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# A NEURAL NETWORK-BASED METHOD FOR GAS TURBINE BLADING FAULT DIAGNOSIS

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## Abstract

In this paper artificial neural networks are used with promising results in a critical, and at the same time, very difficult problem concerning the diagnosis of gas turbine blading faults. Neural network-based fault diagnosis is treated as a pattern recognition problem, based on measurements and feature selection. Emphasis is given to the design of the appropriate neural network architecture and the selection of the appropriate measuring instruments, which are of critical importance for achieving good performance (high success rates and generalization capabilities). Initially the performance of the classical neural network architectures, namely MultiLayer Perceptron (MLP), Learning Vector Quantization (LVQ), Modular MultiLayer Perceptron and Radial Basis Function (RBF), are investigated for this problem. The implemented neural network structures are trained to classify faulty and healthy patterns coming from twelve different measuring instruments. The performance of the above neural network structures is investigated, and the diagnostic capabilities of the measuring instruments are examined. Next, in order to improve the generalization capabilities, which are critical for this specific diagnostic problem, a new multinet architecture is developed, based on the idea of 'majority rule' decision. Compared with the classical architectures, this new multinet architecture is characterized by higher generalization capabilities and robustness. A first approach to the design of the appropriate multinet architecture and the selection of the appropriate measuring instruments, in order to provide the basis of a high-performance automated diagnostic system, is proposed. The conclusions derived are of general interest and applicability.



## Key Words

Fault diagnosis, gas turbines, neural network architectures



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## 1. Introduction

Development of effective gas turbine condition monitoring and fault diagnosis methods has been the target of considerable research in recent years. This is due to the high cost, sensitivity, and importance of these engines for most industrial companies. Most of this research is directed towards the diagnosis of gas turbine blading faults, because of the catastrophic consequences that these faults can have if they are not diagnosed in time. Even minute blading faults can rapidly grow and result in huge destruction [1–3]. Blading faults diagnosis is regarded as very difficult problem, because of the high levels of noise in all relevant measurements and the high interaction between the numerous gas turbine blading rows. Therefore, it is important to take advantage of the processing power of modern computers, in order to provide a fast and reliable engine condition diagnosis from available measurements and to develop the highest possible level of intelligence and assistance to the operation and maintenance personnel.

The gas turbine blading fault diagnosis problem was originally addressed in [4, 5], based on classical pattern recognition methods. In the present paper a (NN) approach is developed for this problem. A number of different neural network architectures are implemented for the classification of faulty and healthy patterns, considering twelve different measuring instruments. The first goal of this work is to evaluate the suitability of the various (NN) network architectures for this important and difficult diagnostic problem. Among the evaluated architectures are included both the classical ones (MLP, LVQ, RBF) and a new multinet architecture based on the idea of the 'majority rule' decision [6]. The second goal is to evaluate the diagnostic abilities of the investigated measuring instruments for NN-based diagnosis. The above evaluations also include the generalizing abilities of the implemented NN architectures, a very important issue that has not been examined in the original approach. The third goal of this work is to suggest a way of selecting the most appropriate NN architectures and measuring instruments in order to provide the basis of an effective automated diagnostic system.

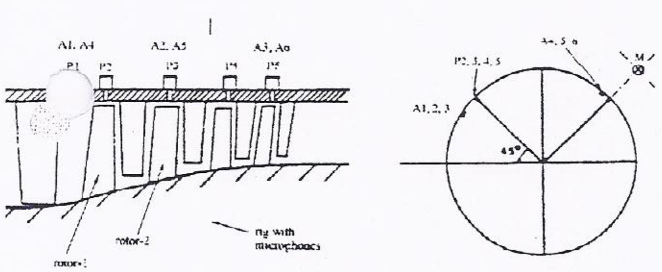
The outline of this paper is as follows: in Section 2, the gas turbine blading fault diagnosis problem is described, as well as the specific faults to be diagnosed and the type of instrumentation and measurements used. In Section 3, the preprocessing of the measurement data is described, from which the corresponding pattern (feature vector) is calculated. In Section 4, the implementation of the NN approach to the blading fault diagnosis problem is lescribed. In Section 5, the application of the classical NN architectures to the gas turbine fault diagnosis problem s presented and the obtained results are evaluated. In Section 6, a new multinet architecture is developed and evaluated. Finally, the conclusions derived from this work are given in Section 7.

## 2. The Gas Turbine Blading Fault Diagnosis Problem

The present work is based on data acquired from dynamic nea ments on an industrial gas turbine into which liff nt faults were artificially introduced [1]. During the experimental phase, four categories of measurements were performed simultaneously:

1. unsteady internal wall pressure (using fast response transducers P2 to P5)
2. casing vibration (using accelerometers A1 to A6 mounted to the outside compressor casing)
3. shaft displacement at compressor bearings (using transducer B)
4. sound pressure levels (using double-layer microphone M)

A schematic of the gas turbine illustrating the arrangement of the measuring instruments is shown in Fig. 1.



igure 1. Arrangement of the measuring instruments.

