



## ESTIMATION OF AE PARAMETERS FOR MONITORING SPINDLE BEARING IN A DRILLING MACHINE USING MULTIPLE REGRESSION AND GMDH

\*G. V. Naveen Prakash<sup>1</sup> and H. V. Ravindra<sup>2</sup>

<sup>1</sup>Department of Mechanical Engineering, Vidyavardhaka College of Engineering, Mysore – 570 002, India

<sup>2</sup>Department of Mechanical Engineering, P. E. S. College of Engineering, Mandya – 571 401, India

### ABSTRACT

Among various methods of condition monitoring, Acoustic Emission monitoring is a better method for the early detection of failure. Defects that can occur in bearings should be detected as early as possible to avoid fatal breakdowns of the machines to which they are so critical. Present work involves studying the variation of AE signals acquired from spindle bearing housing of a Drilling machine for various cutting conditions. Simple functional relationships between the parameters were plotted to arrive at possible information on bearing condition. But these simpler methods of analysis did not provide any information about the status of the bearing. Thus, there is a requirement for more sophisticated methods that are capable of integrating information from multiple sensors. Hence, methods like multiple regression analysis and Group Method of Data Handling (GMDH) have been applied for the estimation of AE Counts and AE Energy. From the Experimental data it was observed that as the cutting condition increases there is an increase in the signal level of AE parameters. This is due to increase in load acting on the bearing at higher cutting conditions. Estimates from multiple regression and GMDH were compared and it was observed that, GMDH with regularity criterion gives better results.

**Keywords:** *Acoustic Emission, Drilling Machine, Multiple Regressions*

### 1. Introduction

Maintenance is an important determinant of industrial productivity. A predictive rather than a reactive maintenance policy is desired as the most effective way of reducing costs due to unexpected failure and stoppage of equipment. Condition-based predictive maintenance can be implemented by manufacturing industries to detect faults, troubleshooting and anticipating equipment failure. Successfully implementing a condition monitoring programme allows the machine to operate to its full capacity without having to halt the machine at fixed periods for inspection. [1- 3].

Bearing condition monitoring has been received considerable attention for many years because the majority of problems in rotating machines are caused by faulty bearings. The classical failure mode of rolling element bearings is localized defects, in which a sizable piece of the contact surface is dislodged during operation. This is usually due to fatigue cracking in the bearing under cyclic contact stressing. Thus, failure alarms for a rolling element bearing are often based on the detection of the onset of localized defects.

Among various methods of condition monitoring Acoustic Emission monitoring is a better method for the early detection of failure. Acoustic emissions (AE) is the phenomenon of transient elastic wave generation due to a rapid release of strain energy caused by a structural alteration in a solid material under mechanical or thermal stresses. Generation and propagation of cracks, growth of twins etc associated with plastic deformation is among the primary sources of AE. Hence it is an important tool for condition monitoring through non-destructive testing. [4, 5] AE instrumentation consists of a transducer, mostly of the piezoelectric type, a preamplifier and a signal-processing unit. The transducers, which have very high natural frequency, have a resonant-type response. Using a suitable filter in the preamplifier can control AE signal bandwidth. The commonly measured AE parameters are counts, events, RMS, Energy, Signal Strength, peak amplitude etc., of the signal. Counts involve number of times the signal amplitude exceeds a preset voltage level in a given time and gives a simple number characteristic of the signal. An event consists of a group of counts and signifies a transient wave. RMS is an electrical engineering power term defined as the rectified, time averaged AE signal, measured on a linear scale and

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\*Corresponding Author - E- mail: [npgvi@yahoo.co.in](mailto:npgvi@yahoo.co.in)

reported in milli-volts. It is a measure of signal intensity. Energy is derived from the integral of the rectified voltage signal over the duration of the AE hit. The unit of measured energy parameter is 10 $\mu$  volt-sec/count. Signal strength is defined as the integral of the rectified voltage signal over the duration of the AE waveform packet. The unit of measured signal strength parameter is 3.05 Picovolt-sec. This feature is similar to energy except that is calculated over entire AE.

