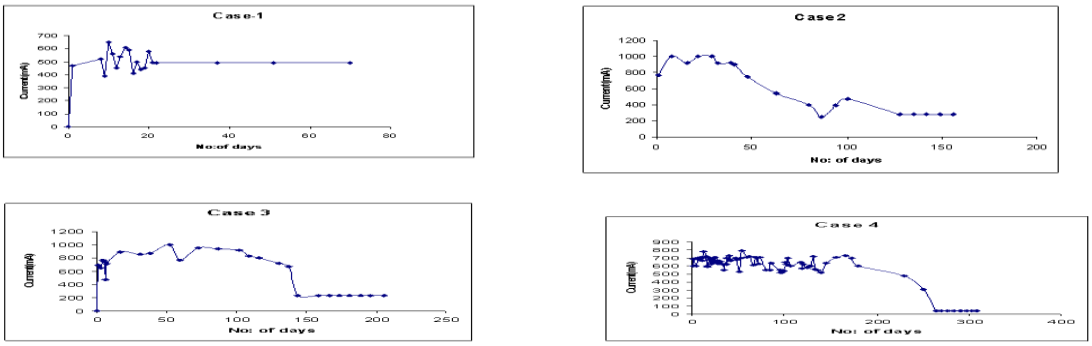


Figure 2: Real time experimental output responses for the four tibia fracture cases.

Empirical Model For Tibia Fracture

Three different empirical models were developed to predict the healing of fracture and error analysis was performed. Model relies on input/output data for its training and capturing the dynamics of the process. In this study, the applied DC voltage is the input variable and the current across the tibia fracture is the output variable. A sampling time of 0.1ms is used for the simulation. For the applied DC voltage the resulting current values are stored in the MATLAB workspace. Here, the Empirical model of the tibia fracture is obtained by training the model with an input and output data of 1000 sets. Of these, 600 data pairs are used for training and the remaining 400 are used for validation of the network. The development of FOPDT, FOPDTZ (First Order plus Dead Time with Zero), Higher order empirical models are discussed in brief.

FOPDT Model

In process control industries the general methodology for modeling is to develop a FOPDT (First Order plus Dead Time) model. The first step in modeling is parameter identification. To develop an Empirical model for the tibia fracture, available data is plotted to visualize the overall trends in the data to set a form for the model. After the model form is set the unknown model parameters are calculated using semi log plot/S-curve/Process reaction curve methodology [13].S-curve is a plot of the output response of a process to a step change in input which is the most widely used method for identifying dynamic model. It is an S shaped curve and FOPDT model is obtained. The general form of FOPDT model is given by equation 1.

$$G(s) = \frac{K_p e^{-\tau_d S}}{\tau S + 1} \tag{1}$$

Where Kp is the process gain; τ is the process time constant and τ_d is the measurement delay. Several methods are available to obtain FOPDT model parameters, out of which Sundareson and Krisnaswamy has proposed estimation of model parameters in time, frequency and Laplace domains in the year 1978. In S-curve methodology as shown in Figure 3, plot will be drawn using the measured current output in Y axis to no: of days in X-axis. A tangent to the plot is drawn. The distance between the point of inflection where the tangent meets the X-axis from the origin gives the delay time (τ_d).The slope gives the process gain Kp. The distance between the point where tangent meets the X-axis and the 63.2% of final value of set point gives the time constant(τ).

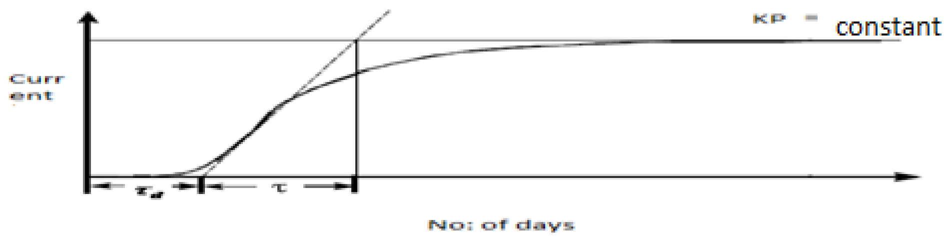


Figure 3: Process Reaction Curve/S-cure for Tibia fracture model

Real time data recorded at different periods until fracture reunites was used to generate the model using MATLAB software. The FOPDT model is given in equation 2.