Five experiments were performed, testing the datum ealthy engine and a similar engine with the following four pical small (but quite rapidly growing, as mentioned in e Introduction), not easily diagnosable faults:

ault-1: rotor fouling
ault-2: individual rotor blade fouling
ault-3: individual rotor blade twisted (by approximately ght degrees.)
ault-4: stator blade restaggering

Tests were performed at four different engine loads ull load, half load, quarter load, and no load), both for e healthy engine as well as for the above four faults. At each load, four series of time-domain data were acquired for each instrument (two series in each of the two sampling frequencies, $l = 13$ kHz and $m = 32$ kHz).

## 3. Preprocessing

Based on the conclusions of [1] and [2], the fault signatures were initially calculated in the form of spectral difference patterns, defined by the following expression:

$$P(f) = 20[\log(sp(f)) - \log(sph(f))] \qquad (1)$$

where $P(f)$ is the spectral difference pattern, which is a function of frequency $f$, $sp(f)$ is the power spectrum of the signal of the measuring instrument from a faulty engine. and $sph(f)$ is the signal spectrum from a healthy engine at the same load, sampling frequency, and measurement series. Also, according to the conclusions of [1] and [2], the most useful diagnostic information is contained at the harmonics of the shaft rotational frequency. This led to filtering out the values of $P(f)$ at frequencies other than the shaft rotational frequency harmonics. The resulting pattern from this filtering, $Pr(f)$, is referred to as the reduced spectral difference pattern (and for simplicity, 'pattern', in the following), and is given by the following equation:

$$Pr(f) = P(f)H(f) \qquad (2)$$

where $H(f) = 1$, if $f$ is a rotational harmonic, and $H(f) = 0$, for all other frequencies. Patterns were calculated for frequencies up to the 27th harmonic of the shaft rotational frequency, that is to say, patterns belong to a 27-dimensional space. An example of the pattern calculation procedure described above is shown in Fig. 2 for power spectra of unsteady pressure transducer P2.

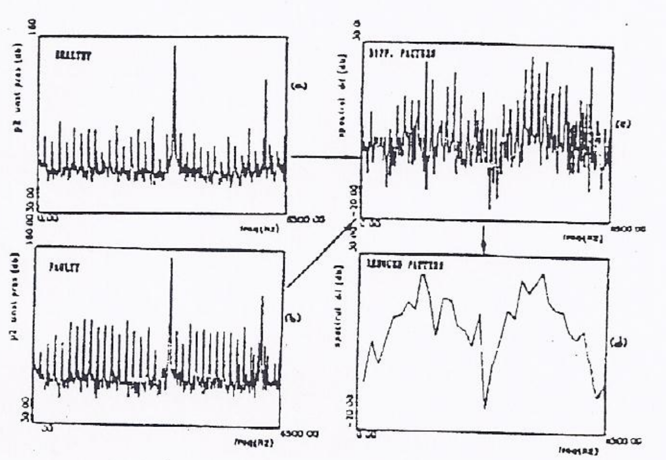


Figure 2. Pattern calculation procedure for power spectra of unsteady pressure transducer P2.

## 4. Implementation of the Neural Network Approach

### 4.1 Characteristics of the Neural Network Architectures

The NN architectures initially selected for the blading fault diagnosis problem (MLP, LVQ, RBF) have different structures and use different training algorithms. They all belong to the family of feedforward neural networks, and also have the same input and output layer dimensions. Input layer dimension $k$ equals the one of the pattern space, that is $k = 27$. Output layer dimension $n_c$, equals the number of pattern classes representing healthy and faulty engine conditions, that is $n_c = 5$. Each network output neuron, when active, corresponds to a specific engine condition. The mapping of pattern classes to output neurons is as shown in Table 1.

Table 1
Mapping of Pattern Classes to Output Neurons

| Output Neuron | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Class | Healthy Engine | Fault-1 | Fault-2 | Fault-3 | Fault-4 |

In the implemented MLP structures, target values for a pattern belonging to the $i$th class, $i = 1, 2, 3, 4, 5$, are set to 0.9 (active) for the $i$th output neuron and to 0.1 (inactive) for all other neurons. Use of upper and lower threshold values was adopted in the interpretation of the continuous MLP network outputs, in order to increase the reliability of the classifications, but at the price of lower success rates. Namely, a pattern is classified to the $i$th class, if the output of the $i$th neuron is greater than $T1 = 0.8$ and all other neurons have activation values below the threshold $T2 = 0.2$. If this is not happening for any of the classes, the pattern is rejected, that is to say, it cannot be reliably classified to any of the classes. This scheme is similar to the $T1\&T2$ rule described in [6] and will be referred to also as $T1\&T2$ in the present work. The $T1\&T2$ scheme adopted for the classification of the input patterns cannot deal with multiple-fault conditions. The situation of simultaneous multiple faults has not been considered in the work presented in this paper, since it is highly unlikely in practice and also no training data were available for such faults.