The advantage of Acoustic emission monitoring over vibration monitoring is that the AE monitoring can detect the growth of subsurface cracks whereas the vibration monitoring can detect defects only when they appear on the surface. [6, 7]. Several studies has been conducted to investigate the AE response of defective bearings in Test Rigs. [8, 9, 10].

Drilling machine tool is one of the most versatile machine tool used in manufacturing industries. The quality of the finished products depends mainly on the stability and rigidity of different machine components of a drilling machine tool. The present work involves study of variation of AE signals acquired from spindle bearing housing of the drilling machine tool for various cutting conditions. Simple functional relationships between the parameters were plotted to arrive at possible information on bearing condition. But these simpler methods of analysis did not provide any information about the status of the bearing. Thus, there is a requirement for more sophisticated methods that are capable of integrating information from multiple sensors. Hence, methods like multiple regression analysis and GMDH has been applied for the estimation of AE Counts and AE Energy.

### 1.1 Multiple regression analysis

The objective of multiple regression analysis is to construct a model that explains as much as possible, the variability in a dependent variable, using several independent variables. The model fit is usually a linear model, though sometimes non linear models such as log-linear models are also constructed. When the model constructed is a linear model, the population regression equation is,

$$Y_i = \alpha + \beta_1 X_{1i} + \dots + \beta_m X_{mi} + e_i \quad (1)$$

Where  $Y_i$  is the dependent variable and  $X_{1i}, \dots, X_{mi}$  are the independent variables for  $i$ th data point and  $e_i$  is the error term. Error term is assumed to have zero mean. This error term is the combined effect of variables that are not considered explicitly in the equation, but have an effect on the dependent variable. The co-efficients  $\alpha, \beta_1, \dots, \beta_m$  are not known and estimates of these values, designated

as  $a, b_1, \dots, b_m$  have to be determined from the sampled data. [11]

### 1.2 Group method of data handling (GMDH)

The GMDH is a heuristic self-organizing modeling method introduced by Russian cyberneticist, A. G. Ivakhnenko. The algorithm is ideal for complex, unstructured systems and useful in solving the problem of modeling multi-input to single-output data. The approach here is to fit a high degree polynomial using a multilayered network like structure. Each element in the network is a partial polynomial (a quadratic function) of two inputs. The co-efficient of the quadratic functions are determined data from the training set. All the combinations of inputs, taken two at a time, are evaluated. The combinations that are allowed to pass to the next layer and self-organizing is terminated when optimum complexity is reached, by evaluation of a criterion function from data in the checking set.

Three different criterion functions – Regularity, Unbiased and Combined criteria are available in the GMDH. Regularity criterion has good predictive power but it is sensitive to noise. Unbiased criterion selects models that are insensitive to data from which it is built and hence gives good noise immunity but may not have good predictive power. Combined criterion is a combination of Regularity and Unbiased criteria. [12, 13].

## 2. Experimental Setup

The experimental work consisted of drilling S.G cast iron block using high-speed steel drill bit. The diameter of the drill bit used was 10 mm. The thickness of the work-piece used was 100 mm. The machining was carried out in automatic drilling machine tool. Fig. 1 shows main drive assembly of the drilling machine tool along with the location of spindle bearings. The experiments were conducted for various cutting conditions. AE parameters viz., RMS, Energy, Signal Strength, Counts, Amplitude, Average signal level, Rise Time, Average frequency, etc., were measured using AE measuring system from the spindle bearing housing. The AE measuring system consists of an AE sensor of operating frequency 100 – 1000 KHz. The output from the sensor was amplified by using 2/4/6 pre amplifier. Various filters were used to isolate the AE signals from the noise. The filtered signals were acquired to computer through PCI-2 AE System. Vibration readings were recorded using Machine Condition Tester T 30. Machining was stopped at regular intervals and average flank wear was measured using Tool Maker's Microscope. Drill bit was considered as worn out when the average tool flank wear width exceeded the limit of 0.3 mm.