$$G(s) = \frac{-30e^{-8.69s}}{0.12s+1} \tag{2}$$

Where model parameters are process gain (Kp) =-30, time constant (τ) = 0.115385, time delay (τ_d) = 8.69231.The FOPDT model output response of the tibia fracture is shown in Figure 4. The frequency response characteristics are shown in Figure 5 and it was inferred from phase characteristics that the system is unstable. The error analysis was performed for the above model which is shown in Figure 6 and it was observed that measured and predicted data were identical up to a certain period of time but deviated largely in certain regions(unable to predict the constant region). Irregularities are present in phase shift characteristics of the system.

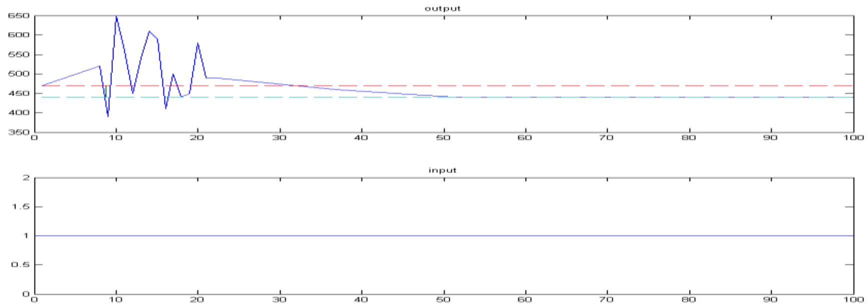


Figure 4: FOPDT Model Output Response for tibia fracture

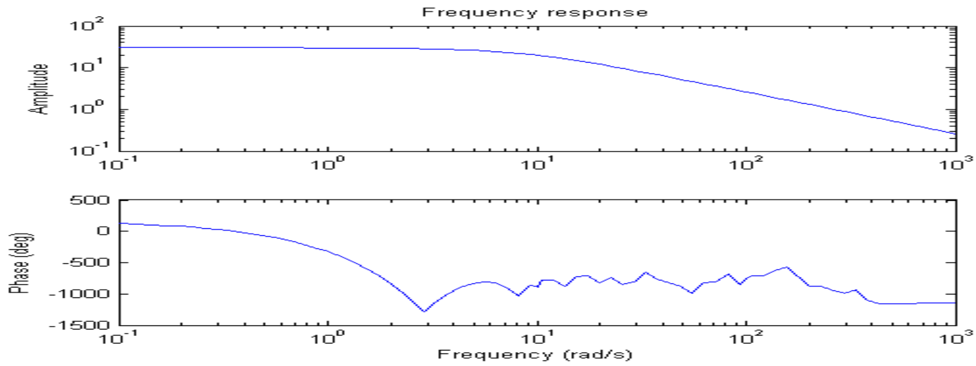


Figure 5: Frequency response characteristics for tibia fracture (FOPDT) modeled via S-Curve

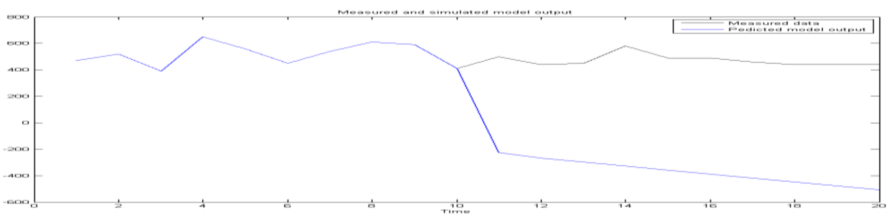


Figure 6: Comparison of Measured and Predicted output characteristics for Tibia Fracture (FOPDT) modeled via S-Curve

However when the FOPDT model output was compared with experimental output it was observed that the Average Performance Error (APE) was high indicating that Zero cannot be neglected in the tibia fracture modeling as current has to become constant indicating the healing period.