For reasons of simplicity and uniform interpretation of classification results, target output values for the RBF structures are set to those of the MLP structures. The same holds regarding the use of the $T1\&T2$ classification scheme. LVQ networks have binary output neuron transfer functions. Output values for a pattern classified in the $i$th class, are equal to 1 (active) for the $i$th output neuron and to 0 (inactive) for all other neurons. Therefore, a pattern rejection scheme based on network output values cannot be applied in the case of the LVQ network architecture.

### 4.2 Selection of Training and Test Pattern Sets

In practical situations, where the cost of measurements is high, we are very much interested in the ability of a trained NN to generalize successfully. In order to examine the generalization abilities of the implemented network architectures, the complete pattern set of each instrument was divided in two complementing subsets. The first subset, formed by 63 patterns (7 healthy plus 14 for each fault) selected randomly out of the 72 patterns of the complete set, was used as the training set, while its complement formed by the remaining 9 patterns (1 healthy plus 2 for each fault) was used as the test set for the specific instrument.

## 5. Results of Gas Turbine Fault Diagnosis with Neural Networks

### 5.1 Multilayer Perceptron (MLP) Architecture

For each of the twelve measuring instruments, a three-layered feedforward NN structure was trained to classify patterns by means of a fast backpropagation algorithm with epoch training, momentum, and adaptive learning rate [7–9]. The use of more hidden layers was investigated, but it was found that one hidden layer with dimension $h = 10$ was sufficient for the specific learning tasks. The logistic sigmoid was used as the transfer function for the hidden and output layer neurons, because it was found to give the best results in terms of training speed, compared to the alternatives of hyperbolic tangent for both layers, or a combination of hyperbolic tangent and logistic sigmoid transfer functions. Network weights and biases for both hidden and output layers were initialized randomly from a uniform distribution in the interval $[-0.5, 0.5]$. The training procedure was considered successfully completed when the summed square error between actual and desired network outputs over the training set reached a predefined error goal value. An error goal value of 0.05 has been experimentally found to be satisfactory for the specific learning tasks. A schematic diagram of the MLP architecture is shown in Fig. 3.

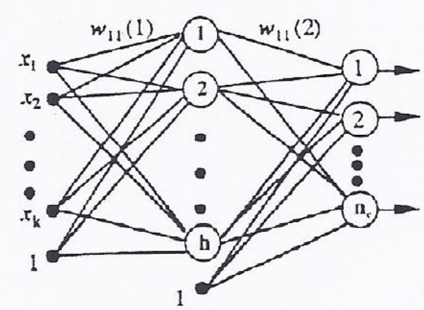



Figure 3. MLP neural network architecture.

The required training times for all implemented structures were in the order of a few minutes. The classification success rates over the training set, the test set, and the complete pattern set for all twelve instruments using the MLP architecture are shown in Fig. 4. It can be seen that

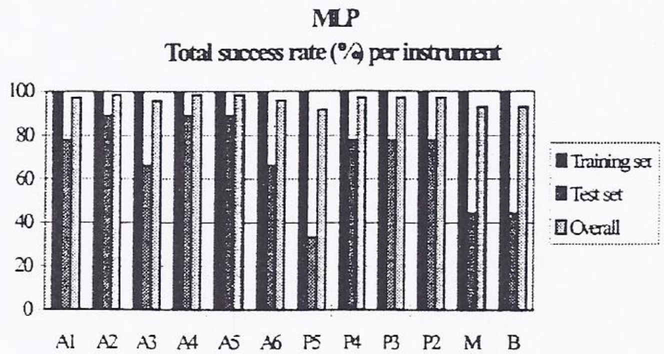



Figure 4. Total classification success rates for the MLP architecture.

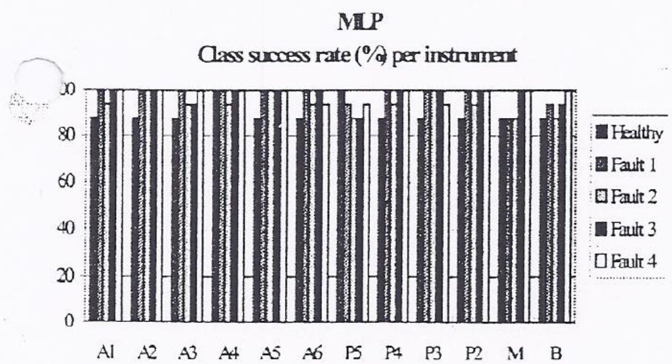



Figure 5. Classification success rates per class for the MLP architecture.

the rates of success over the training set are very high and reach 100% for all instruments. This is not the case when the test set is considered, where success rates are poor, varying from 33.3% for instrument P5 to 88.9% for instruments A2, A4, and A5. Therefore, the generalizing capabilities of this architecture are poor. The overall classification success rates (considering the complete pattern set) vary from 91.7% for instrument P5 to 98.6% for instruments A2, A4, and A5. The classification success rates, obtained over the complete pattern set for the twelve instruments for each of the five different pattern classes, are presented in Fig. 5. These class success rates are a quantitative measure of the diagnostic abilities of each instrument for each fault, when the MLP architecture is used. It can be seen that the healthy class is characterized by the lower success rate in nearly all instruments (except P5), therefore, by using the MLP architecture, there is a high probability of false alarms.

