CHAPTER 8
CONCLUSIONS

In this thesis Acoustic Emission and surface roughness signals have been used for tool wear monitoring in face milling operations. Some improved neural network models like RBF neural networks, Resource Allocation Network and GCS networks have been used for tool wear monitoring and the results obtained have been compared with MLP neural networks trained using BP algorithm.

1. Tool wear monitoring is very crucial in any machining operation. The automation and optimization of the machining processes is influenced by the condition of the tool. Tool wear affects product quality, increases machine downtime and sometimes affects the machine tool and personnel. Acoustic emission (AE) is one of the most widely used signals for tool wear monitoring, as the signal is generated by major activities of machining such as plastic deformation, friction between the tool and chip, tool wear / fracture etc. Information from a single signal is not sufficient to monitor the condition of the tool. Hence 'sensor fusion' has been adopted. In this research work, AE and surface roughness data have been acquired by conducting several experiments on three different workpiece materials under different cutting conditions. The AE parameters include Ring down count, rise time, RMS voltage, energy, event duration and mean rise time and $R_a$, $R_t$ or $R_q$, $R_z$ and $R_{max}$ constitute the surface roughness parameters. These parameters along with cutting conditions (c.speed and feed/tooth) have been used to form the data set to train different neural network architectures. Neural networks provide effective tool wear monitoring in machining applications, since they are capable of handling large amount of data.

2. Tool wear monitoring is a complex task, which requires different signals for effectively evaluating the condition of the tool. Signals are acquired at different stages of tool wear. But tool wear is a complex and continuous phenomenon, it is very difficult to acquire all the signals for every small change in the tool condition.
Thus there is a need to have an intelligent system in place, which will be able to provide an estimate of tool wear based on the acquired signals acquired. This is evident from the numerous contributions in the referred journals and conference proceedings. Neural networks have the ability to interpolate very effectively, even when the data is limited and contain noise. It is able to effectively model the underlying distributions in the data and establish the relationship between input and output data. Therefore the research has been focused on developing a compact and optimal neural network architecture, which is able to provide good generalization ability i.e., the ability to recognize unseen patterns or signals and estimate the tool wear and hence monitor the condition of the tool.

3. Multi Layer Perceptron (MLP) trained using Back-Propagation (BP) algorithm is the most widely used neural network for tool wear monitoring. In this research work, MLP has been used for tool wear monitoring and the results obtained have been compared with that obtained from other neural network architectures. The AE and Surface Roughness data for all the three workpiece materials has been converted into three specific formats and the MLP is trained till convergence. This experiment has revealed that MLP performs well when both input and output data patterns are continuous in nature. Investigations have also been carried out on fusing two MLP networks to study their performance. Improved performance has been found with network fusion. Numerous experiments on training and testing MLP with different data types, for different workpiece materials indicate that MLP neural networks can clearly distinguish the tool status efficiently. MLP, though robust and accurate in estimating the tool wear values, requires longer training time and several experiments have to be carried out to determine the optimum number of hidden neurons.

4. RBF neural networks are a new class of Robust neural networks which has a powerful structure for solving pattern classification problems. Their applications to tool condition monitoring has not been fully explored. RBF networks also require fixing the number of RBF units in the hidden layer in the network. The RBF units are characterized by two parameters, a center $x_j$ and width $\sigma_j$. Three learning strategies have been implemented for initializing the centers of RBF units. They are random
selection, batch fuzzy c-means algorithm and gradient descent approach. It has been found that batch fuzzy c-means algorithm generates good architecture, which exhibits good generalization ability. RBF networks do not get trapped into local minima and perform well on seen and unseen data. But these RBF networks also suffer from limitations like fixing the number of hidden units before training. Therefore the research has been focused towards learning algorithms that build the network architecture dynamically during learning.

5. Resource allocation network (RAN) is a variant of RBF neural networks. It is a dynamic learning algorithm that builds the network architecture during learning. This algorithm has been applied to tool wear monitoring. The results indicate RAN learns very fast compared to other neural network architectures. However, it memorizes the data and hence generalizes very poorly. The number of RBF units added is large and is almost equal to the number of input patterns. Although RAN alleviates the problem of fixing the number of RBF units apriori, it often builds large size architectures and exhibits poor generalization with unseen data. Therefore the study focused on learning algorithms, which generate an optimal architecture, by not only adding RBF units based on the novelty in the input data, but also removes those units which do not contribute much to the performance of the network.

6. The growing cell structures (GCS) is a powerful constructive learning algorithm for RBF neural networks. This is an incremental neural network model, which adds and removes RBF units based on certain performance criterion. This network has been found to perform very well on low dimension problems. We have extended it to multi-dimensional problems like tool wear monitoring. The results obtained show that GCS generates compact RBF networks. The algorithm converges fast and its generalization ability is good, being able to classify most of the seen and unseen patterns. It is evident from the results that GCS learn the internal mapping between input and output pattern very well in less number of epochs and generate an optimal architecture during learning. GCS has been found too classify unseen data well.
7. In summary, the investigations in this Research work have explored different neural network architectures for evaluating the status of the tool wear. Off-line data has been taken from AE and Surface roughness signals on different operating conditions and on three different workpiece materials. The data has been carefully selected from the raw experimental data, so as to minimize the training effort. The GCS has been found to perform well for Tool wear Monitoring application in face milling operations, when compared with all other neural network architectures.