FOPDTZ Model

To improve the stability of the FOPDT model obtained in equation (9) Zero was introduced into the numerator of the model and FOPDTZ (First Order plus Dead Time

Zero) model was obtained, using process model estimation[14] in MATLAB with FOPDT model parameters as initial parameters as shown in equation (3)

$$G(s) = \frac{-3233.3(1-244.8s)e^{-30s}}{1+13846s} \tag{3}$$

where model parameters are Process gain (Kp)= -3233, Time constant(τ)= 13846, Time delay

(τ_d)= 30.The error analysis was performed for the above model which was shown in Figure 7. It was observed that measured and predicted data were identical and the Average Percentage Error(APE) is Zero. The system is able to predict the constant region due to introduction of Zero in model. The Frequency response characteristics are shown in Figure 8 and it was inferred from phase characteristics that there is no irregular phase shifts.

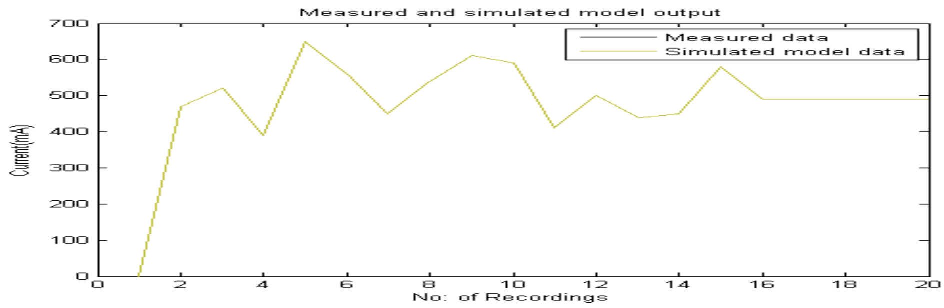


Figure 7: Comparison of Measured and Predicted output characteristics for Tibia Fracture (FOPDTZ) modeled after introduction of Zero

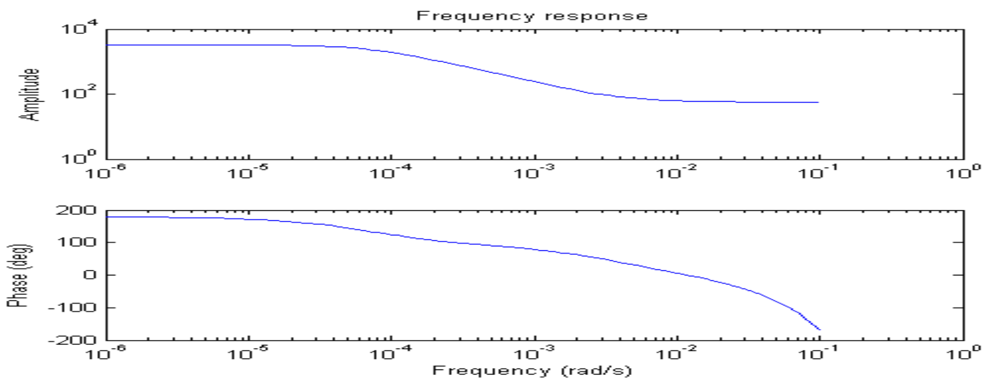


Figure 8: Frequency response characteristics for Tibia Fracture (FOPDTZ) modeled after introduction of Zero

When the model was validated it was observed that the Average Performance Error (APE) was minimum.

Higher Order Model

Assuming fracture to be highly nonlinear, we tried to fit our data to higher order model. An attempt to fit tibia fracture to higher order model considering fracture to be highly nonlinear was made. It was observed that Average Performance error was very high. It was observed that the process gain (Kp) became positive. The model obtained is represented in equation (4)

$$G(s)=\frac{306.27(1-1288s)e^{-19s}}{(1+(0.049s)+0.49s^2)(1+0.001s)} \qquad (4)$$

The error analysis performed as shown in Figure 9 inferred that experimental and modeled data error (APE) deviated by factor 10.