### 5.2 LVQ Architecture

In order to improve the generalizing capabilities, a feed-forward NN structure, trained with the Learning Vector Quantization (LVQ) algorithm [8–9], was implemented for each of the twelve measuring instruments. Network initial weight (class reference) vectors were randomly selected among training set patterns of the corresponding class. The learning rate parameter was set to $\eta(t) = \eta(0) = 0.01$,

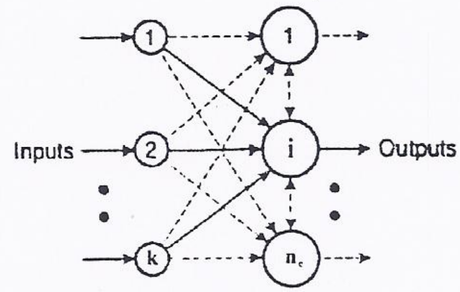



Figure 6. LVQ neural network architecture.

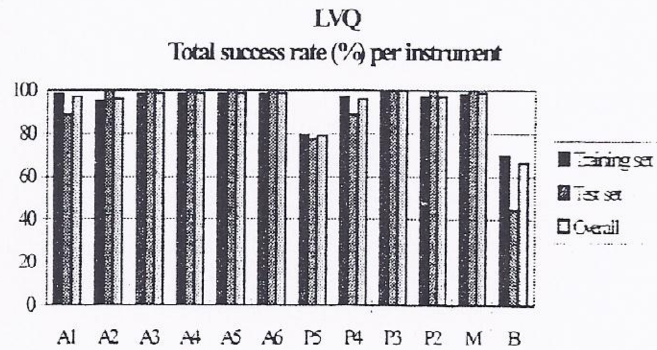



Figure 7. Total classification success rates for the LVQ architecture.

$\forall t$. Training was accomplished by random presentation of patterns up to a maximum number of 5000 presentations. A schematic diagram of the LVQ architecture is shown in Fig. 6.

Training times obtained for this value of the maximum number of presentations were much smaller than in the MLP architecture for all implemented structures (in the order of 100 seconds). The classification success rates over the training set, the test set, and the complete pattern set for the twelve instruments using the above LVQ architecture are shown in Fig. 7. It can be seen that the rates of success over the training set are lower than in the MLP architecture and take values above 95% for all instruments, except P5 and B (with success rate values of 79.4% and 69.8%, respectively). However, the rates of success over the test set are much higher than in the MLP architecture, taking values from 88.9% to 100% for all instruments, except for P5 and B (whose success rates are 77.8% and 44.4%, respectively). Therefore, the generalizing ability of successfully trained LVQ network architectures is much better compared with the MLP architecture, a fact anticipated due to the simplicity of the LVQ architecture. However, the performance of the LVQ architecture in the training set is lower than the performance of the MLP architecture. The overall success rates over the complete pattern set take values above 95% for all instruments, except for P5 and B (whose success rates are 79% and 66.7%, respectively.

The classification success rates obtained over the complete pattern set for the twelve instruments for each of the five different pattern classes are presented in Fig. 8. It can be observed that the success rate achieved for healthy classes, as well as for faulty classes, are in most of the

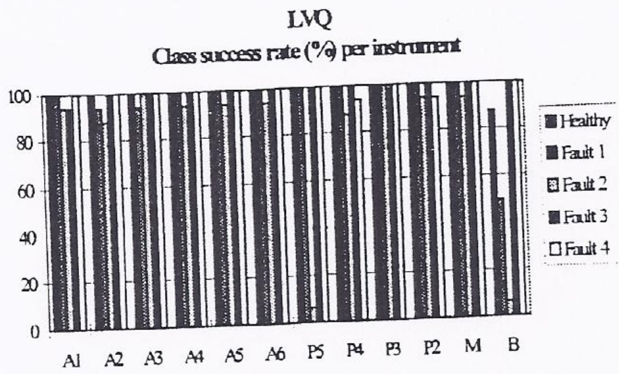



Figure 8. Classification success rates per class for the LVQ architecture.

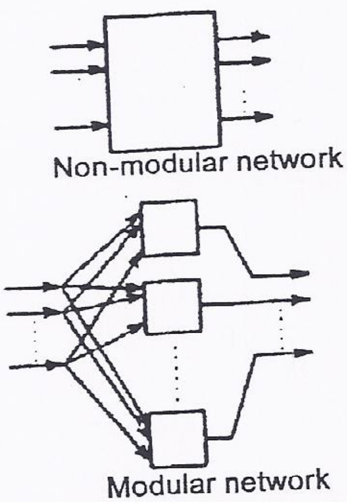



Figure 9. Modular neural network architecture.

cases high. We can see that instrument P5 has a very low success rate in recognizing patterns of Fault-2 (which is not a severe fault), which is responsible for the low overall success rate achieved by this instrument. Also we can see that instrument B has a very low success rate in recognizing Fault-2 patterns, and also Fault-1 patterns (another fault that is not very severe), which is responsible for the low overall success rate achieved by instrument B. The reason for these failures lies in the unsupervised nature of the LVQ training algorithm allowing for self-organization, which may not be successful for the case of less severe faults, even for training set patterns. Therefore, the LVQ architecture is not suitable for diagnosing less severe faults.