Before acquiring AE signal, first step is to fix the threshold level. This preset voltage level helps in avoiding the noise signals getting along with the AE signals. Experimental trials were conducted in non-cutting condition and the noise level was fixed to 40 dB. Later on AE signals were acquired during drilling.

Estimation of AE Counts and AE Energy has been carried out by using sophisticated methods of signal analysis like Multiple Regression Analysis and Group Method of Data Handling (GMDH). These methods have been explored for their capability to integrate information from different sensors. For estimation, parameters considered are drilling time, cutting speed, feed, vibration velocity, AE RMS, AE Signal Strength, AE Energy, AE Counts and flank wear (average). In GMDH all the three criteria are considered for estimation. Different GMDH estimates were obtained for different percentage of data in the training set viz., 50%, 62.5% and 75%, with different criteria used for guiding the self-organization procedure.

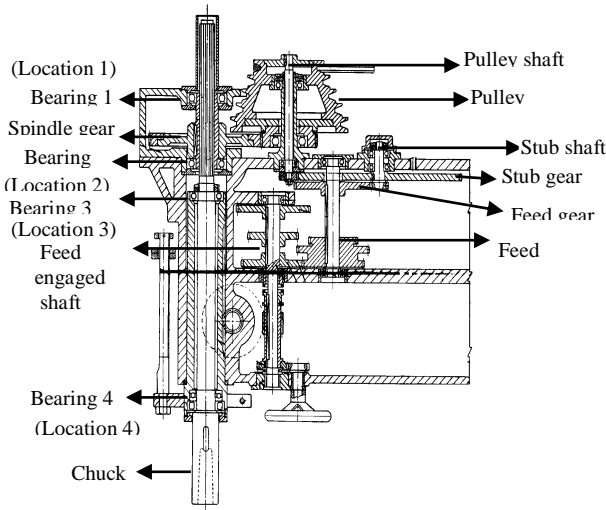


Fig. 1 Main Drive Assembly with Location of Spindle Bearings

### 3. Result and Discussion

Experimental and theoretical analysis results are presented in this section, so that a clear insight can be obtained about the signals involved. Functional relationship between the parameters obtained have been plotted to derive a basis for more detailed analysis.

Fig. 2 gives the vibration velocity in mm/sec from four spindle bearing locations at cutting speed of 21.36 m/min and feed 0.285 mm/rev. From the figure it was observed that vibration velocity at bearing 1 (B1) is more compared to other bearings. Also, same trend was observed for other cutting conditions. This may be due

to bearing 1 nearer to the source of transmission of motion. Hence, further studies are concentrated on first bearing housing.

Fig. 3 gives measured AE RMS with drilling time at cutting speed of 11.309 m/min for various feed viz., 0.095 mm/rev, 0.190 mm/rev and 0.285 mm/rev. AE RMS in the above graph can be divided into three stages. In the first stage i.e., at the initial period of drilling the signal increases sharply. During the initial period of drilling more loads will act on the bearing.

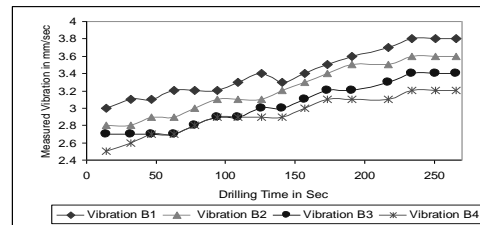


Fig. 2 Vibration from Spindle Bearing Housings at Cutting Speed of 21.36 m/min and Feed 0.285 mm/rev

This is because at the initial stage there will be run-in wear of the drill bit and produce more load, which is finally transmitted to spindle bearing. The signal reduces and becomes constant during the second stage. At this stage, there will be constant load on the bearing as the drill bit experiences steady wear. With further drilling, increase in the signal values takes place in the third stage. This is because of more load acting on the bearing which is due to rapid wear of the drill bit.