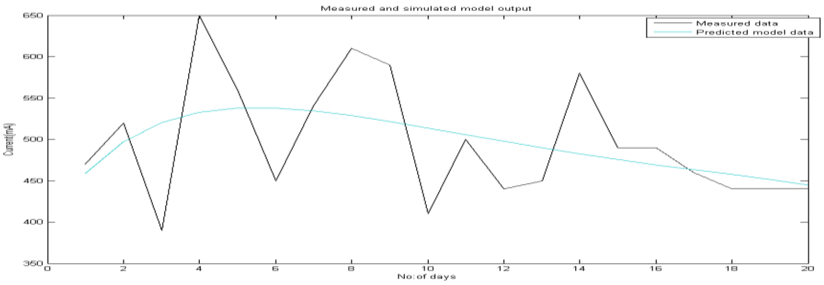


Figure 9: Comparison of Measured and Predicted output characteristics for Tibia Fracture modeled as higher order system

Based on the error analysis we can confirm that tibia fracture best fits experimentally into FOPDTZ model.

Neural Network Modeling For Tibia Fracture Healing Process

A three layered feed forward neural network model trained using Levenberg-Marquett (LM) Back propagation algorithm with 2 neurons in input layer 20 neurons in hidden layer and two output neurons as shown in figure 10 was used to predict the fracture healing. The back propagation algorithm updates the network weights and bias values to decrease the square sum of the difference (SSE) between the desired output (td) and an output values computed by the net (yd) using gradient decent method which is given in the following

SSE =1/2 N ∑ (td- yd) 2 (1)

where N represents the number of experimental data points used for the training. The steps involved in Back propagation algorithm are as follows:

1. The training data is presented to the input layer of the network.
2. The actual and desired output are compared .
3. The error in each neuron is calculated.
4. The output for each neuron is obtained
5. The weights are updated to minimize the error.

The neural model network process consists of three operational steps: prediction, correction and control move determination. The real time experimental data recorded across fracture limb was used to train the network. In this work the current recorded during various time intervals (days) was the output and input variable respectively. A sampling time of 10 seconds was used for the simulation. A total of 2000 data were taken continuously and it was saved in file. By training the input output data the NN model of the non-linear process was obtained. The back propagation algorithm was used for training the recurrent network. For the network training and validation, the LM back propagation algorithm being known for fast convergence was used. The convergence criterion was selected as 10-3, and this was achieved in between 18and 65 epochs for various groups of patients. The neural network output is shown in the figure3. From the Figure 11 it was observed that neural network was not able to track the sudden nonlinear variations present at the input data. The validation of data was given in Table1.

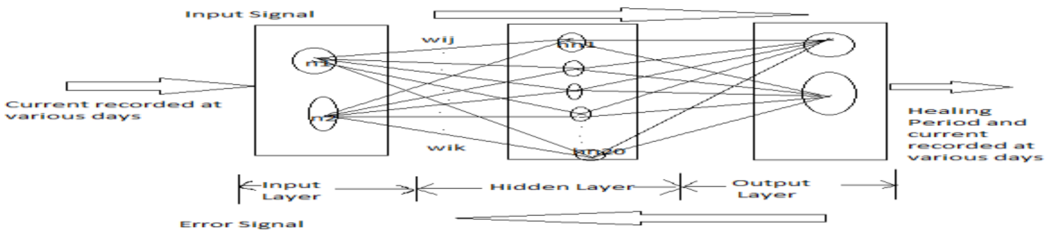
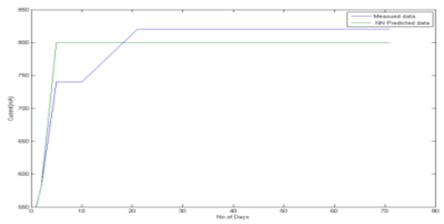
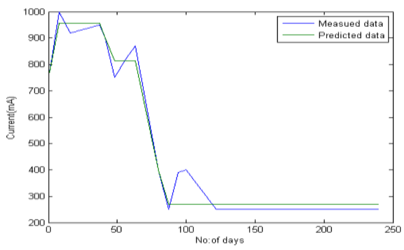