### 5.3 Modular MLP Architecture

In order to overcome the problems of the architectures examined in Sections 5.1 and 5.2, a modular NN structure [10], consisting of two individual MLP networks, was implemented for each of the twelve measuring instruments. The first module is a single-output MLP network, trained to distinguish between healthy and faulty patterns, while the second module is trained to classify faulty patterns in the right class. The network structures of these modules (hidden layer dimensions - neuron transfer functions), as well as the initial weights and biases, were selected as described in Section 5.1 for the non-modular MLP architecture. It was found that for both modules, a three-layered structure, with a dimension of $h = 5$ for the hidden layer, was sufficient. Likewise, training was accomplished for each module by means of the aforementioned fast backpropagation algorithm. Error goal values of 0.02 and 0.05 for the first and the second modules, respectively, were experimentally found to be satisfactory. A schematic diagram of the modular MLP architecture is shown in Fig. 9.

Training times were in the order of seconds for all first module structures, as expected from the small network dimensions. For the second module structures, training times were also small, similar to those of the corresponding non-modular MLP structures. The classification success rates over the training set, the test set, and the complete pattern set for the twelve instruments are presented in Fig. 10. We can see that success rate values over the training set are generally high, above 98% for all instruments. Also the success rates over the test set are higher than those of the simple MLP architecture, but lower than those of the LVQ architecture, taking values in the range of 66.7%, for instruments A3, A5, and B, to 100% for instrument A2. Success rates over the complete pattern set are generally good, taking values above 94% for all instruments. The classification success rates obtained over the complete pattern set for the twelve instruments for each of the five different pattern classes are presented in Fig. 11. We can see that with this architecture, we do not encounter the

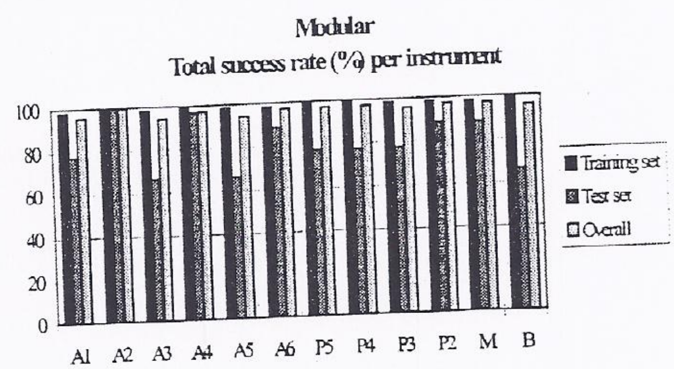



Figure 10. Total classification success rates for the modular architecture.

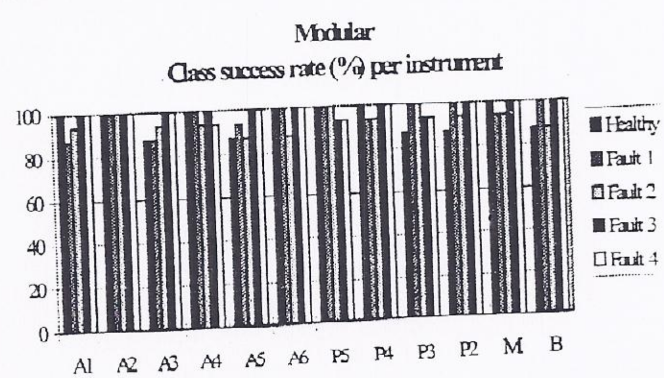



Figure 11. Classification success rates per class for the Modular architecture.

problem of low success rates for instruments P5 and B for the less severe Fault-2, which we had with the LVQ architecture. Therefore, this architecture is much better than LVQ in diagnosing less severe faults.

From the results presented above it can be concluded that the modular MLP approach shows an overall satisfactory performance, offering improved generalization abilities in comparison to the MLP approach (see Figs. 1 and 5). Therefore, the specialization of structures results in a significant improvement of the overall performance.

### 5.4 Radial Basis Function Architecture

A Radial Basis Function (RBF) network architecture [9–11], designed with the Orthogonal Least Squares (OLS) algorithm [12], was also implemented for each measuring instrument. The objective was to examine if, with this architecture, a better performance can be achieved than with the other architectures previously examined in Sections 5.1 to 5.3. Gaussian functions of the form:

$$\varphi_j(\mathbf{x}) = \exp\left(-\frac{\|\mathbf{x}-\mu_j\|^2}{2\sigma_j^2}\right) \tag{3}$$

were added sequentially to the network's hidden layer until an acceptable representation error over the training set was achieved. Their centers $\mu_j$ were selected among the training set patterns. A summed-square error goal value of 0.05 for all implemented structures was adopted experimentally as an acceptable representation index. The values of variance $\sigma_j$ suitable for the specific problem had to be found experimentally by the designer. A value of variance $\sigma_j$ was selected so that the spread (distance between 0.5 cross-overs) of the basis functions was set to 60. The need for such widely spread basis functions can be explained by the need to span the 27-dimensional input space with a relatively small number of available training patterns. A schematic diagram of the RBF architecture is shown in Fig. 12.