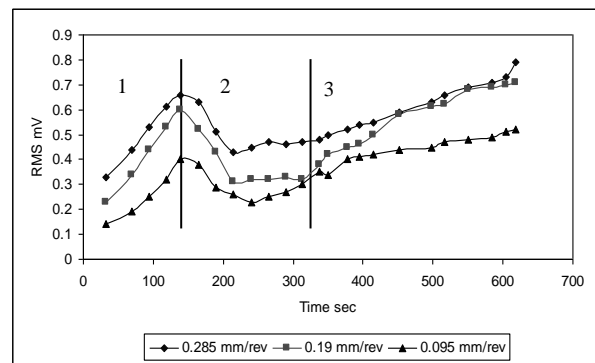


Fig. 3 AE RMS with Drilling Time at Cutting Speed of 11.309 m/min

Fig. 4 shows the measured AE counts with drilling time at feed of 0.285 mm/rev for various cutting speed. From the figure it is observed that during initial period of drilling the count reduces. In the first stage

since their will be more load on the bearing, it causes liberation of high strength AE signal. Thus, there will be high amplitude of signals resulting in less number of counts. During second stage, counts increases and becomes constant. Here the load on the bearing will be constant which gives rise to more number of counts due to less amplitude of signals. More loads will be acting on the bearing in the third stage, which again results in high strength AE signal. Hence, there will be high amplitude of signals resulting in less number of counts. Thus, AE Counts reduces.

It can also be observed from Fig. 3 and 4 that as the cutting conditions increases there is an increase in the signal level of AE parameters. This is due to increase in load acting on the bearing at higher cutting conditions. AE parameters viz., Energy and Signal Strength followed the trend of AE RMS. But the other AE parameters viz., Average Signal Level, Rise Time, Amplitude and Average Frequency, did not correlate well with the variation of load on the bearing during drilling.

Fig. 5 and Fig. 6 show Power Spectral Density plots of AE signal from the spindle bearing 1 location for sharp state and worn-out state of the drill bit respectively. From the figures it is observed that more number of frequency components dominates at the later stage of drilling. As the tool wears out, more power is required for drilling. This causes excitation of other machine elements and increases in the load acting on the bearing.

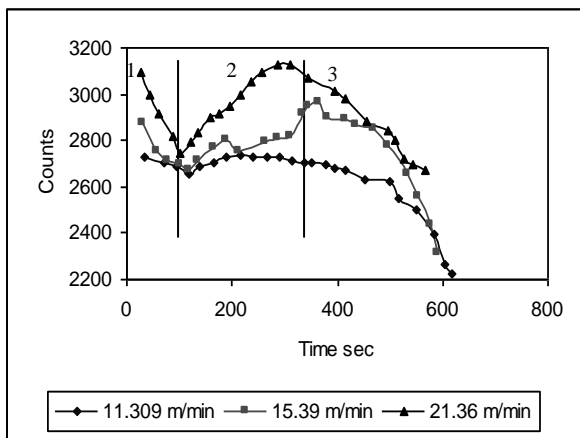


Fig. 4 AE Counts at Feed of 0.285 mm/rev

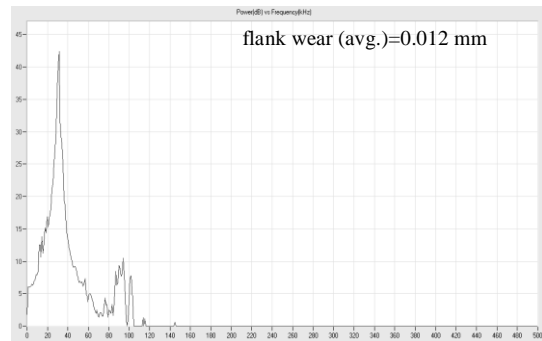


Fig. 5 Power Spectral Density Plot of AE Signal from Spindle Bearing 1 for Sharp State of the Drill Bit



Fig. 6 Power Spectral Density Plot of AE Signal from Spindle Bearing 1 for Worn-out State of the Drill Bit