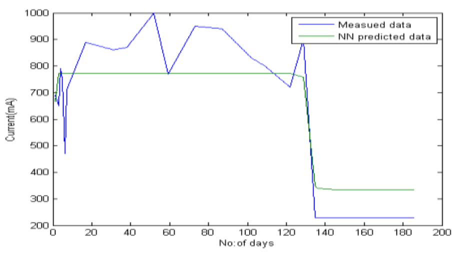
Figure 10: Multilayer Feed Forward Neural Network Using Back Propagation



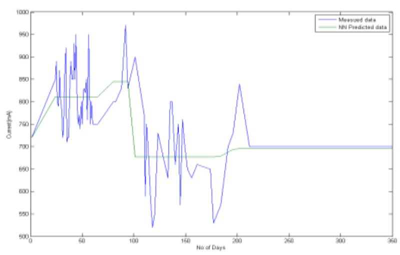
Case-1



Case-2



Case- 3



Case -4

Figure 11: Neural Network Predicted Output responses for the four tibia fracture cases

Results and Discussion

From the Table 1 it is observed the Average Percentage Error(APE) is zero and in the range 0.2 to 0.1 for the healing days predicted using FOPDTZ model and for higher order model respectively .The large variation of APE from 25 to 6 is found in FOPDT model .

From the Table 2 it is observed that neural network predicted output matches exactly with the experimental output for case-3 i.e the patient presented after long delay.

For rest of the cases there is a deviation in the prediction. The relative absolute error varies from 3.5 to 0.2 as observed from table 3 .

From the error analysis it is inferred that FOPTZ model predicts the fracture healing more accurately than the other empirical model .Neural network model is not able to track the variations in the output. This limitation of neural network can be overcome by adding knowledge reasoning i.e by developing neuro fuzzy model which will the scope of future work.

Table 1: Validation of Empirical Model output

S. No	Patient	Process Model	Order	Pole	Zero	Model Parameters					APE (%)
						K_p	τ	τ_1	τ_2	τ_d	
1.	Case-1	$\frac{-30e^{-8.69s}}{0.12s+1}$	First	1	0	-30	0.12	0	0	8.69	7.63
2.		$\frac{-3233.3(1-244.8s)e^{-30s}}{1+.13846s}$	First	1	1	-3233	.13846	0	0	30	0
3.		$\frac{19.5(1-4.5s)}{(1+63.9s)(1+4.5s)(1+4s)}$	Third	3	1	19.5	63.9	4.5	4	0	0.10
4.	Case-2	$\frac{280}{(1+0.3636s)}$	First	1	0	280	0.3636	0	0	0	6
5.		$\frac{-2868(1+6e^{5}s)e^{-29s}}{1+0.003s}$	First	1	1	-2868	0.003	0	0	29	0
6.	Case-3	$\frac{230}{0.33s+1}$	First	1	0	230	033	0	0	0	25
7.		$\frac{-3.8e^{12}(1+4.2e^{8})e^{-30s}}{(1+16.4s)}$	First	1	1	-3.8e^{12}	16.4	0	0	-30	0
8.	Case4	$\frac{-560e^{-14.1s}}{4.308s+1}$	First	1	0	-560	4.3	0	0	0	8
9.		$\frac{-5.8e^{6}(1+2.6)e^{-30s}}{(1+17e^{6}s)}$	First	1	1	-5.8 e^{6}	$17e^{6}$	0	0	30	0.2

Table 2: Comparison of ANN Healing Prediction with Actual Healing

S. No	Case	X-Ray Healing indication in days	Experimental Output (Healing indication) in days	ANN Output (Healing indication) in days
1.	Case1	18	18	4
2.	Case2	135	135	95
3.	Case3	139	139	139
4.	Case4	220	220	195

Table 3: Validation of Neural Network Output

S. No	Case	Experimental Output (Healing indication) in days	ANN Output (Healing indication) in days	Absolute Error	Relative Absolute Error
1.	Case1	18	4	14	3.5
2.	Case2	135	95	40	0.5
3.	Case3	139	139	0	0
4.	Case4	220	195	25	0.12

Conclusion
Comparison of fracture healing period diagnosed using empirical models like FOPDT (First order plus dead time), FOPDTZ (First order plus dead time and Zero) and higher order model and Neural Network were performed. FOPDTZ model and neural network back propagation training algorithm was able to predict the fracture reunion prediction with minimum error.

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