The number of basis functions needed to design a network of satisfactory performance ranged from $h = 40$ (for instrument P2) to $h = 58$ (for instruments P4 and P5),

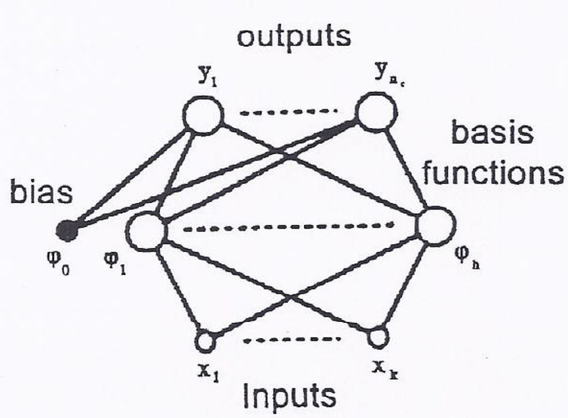



Figure 12. RBF neural network architecture.

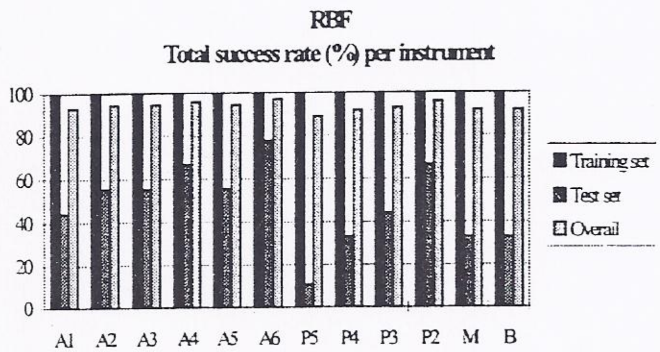



Figure 13. Total classification success rates for the RBF architecture.

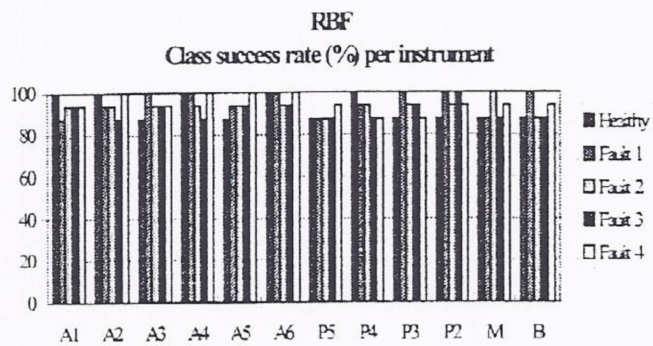



Figure 14. Classification success rates per class for the RBF architecture.

corresponding to training times of 40 and 75 seconds, respectively. The classification success rates obtained over the training, the test, and the complete pattern set for the twelve instruments with the implemented RBF network architectures are shown in Fig. 13. We can see that the rate of success for the training set patterns reaches 100% for all instruments. However, the success rates over the test set are much lower and only exceed 66% for 3 out of the 12 instruments, showing an overall poor generalization performance. A possible reason for this is the inadequacy of the training set population related to the high-dimensional pattern space. RBF networks construct local approximations to nonlinear input-output mapping, and therefore, may not be able to generalize well in regions of the pattern space where no training data are available. The overall classification success rates for the complete pattern set vary from 88.9% (for instrument P5) to 97.2% (for instrument A6). The classification success rates obtained over the complete pattern set for the twelve instruments for the five different pattern classes are presented in Fig. 14.

## 6. Development of a Multinet Architecture for Automated Diagnosis

The basic requirement for an efficient diagnostic system is to provide detailed diagnostic information with the highest possible reliability, with the least possible training (because the measurements required for this training are usually costly) and the highest possible generalization capabilities. In the case of an NN-based diagnostic system, the level of satisfaction of the above requirement for a specific problem depends critically on the selection of the measuring instruments and NN architectures most suitable for this problem.

For the gas turbine blading fault diagnosis problem, which is studied in the present paper, a first step towards the development of an efficient NN-based diagnostic system could be the selection of this particular "measuring instrument/NN architecture" scheme, achieving the highest overall classification success rate over the complete pattern set. From the results obtained in the previous sections, it was observed that the use of an LVQ architecture for instrument P3 or the use of a modular MLP architecture for instrument A2 lead to an overall success rate of 100% (see Figs. 3 and 5, respectively). Between these two schemes, the "A2/modular" scheme should be finally selected, because the external measurement A2 of the casing vibration is much easier and less costly to implement than the internal measurement P3 of the unsteady pressure.