The variations of estimation from multiple regression analysis with drilling time have been studied. Fig. 7 shows multiple regression estimates of AE counts for various feed at a cutting speed of 11.309 m/min. Fig. 8 shows multiple regression estimates of AE Energy for various cutting speed at a feed of 0.285 mm/rev. From the figures it is observed that most of the estimates follow the observed trend of AE Counts and AE Energy. Among the correlations a better estimation is obtained at lower cutting conditions. The same trend was observed for other cutting conditions. At lower cutting conditions, magnitude of the different AE parameters will be less. But as the cutting conditions increases we observe that the signal level spreads out as shown in Fig. 6. This contributes to increase in the magnitude of the different AE parameters. It may be observed that, due to lower magnitude of the parameters, multiple regressions have better correlation at lower cutting conditions.

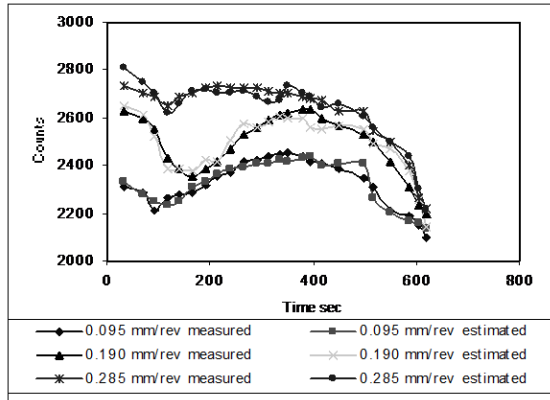


Fig. 7 Regression Analysis Estimates of AE Counts at 11.309 m/min

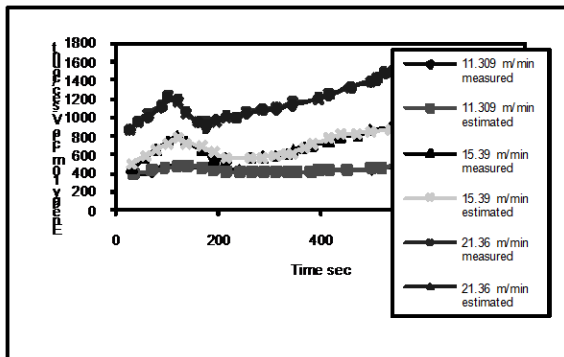


Fig. 8 Regression Analysis Estimates of AE Energy at 0.285 mm/rev

AE Counts and AE Energy estimates are done using GMDH. Different GMDH models were obtained for different criteria viz., regularity, unbiased & combined criteria and for different percentages of data viz., 50%, 62.5% & 75% in the training set. The estimates obtained at different cutting conditions are as explained below.

Fig. 9 shows the GMDH estimates of AE counts for 62.5% of data in training set at cutting speed of 11.309 m/min and feed 0.190 mm/rev for various criteria. Fig. 10 shows the GMDH estimates of AE Energy for 75% of data in training set at cutting speed of 21.36 m/min and feed 0.285 mm/rev for various criteria. Referring to the above graphs it is observed that the AE parameter estimates obtained using regularity criterion correlates well with the measured AE parameters. Whereas unbiased and combined criterions are give poor results. The same results were observed in estimating AE Counts and AE Energy for the other cutting conditions. Also figure shows the disadvantages

of unbiased criterion. Unbiased criterion does not have good predictive power and usually tends to wrongly estimate the variations in the dependent variable. The regularity criterion, which has better predictive ability, works well in the absence of noise. Hence regularity criterion gives better predicted AE parameter estimates.