In order to study in more detail the generalization capabilities of the above selected diagnostic scheme, an alternative training procedure was carried out with a smaller training set. In this procedure, the training set was formed by 54 patterns (6 healthy plus 12 for each fault) selected randomly from the complete pattern set, while the remaining 18 patterns (2 healthy plus 4 for each fault) composed

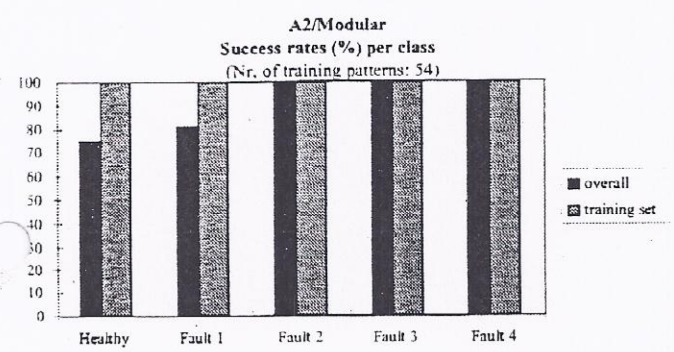



Figure 15. Performance of the "A2/Modular" scheme for a smaller training set.

the test set. Because of this reduction in the training set (54 patterns instead of the initial 63 patterns), the diagnostic task now becomes more difficult.

The classification success rates obtained over the training set and the complete pattern set for the five different pattern classes using the above "A2/modular" scheme are shown in Fig. 15. It can be observed that the classification success rates for healthy and Fault-1 patterns over the complete pattern set decrease significantly and reach 75% and 81%, respectively. This result shows that the reliability of the "A2/modular NN"-based diagnostic system decreases significantly if the training set becomes smaller.

In order to achieve high performance and generalization capabilities with small training sets (which is usually the case in industrial reality), a more flexible approach to the development of an NN-based system for the gas turbine blading fault diagnosis problem (and generally for all highly complex and difficult diagnostic problems) can be adopted, based on the synthetic use of a small number of "measuring instrument/NN architecture" schemes with complementing diagnostic abilities.

The main criteria for the selection of measuring instruments should be the maximization of diagnostic performance and the minimization of the total instrumentation cost (both initial and maintenance cost). This means, practically, that a small number of easy measurements, which are sensitive to the fault we want to diagnose, should be selected. In our specific problem, casing vibration, emitted sound, and shaft displacement at the compressor bearings are measurements easy to implement (the latter being one of the most usual diagnostic measurements in gas turbines), and also, as concluded in the previous sections, sensitive to blading faults. Therefore, accelerometers, microphones, and bearing instruments were selected in order to develop the NN-based diagnostic system.

Concerning the selection of NN architectures, as it was concluded in Section 5, NN architectures trained with supervised learning algorithms (MLP, Modular MLP, RBF) achieve successful classification of training set patterns at rates reaching 100%, while successfully trained LVQ architectures possess very good generalization properties. Also, RBF networks trained with the OLS method are characterized by the easiest and most straightforward design and training procedure among all the examined supervised NN

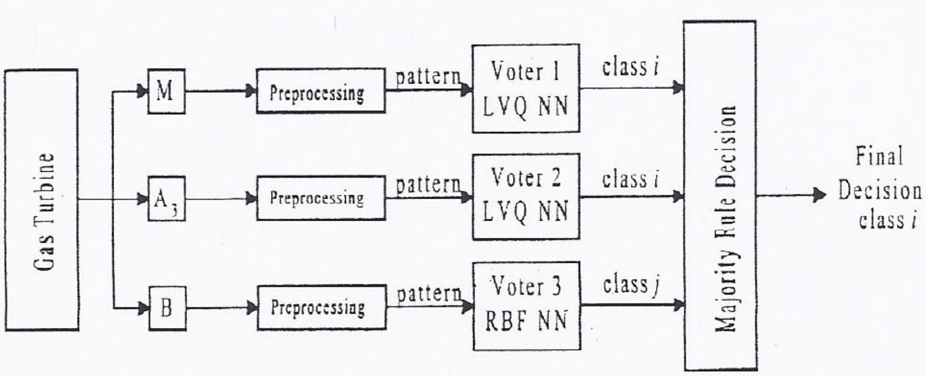



Figure 16. The Multinet architecture.

architectures. Therefore, suitable combinations of LVQ and RBF NN architectures, synthesized in a multinet architecture, are expected to achieve high diagnostic performance and generalization capabilities, offering also the advantage of simpler design and training compared to the classical MLP NN approaches.

There exist a number of possible schemes for the above synthesis of different NN architectures and the design of a multinet architecture. A voting scheme, based on the idea of the 'majority rule' proposed in [6], was developed in order to make the final decision regarding the gas turbine condition, when a number of different architectures-classifiers (voters) are used in parallel. The structure of this multinet architecture is shown in Fig. 16, where three independent NN classifiers, each trained to classify patterns from a specific instrument, are synthesized in a voting scheme. As can also be seen from Fig. 16, according to majority rule, the gas turbine condition is assigned to class $i$ if the majority (at least two) of the classifiers 'vote' for this class, that is to say, classify their input pattern to class $i$.