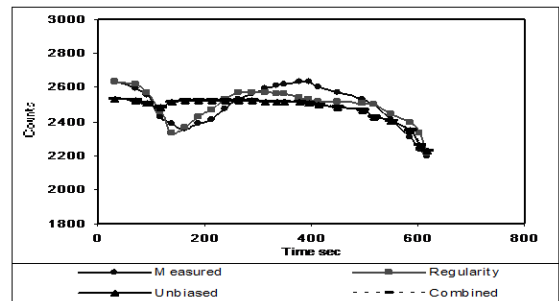


Fig. 9 GMDH Estimates of AE Counts for 62.5% of Data in Training Set

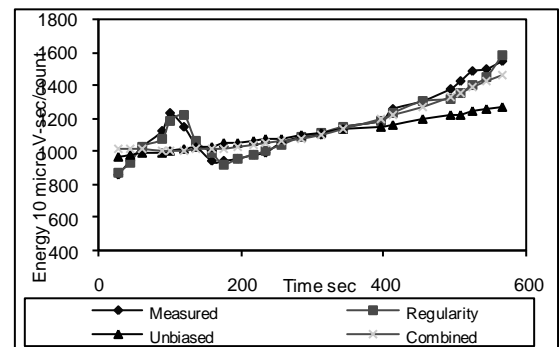


Fig. 10 GMDH Estimates of AE Energy for 75% of Data in Training Set

Fig. 11 shows the GMDH estimates of AE Counts for regularity criteria at cutting speed of 21.36 m/min and feed 0.190 mm/rev for various percentages of data in the training set. Fig. 12 shows the GMDH estimates of AE Energy for regularity criteria at cutting speed of 15.39 m/min and feed 0.095 mm/rev for various percentages of data in the training set. The least error of estimation for AE Counts and AE Energy were 5 counts and 10 micro V-sec /count respectively when 75% of data was used. Hence, best fit is found when 75% of data is used in the training set. The same results were observed in estimating AE Counts and AE Energy for the other cutting conditions. This is because, as the data in the training set is more, the capability of the algorithm to learn and estimate will be more.

Fig. 13 (a), (b) & (c) gives a diagrammatic representation of the GMDH model of regularity, combined and unbiased criterion respectively, for AE Counts estimation considering cutting speed of 21.36 m/min, feed 0.285 mm/rev and 75% of data in the training set. The variables that enter into the final equation and the interactions among the variables can be clearly seen from the figure. It can be observed that regularity criteria of GMDH have considered drilling time and AE Energy as the first set of input variables. In the second set it has considered AE RMS and AE Signal Strength (SS) as the input variables. From these two sets it has been estimated the AE Counts in the second level. Where as for the same conditions combined criterion model has estimated AE Counts in first level by considering AE RMS and AE Signal Strength and unbiased criterion model has estimated the AE Counts considering drilling time and cutting speed in the first level. Since, regularity criterion model has given better prediction, it can be inferred that, the estimation depends on the variables that the model selects and on the level at which it predicts.

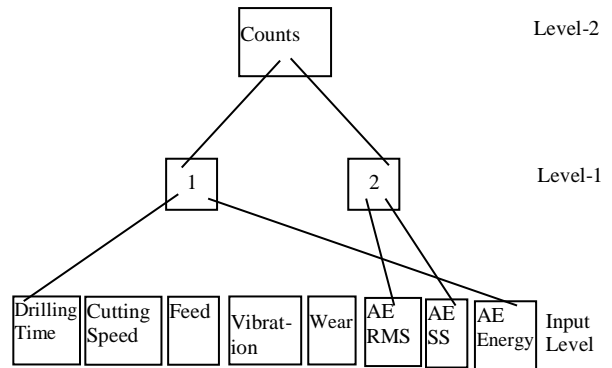


Fig. 13 (a) Regularity Criterion Model for AE Counts

Fig. 14 shows the comparison of GMDH and Multiple Regression estimates of AE Counts at cutting speed of 11.309 m/min and feed 0.285 mm/rev. From the graph, it is observed that good correlation is obtained for estimation from GMDH with regularity criterion. Same result was obtained when estimates were compared for the other cutting conditions.

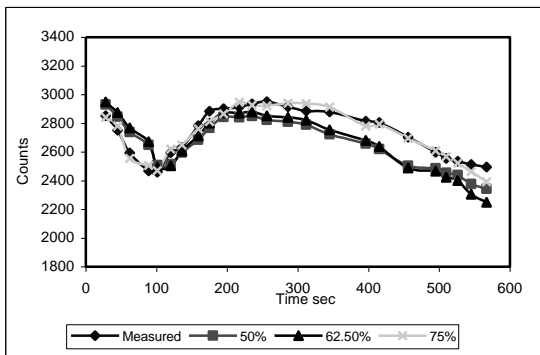


Fig. 11 GMDH Estimates of AE Counts for Regularity Criteria

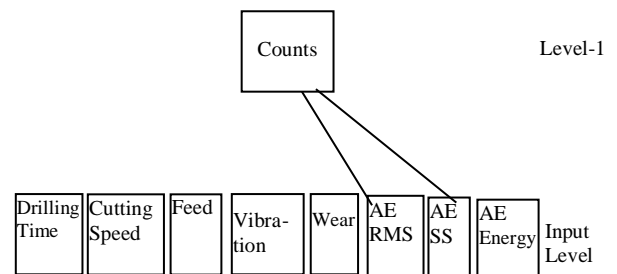


Fig. 13 (b) Combined Criterion Model for AE Counts

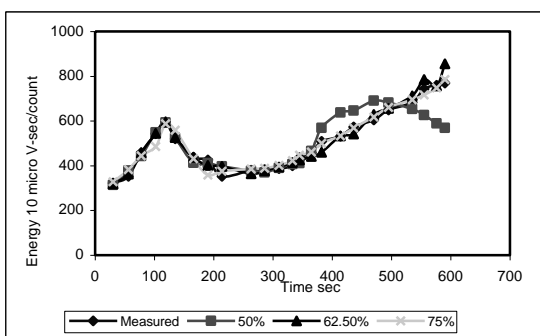


Fig. 12 GMDH Estimates of AE Energy for Regularity Criteria

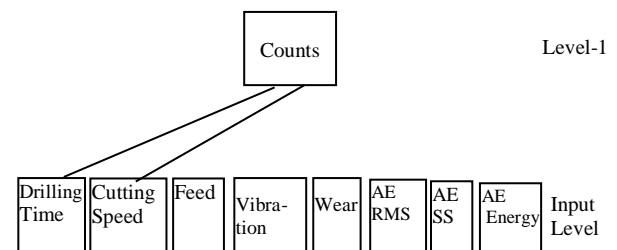
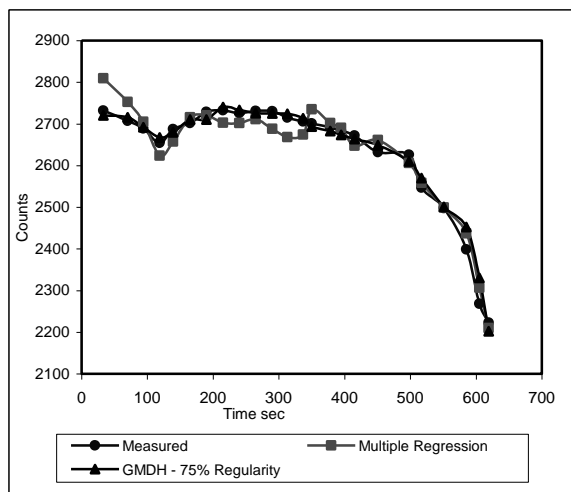


Fig. 13 (c) Unbiased Criterion Model for AE Counts

#### 4. Conclusion

Monitoring was concentrated on the critical spindle bearing of drilling machine tool. From the AE signals obtained, it was observed that the AE parameters viz., RMS, Energy, Signal Strength and Counts varied

in accordance with variation in the load on the bearing. Also it was observed that, there is an increase in the signal level of AE parameters for increase in cutting conditions. This is due to increase in load acting on the bearing at higher cutting conditions. From the Multiple Regression Analysis good correlation of AE Counts and AE Energy was observed at lower cutting conditions. In GMDH, better prediction was obtained for regularity criterion with 75 % of data in the training set. From the comparison of multiple regression analysis with GMDH estimates, it was observed that, GMDH with regularity criterion give better results.



**Fig. 14 Comparison of GMDH and Multiple Regression Estimates of AE Counts**

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