By examination of the results of the previous sections, it was found that the synthesized use of the schemes "M/LVQ", "A3/LVQ" and "B/RBF", in a multinet architecture based on majority rule, results in 100% success for all classes, when the initial training set of 63 patterns is used. This is shown in Fig. 17, where we can see the classification success rates obtained over the complete pattern set for the five different pattern classes with each of the three classifiers-voters and also with this multinet architecture. Next, the smaller training set of 54 patterns that was previously described for the "A2/Modular" scheme, is used for the training of each of the voters "M/LVQ", "A3/LVQ", and "B/RBF". The classification success rates, obtained over the complete pattern set for the five different pattern classes with each of the three voters and with the multinet architecture, are shown in Fig. 18. Therefore, by decreasing the training set, the performance of the multinet architecture does not decrease (as in the case of the "A2/Modular" scheme), but is maintained at high levels, achieving a success rate of 100% for all classes. Conclusively, the multinet architecture achieves superior performance by successfully synthesizing the independent classifiers-voters, resulting in more reliable classifications.

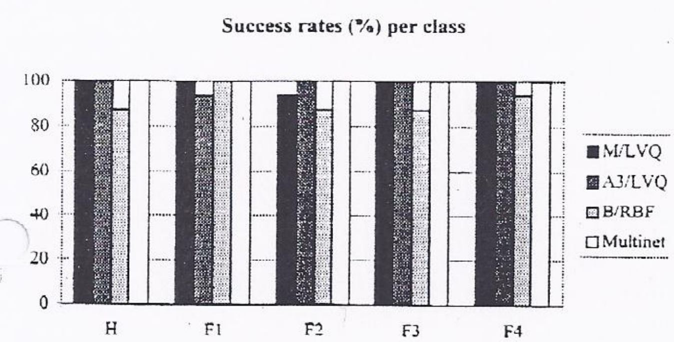



Figure 17. Performance of the three voters and the Multinet classifier.

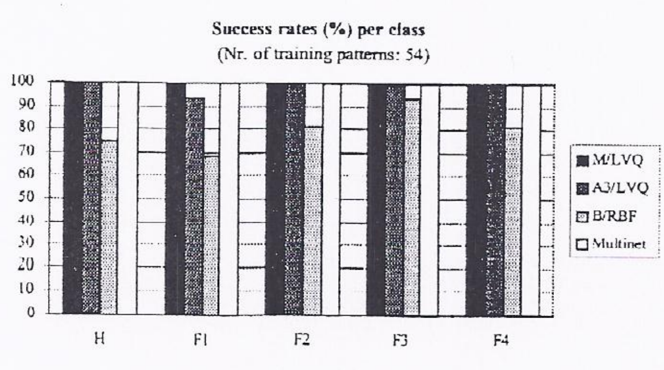



Figure 18. Performance of the three voters and the Multinet classifier for a smaller training set.

From the above it can be concluded that the proposed multinet architecture provides a useful basis for the development of an automated diagnostic system with high performance, reliability, robustness, and generalization capabilities with small training sets. It should also be mentioned that these features are achieved with a small number of easy to implement measurements, a matter of great practical importance in the industrial reality.

## 7. Conclusions

Initially a number of classical neural network architectures have been evaluated for the gas turbine blading fault diagnosis problem, which is regarded to be one of the most critical, and at the same time, difficult diagnostic problems, for 12 measuring instruments and 4 typical blading faults. As criteria for this evaluation, a number of issues, such as structural simplicity, training algorithm effectiveness, and overall performance (success rates and generalization capabilities) were considered.

The MLP architecture relies critically on the experimental selection of a number of design parameters. The success rates of the MLP architecture are found to be satisfactory in the training set, but the generalizing abilities of this architecture are inadequate. The LVQ architecture offers the advantage of a very simple topology. Also because of the absence of a hidden layer and the uniquely defined competitive output layer, there is no need for an experimental network design. The generalizing ability of successfully trained LVQ network structures is found to be very good. On the other hand LVQ, being an algorithm allowing for self-organization, is not successful for less severe faults even for the training set patterns, as it was observed in some cases. The modular MLP architecture shows improved generalization abilities compared to the original MLP architecture. Finally the RBF architecture, trained by the OLS algorithm, offers the advantage of a short design procedure. The success rates of the RBF architecture are satisfactory over the training set, but show an overall poor generalization performance in the high-dimensional pattern space of the present diagnosis problem.

In order to improve the generalization abilities shown by the above classical architectures, a new multinet architecture was developed. As criteria for the design of this multinet architecture, the maximization of diagnostic performance and the minimization of the total instrumentation cost were used. A multinet classifier based on the idea of the 'majority rule' decision was developed, as a combination of two LVQ and one RBF network architectures based on instruments A3, M, and B, respectively. The results obtained using this multinet architecture are very promising, showing that it can provide a useful basis for an automated diagnostic system of high accuracy, reliability, generalization capabilities, and robustness to variations of training data. Further research is needed for the development of a systematic multinet classifiers design methodology, for the selection of the appropriate neural network architectures and measuring instruments to be used as the basis of an automated diagnostic system with desirable characteristics.

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